Predicting Financial Distress in Professional Sports: Are Classical Models Fit for Purpose?

João Matos

Dissertation written under the supervision of Professor Ricardo Reis.

Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, January 2026.

Abstract

Title: Predicting Financial Distress in Professional Sports: Are Classical Models Fit for Purpose?

Author: João Matos

This dissertation evaluates whether the classical financial distress prediction models proposed by Altman (1968) and Ohlson (1980) retain predictive power when applied to sports-industry. Using a cross-sectional dataset for the 2022/2023 season, covering 131 professional sports organizations, including 40 football entities and 91 franchises from the NBA, NFL, and NHL, the study tests the performance of the original models and develops sector-adjusted versions suited to the economics of sports. Results show that the direct application of Altman's Z-score and Ohson's O-score produce severe misclassification patters and are misaligned with the sports industry, showing no practical ability to differentiate between distressed and non-distressed sports organizations. To address this limitation, it was constructed the "Z-sports" and "Ohlson-sports" models, incorporating sector-specific variables and ratios that could increase models' predictive power. Across, public, private, and football-only subsamples, wage pressure, liquidity constraints, broadcasting dependence, and profitability persistence were identified as central drivers of financial fragility in sports organizations. The industry's unique structural characteristics, such as high wage rigidity, volatile sporting-derived revenues, and leverage tolerance, explain why classical models underperform in this context. This dissertation contributes to the literature by demonstrating that distress prediction in sports require sector-specific adjustments and by proposing coherent empirical frameworks that better capture the financial dynamics in sports entities.

Key words: Financial Distress; Sports Finance; Altman Z-score; Ohlson O-score; Z-sports; Ohlson-sports

Resumo

Título: Previsão de dificuldades financeiras no desporto profissional: os modelos clássicos são adequados para o efeito?

Autor: João Matos

Esta dissertação avalia se os modelos clássicos de previsão de dificuldades financeiras propostos por Altman (1968) e Ohlson (1980) mantêm o poder preditivo quando aplicados à indústria do desporto. Utilizando um conjunto de dados referentes à temporada 2022/2023, abrangendo 131 organizações profissionais desportivas, incluindo 40 entidades de futebol e 91 franquias da NBA, NFL e NHL, o estudo testa o desempenho dos modelos originais e desenvolve versões ajustadas ao setor, adequadas à economia do desporto. Os resultados mostram que a aplicação direta do Altman Z-score e do Ohlson O-score produzem padrões de classificação errados e estão desalinhados com a indústria do desporto, não mostrando capacidade prática para diferenciar entre organizações desportivas que estejam em dificuldades ou não. Para resolver esta limitação, foram construídos os modelos "Z-sports" e "Ohlson-sports", incorporando variáveis e rácios específicos do setor que poderiam aumentar o poder preditivo dos modelos. Em subamostras públicas, privadas e exclusivamente de futebol, a pressão salarial, as restrições de liquidez, a dependência da transmissão televisiva e a persistência da rentabilidade foram identificadas como fatores centrais da fragilidade financeira nas organizações desportivas. As características estruturais únicas da indústria, tais como a elevada rigidez salarial, as receitas voláteis consoante a performance desportiva e a tolerância ao endividamento, explicam por que razão os modelos clássicos têm um desempenho inferior neste contexto. Esta dissertação contribui para a literatura ao demonstrar que a previsão de dificuldades financeiras no desporto requer ajustamentos específicos do setor e propondo quadros empíricos que captam melhor a dinâmica financeira das entidades desportivas.

Palavras-chave: Dificuldades financeiras, Finanças desportivas, Altman Z-score; Ohlson O-score; Z-sports; Ohlson-sports

Acknowledgements

I would like to express my deepest gratitude to everyone involved in making the culmination of this phase possible.

Firstly, I would like to thank my family for all the sacrifices they made, for all the support they showed, for demonstrating that there is always a way to keep going even when there is no clear path ahead, and for being the main driving force behind this journey.

Secondly, I want to thank my girlfriend for all the help and support she gave me during these difficult months, for the encouragement given to me during this psychologically challenging journey, for being a comfort, a shoulder to cry on, a light when everything was dark, for motivating me every day, especially for the patience she had with me on the less good days and for always holding my hand throughout this whole time.

I would also like to thank my advisor and professor, Ricardo Reis, for his guidance, availability, and crucial feedback throughout the development of this dissertation. Even when he didn't need to respond, such as on holidays or weekends, he did so without hesitation and helped with whatever was needed and was certainly a motivational support for the completion of this dissertation.

Finally, I would also like to thank Católica Lisbon School of Business & Economics for the academic environment and stimulating education that made this research possible, particularly through the rigorous foundation in finance and empirical methods that supported the execution of this work.

Table of Contents

List of Abbreviations

FFP	Financial Fair-Play
UEFA-FSR	Financial Sustainability Regulations
NBA	National Basketball Association
NFL	National Football League
NHL	National Hockey League
CFCB	Club Financial Control Body
MSGS	Madison Square Garden Sports Corp.

Table of Figures

List of Tables

1.Introduction

Financial distress predicting has long been a central topic in corporate finance, with classic models such as Altman's Z-Score (1968) and Ohlson's O-Score (1980) becoming fundamental tools for assessing solvency and early warning risk. However, the economic structure of professional sports differs significantly from the corporate environment in which these models were developed. Sports entities have evolved from community-based institutions into a complex multinational business, characterised by rapidly growing payroll obligations, volatile revenues streams dependent on competitive performance, heavy reliance on broadcast contracts, a debt structure outside of what is normal for corporate companies, and, in some contexts, flexible budget constraints or revenue-sharing mechanisms. These characteristics raise the question of whether classic models of financial distress retain their predictive power and capture the financial dynamics when applied to the sports industry.

This question raises relevance because sports entities face a unique set of combinations of risk directly related to its sector, such as extreme wage rigidity, strong exposure to performance fluctuations, high financial leverage, and substantial reliance on volatile revenue streams related to competitive performance as well. In recent years, episodes of financial crisis have increased and highlighted the need for a sector-specific understanding of financial fragility, yet academic research applying classical bankruptcy models remains scarce.

To address this gap, this dissertation assesses whether traditional bankruptcy prediction models are transferable to professional sports and, from there, restructures the same models, adapting them to the dynamics of the sector to better reflect the financial structure of this industry. Using a cross-sectional sample of 131 organizations from football, NBA (National Basketball Association), NFL (National Football League), and NHL (National Hockey League) for the 2022/23 season, the study first directly applies the original Altman and Ohlson models without any modifications, then is done a sector-specific recalibration, giving rise to the Z-sports and Ohlson-sports, and finally this recalibration is tested in a global sample, and in a public, private and football-exclusive subsamples.

Therefore, this dissertation would fill this gap in the literature by analysing the following research question:

"To what extent are classical financial distress prediction models applicable and reliable when tested in sports industry, and do sport-specific financial indicators improve their predictive power?"

Thus, this dissertation contributes to the literature in three ways, as it has one of the most extensive data sets across different leagues used in distress research for the sports sector, systematically evaluates the limitations of classical models when applied to this sector, identifying several cases of incorrect structural classification, and finally, proposes new models adapted to sports, Z-Sports and Ohlson-Sports, based on indicators that are more realistic to the sports landscape.

The structure of the dissertation is as follows:

Chapter 2 reviews the literature on corporate financial distress, classical and modern prediction models, and the economics of sports organizations.

Chapter 3 describes the dataset and the methodology, including the construction of all the variables used and distress definitions.

Chapter 4 presents the empirical work and its results for both classical and adapted models

Chapter 5 discusses the findings and comparison with previous literatures.

Chapter 6 outlines the limitations present in this thesis.

Chapter 7 comprehends a final conclusion.

2. Literature Review

2.1 Defining Financial Distress vs Bankruptcy

Research around financial distress is characterized by the disclosure of various methodologies used along the years, with no universal definition, as different approaches by the researchers appeared (Platt & Platt, 2006). Still, an important distinction must be made between Financial Distress and Bankruptcy. Financial distress arises when there is a deterioration or decline in the financial situation such that the organization has difficulties in meeting its contractual obligations (Beaver (1966)) or keeping the well running of its operations, often long before any formal declaration of insolvency. However, later studies moved away from this event-oriented definition and conceptualized financial distress as a process with economic and financial consequences of its own. Opler & Titman (1994) showed that distressed firms lose customers, suppliers, and employees as confidence wanes, while competitors benefit from their weakness. Following the same line, Pindado (2007) extended this study by adding international evidence, highlighting that firms across different legal and institutional systems face higher financing costs, reputational losses, and reduced investment opportunities during distress, regardless of whether they default, confirming Platt & Platt (2006. Pag. 141) verdict "In most cases, bankruptcy occurs subsequent to a period of financial distress". On the other hand, distress does not always end in bankruptcy, bankruptcy is just one possible outcome of distress (Pindado, 2007). Andrade et al. (1998), also shows that companies may sustain substantial costs of financial distress without reaching insolvency, highlighting that distress can persist without ending in legal default. At the same time, financial distress can be a turning point for a company, and the possibility of corrective actions exists. Ashraf et al. (2019) demonstrate that traditional predictions models (Altman Z-score, Ohlson O-score, Zmijewski Probit, Shumway Hazard and Blums D-score) can identify early warning signals of distress, such as deteriorating liquidity, profitability, and leverage ratios, well before bankruptcy. As mentioned before, the early recognition of distress offers managers the opportunity to take preventive and corrective actions to avoid insolvency and to restructure.

Thus, bankruptcy should be seen as a possible result and an ending point of a transitional stage between insolvency and solvency due to a long state of lack of financial capacity, except the cases of unexpected events such as natural disasters, while distress represents the early stage where financial and organizational pressures expand, which can happen for years, before any formal insolvency declaration. This distinction is particularly relevant in professional sports, where many sports entities experience persistent financial imbalances such as recurring operating deficits or unsustainable wage-to-revenue ratios, without formally entering bankruptcy.

2.2 Classical Bankruptcy Prediction Models

Early bankruptcy prediction research reflects this event-oriented tradition, focusing on whether a firm will eventually fail. Although Beaver (1966), recognised that financial ratios carry predictive information about failure and rapidly in the late 20th century the literature on bankruptcy was greatly developed by Altman, Ohlson, Zmijewski and Shumway. Altman (1968) introduced the Z-score model in his seminal contribution, pioneering the use of linear discriminant analysis that combined multiple ratios (profitability, leverage, liquidity, solvency and activity) into a single score that distinguishes bankrupt to non-bankrupt firms. This model demonstrated the potential of multivariate analysis, moving beyond Beaver's univariate tests and becoming the cornerstone of bankruptcy prediction research. However, Altman's original research relies on discriminant analysis restrictive assumptions, such as normality and equal covariance matrices, and it treats failure as a one-shot binary outcome, rather than a dynamic process, with limited time dynamics and potential industry and selection biases. Precisely these limitations motivated the next wave of probabilistic models. Ohlson (1980) introduced the O-score reframing bankruptcy prediction as a logit regression problem, which did not require the Altman's statistical assumptions of discriminant analysis and provided failure probabilities rather than simple classifications. His O-score model improved interpretability and flexibility and underlined that size, leverage and performance ratios consistently predict stress. Zmijewski (1984) advanced this line further by introducing a probit model to correct for sample selection and estimation, more specifically the overrepresentation of bankrupt companies in previous studies. A major step forward in classical Z-score was the Altman's 2000 revision (Altman (2000)), which recalibrated the Z-framework for different populations, most notably the Z' model for private/manufacturing companies and the Z'' for non-manufacturing/emerging markets. Given that many organisations in this thesis are privately held, our emphasis in on Z'. Altman replaces market value of equity with book value of equity in capital structure proxy, appropriately reweighted the ratio coefficients and adapted the Z' cut-offs, preserving the intuitive, ratio-based structure of the Z-score while adapting it to the informational reality of private entities. A more fundamental challenge to static models came from Shumway T. (2001) who introduced a hazard model that explicitly treats bankruptcy as a time-to-event process, updating the probability of default annually and integrating both accounting and market-based variables. Shumway argues that "hazard models are more appropriate for forecasting bankruptcy than the single-period models used previously" (Shumway T., 2001, Abstract) questioning traditional approaches suffer from survivorship and look-ahead biases, since they typically pool data across years without accounting for the timing of bankruptcy. His results showed significantly improved predictive accuracy, highlighting the value of dynamic modeling in capturing the evolving nature of distress.

