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Capital Investment and Squad Value as Determinants of Sporting Success:

A Panel Data Analysis of UEFA Champions League Clubs

Investimento di capitale e valore della rosa come determinanti del successo sportivo:

un’analisi di dati panel dei club della UEFA Champions League

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Abstract

In professional football, sporting success and financial performance are closely linked, making the efficient allocation of capital increasingly relevant for club management and academic research. This study examines the extent to which capital investments and squad value determine the sporting success of UEFA Champions League clubs. The empirical analysis consists of two paths and is based on a panel dataset of 15 UEFA Champions League clubs observed over ten seasons (2015/16 – 2024/25). For Path a, the First Difference approach is used, while Path b is based on the Two-Way Fixed Effects method. In terms of explanatory power, squad value is the dominant predictor of sporting success, followed by transfer expenditures and salaries. While transfer expenditures have a negative direct effect on sporting performance, they positively influence squad value, indicating an indirect rather than direct contribution. This indirect effect suggests that the quality of player acquisition, as well as their integration into the team, is more important than the quantity of transfer expenditures. Clubs should therefore focus on targeted player acquisition and successful team integration rather than maximising transfer expenditures.

Abstract

Nel calcio professionistico, il successo sportivo e la performance finanziaria sono strettamente legati, rendendo l'allocazione efficiente del capitale sempre più rilevante per la gestione dei club e la ricerca accademica. Questo studio esamina in che misura gli investimenti in capitale e il valore della rosa determinano il successo sportivo dei club della UEFA Champions League. L'analisi empirica si articola in due percorsi ed è basata su un panel dataset di 15 club della UEFA Champions League osservati nel corso di dieci stagioni (2015/16 – 2024/25). Per il Percorso a viene utilizzato l'approccio delle First Difference, mentre il Percorso b si basa sul metodo dei Two-Way Fixed Effects. In termini di potere esplicativo, il valore della rosa è il predittore dominante del successo sportivo, seguito dalle spese per i trasferimenti e dagli stipendi. Sebbene le spese per i trasferimenti abbiano un effetto diretto negativo sulle prestazioni sportive, esse influenzano positivamente il valore della rosa, indicando un contributo indiretto piuttosto che diretto. Questo effetto indiretto suggerisce che la qualità dell'acquisizione dei giocatori, nonché la loro integrazione nella squadra, è più importante della quantità delle spese per i trasferimenti. I club dovrebbero quindi concentrarsi su un'acquisizione mirata dei giocatori e su un'integrazione efficace nella squadra, piuttosto che massimizzare le spese per i trasferimenti.

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List of Abbreviations

CapEx	Capital Expenditure
CSD	Cross-sectional Dependence
EMH	Efficient Market Hypothesis
EUR	Euro
FD	First Difference
FE	Fixed Effects
FFP	Financial Fair Play
FSR	Financial Sustainability Regulations
GBP	Great British Pound
IAS	International Accounting Standards
IFRS	International Financial Reporting Standards
OLS	Ordinary Least Squares
OpEx	Operating Expenditure
RBV	Resource-Based View
RE	Random Effects
TWFE	Two-Way Fixed Effects
UEFA	Union of European Football Associations
VIF	Variance Inflation Factor
VRIN	Valuable, Rare, Inimitable, and Non-substitutable

1. Introduction

Football is not only one of the most popular sports worldwide, but also represents a major economic market (Müller et al., 2017). European football clubs account for more than 80% of global transfer expenditures, but generate only 50% of global revenue in the football industry (Deloitte Sports Business Group, 2025; FIFA, 2025). Given that sporting success is one of the main drivers of revenue generation in football, this disparity represents a central economic paradox of professional football and raises the question of whether high transfer expenditures can be justified by a positive impact on sporting success (Rohde & Breuer, 2016).

Previous studies have examined the effect of transfer expenditures and squad value on sporting success, but have treated them as separate predictors. Matesanz et al. (2018) investigate the effect of transfer expenditures on sporting success, whilst Lepschy et al. (2020) and Gómez & Amat (2025) test the influence of squad value on sporting performance. However, no study has yet analysed both variables jointly within a single analytical framework. Moreover, the relationship between transfer expenditures and squad value has not yet been addressed. Whether both determinants operate independently or whether transfer expenditures indirectly affect sporting success through squad value remains untested. Disregarding this indirect relationship may lead to an incomplete understanding of how financial resources affect sporting success.

Building on this research gap, this study aims to address the research question of the extent to which capital investment and squad value influence the sporting success of UEFA Champions League clubs. To test this empirically, 15 UEFA Champions League clubs are examined over a period of ten seasons (2015/16 – 2024/25). The analysis is divided into two sequential paths. Path b identifies determinants of sporting success using the Two-Way Fixed Effect method. Subsequently, Path a tests whether transfer expenditures have a significant positive effect on squad value. The results of both analyses are confirmed by several robustness checks.

The theoretical framework is developed in Chapter 2 and is based on human capital theory (Becker, 1993), resource-based theory (Barney, 1991), investment theory (Jorgenson, 1963), and the efficient market hypothesis (Fama, 1970). Furthermore, the conceptual framework is based and developed on these theories and illustrates the mediator structure (transfer expenditures → squad value → league points). Chapter 3 justifies the sample selection and provides an overview of the descriptive statistics of the data. Thereafter, the methodology is explained in Chapter 4 and validated by specification tests. The results of the empirical analysis are presented in Chapter 5 and discussed and interpreted in Chapter 6. Furthermore, Chapter 6 outlines the limitations of the study and provides suggestions for further research. Lastly, Chapter 7 summarises the key findings and presents implications for club management.

2. Theoretical Framework

Professional football has fundamentally changed in recent years (Andreff, 2024). In the past, the focus was mainly on the clubs' sporting performance, but it has shifted to a complex ecosystem that combines economic, social, and sporting dimensions (Andreff, 2024; Müller et al., 2017). Football clubs are now seen as businesses with a wide range of stakeholders, such as shareholders, managers, players, and fans (Müller et al., 2017; Reschke et al., 2025). Consequently, football is not only one of the world's most popular sports today, but also a major economic sector (Müller et al., 2017).

From a business perspective, European football clubs operate in the sporting and commercial market (Budzinski & Satzer, 2011; Calahorro-López et al., 2024). Both markets are distinct but closely related (Budzinski & Satzer, 2011; Calahorro-López et al., 2024). The sporting market aims to achieve sporting success by winning competitions or securing league points, whilst the commercial market focuses on maximising financial profits by generating revenue from ticket sales, media rights, sponsorship, and merchandising (Gómez & Amat, 2025; Stewart & Jones, 2010). In these two markets, football itself is perceived as the end product, where various stakeholders, such as associations, clubs, the sports goods industry, and media companies, are involved in its production (Stewart & Jones, 2010). The product is then consumed by fans, either by attending matches at the stadium or by watching them on media platforms (Stewart & Jones, 2010). The amount of revenue a club generates is directly linked to its sporting performance, as national and international success drives financial returns through increased media exposure, sponsorship, and prize money (Amir & Livne, 2005; Rohde & Breuer, 2016). Thus, the dual market is characterised by the strong interaction between the sporting and commercial market, in which sporting success is not only a club's primary objective, but also a critical factor for economic success and thus a key driver of financial performance (Carlsson-Wall et al., 2016; Rohde & Breuer, 2016). Clubs, therefore, aim to increase their sporting performance to achieve long-term financial success (Matesanz et al., 2018). However, this interdependence is not always without tension (Carlsson-Wall et al., 2016). When an action or event generates both financial and sporting benefits, the sporting and financial objectives are aligned (Carlsson-Wall et al., 2016). However, this is usually not the case (Carlsson-Wall et al., 2016). For example, signing new players can improve sporting performance, whilst financial performance declines at the same time (Carlsson-Wall et al., 2016). Financial expenditures are therefore often necessary to improve sporting performance (Carlsson-Wall et al., 2016). In the long-term, these investments in sporting performance can yield positive financial effects through generating new revenues, for example, by winning a league title (Carlsson-Wall et al., 2016). It is precisely this interdependence that represents the economic core of professional football and is of central importance to this study.