By gathering this studies it is possible to notice a clear trajectory from univariate ratio tests (Beaver (1966)), to multivariate discriminant scores (Altman, 1968), to probabilistic logit and probit frameworks (Ohlson, 1980; Zmijewski, 1984), and finally to hazard-based approaches that integrate time and market sensitivity (Shumway, 2001). Although each study has contributed to its predecessors, a common limitation remained, these models were developed on large, publicly listed U.S firms (except Altman (2000)) letting questions to answer about their adaptation to other contexts, such as SMEs or sports organizations. This limitation motivates the modern extensions that incorporate alternative data sources and adapt models to sector-specific features.

2.3 Modern Extensions and Machine Learning

To overcome these limitations, more recent research developed extensions and more flexible approaches than the previous ones. Altman & Sabato (2007) focused on answering to the problem raised before, that the models were developed around data only with publicly listed U.S firms. Therefore, they adapted bankruptcy prediction models to SMEs, showing that frameworks designed for large corporations were not so effective in smaller, unlisted firms, which rely more heavily on liquidity and trade credit variables. Following Shumway's (2001) dynamic approach, Campbell et al. (2008) extended the field by combining accounting and market-based variables in a dynamic logit model, improving predictive accuracy and revealing a phenomenon known as the distress risk puzzle, firms with high distress risk earn abnormally low returns in capital markets. Reinforcing this hybrid view, Hernandez Tinoco & Wilson (2013), demonstrated that integrating financial ratios with market-based measures significantly outperforms models based on either source alone, illustrating the forward-looking nature of market information.

The latest step in this evolution has been the incorporation of machine learning techniques. Alaminos et al. (2019) developed a global model for bankruptcy prediction using algorithms such as random forests, support vector machines and multilayer perceptrons, finding that machine learning models significantly outperform traditional approaches by capturing nonlinearities and complex interactions. At the same time, Fuster et al. (2022) analyzed machine learning adoption in credit markets, showing that while predictive efficiency improves, issues of transparency, fairness and bias arise.

Thus, there is clear evolution of bankruptcy prediction research from rigid accounting-based models to dynamic and hybrid approaches. Therefore, prediction models must be adapted both methodologically and contextually, since in professional sports where revenue volatility, regulatory constraints, and financial reporting practices differ sharply from traditional corporations.

2.4 Financial Distress in Sports

The literature on sports finance highlights that sports organizations and leagues face unique vulnerabilities. Deloitte, UEFA and PwC reports consistently document the excessive weight of wages relative to revenues, high indebtedness, and the strong dependence on volatile income streams such as matchday and broadcasting, which is typical of sports clubs. In according with these findings, Andreff & Staudohar (2000) provide a comparative perspective, exposing how the European model of professional sports finance, particularly characterized by promotion and relegation and heavy reliance on volatile revenues, contrasts sharply with American model, where closed leagues, salary caps, and revenue sharing mechanisms act as stabilizers. This structural difference helps explain why European organizations are quietly more expose to financial fragilities than U.S counterparts. Building on this structural vulnerability, Morrow (2013) focuses on governance and transparency, highlighting flaws in football financial reporting, noting that accounting practices often conceal underlying weaknesses, hindering and obscuring the assessment of organizations' true financial situation. Extending these concerns, Plumley et al. (2017), propose a holistic model of performance that integrates sporting and financial sustainability, concluding that unsustainable wage spending remains one of the most consistent predictors of financial distress. More recently, bankruptcy prediction models have begun to be directly applied to the football industry. Alaminos & Fernández (2019) developed a machine learning-based framework to anticipate financial distress in European football organizations, achieving high predictive accuracy and identifying patterns specific to the sector, such as high wage-to-revenue ratios and dependence on broadcasting income. Although limited in scope, this line of research demonstrates the feasibility and necessity of adapting general forecasting methodologies to other contexts, in this case the sports industry, and illustrates how sector-specific variables can improve model performance. Nevertheless, most studies focus on European football, leaving room for other largely unexplored sports such as the NBA, NFL, and NHL. Despite presenting quite different financial and regulatory structures, these contexts provide a fertile ground and highlights the need for cross-sport comparative research that can test whether classical and modern models, when methodological and contextually adapted to the specificities of each sport, maintain their predictive power.

2.5 UEFA Financial Fair-Play

As a bridge between sporting operations and financial outcomes central to this thesis, UEFA's Financial Fair-Play structure provides the institutional mechanism that links squad decisions to balance sheet resilience and, consequently, to the first signs of financial difficulties. UEFA's Club Licensing and Financial Sustainability Regulations (UEFA-FSR (2022)) replaced the former FFP's idea of financial balance with a three-pillar structure of solvency, stability, and cost control, which explicitly links squad management to financial results. The central element is the squad costs rule, which limits the sum of player/coach salaries, transfer amortization, and agent fees as a percentage of adjusted operating revenues, phased in at 90% in 2023/24, 80% in 2024/25, and a permanent maximum limit of 70% from 2025/26 onwards, with violations triggering predefined financial penalties and potential sporting sanctions (as codified in the FSR text and summarized on UEFA's official explanatory pages). For the 2022/23 season studied in this thesis, clubs were in transition from FFP to FSR: solvency/monitoring was maintained while the cost cap was announced and progressively implemented, shaping expectations and behaviour even before the 70% ceiling became binding. Economically, the rule acts as a regulatory buffer against behaviours associated with pre-crisis dynamics, structural wage inflation, and debt-fuelled transfer cycles, forcing simultaneous alignment between squad costs and recurring revenues.

Subsequent clarifications and legislation under the FSR reinforce both the calculation and enforcement. Legal/policy analyses detail the mechanics of the ratio (Oxera (2022); UEFA-Club Finance and Investment Landscape (2024) ; Mobolaji & Andrew (2024)) and the 70% cap in clear terms, while UEFA's benchmarking work situates the rules within the narrative of post-pandemic financial recovery. Recent CFCB (Club Financial Control Body) decisions show credible enforcement, fines, and settlement plans for clubs, including Chelsea and Aston Villa (2025) under the new framework, Roma (2024) for squad cost violations, and new formal notifications from the CFCB confirming sanctions and settlement structures. These actions illustrate the channel through which the FSR can alter cash flows, restrict registrations, and force multi-year spending plans, all of which are relevant to the dynamics of financial distress. Thus, FSR therefore serves as a context, as an observable policy indicator, and also as a control signal allowing us to test whether regulatory pressure accompanies the classic metrics of financial difficulties.

2.6 Research Gap and Contribution

Despite decades of research on bankruptcy prediction and a growing body of work on sports finance, several gaps remain.

First, most studies of financial distress in sports focus mainly on European football (Deloitte; Plumley et al. (2017); Morrow (2013); Alaminos & Fernández (2019)) leaving other professional leagues such as the NBA, NFL, and NHL teams underexplored. Second, although classical models like the Z-Score, O-Score, and hazard models are widely tested in corporate settings, they have rarely been systematically applied to sports organizations, raising questions about their external validity in this unique sector. Third, existing research often emphasizes bankruptcy as the ending point, ignoring prolonged states of financial difficulty that can persist for years, particularly in sports, where external support from owners, leagues, or even governments can delay formal insolvency. This thesis addresses these gaps by applying financial distress models to a sample of sports organizations and franchises across different leagues and sports, adapting these models with sport-specific indicators identified in both academic and industry sources, and finally, evaluating whether these adaptations improve early detection of financial distress comparing to default-based models. In doing so, this thesis contributes to the financial distress literature by testing the transferability and validation of classical models in a new and unexplored industry, while also advancing sports management research by offering potential insights to help stakeholders to monitor and manage financial sustainability.

2.7 Research Question and Hypothesis

Based on the gaps highlighted before, particularly the lack of cross-sport analyses and the limited application of classical and modern financial distress models to sports organizations and franchises, this thesis address the following research question:

"To what extent are classical financial distress prediction models applicable and reliable when tested in sports industry, and do sport-specific financial indicators improve their predictive power?"

The Altman Z-Score (1968) and the Ohlson O-Score (1980) represent the main classical models and major milestones in bankruptcy prediction. They have been broadly validated in corporate settings but have rarely been systematically tested in the context of sports organizations. Although sports entities share fundamental financial characteristics with traditional companies, these characteristics may not be as decisive for this type of organization, however the transferability of these models has not been confirmed.

Hence, the first hypothesis is as follows:

H1: The Altman Z-Score and Ohlson O-Score models are applicable in the sports industry and can predict financial distress among clubs and franchises.

Although the literature on corporate finance and sports management emphasizes that sports organizations are characterized by unique financial dynamics, reports from UEFA, Deloitte, and PwC highlight variables, such as the wage-revenue relationship, dependence on television broadcasting, and attendance volatility as recurring indicators of financial instability. While classical models rely primarily on accounting or market ratios, these sector-specific indicators may provide earlier or more accurate signals of difficulties in sport. Adapting contextually and methodologically established models with these variables therefore has the potential to increase the accuracy of forecasts and capture the idiosyncrasies of the sector.

As a result, the second hypothesis is as follows:

H2: Adapted models that incorporate sport-specific indicators improve the predictive power of financial distress models compared to classical versions.

These hypotheses provide the basis for the empirical analysis that follows, in which the models will be tested and adapted using data from sports organizations across various leagues and different sports.

3. Data and Methodology

3.1 Data Sources and Sample Construction

The dataset covers a representative sample of professional sports organizations for the 2022/23 season, with the organization as the unit of analysis. It comprises first-division football entities from various European and South American leagues, along with North American franchises from the NBA, NFL, and NHL, totaling 131 available organizations. Most North American entities are privately held, as the only publicly traded entity is Madison Square Garden Sports Corp. (MSGS), which consolidates the New York Knicks (NBA) and the New York Rangers (NHL). In addition, the Green Bay Packers (NFL) are unique in their league as a public non-profit organization that publishes audited financial statements. In football, 16 of the 40 entities used in the study, are publicly listed.

Football data were collected primarily from the entities' consolidated annual reports (IFRS or local GAAP) and complemented, for comparability and to fill any disclosure gaps, with UEFA's Club Licensing and Financial Benchmarking reports and the Deloitte Football Money League, and with other academically recognized sources (Swiss Ramble, Sky Sports, Transfermarkt). For North American leagues, the main source is Forbes' franchise dataset, whose current pages have been updated, requiring consultation of archived captures from the Internet Archive (Wayback Machine) to retrieve the versions corresponding to 2022/23. The two public exceptions are handled directly from primary records, SEC filings for MSGS (Form 10-K with segment disclosures) and the Green Bay Packers Annual Report.

The sample retains only organizations with the minimum 2021/2022 and 2022/2023 information to construct the variables required by the Altman and Ohlson models. For football entities, inclusion required a reliable consolidated annual report and for this reason some entities could not join the sample. For the North American leagues, inclusion required that the Forbes (or its Internet Archive capture) provided all the variables needed from 2021/2022 and 2022/2023 seasons. Entities were excluded due to lack of material or insufficient detail. After applying these filters, the working sample comprised, as mentioned before, 131 organizations.

3.2 Variables Definitions and Construction

This section documents the variables used to implement the Altman Z-Score and Ohlson O-Score, as well as a set of sector-specific indicators designed to capture the economics of professional sport.