2.1 Determinants of Sporting Success in Football

Based on the dual market structure, an understanding of the factors driving sporting success is essential to this study, as sporting performance is a key driver for a club's financial success (Rohde & Breuer, 2016). In football, sporting success is defined "as the ability of a club to obtain a large number of victories in the competitions in which it participates" (Gómez & Amat, 2025, p. 492) and can be measured by the final position in the competition, average points per league match, or the team's position in the Union of European Football Associations (UEFA) Season Club Coefficient (Gómez & Amat, 2025; Hägglund et al., 2013). Previous studies have mainly used league points or the final league position as indicators, as these variables reflect both a club's absolute performance over the season and its relative competitive position (Gómez & Amat, 2025).

The literature shows that various variables influence sporting success. These variables can be divided into two groups: financial factors and non-financial factors. Financial factors include turnover, transfer expenditures, and market value (Gómez & Amat, 2025). Matesanz et al. (2018) state that transfer expenditures are a key determinant of sporting success, as clubs with higher transfer expenditures tend to be more successful. Lepschy et al. (2020) observe that sporting success increases if the total market value of the starting formation of a team is higher. Gómez & Amat (2025) argue that the main driver of sporting success is the club's revenue. Their study shows that 80% of the variation in league points can be explained by revenue (Gómez & Amat, 2025). Additionally, factors such as transfer revenues, transfer expenditures and squad value correlate strongly with league points and revenue, suggesting a high degree of co-linearity (Gómez & Amat, 2025). This potential multicollinearity between the financial variables is formally tested by using the variance inflation factor (VIF) in Section 4.1.

In addition to financial factors, sporting success is influenced by non-financial factors. A team led by a high-quality coach achieves greater sporting success than other teams (Frick & Simmons, 2008). However, changes of coach have little or no impact on sporting performance (Bryson et al., 2024). Therefore, the quality of the coach influences the team's performance, but it cannot be said whether keeping the same coach for a longer period is better than changing coaches frequently (Bryson et al., 2024; Frick & Simmons, 2008). Furthermore, sporting success depends on the age and injury rate of individual players (Hägglund et al., 2013; Poli et al., 2018). To increase the likelihood of winning, research suggests that a team should consist of both young players and more experienced players (Poli et al., 2018). According to the CIES Football Observatory report, the optimal average team age is 26.5 years (Poli et al., 2018). Additionally, Hägglund et al. (2013) note that a higher injury rate is negatively correlated with a team's sporting success. The more injured players there are in the squad, the lower the league points at the end of the season (Hägglund et al., 2013). Moreover, Lepschy et al. (2020) observe that teams tend to be more successful when playing at home. Furthermore, Gásquez & Royuela (2016) state that the best temperature for sporting success is 14°C. If the temperature is higher or lower than this optimum, sporting success decreases (Gásquez & Royuela, 2016). This highlights that football is dependent on fortuity and coincidence.

Whilst literature shows that all the factors discussed above influence sporting performance, financial indicators such as market value and squad value can be understood as proxies for player talent, which has been identified as the most important driver for sporting success (Ciliberto et al., 2025; Müller et al., 2017). Human capital theory provides the theoretical foundation for understanding how investments in players generate sporting and financial returns.

2.2 Human Capital Theory

Human capital theory states that intangible assets, such as a person's knowledge, skills, and experience, represent a form of capital that influences a company's future economic productivity (Becker, 1962; Schultz, 1961). In contrast to physical or financial capital, human capital is inseparable from the individual (Becker, 1993). Consequently, human capital can only be increased through investment in education, training, medical care, or by obtaining new information (Becker, 1993). Among these various forms of human capital, Becker (1993) identifies education and training as the most significant drivers of human capital development. To increase a company's future economic productivity, companies must cover certain costs (Becker, 1993). These include, according to Becker (1993, p. 31), "the time and effort of trainees, the "teaching" provided by others, and the equipment and materials used". These costs represent the company's opportunity costs as if these resources had not been used to enhance human capital, the company could have used them to generate additional output (Becker, 1993).

Human capital can be further divided into general and firm-specific human capital (Becker, 1993). The distinction relates to which company benefits most from the training outcome (Becker, 1993). By building up general human capital, several companies can benefit, regardless of the firm or institution providing the training (Becker, 1993). This includes, for example, a university degree, as the person acquires knowledge that can benefit several companies (Becker, 1962). Firm-specific human capital, on the other hand, mainly benefits the company providing the training (Becker, 1993). This primarily involves on-the-job training, whereby employees acquire new knowledge and skills or improve existing ones (Becker, 1993). In the case of on-the-job training, it is often not possible to distinguish between general and firm-specific training, as general human capital is frequently a by-product of firm-specific training (Becker, 1993). Nevertheless, on-the-job training falls under firm-specific training, as the providing company benefits more than other companies (Becker, 1993). Additionally, in the case of company-specific training, the associated costs are distributed between the company and the employee to reduce the incentive of either party to terminate the work relationship prematurely and thereby sacrifice the returns on investment generated by the enhancement of human capital (Hashimoto, 1981).

Furthermore, human capital, just like physical capital, can depreciate (Becker, 1993). The quality of human capital is usually reflected in a person's salary (Becker, 1993). The higher the salary, the greater the benefit for the company (Becker, 1993). Age represents the primary driver of human capital depreciation, as Becker (1993) observes that a person's salary is low at the start of their career, then gradually increases, before declining again from a certain age onwards. This inverted U-curve illustrates the age-related depreciation of human capital.

2.2.1 Human Capital in Professional Football

Human capital theory plays an important role in professional football, as players have a major influence on the club's success, both economically and in terms of sporting performance (Fűrész & Rappai, 2022; Müller et al., 2017). In contrast to other businesses, the primary focus is not on physical capital, but on human capital (Müller et al., 2017; Rubio Martín et al., 2022). In general, human capital builds up through successful training and can be developed either internally or externally (Feess & Muehlheusser, 2003; Matesanz et al., 2018). Internal human capital is developed by investing in young players, whereas external human capital can be created by acquiring new players on the transfer market (Matesanz et al., 2018). In the case of internal human capital, clubs identify promising young talent and develop them progressively through their academic structures until they are integrated into the professional squad (Matesanz et al., 2018). As these players have not yet been traded on the transfer market, their market value is often lower at the initial stage, and the player is undervalued in the club's financial statements (Rowbottom, 2002; Stolowy & Wu, 2025). External human capital, on the other hand, is generated by acquiring players on the transfer market (Matesanz et al., 2018). In this case, the player's previous club has built up human capital through successful training, which is now traded on the transfer market (Feess & Muehlheusser, 2003). The transfer fee reflects the value of human capital (Frick, 2007). In practice, both strategies (internal and external human capital acquisition) are often combined (Fűrész & Rappai, 2022; Matesanz et al., 2018).

Furthermore, in professional football, as in human capital theory, a distinction can be made between general and firm-specific human capital (Becker, 1993; Lanza & Simone, 2025). General human capital refers to a player's abilities, from which another club could also benefit after a transfer (Feess & Muehlheusser, 2003). These general abilities include, for example, technical skills, athletic attributes, or tactical decision-making (Daumann et al., 2025). Firm-specific human capital in professional football refers to knowledge that enhances productivity only within a specific club (Becker, 1993; Lanza & Simone, 2025). This includes, for example, knowledge of the tactical system or established automatisms with teammates (Daumann et al., 2025). This distinction between general and firm-specific human capital explains why a player's transfer fee does not necessarily reflect his actual value contribution to a specific club, as firm-specific capital cannot be priced on the transfer market (Daumann et al., 2025; Frick, 2007).

Another aspect of human capital theory that can be observed in professional football is the age-related depreciation of human capital (Dendir, 2016; Rowbottom, 2002). This effect is reflected in the player's market value (Dendir, 2016). Initially, their market value is low, then rises steadily, before falling again from a certain point onwards (Campa, 2022; Franceschi et al., 2024). This depreciation pattern is also reflected in team composition. Compared to other industries, the peak in professional football at which human capital achieves the greatest increase in productivity is lower (Dendir, 2016; Poli et al., 2018). As part of a long-term study, the CIES Football Observatory analysed 31 teams from the top divisions of European leagues in the period 2009 - 2017 and found that the median age of successful teams is 26.5 years, suggesting that a team that has many young players tends to achieve greater sporting success (Poli et al., 2018).

2.2.2 From Human Capital to Club Resources

Whilst human capital theory explains the value of an individual football player, the resource-based view (RBV) extends this theory to the club level and explains how aggregated human capital leads to competitive advantages (Barney, 1991; Becker, 1962). According to Penrose (2009) a company can be defined by its resources, with companies owning different assets (Barney, 1991). A competitive advantage can be achieved if the resources meet four criteria: value, rarity, inimitability, and non-substitutability (Barney, 1991). Valuable resources enhance a company's efficiency and effectiveness (Barney, 1991). However, to gain a competitive advantage, resources must not only be valuable but, more importantly, rare (Barney, 1991). If several companies possess the same resources, none can gain a competitive advantage (Barney, 1991). Resources are considered rare if they are not widely available across competing companies in the market (Barney, 1991). Moreover, resources should not be easily replicable or replaceable by other companies (Barney, 1991). According to Barney (1991), a sustained competitive advantage can only be achieved if the company's resources fulfil all four criteria.

Professional football players satisfy these criteria. They are valuable because their skills directly impact sporting success, rare because top-quality players are scarce, and they are inimitable and non-substitutable, as each player offers a unique combination of characteristics and talent that cannot be replicated (Gerrard, 2005; Müller et al., 2017). In football, a club's total resource stock is reflected by the aggregated squad value (Daumann et al., 2025). This value includes all players and consists of the club's consolidated human capital (Daumann et al., 2025). Barney (1991) argues that aggregated human capital leads to competitive advantages, which is supported by several studies showing that clubs with higher squad value are more successful in terms of sporting performance (Gómez & Amat, 2025; Leksowski, 2021; Lepschy et al., 2020). Thus, from an RBV perspective, transfer expenditures are considered an investment in strategic resources, as they increase a club's resource stock, strengthen its competitive position, and provide the foundation for sporting success. This relationship between the aggregated capital stock and investment theory is discussed further in the following section.

2.3 Capital Stock and Investment Theory

Human Capital Theory shows that investments increase a company's future productivity (Becker, 1993). To explain this relationship economically and demonstrate why companies invest, Jorgenson's (1963) neoclassical investment theory will be used. The theory states that a company's primary objective is to maximise its net worth, which equals the present value of all future net revenues, and can be achieved by optimal capital accumulation (Jorgenson, 1963). Jorgenson (1963) distinguishes between capital stock (K) and investments (I). K refers to all assets held by a company at a given point in time, which is used to generate future returns, while I describes the periodic changes in K (Jorgenson, 1963).

Furthermore, a distinction can be made between the actual capital stock (K) and the desired capital stock (K^*) (Jorgenson, 1963). If these stocks differ, investments are made to close the gap (Jorgenson, 1963). However, the K responds with a delay to the investment, as projects take time due to planning and implementation (Hall & Jorgenson, 1967). The company reaches its optimal investment level when the productivity gains from additional capital no longer exceed its costs (Hall & Jorgenson, 1967).

Investments are divided into expansion investments and replacement investments (Jorgenson, 1963). Expansion investments increase K, whilst replacement investments maintain the existing K (Jorgenson, 1963). Expansion investments include the purchase of new machinery or licenses. Replacement investments, on the other hand, replace existing capital to ensure that the K remains constant, as assets depreciate over time (Jorgenson, 1963). The amount of replacement investments depends on the size of the existing K (Jorgenson, 1963). This means that the larger the K, the more a company must invest in replacement investments to maintain its level (Hall & Jorgenson, 1967).

From a business perspective, Jorgenson's (1963) investment theory can be applied to the financial distinction between capital expenditure (CapEx) and operational expenditure (OpEx). CapEx refers to capital expenditures that increase or maintain a company's K (Brealey et al., 2014). This includes both expansion and replacement investments (Jorgenson, 1963; Kieso, 2010). Under the International Financial Reporting Standards (IFRS), these expenditures are recognised as assets in the balance sheet (International Accounting Standards Board, 2026a, para. 5.6, 2026b, para. 16.7, 2026c, para. 38.21). OpEx, on the other hand, do not affect a company's K and are recognised as expenses in the income statement of a company (International Accounting Standards Board, 2026a, para. 5.6). As both indicators represent expenditures but are accounted differently and fulfil different economic functions, they are examined separately in this study.

2.3.1 Capital Accumulation in Professional Football

In professional football, these concepts can be applied to a club's expenditures. K is represented by the club's squad, implying that a club's K is the aggregated market value of all players and reflects the club's total human capital (Daumann et al., 2025). In general, clubs aim to obtain a K^* to reach their targeted sporting and financial objectives (Jorgenson, 1963; Rohde & Breuer, 2016). To achieve this, clubs buy and sell players on the transfer market until K equals K^* (Jorgenson, 1963; Rohde & Breuer, 2016). These purchases refer to a player's contractual registration right and not to the players themselves (Maroun et al., 2022; Stolowy & Wu, 2025). From an accounting perspective, these expenditures are classified as CapEx as they are non-recurring expenditures, increase a club's K, and are expected to generate future revenue (International Accounting Standards Board, 2026a, para. 5.6). Under the International Accounting Standard (IAS) 38, the purchased rights are recognised and amortised as intangible assets (Stolowy & Wu, 2025). Thus, the K decreases over time due to the amortisation. To maintain K at a constant level, additional players are purchased, which, according to Jorgenson's (1963) investment theory, corresponds to replacement investments. In contrast, home-grown players cannot be recognised as intangible assets as the associated development expenditures cannot be accurately assessed, implying that the criteria for an intangible asset are not fulfilled (International Accounting Standards Board, 2026c, para. 38.21; Maroun et al., 2022; Stolowy & Wu, 2025). However, under specific conditions, home-grown players can be recognised as intangible assets with a book value of zero or close to zero (Stolowy & Wu, 2025). Clubs that primarily focus on developing young players, therefore, report lower total assets on their balance sheet than clubs that actively acquire new players (Maroun et al., 2022).

Salaries do not meet the criteria under IAS 38 either and are therefore recognised as OpEx in the income statement as they do not affect K (International Accounting Standards Board, 2026a, para. 5.6, 2026c, para. 38.21). However, a higher salary may serve as an incentive for the player to improve their skills, thereby indirectly enhancing their individual human capital and increasing K (Ribeiro et al., 2022). Nevertheless, the type of contract can influence a player's performance (Frick, 2011). Frick (2011) argues that players with a fixed contract tend to perform better before renegotiating the contract. After signing a new contract, their sporting performance decreases again (Frick, 2011). Frick (2011) calls this phenomenon moral hazard. The classification of transfer expenditures as CapEx and salaries as OpEx provides the foundation for the empirical analysis in this study.