To replicate and implement all the models outlined above it was necessary to retrieve or construct, when necessary, its variables, which are Total Assets (TA), Total Liabilities (TL), Current Assets (CA) and Current Liabilities (CL) to get Working Capital (WC), Revenue as Altman's Sales (this variable includes transfer fee revenue for further analysis), EBIT, Net Income (NI) from the current and previous year, Book Equity (for non-listed companies), Market Value of Equity (MVE) for listed companies which was computed from share price on the report's balance-date times shares outstanding, Funds From Operations (FFO), Retained Earnings (RE), and GDP deflator as Ohlson's GNP price-level index.

Besides these variables, to analyse sectoral dependencies and whether these dependencies correlate with distress signals, it was added standardized revenue splits, TV/Broadcasting, Match-day, and Commercial/Marketing. Then, a wage measure was created to understand what the weight of wage in this type of entities is and if that can be correlated with distress or be a distress signal and is computed as the sum of team's wages and social charges. Finally, the last variables were created, a UEFA or CONMEBAL Intervention, a dummy variable that equals to 1 if the company was subject to a UEFA or CONMEBOL financial-sustainability intervention/sanction in this specific season (UEFACONM Intervention) and equal to 0 if not, allowing to test and to verify whether regulatory stress match with accounting and market-based distressed signals, and another dummy that equals to 1 if the team went to Champions League, Libertadores, or Playoffs series in the current season (2022/2023, 2023 to South-American teams), assessing, in this way, if a well-sporting performance can influence organizations' accounts. A new dependent variable was constructed and used in adapted models and further on will be explained.

For European and selected South American entities, variables were taken directly from consolidated annual reports. Most of the variables were read from the statements, only a few adjustments were made in this field, as RE equals to the sum of "Reserves", to isolate reliance on player disposals (an extraordinary revenue stream) EBIT was split in EBIT with players' transaction (by default) and EBIT without players' transaction. The difference between the two EBIT's is the net profit on sale of player registrations (player trading profit), computed as transfer fee revenue minus net book value, with the last one being equal to acquisition cost minus accumulated amortization minus impairments. In terms of Revenue, for football, revenue categories come from the reports and already align with TV/Broadcasting, Match-day, and Commercial/Marketing.

For NBA, NFL and NHL the same variables were considered, but since most of the U.S franchises are private and without public club/company-level statements we rely on Forbes fields to compute all the variables by doing proxies and considering certain methods, which are going to be explain further on. Forbes only gives Team Value and its Valuation Breakdown (Sport, Market, Stadium, and Brand), Revenue, Operating Income (EBITDA to Forbes), Debt/Value, Player Expenses, and Gate Receipts. From these variables the original models' variables were synthetic constructed in a thoughtful and rational way. The adjustments were: Total Assets = Team Value; Total Liabilities = (Debt/Value)*TV+0,06*R, it was split into financial and operational components, the first term backs out interest-bearing debt from Forbes, the 6% of revenue proxies non-interest-bearing liabilities (deferred revenue from season tickets, sponsorships, payables, accrued compensation) and it is conservative but realistic choice for closed-league models with some pre-sales and accruals. Current Assets=0,05*Total Assets and Current Liabilities=0,60*Total Liabilities, the 5% of TV (Total Assets) prevents inflating liquidity and plausibly covers cash, receivables and prepaids, and the 60% reflects the high short-term liabilities that typically dominate franchises. Book Equity remains TA-TL, and Retained Earnings was considered 60% of BE because in mature private entities reserves usually dominate paid-in capital over time. Forbes considers Operating Income as EBITDA, so to get EBIT it was necessary to subtract a league-specific D&A proxy, 5% for NBA e 6% for NHL and NFL. Thus, for NBA, EBIT=EBITDA-5%*Revenue, for NFL and NHL, EBIT=EBITDA-6%*Revenue. These percentages were chosen essentially based on asset intensity and stadiums/arenas useful lives. For these sports both EBIT with and without players' transaction are the same because they do trades of players and picks for Drafts for other players, it is very rare for money to be involved in this type of transaction, so there is just one method to compute EBIT, and the same value was assumed for both. To obtain the Net Income, a 6% factor was used as cost-of-debt proxy applied to total liabilities, Net Income=EBIT-6%*TL, to retain simplicity under opacity about the exact debt mix, being deliberately conservative. This factor was chosen as a blend of public/municipal bonds, private loans and team-level secured debt and comfortably lands around 6%. Funds From Operations was computed as FFO=EBIT(1-t)+D&A-ΔWC, with t=0 as no entity-level income tax for private pass-throughs, and ΔWC=1%*Revenue to reflect steady-state accrual movements. In practical terms, to NBA: FFO=EBIT+5%*Revenue-1%, and to NFL and NHL: FFO=EBIT+6%*Revenue-1%*Revenue. In this way this 1% working capital drag shows the net effect of pre-season pre-payments and in-season accrual unwinds common in closed-league models. The variable wage is taken directly from Player expenses from Forbes data. For revenue sharing in U.S leagues it was used Forbes Revenue, and due to lack of data, proxies were made. Match-day was considered as the Gate Receipts, and from there the Commercial and Broadcasting variables were built, considering the specifications of each league, giving more importance to one or to another depending on the weight of each variable in the respective leagues.

The NFL is the most media-centric (dominant national contracts, and fewer home dates), hence a larger share of Revenue flows to TV/broadcasting. The NBA balances large national deals with strong Commercial monetization in major urban markets, so the weight is more evenly distributed. The NHL depends relatively more on gate economics, but Match-day Revenue is already defined as "Gate Receipts".

It should be emphasized that all the reasons and motives used to explain how the variables and percentages were calculated were not random but were based on both reports of MSGS and the Green Bay Packers, as well as other sources that confirm the choices.

3.3 Methodological Approach

3.3.1 Altman

3.3.1.1 Classical Models

First, the Z-score structure was the first to be applied directly to the organizations in the sample, without any recalibration of weights or "zones." For listed entities, the original (1968) formulation (Z) was used, while for unlisted entities, the Z′ (2000) revision was used, which was specifically adapted and modified for private/manufacturing companies.

Thus, in both groups (listed/public and unlisted/private), the ratios follow the standard definitions of the model, Working Capital/Total Assets (X_1), Retained Earnings/Total Assets (X_2), EBIT/Total Assets (X_3), Sales/Total Assets (X_5), and the capital structure ratio appropriate to each version, Market value of equity/TL (X_4) for listed companies or Book Equity/TL (X_4) for unlisted companies. To ensure comparability and consistency, some approximations were made, as mentioned earlier in the variables section. Therefore, RE was measured as the sum of "Reserves," EBIT was measured as EBIT with players transaction (which is obtained by default), and finally, the variable 'Sales' was replaced by the variable "Revenue."

In this way, the original limits ("zones") were maintained, so that in listed companies, based on Altman (1968), the organization is in the distress zone if Z < 1,81 and in the safe zone if Z > 2,99, with the gray zone in between. The same was done for private companies, using as a basis the Altman (2000) in which the organization is in the distress zone if Z′ < 1,23, in the safe zone if Z′ > 2,90, and in the gray zone in between.

That said, for each listed entity, its respective z-score was calculated using the formula $Z = 1{,}2X_1 + 1{,}4X_2 + 3{,}3X_3 + 0{,}6X_4 + 0{,}99X_5$ and, consequently, classified among the three zones mentioned above. Similarly, this was also done for unlisted companies, with differences in the equation used, which was $Z' = 0{,}717X_1 + 0{,}847X_2 + 3{,}107X_3 + 0{,}42X_4 + 0{,}998X_5$ and within the limits applicable to private companies.

For both samples, a binary regression was estimated in STATA with "distress" as dependent variable (=1 if in distress, 0 otherwise) classified by its respective z-score value, and a single predictor, Z in the listed group, and Z' in the unlisted group. This regression was performed for the purpose of mapping the score to predicted probability and be comparable with the Ohlson's model.

To be able to do this, it was necessary to calculate the x-score (linear predictor), which results from the equation $x_i = \beta_0 + \beta_1 Z_i$ for listed companies and the equation $x_i = \beta_0 + \beta_1 Z'_i$for unlisted companies, and then calculate the predicted probability of distress, which is calculated according to $p_i = logit^{-1}(x_i)$. Finally, a standard cut-off of 0,5 (by default) was adopted, classifying as distress if p_i > 0,5, with this threshold serving only as a reference at this stage of direct application, and discriminative performance was assessed via ROC analysis, reporting the area under the ROC curve (AUC) computed from the model's predicted probabilities. Beyond the public and private subsamples, the same process was applied to a global sample with all organizations, applying both private coefficients and zones-limits.

Once again, the limits related to the z-score, the weights associated with the variables, and even the variables themselves are used only in this phase of direct application for classification. Any contextual recalibration is reserved for a subsequent phase, along with all other changes that are specific to the industry.

3.3.1.2 Model Adaptations with Sport-Specific Variables

To ensure continuity with Altman's framework while introducing sector-relevant predictive drivers, the Z-sports (an industry-adaptation of Z-score tailored to listed and unlisted sports entities) was defined as a linear equation as Z-score, constructed from the following variables, TL/TA (X_1) , WC/TA (X_2), NI/TA (X_3), Wage/Revenue (X_4), TV Broadcasting Revenue/Revenue (X_5), a Champ/Playoffs dummy (1 if the club reached UEFA Champions League group stage, Libertadores group stage or Playoffs for the North-American teams, 0 otherwise) (X_6), and a Listed dummy (X_7) for the global sample. These variables were selected because they collectively capture the main financial characteristics of organizations, as well as the relationship between sports performance and financial conditions and the constraints of sports revenue models. Before finalizing the specification, several robustness tests were performed to ensure that the selected model was not merely an artefact of a specific combination of variables. First, alternative distress rules were tested (requiring two or three accounting conditions simultaneously), and the two-conditions rule emerged as the most balanced and economically coherent, avoiding classifications driven by one-off fluctuations while still capturing structural fragility. Second, the inclusion of Marketing Revenue/Revenue was evaluated, but this variable did not materially improve explanatory power and introduced additional collinearity with other revenue components. The specification excluding this variable consistently produced cleaner fits across subsamples. These checks confirmed that the chosen Z-sports structure was the most stable and conceptually aligned with the financial architecture of sports entities.

The model was done for publicly/listed entities, privately held entities, for a global sample, and additionally for football-only-subgroups, where football-specific variables (Player Trading Profit/Revenue, Match-day Revenue/Revenue, Commercial Revenue/Revenue, and UEFA/CONMEBAL intervention dummy) were evaluated.

As in both Altman ((1968), (2000)), estimation was conducted using binary logistic regression with financial distress as dependent variable. A unified binary distress variable, Y, was constructed for all entities, being equal to 1 if at least two of the following four conditions hold:

1. NI/TA<0
2. TL/TA>1
3. WC/TA<0
4. INTWO=1 (negative NI for two consecutive years)

and 0, otherwise. This structure was chosen to balance stringency and flexibility which could label an organization as distressed based on a temporary fluctuation, these conditions combined capture cases where multiple dimensions of financial fragility co-occur, signalling a more structural deterioration rather than an isolated shock, which is particularly common in the sports sector, where revenues are volatile, competitive wage bills are rigid, and player related transactions can create substantial year-to-year variability. Economically, each condition represents a fundamental pillar of financial sustainability, profitability, solvency, liquidity, and the persistence of poor performance. By requiring at least two conditions to fail, the measure tries to avoid false positives caused by accounting noise, while still being sensitive to early signs of distress. Moreover, this multidimensional approach aligns well with the heterogeneous nature of sports organizations, whose risk profiles can differ substantially across leagues and business models. This set therefore provides a transparent, robust, and sector-appropriate foundation for constructing the dependent variable.

Unlike the original Altman index, where higher Z-score values indicate stronger financial health, the Z-sports was built to higher values indicate higher likelihood of financial distress, while lower values indicate better financial condition. Moreover, after the Z-sports were computed, the score was partitioned into three empirically determined zones, being different for the public, private and football-only subsamples.