The investment theory outlines how clubs use player investments to increase and maintain their K. The following section analyses whether the transfer market operates efficiently and whether transfer fees accurately reflect the value of players by relying on the Efficient Market Hypothesis (EMH).

2.4 The Efficient Market Hypothesis

The EMH is based on Fama's (1970) research and represents a fundamental concept in current financial market theory. In an efficient market, prices deliver reliable information for capital allocation (Fama, 1970). Additionally, companies and investors base their investment decisions and choice of alternative assets on the assumption that prices completely represent all available information at any given time (Fama, 1970). According to Fama (1970, p. 387), a market is efficient if "(i) there are no transactions costs in trading securities, (ii) all available information is costlessly available to all market participants, and (iii) all agree on the implications of current information for the current price and distributions of future prices of each security". If all three conditions are fulfilled, the outcome is a market in which the entire available information is reflected in the market price of the asset (Fama, 1970). In reality, such a market with complete transparency of information and homogeneous expectations does not exist (Fama, 1970). Fama (1970) clarifies that markets can still be efficient even when these conditions are only partially met. For example, market prices may be information-efficient even though high transaction costs restricted trading significantly (Fama, 1970). The same applies to restricted access to information, as restricted information access does not necessarily undermine efficiency as long as enough participants are adequately informed (Fama, 1970). Transaction costs, information asymmetries, and differing expectations can therefore lead to inefficient markets, but are not always necessarily the cause of it (Fama, 1970). In reality, all three factors are present in the market to some extent, whereby the weighting determines whether the market is efficient or inefficient (Fama, 1970).

Within these three conditions, Fama (1970) further distinguishes between three interrelated forms of information efficiency: weak, semi-strong, and strong forms of market efficiency. These differences are based on the information incorporated into the market price (Fama, 1970). The weak form of market efficiency incorporates only historical prices into the current market price (Fama, 1970; Mondello, 2013; Vaughan Williams, 2005). Price forecasts based on historical data are therefore ineffective, as this information is already reflected in the market price (Mondello, 2013; Vaughan Williams, 2005). Price changes can arise due to the release of new information and may result in abnormal returns (Mondello, 2013; Vaughan Williams, 2005). In developed countries, the theory of weak form market efficiency is supported, whereas in emerging countries it is possible to generate abnormal returns based on historical information, as this data is not yet fully incorporated into market prices (Mondello, 2013). This suggests that the weak form of market efficiency is not supported in emerging countries (Mondello, 2013).

The semi-strong form of market efficiency expands the weak form by considering publicly available information in addition to historical data (Fama, 1970; Mondello, 2013; Vaughan Williams, 2005). Such information influences market prices and includes any data publicly available to all market participants, including financial disclosures or corporate announcements (Fama, 1970; Mondello, 2013). Event studies are conducted to empirically test whether the semi-strong form of market efficiency holds (Mondello, 2013). These studies test whether the release of public information is fully reflected in market prices and analyse how quickly this information is evident on the market (Mondello, 2013). As with the weak form of market efficiency, the semi-strong form is supported in developed countries, whilst it does not hold in emerging markets (Mondello, 2013).

The third form of market efficiency takes it one step further. In addition to historical and public information, the strong form of market efficiency also incorporates private information into market prices (Fama, 1970; Mondello, 2013). Private information refers to internal company knowledge, such as information about financial statements or upcoming mergers that only management has access to (Mondello, 2013). The strong form of market efficiency states that this information is already incorporated into market prices, making it impossible to generate abnormal returns (Fama, 1970; Mondello, 2013; Vaughan Williams, 2005). However, studies show that the strong form of market efficiency does not exist in reality, as market participants with insider knowledge can generate above-average returns (Mondello, 2013). This suggests that, in reality, private information is not fully incorporated into market prices.

Despite the EMH being the theoretical basis of financial market research, the theory has been the subject of criticism in recent years (Grossman & Stiglitz, 1980; Malkiel, 2003; Shiller, 2003). Studies focusing on behavioural finance combine financial approaches with findings from psychology and sociology, and argue that, in practice, not all market participants operate rationally (Shiller, 2003). The EMH is based on the assumption that fully informed, rational market participants offset such behaviour, but critics argue that this is not entirely achievable (Shiller, 2003). Another critical aspect regarding the EMH is related to the psychological behaviour of investors (Shiller, 2003). In this context, critics argue that price changes do not occur based on new information, but rather as a result of speculative behaviour by several market participants (Shiller, 2003). This behaviour leads to speculative bubbles, which conflict with the EMH, stating that prices are based solely on current available information (Fama, 1970; Shiller, 2003). Another criticism of the EMH is the existence of information costs (Grossman & Stiglitz, 1980). Some argue that perfect market efficiency is unachievable because no one would gather information if it were already fully reflected in prices (Grossman & Stiglitz, 1980). Even though critics have demonstrated that markets are not perfectly efficient, the EMH cannot be dismissed (Grossman & Stiglitz, 1980; Malkiel, 2003). Deviations from the EMH are usually short-term, meaning that no permanent above-average returns can be achieved through an irrational investment strategy (Malkiel, 2003; Shiller, 2003). Furthermore, the assumption that prices reflect available information is also well supported empirically by critics (Grossman & Stiglitz, 1980; Malkiel, 2003). Therefore, the EMH remains a central concept in financial market research.

2.4.1 Market Efficiency on the Football Transfer Market

The football transfer market is a place where clubs can buy new players and sell existing ones (Rowbottom, 2002). Transfers involve the payment of a transfer fee, which is negotiated between the selling and buying clubs (Dobson & Goddard, 2001; Rowbottom, 2002). Additionally, the transfer fee depends on a player's quality, their characteristics, and popularity (Franck & Nüesch, 2012). Structurally, the transfer market differs from the traditional capital market because prices are not standardised, as they often rely on rumours, there is no centralised trading platform, and there are only a limited number of market participants (Dobson & Goddard, 2001; Fűrész & Rappai, 2022). Moreover, market participants are often driven by emotions rather than rationality (Fűrész & Rappai, 2022). Whether the football transfer market represents an efficient market, and what form of market efficiency exists, has been discussed in previous literature.

An efficient market would exist if the market value of a player equals the actual transfer fee, meaning that all relevant information is incorporated into the price. Nowadays, market values are primarily set by the community and then published on Transfermarkt.de (Müller et al., 2017; Prockl & Frick, 2018). Studies show that crowdsourced market values are almost identical to actual transfer fees and that clubs use this data as a basis for their salary negotiations and transfer price determination (Herm et al., 2014; Müller et al., 2017; Prockl & Frick, 2018). Poli et al. (2024) show that up to 85% of transfer prices can be explained by publicly available information. This confirms that price-relevant information is included in the transfer price, which, by definition, indicates an efficient market (Franceschi et al., 2024).

However, despite the strong predictive potential of statistical models, individual transfer fees can deviate significantly from model-based estimates (Poli et al., 2024). These deviations are referred to as hyperinflations and can be explained by non-performance factors, such as a player's popularity (Franck & Nüesch, 2012; Matesanz et al., 2018). Franck & Nüesch (2012) claim that these factors are not reflected in the market value of a player but are included in the transfer fee, supporting the theory that transfer fees rely on irrational and emotional factors rather than being solely based on performance-related information (Franck & Nüesch, 2012; Fűrész & Rappai, 2022). Furthermore, Fűrész & Rappai (2022) state that the share prices of listed football clubs react prematurely to information that has not yet been published. This may also be the case in the transfer market, contradicting the assumption of information asymmetry, which is the basis for an efficient market.