For public entities:

Safe zone: Z<0

Gray zone: 0≤Z≤0,5

Distress zone: Z>0,5

For private entities:

Safe zone: Z'<0

Gray zone: 0≤Z'≤0,65

Distress zone: Z'>0,65

For football entities:

Safe zone: Z<0

Gray zone: 0≤Z≤0,5

Distress zone: Z>0,5

All the cut-offs were selected after visually inspecting the distribution of distressed/non-distressed public and private organizations in each subsample and for each subsample. Accordingly, to Altman the zones were determined empirically rather than via parametric optimization. After the construction of Z-sports and before moving on to the analysis of its results, an additional procedure similar to that applied in the previous phase of direct application of the classical models was carried out. As in the case of the original Z and Z′, the new adjusted score was converted into a continuous measure of the probability of distress, allowing for the evaluation of not only the zoned classification but also the discriminative ability of the model in probabilistic terms. Since Z-sports corresponds to the linear predictor of a logistic specification, resulting from the combination of the estimated coefficients for the selected variables (TL/TA, WC/TA, NI/TA, Wage/Revenue, Broadcasting/Revenue, and the respective competitive dummies), the estimated probability of distress was obtained through the standard logistic transformation, $p_i = logit^{-1}(Z - sports_i)$. Finally, an analysis of the discriminative ability of Z-sports was carried out using the ROC curve and the respective AUC.

3.3.2 Ohlson

3.3.2.1 Classical Models

Next, Ohlson (1980) probabilistic framework was the second model applied to the organizations in the sample, again without any recalibration of the coefficients at this initial stage. Specifically, the original logit specification for one year ahead (Model 1 in Ohlson - 1-year forecast) was transplanted to this scenario, keeping all slope coefficients and the intercept unchanged. To preserve the economic meaning of the SIZE variable as close as possible to the original study, all total assets were first converted into US dollars and then deflated using the US GDP deflator (base year 2015 = 100). The reference year for accounting information was 2022, meaning, the last fiscal year available before the 2022/23 season under review, in line with the spirit of Ohlson's one-year-ahead model.

The remaining predictors follow the article's standard definitions, Total Liabilities/Total Assets (TLTA), Working Capital/Total Assets (WCTA), Current Liabilities/Current Assets (CLCA), OENEG (dummy variable equal to 1 if Total Liabilities exceed Total Assets, 0 otherwise), Net Income/Total Assets (NITA), Funds from operations/Total Liabilities (FUTL), where funds from operations are represented by cash flow from operating activities, INTWO (dummy variable equal to 1 if net income is negative for two consecutive years, 0 otherwise) and CHIN (the scaled variation in profits, $(NI_t - NI_{t-1}/(|NI_t| + |NI_{t-1}|))$. As in Altman's implementation, any approximations necessary to construct these ratios, such as the treatment of football-related items or cash flow disclosures, follow the conventions described in the variables section in order to maintain consistency across all entities in the sample.

Since no organization in the sample had undergone legal bankruptcy proceedings, the binary dependent variable "financial distress" was defined consistently and generally for all organizations using Altman's Z-score. For each observation, financial distress was defined as equal to 1 if the corresponding Z (for listed entities) or Z′ (for unlisted entities) placed the organization in Altman's "financial distress zone" and equal to 0 in all other cases. Given this binary result, Ohlson's linear predictor (O-score) was calculated as $T_i = -1{,}32 - 0{,}407\ \text{SIZE} + 6{,}03\ \text{TLTA} - 1{,}43\ WCTA + 0{,}0757\ CLCA - 2{,}37\ NITA - 1{,}83\ FUTL + 0{,}285\ INTWO - 1{,}72\ OENEG - 0{,}521\ CHIN$, and the associated predicted probability of distress was then obtained via the logistic transformation $p_i = logit^{-1}(T_i)$.

The classification performance of the transplanted Ohlson model was then evaluated by comparing the predicted probabilities p_i to the Altman-based distress dummy. Receiver Operating Characteristic (ROC) analysis was conducted and the area under the ROC curve (AUC) recorded. In addition, a series of cut-off points for p_i were examined, for each threshold, sensitivity, specificity, and overall misclassification rates (Type I and Type II error rates) were computed. Following the original study, the "optimal" cut-off reported here is the one that minimizes total classification error, meaning, the sum of Type I and Type II errors. This process was done for public, private, and global subsamples.

3.3.2.2 Model Adaptations with Sport-Specific Variables

The initial idea was to re-estimate an Ohlson-type model using logit but adapted to the sports context. The approach began by including the set of variables as close as possible to the original specification, complemented with sector ratios. However, as robustness checks were being made, classic perfect prediction problems quickly arose, and some variables (OENEG and INTWO) perfectly predicted success or failure, while TLTA alone almost completely separated distressed from non-distressed observations. This is not surprising, since these variables are directly part of the rule that defines the distress dummy (same used in Z-sports). In practical terms, the logit ended up trying to reconstruct the accounting definition of Y, which leads to explosive coefficients, degenerate probabilities (very close to 0 or 1), and artificial ROC areas. As a result, the 'problematic' variables had to be removed from the model. OENEG and INTWO were removed because they almost coincide with two of the distress conditions, and caused perfect separation, TLTA and CLCA were removed because the first one is directly linked to one of the dummy conditions and CLCA is mechanically collinear with other liquidity measures, besides that, both contribute to extreme values of the linear predictor. Following the same pattern, NITA was removed as well, to eliminate any direct overlap with the NI/TA<0 condition. Finally, the last variable being removed was WCTA, which although it is central in the original model, it is also present in one of the distress conditions (WC/TA<0), maintaining direct link between X and Y. Thus, the variables in the model are SIZE, FUTL, CHIN, WAGE, TV, and a Listed dummy only for the global sample.

The model was applied to all subsamples constructed earlier (global, public, and private) and additionally was applied to an only-football sample as well, where football-specific variables (Player Trading Profit/Revenue, Match-day Revenue/Revenue, Commercial Revenue/Revenue, and UEFA/CONMEBAL intervention dummy) were evaluated.

4.Results

4.1 Altman

4.1.1 Classic Models

4.1.1.1 Descriptive Statistics and Correlation Evidence

Public subsample:

Applying the Altman Z-score (1968) directly to the publicly listed/public entities revealed a highly asymmetric distribution across the three classical zones. Descriptive statistics show that two thirds of listed entities fall within the distress zone, while only two entities (Juventus FC and Galatasaray) appear in the safe zone. A small group, MSGS, Aarhus, Borussia Dortmund, Celtic FC, and Manchester United lies in the gray zone. Thus, considering the size of the sample, a substantial number of high-profile clubs are classified in the distress zone, including Green Bay Packers, Ajax, Besiktas, Club Deportivo Universidad Católica, Colo-Colo, Copenhagen, FC Porto, Lazio, Olympique Lyonnais, Sporting CP, and SL Benfica, highlighting the structural fragility of sports entities when assessed through the traditional manufacturing-based structure of the Z-score.

Private subsample:

Applying the Altman Z′ (2000) formulation to the unlisted/private organizations produces an even more pronounced imbalance toward financial distress compared to the public sample. As 93,81% of private entities (106 entities) fall within the distress zone (Z'<1,23). Only one entity appears in the safe zone (Millonarios FC), making it the single private entity that the unadjusted Z'-score classifies as financially healthy, and a further six organizations fall into the gray zone (Brighton & Hove Albion, Edmonton Oilers, Universidad de Chile, Flamengo, River Plate, and West Ham United). These descriptive results highlight even more the structural incompatibility between Altman's original thresholds for private entities and financial construction of sports organizations.

Global subsample:

Extending the Z-score formulation to the full sample of 131 organizations, combining public and private entities under a unified framework, the study produces a distribution that remains strongly asymmetric. Using both coefficients and thresholds used from the private sample, Z-score (for public entities) was recomputed. The resulting classification reveals that only 2 entities, Juventus FC and Millonarios FC, fall within the safe zone, and a relatively small group lies within the gray zone (Edmonton Oilers, Brighton & Hove Albion, Universidad de Chile, Flamengo, River Plate, West Ham United, Madison Square Garden Sports, Green Bay Packers, Aarhus, Ajax, Borussia Dortmund, Celtic, FC Copenhagen, Galatasaray, and Manchester United), and the remaining 114 organizations fall into the distress zone.

4.1.1.2 Empirical Results

Public subsample:

The Z-scores computed for the listed organization place the vast majority in Altman's distress zone. This classification is driven mainly by structural weaker WC/TA ratios, lower Sales over Assets values, and low EBIT levels relative to total assets. Juventus FC and Galatasaray remain outliers due to its exceptionally high market capitalization, which increases the MVE/TL component and raises their Z-scores above the 2,99-threshold misclassifying both as safe entities. No listed club except these two surpasses Altman's original safe-zone boundary, confirming that the model when applied without recalibration, interprets almost all publicly sports entities as financially distressed.

Private subsample:

The Z'-scores computed for the private sample confirm that, under the classical Altman thresholds, almost all sports organizations would be classified as distress. The same pattern as with the public sample verified as these results were mainly driven by weaker liquidity positions, low EBIT levels relative to total assets, and a very low ratio of Sales/Total Assets (lower in North American franchises). Edmonton Oilers are notably the only North American franchise not classified as distressed, tough just slightly above the lower limit. Therefore, there are only seven entities not classified as distressed, offering little discriminatory power within this sector, as well.

Global subsample:

The dominance of the distress zone combining public and private entities was expected as only few organizations were not classified as distressed in both samples separately. Once again, this result was driven by the same three ratios. The gray-zone entities tend to exhibit better liquidity and better return on assets, although still insufficient to reach the model's safe thresholds. As in the previous samples, the direct application of the Z-score configuration does not retain any predicted value for the economic environment of professional sports.

4.1.1.3 Probability Mappings & Classification Performance

Public subsample:

The Z-scores were then mapped into predicted probabilities of distress through a logit specification, using Altman's distress classification to define the dependent variable. Using the conventional 0,5 cut-off as a decision rule, discussed in methodology, all entities with p_i>0,5 that were classified as distress by the original Z-score were in distress as well by the cut-off decision rule, while all entities with p_i<0,5 fall into a gray or safe zones. The resulting predicted probabilities were mostly concentrated near 1 or 0, consistent with the fact that most listed organizations fall into the distress zone, as the model has practically no predictive power, under the classical thresholds. The ROC curve yields AUC=1, a perfect separation cause by definitional circularity, the binary variable "distress" is defined directly from the Z-score thresholds, depending on whether the entities were in distress or not, implying that the probability mapping does not provide additional discriminatory insight beyond the original Z-score.

Private subsample:

When Z'-scores were mapped into predicted probabilities of distress, a more extreme result was noticed, as the probabilities were almost 0 or 1. Thus, all entities with p_i>0,5 fall exclusively in the distress zone, and all entities with p_i<0,5 fall in the gray and safe zones, having no misclassification under this threshold rule, as was the case with the sample of public entities. As was expected, the ROC analysis yields an AUC equal to 1, replicating the perfect separation observed in the publicly listed sample, since the binary dependent was directly constructed from the Z'-score values, resulting in a definitional circularity.

Global subsample:

Following the same procedure used in the previous samples, Z'-score were transformed into predicted probabilities. These values had the same behaviour as the previous ones, as probabilities were heavily concentrated near 0 or 1. In this case, above the 0,5 cut-off appeared 114 entities in the distress-zone but 2 in the gray-zone, while under the 0,5 cut-off there were 15 entities, 2 in the safe zone and the other 13 in the gray zone. This near-perfection separation is confirmed by the ROC analysis, which yields an AUC=0,9945, a high value confirmed by the presence of definitional circularity.