According to the literature, the football transfer market cannot be clearly classified into any of the three categories (strong, semi-strong, or weak form of market efficiency). However, the existence of various findings suggests that the transfer market represents a semi-strong market. Studies show that publicly available information is incorporated into prices, but that private information and emotional factors are not (Fűrész & Rappai, 2022; Müller et al., 2017). Shynkevich (2022) directly tests semi-strong market efficiency in the football transfer market and confirms that information efficiency in the semi-strong form is present. This is further supported by other studies demonstrating that estimated market values align almost perfectly with actual transfer fees (Herm et al., 2014; Müller et al., 2017; Prockl & Frick, 2018). Fűrész & Rappai (2022) show that the strong form of market efficiency does not appear to hold as private information influences transfer market prices ahead of official announcements. Therefore, according to the definition of market efficiency, the football transfer market is semi-strongly efficient, as publicly available information is incorporated into the market value and transfer price, but insider information is not. This means that market values are accurate price indicators that reflect the market's knowledge of a player.

2.5 Conceptual Framework

The conceptual framework combines the theories from Chapter 2 and derives hypotheses to directly test the relationship between capital investments, squad value, and sporting success. Within the theoretical framework, determinants of sporting success are identified (see Section 2.1). Furthermore, the significance of human capital in professional football is discussed in Section 2.2. Section 2.3 focuses on capital market theory and states that the capital stock of football clubs can only be increased by targeted CapEx investments. Lastly, Section 2.4 demonstrates that the football transfer market is a semi-strong efficient market, which justifies the use of transfer market data to assess the market value of individual players.

Matesanz et al. (2018) show that transfer expenditures have a positive impact on sporting success, whilst Lepschy et al. (2020) and Gómez & Amat (2025) found that squad value positively influences sporting performance. Which effect is stronger, and whether the influence is direct or indirect, has not yet been examined by the studies mentioned in Chapter 2. The conceptual framework assumes that the effect of transfer expenditures on sporting success is indirect and is mediated by squad value (see Figure 1).

Based on Barney's (1991) RBV theory, it can be assumed that the effect of squad value is greater than the effect of transfer expenditures on sporting success. The RBV theory states that only resources that meet the VRIN criteria (valuable, rare, inimitable, and non-substitutable) lead to a competitive advantage. As outlined in Section 2.2, the squad value of a professional football club meets these criteria, suggesting that the effect of squad value on sporting success exceeds that of transfer expenditures on sporting success. Furthermore, it can be assumed that the effect of transfer expenditures is indirect. Based on Jorgenson's (1963) investment theory, transfer expenditures are recognised as CapEx, thereby influencing a company's capital stock. Additionally, Becker (1993) states that firm-specific human capital must first be developed by newly acquired players before it can potentially benefit the club.

These findings suggest that the influence of transfer expenditures on sporting success is time-delayed and can only affect squad value, as transfer expenditures increase the capital stock before the potential can be realised.

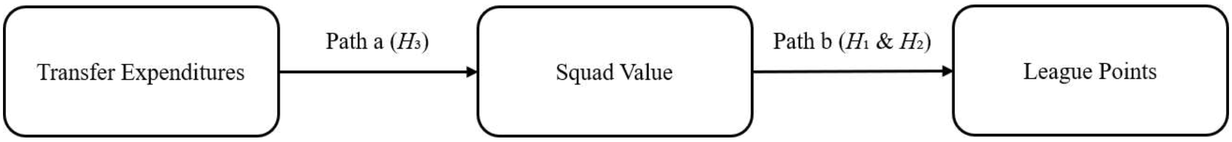
Furthermore, the literature suggests that squad value has a greater impact on sporting success than salary. Squad value represents a club's aggregated human capital and, according to Lepschy et al. (2020) and Gómez & Amat (2025), has a positive influence on sporting performance. Salaries, on the other hand, are OpEx and can only influence sporting success indirectly by providing incentives to improve one's own sporting performance through the amount of the salary. However, Frick (2011) argues that, due to moral hazard, a higher salary does not necessarily lead to increased sporting performance. Therefore, salary may not be a reliable predictor of sporting success.

Moreover, based on the literature, it is assumed that transfer expenditures have a positive impact on squad value. Under IAS 38, transfer expenditures are recognised as intangible assets and directly increase a club's capital stock (see Section 2.3). Combined with the evidence that externally acquired human capital directly increases squad value, this suggests a positive effect of transfer expenditures on squad value (Matesanz et al., 2018).

The findings from the literature are summarised in the conceptual framework and are empirically tested in the following chapters. The relationship between investments, squad value, and sporting success is illustrated in Figure 1. Path b tests whether squad value is the main predictor of league points and enables a comparison between different investment strategies by jointly examining squad value, transfer expenditures, and total salary. Path a examines the effect of transfer expenditures on squad value. In this model, it is assumed that transfer expenditures have no direct positive effect or even a negative effect on sporting success, as high transfer expenditures without proportional squad value gains could indicate inefficient investment. Thus, squad value acts as a mediator between transfer expenditures and sporting success.

Figure 1

Conceptual Framework



Based on the findings in the literature and the conceptual framework, the following hypotheses can be derived:

H_1: The effect of squad value on league points exceeds the effect of transfer expenditures (|β_squad_value| > |β_transfer_expenditures).

H_2: The effect of squad value on league points exceeds the effect of total salary (|β_squad_value| > |β_total_salary|).

H_3: Transfer expenditures have a significant positive effect on squad value (β_transfer_expenditures > 0).

These hypotheses are empirically tested in the following sections.

3. Data

Based on the conceptual framework in Section 2.5, relevant data from various sources have been collected to capture both the financial and sporting dimensions. The first section of this chapter describes the selection process of the 15 sample clubs and states how the data has been compiled. Section 3.2 defines all variables used in the empirical analysis and specifies their respective functions. Lastly, Section 3.3 provides a descriptive overview of the data.

3.1 Data Sample and Source

The empirical analysis is based on a panel dataset of 15 UEFA Champions League clubs observed over ten seasons from 2015/16 to 2024/25 and combines financial and sporting performance data from multiple sources. For the empirical analysis, the last ten completed seasons are used. The current season (2025/26) is excluded, as the results could be distorted by incomplete data. In particular, the incomplete league points distort the results as this metric represents the dependent variable. Additionally, mid-season transfer expenditures do not reflect a club's total investment expenditures, meaning that sufficient comparability between the current season (2025/26) and past seasons cannot be achieved. To counterbalance seasonal fluctuations, ten seasons are included in the empirical analysis, ensuring that single seasons, such as the COVID-19 seasons, are weighted less, minimising the impact on the overall results. This ensures that the results of the empirical analysis capture the relationship between investments and sporting success, rather than being the consequence of season-specific shocks.

Clubs have to meet various criteria to be included in the empirical analysis. For the initial sample, leading European clubs are selected. The sample includes all clubs participating in the UEFA Champions League during the selected time period (see Appendix Table A1). This restriction to European clubs and the participation in the UEFA Champions League was adopted because European football receives a high level of attention worldwide and represents a large share of the market (Deloitte Sports Business Group, 2025). Overall, European football accounts for more than 50% of revenue share generated within the global football industry in 2024/25 (Deloitte Sports Business Group, 2025). Furthermore, participation in the UEFA Champions League is considered an indicator of sporting success, as a club can only participate if it was among the best clubs in its league in the previous season. This criterion ensures that clubs have been successful in previous seasons and is important for the empirical analysis, as this study aims to determine the factors of sporting success. In total, 95 clubs participated in the UEFA Champions League between the 2015/16 and 2024/25 seasons, resulting in a first sample of $N = 95$ clubs.

The initial sample is further narrowed down by restricting it to clubs competing in one of the Big Five European Leagues, namely the Premier League, Bundesliga, La Liga, Serie A, and Ligue 1. These leagues dominate the European football market and share key structural characteristics, such as comparable season lengths, an identical points system, and home and away fixtures (Deloitte Sports Business Group, 2025). These similarities ensure sufficient comparability across clubs. Applying this criterion reduces the initial sample from $N = 95$ to $N = 43$ clubs.

Finally, clubs that have participated in the UEFA Champions League less than six times during the selected time period are excluded. These may include clubs that participated in the tournament only once or infrequently and therefore do not structurally qualify as top clubs. This restriction is important to ensure comparability in terms of sporting success between clubs. Furthermore, this constraint increases the likelihood of data availability, as most data is only publicly available for clubs playing in the first leagues. After eliminating all clubs that do not meet the criterion, a sample of $N = 15$ clubs remains (see Table 1). These clubs are used for the empirical analysis.

Table 1

Club Sample used for the empirical analysis

Team	League	Champions League Participation
FC Barcelona	La Liga	10
Atlético de Madrid	La Liga	10
Real Madrid	La Liga	10
Bayern Munich	Bundesliga	10
Paris Saint-Germain	Ligue 1	10
Manchester City FC	Premier League	10
Borussia Dortmund	Bundesliga	9
Juventus FC	Serie A	9
Liverpool FC	Premier League	7
Inter Milan	Serie A	7
RB Leipzig	Bundesliga	7
Sevilla FC	La Liga	7
Manchester United	Premier League	6
SSC Napoli	Serie A	6
Chelsea FC	Premier League	6

The data used for this study were collected from Transfermarkt.de, Capology.com, and the official websites of the respective leagues. All data were collected in March 2026. Data on squad value, transfer expenditures, transfer revenues, squad size, and average squad age are provided by Transfermarkt.de. The platform was founded in 2000 by Matthias Seidel and is the world's largest football database (Reich, 2025; Transfermarkt, 2026). All data used for this study are freely and publicly available. Transfermarkt.de enables its users to add or edit data, which implies that data is based on the community's estimations and is not officially calculated by clubs or UEFA. The subjective assessment may result in distortions, particularly regarding less popular players. However, for top clubs, it is assumed that the data is sufficiently accurate as studies show that the estimations made by the community are almost identical to actual transfer prices and can therefore be used as variables (Herm et al., 2014; Müller et al., 2017; Prockl & Frick, 2018). Moreover, literature shows that many studies rely on data from Transfermarkt.de (Herm et al., 2014; Müller et al., 2017; Rubio Martín et al., 2022). As this study focuses on clubs participating in the UEFA Champions League, it is assumed that the values estimated by the community are sufficiently accurate. Thus, data from Transfermarkt.de is used for the variables squad value, transfer expenditures, transfer revenues, squad size, and average squad age.

Salary data is provided by Capology.com. Capology.com is a database specialised in salary data for professional football (Capology.com, 2026). The data is compiled using insider knowledge from contract negotiations and media reports (Capology.com, 2026). Where direct information is unavailable, algorithmic estimates are used (Capology.com, 2026). The data is publicly available and free of charge. For this study, the gross fixed salary per club and season is collected. The data is compiled in the respective currency of the country. No salary data has been published for RB Leipzig for the 2015/16 season, as the club was playing in the 2. Bundesliga at that time.

Official websites of the respective leagues are used for collecting data in terms of league points and league position. This data is recorded by official institutions and leaves no room for interpretation. Consequently, no estimates are required, which ensures a high level of data quality. As an additional validation, league points and league positions were cross-checked against data published on Transfermarkt.de. As all data is consistent, the accuracy of the underlying data is confirmed.

3.2 Variables

Variables used for the empirical analysis are defined and organised following the structure of the conceptual framework (see Section 2.5). Path a examines which factors influence squad value, while Path b examines the determinants of sporting success measured in league points. Table 2 provides an overview of all variables used in Path a, specifying their function within the model (dependent, independent, or control variable) and outlining their data source.

Table 2

Variables for Path a

Variable	Unit	Function	Data Source
Squad Value	EUR Million	Dependent Variable	Transfermarkt.de
Transfer Expenditures	EUR Million	Independent Variable	Transfermarkt.de
Transfer Revenues	EUR Million	Control Variable	Transfermarkt.de
Squad Size	Number of Players	Control Variable	Transfermarkt.de
Average Squad Age	Years	Control Variable	Transfermarkt.de

Squad Value. Path a examines variables that influence squad value. Thus, squad value is the dependent variable in this path. It shows the overall market value of all players in EUR millions and serves as a proxy for the accumulated capital stock, as established in Section 2.3. The data is continuously updated throughout the season, ensuring that all transfer windows are included in this metric. The value reflects a club's squad value at the end of the season. The data is retrieved from Transfermarkt.de.

Transfer Expenditures and Transfer Revenues. Transfer expenditures are defined as the sum of all transfer fees paid within a season, including both the summer and winter transfer windows, to capture a club's full annual investment behaviour. Based on the capital stock and investment theory discussed in Section 2.3, transfer expenditures represent the primary investment flow through which clubs accumulate squad value. Expenditures are stated in absolute values in EUR millions and are not deducted from transfer revenues, as net transfer expenditures would distort the effect of transfer expenditures on the squad value. For instance, a simultaneous purchase and sale of players of equal value would result in net expenditures of zero, implying that the influence of transfer expenditures on squad value cannot be meaningfully interpreted when using net expenditures. Gross transfer expenditures, on the other hand, capture investment behaviour independently of a club's cost structure. However, transfer revenues are included as a control variable to avoid overestimating the effect of gross transfer expenditures, as clubs with high transfer revenues may systematically invest more.

Squad Size and Average Squad Age. Further variables are squad size and average squad age. Both variables are expected to influence the squad value and are therefore included as control variables. Squad size refers to the number of players playing for the respective club at the end of each season. Average squad age is the average age of these players and is expressed in years. Both variables are calculated at the end of the season, ensuring that all relevant information throughout the season is incorporated into the variables. As squad value represents the accumulated human capital of all players, clubs with larger squads tend to report higher squad values, independent of individual player quality. The age of individual players further influences the squad value, as the market value of young players tends to be low, increases with experience and playing time, and then declines again (Campa, 2022; Franceschi et al., 2024).

Path b examines the determinants of sporting success. The variables used are shown in Table 3.

Table 3

Variables for Path b

Variable	Unit	Function	Data Source
League Points	Points per Season	Dependent Variable	League Websites
Squad Value	EUR Million	Independent Variable	Transfermarkt.de
Transfer Expenditures	EUR Million	Independent Variable	Transfermarkt.de
Total Salary	EUR / GBP Million	Independent Variable	Capology.com
Squad Size	Number of Players	Control Variable	Transfermarkt.de
Average Squad Age	Years	Control Variable	Transfermarkt.de
League Position	Rank (1 = best)	Robustness Check	League Websites

League Points. The dependent variable is intended to measure a club's sporting performance. As outlined in Section 2.1, sporting success can be measured using various metrics, with most studies employing league points, league position, or the UEFA Season Club Coefficient (Gómez & Amat, 2025; Hägglund et al., 2013). League points measure absolute performance, whilst league position measures a club's relative performance within a league. During an exceptionally strong season, a team may achieve a poor league position despite high points and good sporting performance if competitors have also performed strongly. The UEFA Season Club Coefficient measures sporting success across multiple competitions but is heavily dependent on participation in UEFA competitions rather than league performance (UEFA, 2024). As the focus of this study is on league performance, the UEFA Season Club Coefficient is not suitable as a dependent variable. For this study, league points are used as an indicator of sporting success, as the variable directly reflects sporting performance and is independent of the performance of other clubs. The variable is measured by the total points a club obtains in a season within its respective league. A club receives three points for a win, one point for a tie, and zero points for a loss. The sum of all points within a season equals the league points and is used as the dependent variable in Path b. Additionally, data on league position are collected for the alternative dependent variable robustness check (see Section 5.1.2). This variable describes the club's league position at the end of the season. In contrast to league points, a lower value indicates better sporting performance. The scale ranges from one to the number of clubs participating in the league, with one being the best possible result.