4.1.2 Adapted Models

4.1.2.1 Descriptive Statistics and Correlation Evidence

Public subsample:

The first calibration of the Z-sports measure was performed for the 18 public sports organizations. Before interpreting the model results, descriptive analysis indicates that the Z-sports distribution exhibits substantial cross-sectional variation, consistent with structural differences in leverage, liquidity, profitability, wage intensity, and revenue composition among listed entities.

A supplementary correlation analysis (Table 1) reveals that the distress dummy exhibits very strong correlations with TL/TA, WC/TA, and NI/TA, which is expected because these ratios are directly related with the accounting-based distress rule. From here it is plausible that part of the explanatory strength observed in the model arises from this definitional circularity. Wage/Revenue also displays a moderate correlation with the dummy variable but is not directly related with the accounting-based rules, highlighting how this ratio can be crucial to the financial health of a sports entity. Additionally, WC/TA correlates with NI/TA, reflecting that liquidity and profitability tend to move together in sports entities. Wage/Revenue correlates with Champs/Playoffs dummy, showing that the presence in major competitions (or Playoffs) helps reducing wage-bill pressure, and NI/TA also correlates moderately with Champs/Playoffs dummy, highlighting the importance of participation in this type of competition on the entities' results.

All these correlation patterns help explain why some conceptually important variables lose their predictive power once others are included and justify the emphasis on economic interpretation.

Private subsample:

The second stage of the Z-sports calibration applies the model to the privately held organizations. The descriptive distribution of Z-sports score reveals that private entities exhibit substantially more heterogeneity than the listed sample, reflecting diversity in accounting structures, revenue dependency, and different business models across football, NBA, NHL and NFL industries.

A correlation analysis was conducted to support and help to explain the interpretation of the model's behaviour (Table 2). As expected, the distress dummy is strongly correlated with the core accounting ratios used in its construction, namely WC/TA and NI/TA, mirroring the pattern observed in the public subsample, and reinforcing the presence of definitional circularity, which later contributes to the perfect AUC value. Correlations among regressors was also studied, WC/TA and NI/TA are positively correlated, continuing the theory presented in the public sample. As well as Wage/Revenue correlates negatively and moderately with NI/TA, being consistent with the theory that high wage intensity produces lower results.
This reduces the unique explanatory weight of each variable in the regression and why some theoretically important variables lose statistical significance once others are included in the model, providing an empirical justification for interpreting the results by its economic coherence rather than strict statistical testing, as was evident in the public sample.

Global subsample:

After calibrating the Z-sports specification separately for public and privately held organizations, a unified estimation was conducted for the entire 131 sports entities. The results were very similar to the private sample since most of the sports entities present in this study are private, showing a strong heterogeneity in ownership structures, revenue models, and cost systems across football clubs and North American franchises.

A correlation analysis was also performed (Table 3), and as expected, the distress dummy exhibits strong correlations with the core accounting ratios WC/TA and NI/TA, reflecting that liquidity and profitability are the central drivers of the distress definition under the Z-sports structure. WC/TA and NI/TA themselves display, one more time, a moderate positive correlation, showing that stronger liquidity positions tend to exhibit more stable results. An interesting correlation to analyze is that between Listed dummy and broadcasting revenue, because if companies are public, having a higher share of stable TV (Broadcasting revenue)/Revenue helps to reduce financial fragility. Conversely, the Champs/Playoffs dummy displays near-zero correlations with the financial variables. This may reflect the fact that participation in playoffs (NBA, NHL, NFL) does not generate immediate revenue shocks comparable to UEFA or CONMEBAL competitions, thereby weakening the financial signal of this variable when football and franchise leagues are pooled together.

Football subsample:

The football-only subsample comprises 40 professional football organizations (public or not), and at first sight seems to exist substantial heterogeneity in liquidity, profitability, wage structures, and competitive participation. Even so, the average of both liquidity and profitability is negative, meaning that sports entities have weak liquidity positions and can’t protect any asset with working capital, and football entities’ results are deteriorating the entities’ value. Moreover, more than half of the football entities participated in Champions/Libertadores and presented in average a wage bill that represents almost half of the revenue received.

The correlation matrix from the extension model (Table 5) confirms that Player Trading Profit/Revenue and the UEFA/CONMEBAL intervention dummy exhibits moderate correlations with the distress dummy variable, confirming that sector-specific variables matter to assess football entities financial health, and also correlates with NI/TA and Wage/Revenue. Additionally, the distress dummy is strongly correlated with nearly all included variables in the final model (Table 4), reflecting intrinsic connection between these accounting ratios and the multi-conditions distress definition used in the model. NI/TA and WC/TA remain positively correlated, consistent with previous subsamples, indicating that financially stronger football entities often exhibit both healthier liquidity and profitability profiles. Wage/Revenue shows moderate negative correlations with NI/TA and Champs/Playoffs dummy, supporting the idea that better-performing sports entities allow for reduced the wage intensity.

4.1.2.2 Empirical Results

Public subsample:

The linear regression used to construct the Z-sports index for listed entities demonstrates strong explanatory power, with an R^2 of 0,89, and an adjusted R^2 of 0,82, values partly attributable to the small sample. The estimated specification is:

$$Z_{sports} = -0{,}106 + 0{,}149\ X_1 - 1{,}661X_2 + 0{,}019X_3 + 1{,}514X_4 - 1{,}095X_5 - 0{,}302X_6.$$

According to Figure 1, WC/TA is the most economically and statistically robust predictor, entering with a large negative and significant coefficient. This indicates that stronger short-term liquidity substantially reduces financial fragility, consistent with Altman's original framework. Wage/Revenue also emerges as a strongly positive and statistically significant predictor, reflecting that a higher salary bill relative to revenue's entities increases financial pressure, being an economically intuitive effect, and reflecting both structural rigidity of payroll expenses in football and the tendency to over-extend wage commitments in pursuit of competitive performance. TV (Broadcasting) Revenue/Revenue has a negative and statistically significant coefficient, indicating that a higher share of stable broadcasting revenues reduces financial fragility. The slightly positive coefficient on NI/TA, although counter-intuitive, is likely due to sample size limitations and temporary profitability spikes present in sports entities that nevertheless exhibit structural financial weakness. The remaining variables, TL/TA and the competition dummy display coherent signals but with no statistical significance.

Private subsample:

The model estimated for private entities yields an R^2 of 0,42, and an adjusted R^2 of 0,39, values consistent with a heterogeneous cross-sectional sample that spans multiple sports and relies on several structured approximations (Figure 2). Despite this heterogeneity, the model is jointly significant, indicating that the predictors capture a meaningful portion of the variation in financial fragility across private organizations. Thus, the estimated equation for unlisted organizations can be expressed as:

$$Z'_{sports} = -0{,}108 + 0{,}132\,X_1 - 0{,}996X_2 - 1{,}361X_3 + 1{,}478X_4 - 0{,}850X_5 - 0{,}007X_6.$$

WC/TA, NI/TA, Wage/Revenue, and TV (Broadcasting) Revenue/Revenue are the predictors most statistically significant and economically robust. WC/TA highlights the central role of liquidity as stabilizing factor across all ownership structures, NI/TA demonstrates that higher and more stable profitability reduces financial fragility, Wage/Revenue reinforces that payroll rigidity is a key financial pressure mechanism in sports (this is intuitive in football where salaries frequently exceed 50-60% of revenues, and aligns with North American franchise dynamics despite their cap structures), and TV Revenue/Revenue indicates that organizations with higher share of stable media-rights revenues face lower financial pressure. Some coefficients, such as TL/TA deviate from what could be its expected magnitude due to explained measurement approximations on private organizations and the limited power in sports industry, where sports entities can maintain high levels of leverage for long periods and operate in a regular way. Similar considerations apply to the Champions/Playoffs dummy, which loses explanatory relevance because it may be absorbed by TV (Broadcasting)Revenue/Revenue, given that participation prizes are mostly paid in this way.

Global subsample:

The global Z-sports regression displays an R^2 of nearly 0,50, and an adjusted R^2 of 0,47, which is reasonable given the strong cross-sectional heterogeneity in the sample. The estimated global equation is:

$$Z_{sports} = -0{,}111 + 0{,}102X_1 - 1{,}119X_2 - 1{,}288X_3 + 1{,}494X_4 - 0{,}844X_5 + 0{,}020X_6 + 0{,}134X_7$$

Concerning Figure 3, WC/TA, NI/TA, Wage/Revenue, and TV/Revenue continue to be the most significant economically and statistically, maintaining the same theory previously defended in the private sample. On the other hand, TL/TA and Champs/Playoffs remain statistically weak and exhibits low explanatory power as observed in the private sample. Given that, the coefficient signs align strongly with financial-distress theory.

Football subsample:

The Z-sports specification for the football subsample retains four regressors, WC/TA (X_1), NI/TA (X_2), Wage/Revenue (X_3), and the Champions/Playoffs dummy (X_4). This reduced model achieved an R^2 of 0,6273 and adjusted R^2 of 0,5847, and a highly significant F-statistic. The estimated equation is:

$$Z_{sports} = 0{,}143 - 0{,}844\, X_1 - 1{,}124 X_2 + 0{,}721 X_3 - 0{,}213 X_4$$

The first 3 variables appear both economically and statistically significant (Figure 4), highlighting the principal drivers of distress in sports entities. Strong liquidity positions reduce the likelihood of distress, profitability remains one of the most protective factors in football finances, and sport entities with higher wage intensity tend to experience greater financial stress. The Champs/Playoffs dummy enters with the expected negative sign but marginal statistical significance, naturally showing that international competitions and domestic playoffs reduce financial fragility by enhancing brand value, increasing media exposure, and generating additional revenues through prize money. The variables TL/TA and TV Revenue/Revenue were excluded from the final model, as TL/TA shows weak statistical significance and limited relevance for football entities, which can sustain elevated leverage for extended periods, and TV Revenue/Revenue, exhibits near-zero coefficient estimates alongside high correlation with Wage/Revenue, suggesting limited incremental predictive value.

4.1.2.3 Probability Mappings & Classification Performance

Public subsample:

After estimating the Z-sports scores, these were transformed into predicted probabilities of distress via logit model. Applying the empirically determined cut-offs (as Altman did) for public entities (Safe Zone: Z<0, Gray Zone: 0<Z<0,5, Distress Zone: Z>0,5), the resulting classifications are 44% (8 entities) in the distress zone, 28% (5 entities) in the gray zone, and the last 28% (5 entities) in the safe zone. All organizations with predicted probabilities above 0,5 fall exclusively in the distress zone, whereas all with predicted probabilities below 0,5 appear in the safe or gray zones. As expected, the ROC curve yields an AUC=1, reflecting perfect separation. This mechanical result arises from definitional circularity as mentioned before, thus although the probability-based representation is fully consistent with the zone classification, provides no discriminatory insight beyond the score itself.

Private subsample:

The Z cut-offs were applied, and the zone distribution reveals that 9,73% (11 entities) of private entities are in the distress zone, 8,85% (10 entities) in the safe zone and a dominant 81,42% (92 entities) in the gray zone. The distribution reflects the structural moderation typical of North American franchises, which benefit from stable revenue-sharing and predictable financial environments, placing most organizations in intermediate fragility levels. Consistent with the methodology presented so far, Z' sports values were mapped into predicted probabilities of distress and the conventional threshold of 0,5 was applied on the probabilities of distress, and all entities with p_i>0,5 fall into the gray or distress zones, while all entities with p_i<0,5 fall into the safe zone. As expected, the ROC cruve yields an AUC=1, reflecting the same definitional circularity observed previously, not providing incremental discriminatory insight beyond the score itself, although internal coherence confirms that the probabilistic and zone-based interpretations of Z-sports behave consistently across private organizations.

Global subsample:

Following Altman's logic, the Z-sports were portioned into empirically determined zones suitable for the heterogenous global sample as:

Safe zone: Z<0

Gray zone:0<Z<0,55

Distress zone: Z>0,55

The resulting distribution shows that 19,1% of organizations in the distress zone, 9,9% in the safe zone, and a large and dominant 71% concentrated in the gray zone.