Squad Value, Transfer Expenditures and Total Salary. Independent variables in Path b examine which financial determinants influence sporting success. Variables used for the empirical analysis are squad value, transfer expenditures, and total salary. The use of squad value and transfer expenditures is consistent with the justification in Path a. Salary describes a club's total salary expenditures per season and is included because it represents an alternative investment option to transfer expenditures. Furthermore, salaries reflect a player's quality as top players tend to earn higher salaries (see Section 2.2). Values for Premier League clubs are stated in GBP, and all others in EUR.

Squad Size and Average Squad Age. Squad size and average squad age are used as control variables, as these could have a direct impact on sporting success. With a larger squad, a club may be able to better compensate for player absences due to injuries or suspension. This means that the coach can select the starting formation from a larger pool of players, which could have a positive impact on sporting success. The average squad age also correlates with a club's sporting performance, as a player's fitness and experience are closely linked to age and sporting success (Poli et al., 2018).

3.3 Descriptive Statistics

Table 4 shows descriptive statistics of all variables used in the empirical analysis. The data is based on a panel data set of 15 UEFA Champions League clubs observed over ten seasons from 2015/16 to 2024/25.

Table 4

Descriptive Statistics

Variable	*N*	*Mean*	*SD*	*Min*	*Max*
League Points	150	75.53	12.84	41.00	100.00
Squad Value (M EUR)	150	701.86	268.27	41.05	1460.00
Total Salary (M EUR)	149	158.74	76.29	27.57	386.34
Transfer Expenditures (M EUR)	150	134.23	93.47	0.00	630.25
Transfer Revenues (M EUR)	150	88.76	60.30	0.40	316.30
Squad Size	150	38.82	6.15	28.00	60.00
Average Age (Years)	150	25.42	0.98	22.20	27.70

Note: Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25. Squad value and transfer expenditures in EUR million. Total salary in EUR / GBP million depending on club nationality.

On average, clubs score 75.53 points per season. The standard deviation of 12.84 and the range of 41 to 100 points illustrate that, despite their regular participation in the UEFA Champions League, the 15 clubs achieve different levels of sporting performance in their respective league.

The maximum value of 100 represents a nearly perfect season, whilst the minimum value of 41 indicates that individual clubs only achieve moderate league results in certain seasons.

The squad value has a mean of EUR 701.86 million and a standard deviation of EUR 268.27 million. The high variance suggests that the 15 clubs employ different strategies when selecting their squads. The minimum value of EUR 41.05 million belongs to RB Leipzig in the 2015/16 season (see Appendix Table A2). In this season, the club played in the 2. Bundesliga, which might explain the low squad value.

Transfer expenditures and transfer revenues reflect a club's investment activities. The descriptive statistics show that the 15 clubs invested more than they earned during the selected period. On average, clubs spent EUR 134.23 million but received only EUR 88.76 million. The high standard deviation of EUR 93.47 million in transfer expenditures may reflect not only differences in investment strategies across clubs, but also fluctuations in investment activities within individual clubs over the observed period. Some clubs do not spend any money on transfers in certain seasons, whilst others spend up to EUR 630.25 million in a single season.

The descriptive statistics show that an average of EUR 158.74 million is spent on players' salaries per season. This value exceeds average transfer expenditures, suggesting that salary commitments represent a larger financial obligation for clubs than transfer fees. Within the selected time period, Real Madrid has the highest average salary expenditures, whilst Sevilla FC has the lowest (see Appendix Table A3). The data is based on n = 149, meaning that one observation has been excluded for the empirical analysis. In the 2015/16 season, RB Leipzig played in the 2. Bundesliga. For that reason, this observation has been excluded as salary data is not publicly available for the 2. Bundesliga.

The structural characteristics of the squad (squad size and average squad age) both show little deviation, suggesting that the 15 clubs are homogenous in terms of their structural characteristics. This is to be expected given that the sample consists only of UEFA Champions

League clubs. On average, a club has a squad size between 38 and 39 players with an average age of 25.42 years. This figure aligns almost perfectly with the optimal average age for maximising sporting success (26.5 years), as calculated by CIES Football Observatory (Poli et al., 2018). Chelsea FC had the youngest squad (22.2 years) in the 2023/24 season, whilst Inter Milan had the oldest squad with an average age of 27.7 years in the 2021/22 season (see Appendix Table A2 and Table A4).

The correlation between the different variables and league points (see Appendix Table A5), as well as squad value (see Appendix Table A6), provides initial evidence of the relationship between the independent and dependent variables. Squad value is the only variable showing a significant positive correlation with league points (r = .170, p < .10). None of the other variables displays a significant correlation. Regarding squad value, Δ transfer expenditures (r = .224, p < .01) and Δ squad size (r = .193, p < .05) correlate significantly and positively with squad value (for the first-difference approach and the use of Δ values, see Section 4.2). Δ Transfer revenues and Δ average age show no significant correlation. A regression analysis will be conducted in the following chapters to examine the relationship while controlling for other variables.

Overall, the descriptive statistics show that whilst the 15 clubs differ in their financial and sporting performance, they have a similar squad structure. These findings are consistent with the expectations that financial resources can be an important factor in sporting success and provide the rationale for the empirical analysis.

4. Methodology

To answer the research question, the relationship between investments and sporting success is analysed empirically. The empirical analysis is based on two sequential paths (see Section 2.5). Path b examines the influence of various determinants on sporting success (league points), whilst Path a assesses which variables influence a club's squad value. The empirical analysis first focuses on Path b, as this is particularly important for answering the research question. Furthermore, it must first be confirmed that squad value has a significant positive influence on sporting success before Path a can be tested.

The data follow a standard panel data structure. The sample consists of 15 clubs observed over ten seasons. Thus, the dataset has cross-sectional (i) and temporal (t) dimensions. Furthermore, a panel data structure controls for unobservable club-specific attributes (c_i), which will be discussed in more detail in Section 4.1 (Wooldridge, 2010). In the literature, the use of panel data methods in sport economics studies is standard practice. Rohde & Breuer (2016), Gásquez & Royuela (2016), Müller et al. (2017), and Lanza & Simone (2025) address similar topics in their studies and use Fixed Effects (FE) based on a panel data set to estimate the models. Some other studies, such as Campa (2022), use Ordinary Least Squares (OLS) to estimate the models. However, this means that c_i cannot be controlled for. Therefore, this study employs panel data methods, as controlling for c_i is methodologically necessary and will be empirically justified in the following sections.