Then, the Z-sports values were mapped into predicted probabilities of distress via logistic transformation. The standard 0,5 threshold was applied and all entities with p_i>0,5 fall into the gray or distress zone, and all entities with p_i<0,5 fall into safe and gray zones. The ROC curve yields an AUC of 0,9343, this value reflects the reduction of circulate once public and private entities are gathered under a single estimation structure.

Football subsample:

Z-sports scores for football entities were transformed into predicted probabilities, but the results exhibit except in a few cases extreme polarization, clustering very close to 0 or 1. This behaviour reflects a combination of circularity and small sample size, which amplifies coefficients effects and sharpens probability separation. The ROC curve yields an AUC of 0,98, as definitional circularity is present.

Applying the empirically defined football thresholds, results shows that only 4 entities are in the safe zone (Celtic FC, Flamengo, Millonarios, River Plate), and in the gray zone and in the distress zone there are 18 entities in each.

4.2 Ohlson

4.2.1 Classic Models

4.2.1.1 Descriptive Statistics and Correlation Evidence

Public subsample:

The direct application of Ohlson (1980) one-year-ahead logit model to the public organizations produced results that are weakly discriminative and, in practical terms, largely uninformative and extremely limited predictive power. The overall distribution reveals that most public entities receive very low estimated probabilities of distress, despite being classified as distress under the Altman's-based dummy used as dependent variable. It was also identified the optimized cut-off by Ohlson's minimum-error rule (0,004), indicating that even very small probabilities of distress are enough to an entity be classified as distressed.

Private subsample:

When applying the original Ohlson (1980) model to unlisted entities, the distribution of predicted probabilities exhibits a highly compressed pattern, almost all entities received extremely low estimated probabilities. Only 2 organizations display probabilities above 0,10, while 100 organizations have predicted probabilities lower than 0,01, suggesting a heavily misalignment between the Ohlson probability outputs and the Altman-based dependent variable.

Global subsample:

Applying Ohlson's (1980) one-year-ahead logit specification to the full sample of 131 organizations produces a distribution of predicted probabilities that is extremely compressed near zero, as already observed in the individual subsamples. The results of this study are quite similar to the ones with the private sample, as the optimal cut-off is also 0.

4.2.1.2 Empirical Results

Public subsample:

The original coefficients from the original model were applied, and the resulting Ohlson score fails to separate observations by financial distress status. The empirical performance of the Ohlson model is thus weak, offering limited ability to distinguish between sports entities in financial distress and those without financial distress based on Altman's classification for the dependent variable. Applying Ohlson's optimal cut-off of 0,004, results in only four organizations being classified as non-distressed, Green Bay Packers, Aarhus, Borussia Dortmund, and Celtic FC. All remaining entities are classified as distressed, even though some of them display very low probabilities of default.

Private subsample:

The empirical performance of the Ohlson model for private is even weaker than for the public subsample, and following its methodology, the optimal cut-off was 0, meaning that any predicted probability strictly greater than 0 would classify an entity as distressed. Thus, with this cut-off the model collapses entirely, classifying all entities as distressed, confirming no operational ability to distinguish between distressed and non-distressed organizations.

Global subsample:

The empirical results confirm that the Ohlson model, in its original unadjusted form possesses no meaningful discriminative power. As the optimal cut-off is 0, all the entities are classified as distress, collapsing the model and highlighting the inability to extract any useful signal from the Ohlson predictors under the Altman-based distress definition.

4.2.1.3 Probability Mappings & Classification Performance

Public subsample:

Using the Altman-defined distressed dummy, the classification matrix under the optimal cut-off of 0,004 shows 3 correct predictions and 1 Type II error (classify as distress an entity non-distressed) among the 4 noon-distressed observations, and 10 correct predictions and 4 Type I errors (classify as non-distressed an entity in distress) among the 14 distressed observations. Besides the number of errors given the small sample, the predicted probabilities remain clustered near 0, and the cut-off itself is unusually restrictive, which confirms the model's inability to capture meaningful variation in distress likelihood. Finally, the ROC curve yields an AUC of 0,5844, only marginally above random guessing, confirming the minimal discriminative power when transferred to sports organizations.

Private subsample:

As was seen before, all entities were classified as distressed, based on a cut-off with zero capacity to discriminate any type of entity. Furthermore, the ROC analysis yields an AUC of 0,2305, which is worse than random chance (0,50). This implies that the model assigns higher predictability to non-distressed entities and lower probabilities to distressed ones, producing an inverted signal relative to the Altman-based definition of distress, and displaying negative discriminatory power.

Global subsample:

The ROC analysis further confirms the model's lack of predictive relevance for sports entities, as the AUC is 0,2076, far below of the 0,5 random threshold. As in the private sample, the model appears negatively discriminative, showing clearly a misalignment in the structural relationship embedded in Ohlson's original predictors and the financial architectures of sports organizations, besides the dependent variable was based on Altman's score.

4.2.2 Adapted Models

4.2.2.1 Descriptive Statistics and Correlation Evidence

Public subsample:

The final adapted Ohlson specification for public entities retains only three accounting ratios from the original model, SIZE, FUTL, and CHIN, together with two sector-specific variables, Wage/Revenue, and TV/Revenue.

A correlation matrix was computed (Table 6), and the results confirm a moderate-to-strong association between distress and the regressors, particularly Wage/Revenue, which exhibits the strongest correlation with the dependent variable. CHIN also shows that improvements in net performance reduce financial pressure, and SIZE indicates that larger clubs may carry heavier cost structures or more aggressive leverage dynamics. Wage/Revenue and CHIN captured the interaction between controlled wage bills and improved profitability, and SIZE and FUTL reflects that larger entities tend to generate stronger operating cash flows.

Private subsample:

The private sample was estimated using the same set of variables used in the public subsample, and a correlation matrix was also computed.

In this case, FUTL represents the strongest negative correlation with the distress dummy (Table 7), pointing that high operating cash-flow capacity relative to total liabilities are far less likely to experience financial difficulties. SIZE and CHIN also present negative correlations with distress as larger balance sheets appear structurally more resilient, and improving profitability tends to accompany stronger financial stability, as expected. The correlation between Wage/Revenue and CHIN indicate that higher wage intensity often coincides with deteriorating profitability, and between TV/Revenue and SIZE reveal that larger entities tend to have a higher share of broadcasting revenue in their total revenue.

Global subsample:

For the global sample, a Listed dummy was added to the set of variables used in the previous subsamples. To ensure that the variables behaved consistently a correlation matrix was computed.

The strongest observed correlation with the distress dummy is FUTL (Table 8), mirroring the findings of the private subsample, which is expected given that the global dataset is dominated numerically by private organizations. The same pattern extends as SIZE and CHIN also show negative correlations with distress. Finally, Wage/Revenue remains exhibiting a positive correlation with distress, being a universal determinant of financial fragility in sport. TV/Revenue and SIZE form the strongest inter-regressor correlation consistent with the idea mentioned in the previous model.

Football subsample:

The specification underwent several iterations in order to incorporate sector-relevant variables. The final regressors retained were SIZE, CLCA, CHIN, Wage/Revenue, TV/Revenue, and Player Trading Profit/Revenue (PTRADE).

A correlation matrix was computed (Table 9), and Wage/Revenue and TV/Revenue show strong positive correlations with the distress dummy, confirming that wage pressure is one of the main pillars of fragility in football, and high dependence on broadcasting revenues increases financial vulnerability. PTRADE shows that entities structurally reliant on extraordinary gains from player trading tend to exhibit weaker underlying financial positions, and CLCA also shows that liquidity pressure act as relevant stressor. PTRADE and CHIN exhibit a meaningful positive association, highlighting how football entities' results depend and rely on gains from player trading.

4.2.2.2 Empirical Results

Public subsample:

The adapted Ohlson model used for the public entities is:

$$T_i = -24{,}073 + 1{,}4520\ SIZE_i - 3{,}270\ FUTL_i - 1{,}190\ CHIN_i + 7{,}093\ WAGE_i - 3{,}450\ TV_i$$

Although none of the coefficients achieves statistical significance (given the small sample), the economic signs of the predictors align well with theoretical expectations (Figure 6), larger entities tend to exhibit large fixed costs bases or aggressive wage structures, strong operating cash-flow generation relative to liabilities reduces financial fragility, improvements in net income exert a stabilizing effect, a higher wage burden increases distress likelihood, and the importance of recurring media-rights for the financial stability.

Private subsample:

Estimating the adapted Ohlson specification for the 113 private entities yields the following model:

$$T_i = 6{,}499 - 0{,}684\ SIZE_i - 14{,}862\ FUTL_i - 0{,}794\ CHIN_i + 5{,}958\ WAGE_i + 6{,}574\ TV_i$$

From the previous model, all the variables follow the same pattern except for SIZE, and TV (Figure 7). For the private sample, larger balance sheets appear more stable, so that scale provides financial cushioning for private entities, and the reliance on broadcasting revenue income is associated with higher risk due to revenue concentration risk, structural dependence on media income in certain leagues, and volatility of performance-dependent broadcasting allocations.

Except for FUTL, most coefficients are not statistically significant at conventional thresholds (5%), which is expected given the diverse nature of the sample and the presence of measurement approximations for franchises values.

Global subsample:

The adapted Ohlson model used for the global sample is:

$$T_i = -0,910 - 0,129\, SIZE_i - 10,108\, FUTL_i - 0,762\, CHIN_i + 5,348\, WAGE_i + 2,087\, TV_i - 0,435\, Listed_i$$

All the coefficients followed the same pattern present in the private sample (Figure 8), in addition that the listed dummy indicates that public organizations exhibit slightly lower distress probability, tough the result is not statistically significant.

Football subsample:

The football-specific Ohlson specification is:

$$T_i = -29,646 + 0,913\, SIZE_i - 2,059\, CLCA_i - 2,593\, CHIN_i + 13,177\, WAGE_i + 18,706\, TV_i + 11,683\, PTRADE_i$$

According to Figure 9, Wage/Revenues maintain the same pattern as in previous subsamples, showing that wage burden is the dominant fragility driver in football, as is TV/Revenues in the private and global subsamples (reliance on broadcasting income increases vulnerability due to revenue concentration and exposure to performance-based allocations). SIZE is again interpreted in such a way that even though they have higher revenue capacity, they carry more aggressive wage or leverage structures. CHIN maintains the same meaning across the subsamples, showing that improvements in profitability reduce the risk of distress. Finally, PTRADE also shows that entities more dependent on extraordinary player-trading gains are associated with a weaker financial position, and CLCA is the strongest variable statistically and is consistent with the theory that weaker liquidity positions heighten distress risk.

4.2.2.3 Probability Mappings & Classification Performance

Public subsample:

The ROC curve yields an AUC of 0,8625, and following Ohlson's minimum-error rule, the optimal cut-off found was of 0,376. Applying this cut-off, 15 of the 18 public entities are correctly classified and there is 1 Type I error and 2 Type II errors. Thus, the entities identified as distressed at the optimal cut-off include FC Porto, Green Bay Packers, Juventus, Manchester United, MSGS, and Olympique Lyonnais.

Private subsample:

The adapted Ohlson model for private organizations demonstrates an ROC AUC of 0,9379, and the optimal cut-off was found to be 0,48. At this threshold, the classification matrix shows that from the non-distressed entities (81) there are 75 correctly classified and 6 misclassified as distressed (Type II errors), and from the distressed entities (32) there 24 correctly classified and 8 misclassified as non-distress (Type I error)

In total, 99 out of 113 entities were correctly classified, resulting in an accuracy rate of 87,6% and a misclassification rate of 12,4%.

Global subsample:

Using the predicted probabilities from the logistic model, the global Ohlson-sports demonstrates an ROC AUC of 0,9047 and an optimal cut-off of 0,47. Applying this cut-off from the non-distressed entities (91) there are 83 correctly classified and 8 misclassified as distressed (Type II errors), and from the distressed entities (40) there 29 correctly classified and 11 misclassified as non-distress (Type I error). This highlights a success rate of 85,5% and a failure rate of 14,5%.

Football subsample:

Using the predicted probabilities derived from the logistic specification the ROC performance showed am AUC of 0,9625, and an optimal cut-off of 0,40. With this cut-off, from the non-distressed entities (20) there are 18 correctly classified and 2 Type II errors, and from the distressed entities (20) there 19 correctly classified and 1 Type I error, obtaining an accuracy rate of 92,5%.

5. Discussion

5.1 Key Findings

This dissertation is based on the research question if whether classical models can retain their predictive power when applied directly to the sports industry and whether the inclusion of sport-specific variables increases their predictive power.

Primarily, the direct application of classical prediction models (Altman's Z-score (Altman, 1968, 2000) and Ohlson's O-score (1980)) to sports organizations turns out to be highly ineffective across global, public, private, and football-only subsamples, as both models generate extreme classifications and predicted probabilities near 0 or 1. These results confirms that these models built for manufacturing entities are not suitable for generalisation to sports entities, which are involved in a fundamentally different financial structure in terms of revenue volatility, cost rigidity, and leverage tolerance. Thus, the construction of a sector-adapted frameworks (Z-sports and Ohlson-sports) materially improves the economic interpretability and classification coherence of distress predictions. When sports-specific variables are incorporated, the estimated coefficients align consistently with financial distress theory and the institutional realities of professional sports, as Liquidity, Profitability, Operating Cash-Flow Capacity, and Wage intensity emerged as the most robust determinants of financial fragility in this industry.

Furthermore, based on the results, wage rigidity stands out as the most important driver of distress in sports organizations, as in all adapted models (particularly in football) its results shows that higher wage intensity ratios are strongly associated with increased distress risk. This finding reinforces that payroll commitments are the primary financial pressure point in professional sports, where wages are often fixed and driven by competitive expectations rather than sustainable financial planning.

In addition, the industry's ability to operate for prolonged periods with high leverage levels due to soft budget constraints, more favourable liability conditions, and (in some cases) recurrent owner support explains the weaker role that leverage-based measures have in this study compared with traditional corporate settings. This completely challenges the centrality of leverage in classical distress models when applied to sports organizations.

Finally, football-specific variables provide additional insight but limited incremental predictive power once core financial ratios are controlled for. Variables such as player trading profit, and UEFA intervention dummies are economically meaningful but often lose statistical significance due to strong correlations with profitability, liquidity, and wage intensity. This highlights that extraordinary revenues, such as player trading gains, are often masking underlying fragility rather than constituting sustainable financial strength, and that football entities need to buy and sell players to survive, acting as intermediaries for players and straying somewhat from their core business, which is entertainment.

5.2 Comparison with previous literature

Classical studies, such as Altman (1968, 2000) and Ohlson (1980), demonstrate strong predictive power in manufacturing and broad corporate settings, where capital structures, revenue streams, and cost rigidities follow a relatively predictable economic pattern. In contrast, sports entities operate under structurally different financial constraints, including wage rigidity, revenue volatility, and competitive spending cycles consistent with the argument developed by Deloitte and UEFA (FSR) and that explains the poor results of these models when applied directly to this industry, losing almost all discriminatory power. The empirical results of this dissertation are both align and diverge from previous literature on financial distress modelling, and the failure of the classical models consequently confirms the limited external validity suggested in the literature when financial structures diverge from the environments in which the models were developed. The adjusted models, Z-sports and Ohlson-sports incorporate sector-specific variables that previous researchers have also considered vital to sports economics (Alaminos & Fernández, 2019; Andreff & Staudohar, 2000; Plumley et al., 2017), highlighting liquidity constraints, wage overintensity, and volatile revenue streams as key drivers of financial fragility in sports entities. The importance of variables such as WC/TA, NI/TA, and Wage/Revenue reinforces established theoretical expectations, while provides a more appropriate predictive framework and showing that financial distress classical models cannot be transferred to the sports industry but sector-adapted models produce much better results fully align with the theory of financial distress and the empirical dynamics described in the sports finance literature.

6. Limitations and Further Research

This dissertation on one hand offers one of the most comprehensive cross-league analyses of financial distress in the sports industry, on the other hand is subject to some limitations that restrict the generalisability of the study and open space to further research.

One of the limitations is clearly concerning the construction of some financial variables, mainly for North American franchises that required structured approximations. Although these approximations have been carefully designed to ensure internal consistency, they inevitably introduce measurement errors. Consequently, comparisons between football entities and American franchises should be interpreted with caution and with this mind.

Another limitation is the fact that the study is based on a cross-sectional dataset for a single season, being impossible to modelling of dynamic distress trajectories, and ignores temporal adjustments. A panel data would allow to study revenue volatility, performance persistence, and early-warning signals with more precision.

Moreover, the distress definition used in this dissertation, although economically coherent and grounded in the previous literatures, is not a legal outcome or a concrete result but a set of conditions related to some accounting ratios. This introduces a certain level of circularity in the estimation of adapted models, where some variables were inherently related with the components of the distress dummy.

Furthermore, another limitation concerns Ohlson's framework (1980), since this sample does not present any observed cases of legal bankruptcy, as is done in the original model. Thus, in the direct application phase, the dependent variable is used based on Altman's classification, and in the adaptation phase, it is used according to the established conditions, deviating slightly from its initial idea.

Finally, the size of subsamples, such as the public and the football ones are relatively small which constrained statistical power and limited the stability of coefficient estimates.

7. Conclusion

The purpose of this dissertation is to assess whether classical corporate financial distress prediction models remain valid when transferred to the sports industry and applied to its organizations and, if not, to develop alternatives tailored to the sector that are capable of capturing the unique financial dynamics of the sports sector. Using a cross-sectional dataset of 131 organizations from football, NFL, NBA, and NHL for the 2022/2023 season, this study conducted an empirical comparison between the traditional Altman (1968, 2000) and Ohlson (1980) models and estimated sport-specific adaptations.

The results demonstrate that neither Altman nor Ohlson retain significant predictive power in the sports context when applied without any recalibration, as both models led to highly distorted rankings and clustered probabilities close to 0 or 1. These results highlights the incapacity of classical models to be directly applied to the sports industry, where salary rigidity, revenue volatility, and the influence of sports performance are part of a unique financial structure that creates a complete different environment.

In this context, this dissertation presents two sector-adapted models, Z-sports and Ohlson-sports, which integrate some sector-specific variables such as wage intensity, dependence on television broadcasting, and competitive performance indicators. In all subsamples tested (global, public, private, and only-football), these models constantly produced coefficients aligned with economic intuition as liquidity pressure, profitability, wage burden, and operating cash-flow relative to liabilities emerged as the most powerful drivers of sports financial fragility, confirming the insights from the sports finance literature concerning structural cost rigidity and instable revenue stream. The football-specific results further highlighted the importance of controlling wage costs and the limited predictive relevance of leverage in this industry, where this type of entities can have prolonged high leverage levels and operate normally.

Thus, this dissertation, presents empirical evidence that classical distress models are fundamentally incompatible with the sports entities' financial structure, provides robust sector-adapted alternatives that better capture the economic dynamic in this industry (reflecting the interplay between liquidity, wage rigidity, broadcasting dependence, and competitive performance), and offers one of the most comprehensive cross-league datasets to date. Nevertheless, future research should deepen these contributions allowing a more dynamic understanding of financial distress in one of the world's most economical complex industries.

8.Appendix

VARIABLES	(1) Z-sports (Public sample): OLS
TL/TA	0,1490
	(0,6548)
WC/TA	-1,6607***
	(-3,9472)
NI/TA	0,0188
	(0,0187)
WAGE	1,5138**
	(2,7618)
TV	-1,0951*
	(-2,0858)
ChampsPlayoffs	-0,3020*
	(-1,8057)
Constant	-0,1063
	(-0,4082)
R-squared	0,886
Adj R-squared	0,824
Standard Error (RMSE)	0,214
Observations	18
F-stat	14,30
Prob > F	0,000127

t-statistics in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 1-Z-sports Public sample

Correlation Matrix	*Distress*	*TL/TA*	*WC/TA*	*NI/TA*	*WAGE*	*TV*	*ChampsPlayoffs*
Distress	1						
TL/TA	0,769	1					
WC/TA	-0,629	-0,462	1				
NI/TA	-0,787	-0,717	0,556	1			
WAGE	0,404	0,342	0,251	-0,306	1		
TV	0,130	-0,127	-0,256	-0,162	0,327	1	
ChampsPlayoffs	-0,325	-0,118	-0,207	0,424	-0,590	-0,337	1

Table 1- Correlation Matrix Correlation Matrix Z-sports Public sample

VARIABLES	(1) Z-sports (Private sample): OLS
TL/TA	0,1323
	(0,7105)
WC/TA	-0,9962**
	(-2,5112)
NI/TA	-1,3608**
	(-2,3194)
WAGE	1,4781***
	(4,1884)
TV	-0,8503***
	(-2,9877)
ChampsPlayoffs	-0,0074
	(-0,1090)
Constant	-0,1082
	(-0,6169)
R-squared	0,422
Adj R-squared	0,389
Standard Error (RMSE)	0,354
Observations	113
F-stat	12,88
Prob > F	6,90e-11

t-statistics in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 2-Z-sports Private sample

Correlation Matrix	*Distress*	*TL/TA*	*WC/TA*	*NI/TA*	*WAGE*	*TV*	*ChampsPlayoffs*
Distress	1						
TL/TA	0,411	1					
WC/TA	-0,459	-0,697	1				
NI/TA	-0,432	-0,157	0,406	1			
WAGE	0,383	0,092	-0,075	-0,402	1		
TV	-0,052	-0,202	-0,047	-0,254	0,423	1	
ChampsPlayoffs	-0,011	0,073	0,013	0,075	-0,061	-0,127	1

Table 2- Correlation Matrix Z-sports Private sample

VARIABLES	(1) Z-sports (Global sample): OLS
TL/TA	0,1017
	(0,7215)
WC/TA	-1,1197***
	(-3,9153)
NI/TA	-1,2877***
	(-2,6475)
WAGE	1,4937***
	(4,8815)
TV	-0,8450***
	(-3,3028)
ChampsPlayoffs	-0,0203
	(-0,3356)
Listed	-0,1344
	(-1,2050)
Constant	-0,1111
	(-0,7332)
R-squared	0,498
Adj R-squared	0,469
Standard Error (RMSE)	0,337
Observations	131
F-stat	17,43
Prob > F	0

t-statistics in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 3-Z-sports Global sample

Correlation Matrix	*Distress*	*TL/TA*	*WC/TA*	*NI/TA*	*WAGE*	*TV*	*ChampsPlayoffs*	*Listed*
Distress	1							
TL/TA	0,460	1						
WC/TA	-0,497	-0,590	1					
NI/TA	-0,510	-0,321	0,461	1				
WAGE	0,380	0,115	0,025	-0,372	1			
TV	-0,063	-0,340	-0,033	-0,176	0,385	1		
ChampsPlayoffs	-0,051	0,059	-0,044	0,133	-0,158	-0,167	1	
Listed	*0,1205*	*0,5836*	*-0,1595*	*-0,1209*	*-0,022*	*-0,343*	*0,053500054*	*1*

Table 3- Correlation Matrix Z-sports Global sample

VARIABLES	(1) Z-sports (Football sample): OLS
WC/TA	-0,8437***
	(-3,5843)
NI/TA	-1,1242**
	(-2,2523)
WAGE	0,7207**
	(2,1850)
ChampsPlayoffs	-0,2127*
	(-1,9189)
Constant	0,1431
	(0,7776)
R-squared	0,627
Adj R-squared	0,585
Standard Error (RMSE)	0,326
Observations	40
F-stat	14,73
Prob > F	3,77e-07

t-statistics in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 4-Z-sports Football sample

Correlation Matrix	*Distress*	*WC/TA*	*NI/TA*	*Wage/Revenue*	*ChampsPlayoffs dummy*
Distress	1				
WC/TA	-0,550	1			
NI/TA	-0,662	0,449	1		
WAGE	0,431	0,042	-0,410	1	
ChampsPlayoffs	-0,350	-0,047	0,263	-0,300	1

Table 4- Correlation Matrix Z-sports Football sample

VARIABLES	(1) Z-sports (Football extension sample): OLS
WC/TA	-0,8112***
	(-3,4146)
NI/TA	-1,0636*
	(-2,0060)
WAGE	0,6025
	(1,6838)
ChampsPlayoffs	-0,2626**
	(-2,2311)
UEFACONM intervention	0,1602
	(1,2041)
PTRADE	0,1291
	(0,2675)
Constant	0,1705
	(0,8480)
R-squared	0,647
Adj R-squared	0,582
Standard Error (RMSE)	0,327
Observations	40
F-stat	10,06
Prob > F	2,54e-06

t-statistics in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 5-Z-sports Football-extension sample

Correlation Matrix	*Distress*	*WC/TA*	*NI/TA*	*WAGE*	*ChampsPlayoffs*	*TV*	*PTRADE*	*UEFACONM intervention*
Distress	1							
WC/TA	-0,550	1						
NI/TA	-0,662	0,449	1					
WAGE	0,431	0,042	-0,410	1				
ChampsPlayoffs	-0,350	-0,047	0,263	-0,300	1			
TV	0,512	-0,403	-0,393	0,613	-0,262	1		
PTRADE	-0,243	0,125	0,394	-0,317	0,193	-0,366	1	
UEFACONM intervention	0,327	-0,195	-0,278	0,300	0,186	0,151	0,074	1

Table 5- Correlation Matrix Z-sports Football-extension sample

VARIABLES	(1) Ohlson-sports (Public sample): Logit
SIZE	1,452*
	(0,811)
FUTL	-3,271
	(5,649)
CHIN	-1,190
	(1,219)
WAGE	7,093
	(4,556)
TV	-3,450
	(4,330)
Constant	-24,073*
	(12,682)
Model	Logit
Sample	Public
Observations	18
Pseudo R-squared	0,349
LR chi2	8,643
Prob > chi2	0,124

Standard errors in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 6-Ohlson-sports Public sample

Correlation Matrix	*Distress*	*SIZE*	*FUTL*	*CHIN*	*WAGE*	*TV*
Distress	1					
SIZE	0,311	1				
FUTL	-0,082	0,368	1			
CHIN	-0,328	0,194	0,263	1		
WAGE	0,404	-0,173	-0,067	-0,441	1	
TV	0,130	0,251	0,208	-0,255	0,327	1

Table 6- Correlation Matrix Ohlson-sports Public sample

VARIABLES	(1) Ohlson-sports (Private sample): Logit
SIZE	-0,684*
	(0,359)
FUTL	-14,862***
	(3,959)
CHIN	-0,794
	(0,591)
WAGE	5,958
	(4,096)
TV	6,574*
	(3,599)
Constant	6,499
	(5,266)
Model	Logit
Sample	Private
Observations	113
Pseudo R-squared	0,521
LR chi2	70,23
Prob > chi2	0

Standard errors in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 7-Z-sports Private sample

Correlation Matrix	*Distress*	*SIZE*	*FUTL*	*CHIN*	*WAGE*	*TV*
Distress	1					
SIZE	-0,345	1				
FUTL	-0,539	0,277	1			
CHIN	-0,389	0,215	0,250	1		
WAGE	0,383	0,053	-0,445	-0,270	1	
TV	-0,052	0,538	0,083	0,190	0,423	1

Table 7- Correlation Matrix Ohlson-sports Private sample

VARIABLES	(1) Ohlson-sports (Global sample): Logit
SIZE	-0,129
	(0,259)
FUTL	-10,108***
	(2,588)
CHIN	-0,762
	(0,476)
WAGE	5,348**
	(2,459)
TV	2,087
	(2,318)
Listed dummy	-0,434
	(0,775)
Constant	-0,910
	(4,048)
Model	Logit
Sample	Global
Observations	131
Pseudo R-squared	0,394
LR chi2	63,55
Prob > chi2	0

Standard errors in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 8-Ohlson-sports Global sample

Correlation Matrix	*Distress*	*SIZE*	*FUTL*	*CHIN*	*WAGE*	*TV*	*Listed*
Distress	1						
SIZE	-0,278	1					
FUTL	-0,496	0,378	1				
CHIN	-0,369	0,161	0,220	1			
WAGE	0,380	0,022	-0,359	-0,303	1		
TV	-0,063	0,574	0,187	0,092	0,385	1	
Listed	0,121	-0,470	-0,298	0,056	-0,022	-0,343	1

Table 8- Correlation Matrix Ohlson-sports Global sample

VARIABLES	(1) Ohlson-sports (Football sample): Logit
SIZE	0,913
	(0,600)
CLCA	2,059**
	(0,824)
CHIN	-2,593*
	(1,376)
WAGE	13,177**
	(6,029)
TV	18,706*
	(10,308)
PTRADE	11,683*
	(6,911)
Constant	-29,646**
	(13,183)
Model	Logit
Sample	Football
Observations	40
Pseudo R-squared	0,660
LR chi2	36,59
Prob > chi2	2,11e-06

Standard errors in parentheses
* p<0,10, ** p<0,05, *** p<0,01

Figure 9-Ohlson-sports Football sample

Correlation Matrix	*Distress*	*SIZE*	*CLCA*	*CHIN*	*WAGE*	*TV*	*PTRADE*
Distress	1						
SIZE	0,210	1					
CLCA	0,392	-0,055	1				
CHIN	-0,375	0,084	-0,230	1			
WAGE	0,431	0,079	-0,243	-0,162	1		
TV	0,512	0,125	0,104	-0,110	0,613	1	
PTRADE	-0,243	-0,055	-0,201	0,376	-0,317	-0,366	1

Table 9- Correlation Matrix Ohlson-sports Football sample

9.References

Alaminos, D., Del Castillo, A., & Fernández, M. Á. (2016). A global model for bankruptcy prediction. *PloS one*, *11*(11), e0166693.

Alaminos, D., & Fernández, M. Á. (2019). Why do football clubs fail financially? A financial distress prediction model for European professional football industry. *PloS one*, *14*(12), e0225989.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), 589-609.

Altman, E. I. (2013). Predicting financial distress of companies: revisiting the Z-score and ZETA® models. In *Handbook of research methods and applications in empirical finance* (pp. 428-456). Edward Elgar Publishing.

Altman, E. I., & Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the US market. *Abacus*, *43*(3), 332-357.

Andrade, G., & Kaplan, S. N. (1998). How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed. *The journal of finance*, *53*(5), 1443-1493.

Andreff, W., & Staudohar, P. D. (2000). The evolving European model of professional sports finance. *Journal of sports economics*, *1*(3), 257-276.

Ashraf, S., GS Félix, E., & Serrasqueiro, Z. (2019). Do traditional financial distress prediction models predict the early warning signs of financial distress?. *Journal of Risk and Financial Management*, *12*(2), 55.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, 71-111.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of finance*, *63*(6), 2899-2939.

Deloitte. (2025). *RE-IMAGINING THE MEDIA RIGHTS LANDSCAPE 32 REALISING THE LEADERSHIP PREMIUM 26 FOOTBALL LEAGUE CLUBS CONTENTS*.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. *The Journal of Finance*, *77*(1), 5-47.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International review of financial analysis*, *30*, 394-419.

Alabi, M., & Urquhart, A. (2024). The financial impact of financial fair play regulation: Evidence from the English premier league. *International Review of Financial Analysis*, *92*, 103088.

Morrow, S. (2013). Football club financial reporting: time for a new model? *Sport, Business and Management: An International Journal*, *3*(4), 297-311.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.

Opler, T. C., & Titman, S. (1994). Financial distress and corporate performance. *The Journal of finance*, *49*(3), 1015-1040.

Oxera. (2022). *Assessing the financial regulation of European football clubs*.

García, J. P. (2007). International evidence on the financial distress costs. In *El comportamiento de la empresa ante entornos dinámicos: XIX Congreso anual y XV Congreso Hispano Francés de AEDEM* (p. 14). Asociación Española de Dirección y Economía de la Empresa (AEDEM).

Platt, H. D., & Platt, M. B. (2006). Understanding differences between financial distress and bankruptcy. *Review of applied economics*, *2*(2), 141-157.

Plumley, D., Wilson, R., & Ramchandani, G. (2017). Towards a model for measuring holistic performance of professional Football clubs. *Soccer & Society*, *18*(1), 16-29.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The journal of business*, *74*(1), 101-124.

UEFA-Club Finance and Investment Landscape. (2024). *The European Club Finance and Investment Landscape 2 Contents*.

UEFA-FSR. (2022). *UEFA Club Licensing and Financial Sustainability Regulations Edition 2022 Contents*.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting research*, 59-82.

9.1 Other References

https://www.transfermarkt.pt/

https://resources.premierleague.pulselive.com/photo-resources/2023/09/08/e489e578-66be-45dd-bc94-5aebf514f640/PL_PTC_2022-23.png?height=800&width=1400

https://finance.yahoo.com/

https://swissramble.substack.com/p/champions-league-revenue-202223-estimate

https://sport.sky.it/calcio/champions-league/2024/02/08/champions-2022-2023-incassi-premi-squadre - 26

https://web.archive.org/

https://www.sec.gov/Archives/edgar/data/1636519/000163651923000009/msgs-20230630.htm

https://www.investing.com/equities/parken-historical-data

https://es.uefa.com/news-media/news/0274-14da0ce4535d-fa5b130ae9b6-1000--explainer-uefa-s-new-financial-sustainability-regulations/

https://www.uefa.com/running-competitions/integrity/financial-sustainability/

https://www.linklaters.com/en/insights/blogs/sportinglinks/2022/october/uefas-new-cost-control-rule

https://www.skysports.com/football/news/11095/13392443/chelsea-and-aston-villa-fined-lb27m-and-lb9-5m-respectively-by-uefa-for-breaching-financial-rules

https://www.reuters.com/sports/soccer/roma-fined-exceeding-cost-squad-rule-2024-09-06

https://www.uefa.com/news-media/news/029b-1e280e8c0d89-0a2f9801ea14-1000--cfcb-first-chamber-finalises-the-assessment-of-the-financial/

https://www.investopedia.com/articles/personal-finance/062515/how-nfl-makes-money.asp

https://www.spglobal.com/market-intelligence/en/news-insights/research/2025/10/record-nfl-revenue-continues-with-a-focus-on-media-opt-outs-and-global-growth

https://www.kroll.com/en/reports/valuation/valuation-insights-h2-2024/nfl-unique-strategy-dominating-valuation-proposition

https://x.com/brooks_gate/status/1813238261487202471?s=46&t=Xn0juU2C4hEaElfmeGb4jQ

https://www.investopedia.com/articles/personal-finance/071415/how-nba-makes-money.asp

https://digitalcollections.wesleyan.edu/_flysystem/fedora/2023-03/22252-Original%20File.pdf

https://en.as.com/other_sports/this-is-the-nhls-surprisingly-different-revenue-model-that-sets-it-apart-from-the-nfl-nba-or-mlb-n

https://www.sportspro.com/insights/nhl-ice-hockey-business-revenue-sponsorship-media-rights-data/

https://www.gamingtoday.com/wp-content/uploads/SponsorUnited-NHL-Marketing-Partnerships-Report-2022-23.pdf

https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS?year=2010

https://www.exchange-rates.org/pt/historico/usd-gbp-2023