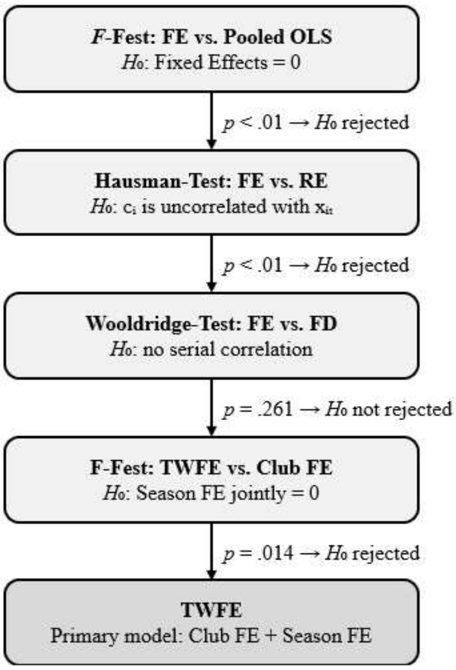
In addition, specification tests are carried out to empirically determine which methodology is suitable for the respective path. These tests ensure that the methodology used is not only reasonable in terms of content but also aligns with the data. The specification tests are carried out for each path individually, as the dependent variables for Path a and Path b may have different characteristics, meaning that different methods may be required to estimate the models. All models are estimated using R (version 4.5.2).

4.1 Path b: Determinants of Sporting Success (Two-Way Fixed Effects)

Panel data models often contain unobservable variables that remain constant over time (Wooldridge, 2010). In the context of this study, these could include club culture, management, infrastructure, or reputation. These variables can influence a club's sporting success but cannot be measured directly. In literature, these variables are referred to as unobservable effects (c_i) (Wooldridge, 2010). Depending on whether these attributes affect the other variables, some methods cannot be used as a sufficient estimate of the model, as they would distort the results. Figure 2 provides an overview of the specification tests carried out for Path b to identify the most suitable model for estimating the variables' impact on sporting success.

Figure 2

Specification Test for Model Selection (Path b)



First, it is determined whether Pooled OLS or FE is more suitable to estimate the model. Pooled OLS considers all 150 observations as independent and only includes c_i in the error term (Wooldridge, 2010). If $c_i = 0$ or if c_i is not correlated with other observations $E(x_{it} \times c_i) = 0$, Pooled OLS is a suitable method (Wooldridge, 2010). If this is not the case, using this method would distort the results (Wooldridge, 2010). Instead, alternative methods, where c_i is explicitly incorporated, such as FE or Random Effects (RE), must be used (Wooldridge, 2010). To test if c_i correlates with other variables, an *F*-test is carried out. If all club-specific fixed effects are zero (H_0), the clubs do not differ significantly in their unobservable characteristics, meaning that Pooled OLS is a suitable method (Wooldridge, 2010). In this study, the test has shown that H_0 is rejected ($F = 4.95$, $p < .01$), meaning that unobservable club-specific characteristics (c_i) influence sporting success. Therefore, Pooled OLS is eliminated as a suitable method to examine the determinants of sporting success.

Next, the Hausman test is used to determine whether the model should be based on FE or RE. The test evaluates whether the RE assumption of zero correlation between c_i and x_{it} (observed values of the independent variables for each club (i) in season (t)) is statistically justified (Wooldridge, 2010). This is examined by comparing the estimates of FE and RE (Wooldridge, 2010). Since FE remains consistent regardless of whether c_i correlates with x_{it}, whilst RE requires this assumption to hold, a significant divergence between those two estimators indicates that RE is not suitable for estimating the model (Wooldridge, 2010). For Path b, the Hausman test returns a result of $\chi^2 = 39.48$ and $p < .01$. Therefore, H_0 (c_i is uncorrelated with x_{it}) is rejected, and FE is the preferred method.

Subsequently, a test is performed to determine which method (FE or First Difference (FD)) is more effective in eliminating c_i. FE uses Within-Demeaning to eliminate c_i by calculating the club-specific average ($\bar{y}_i$) for each variable (y_i) across all $t = 10$ seasons, which is then subtracted from each club observation (y_{it}) (Wooldridge, 2010). Given that c_i is assumed to be constant over time, $\bar{c}_i = c_i$ and is thereby eliminated (Wooldridge, 2010). FD, on the other hand, eliminates c_i by measuring the change to the previous period ($\Delta y_{it} = y_{it} - y_{i,t-1}$) (Wooldridge, 2010). If external shocks, such as injuries of key players, changes in management, or COVID-19, affect the data in the long term, FD is more suitable, as it only calculates the change from the previous period rather than the average of all periods (Wooldridge, 2010). In practice, it is often unclear whether a shock has a short- or long-term effect (Wooldridge, 2010). To empirically justify the choice between FE and FD, the Wooldridge Serial Correlation test is used. The test checks for serial correlation in the FE residuals (Wooldridge, 2010). If this is the case, H_0 (no serial correlation in the residuals) is rejected, and FD is preferred over FE as the appropriate estimator for the model (Wooldridge, 2010). In this study, the Wooldridge Serial Correlation test has a $\chi^2 = 11.21$ and a p-value of .26. This means that no serial correlation is evident in the FE residuals, meaning that H_0 cannot be rejected and FE is preferred over FD.

Lastly, it is determined whether Club FE is sufficient or whether Two-Way Fixed Effects (TWFE) are required for the model estimation. TWFE incorporates Club FE and Season FE. A model based solely on Season FE is not considered, as Club FE is already confirmed as necessary in the first specification test, meaning that removing Club FE would lead to biased results. A model based on Club FE controls only for time-variant club heterogeneity, whereas TWFE additionally controls for common time shocks (Baltagi, 2021). Without considering Season FE, common time shocks are included in the error term (Baltagi, 2021). If they correlate with the variables, using only Club FE would distort the results (Baltagi, 2021). Thus, for this study, TWFE is likely the preferred estimator, as common time shocks are likely to affect all 15 clubs and are not club-specific. Shocks affecting all clubs within a season could be COVID-19 or transfer market inflation. Empirically, the impact of the shocks on the variables can be assessed by using the F-test (Baltagi, 2021). The F-test compares Club FE and TWFE and tests whether Season FE is jointly significant (Baltagi, 2021). H_0 states that the effect of Season FE is zero, implying that Club FE is sufficient (Baltagi, 2021). If Season FE has a significant effect but is nevertheless not included in the model, omission bias would occur, meaning that the coefficients are distorted (Baltagi, 2021). In this study, the F-test ($F = 2.43$) results in a p-value of .014, suggesting that H_0 is rejected. This empirically confirms that common time shocks affect the model and that Season FE is necessary for estimating the model. Thus, based on the results of the specification tests, TWFE is used as a suitable estimator for Path b, as both Club FE and Season FE are empirically necessary.

Before estimating the final model, it is examined whether multicollinearity among the independent variables exists. This is the case when two or more variables are strongly correlated, leading to increased variance in coefficient estimates, larger standard errors, and invalid significance tests (Greene, 2020). In this study, it is crucial to assess whether squad value, transfer expenditures, and total salary are correlated, as all three variables measure a club's financial investment capacity and could therefore potentially be correlated. To test this, the variance inflation factor (VIF) is used (Greene, 2020). The VIF is calculated separately for each independent variable and measures the degree to which this variable correlates with other variables (Greene, 2020). A VIF of 1 indicates that there is no correlation with other variables (Greene, 2020). The higher the value, the stronger the correlation between the variables, and jointly estimating them becomes problematic (Greene, 2020). The results of the VIF test show that all values are close to 1 (squad value: 1.53, transfer expenditure: 1.13, total salary: 1.7, squad size: 1.77, and average age: 1.74), suggesting that no problematic multicollinearity is observed. Consequently, all variables can be included jointly in the model without distorting the results.

The specification tests have shown that common time shocks are present and affect the model. TWFE controls for these through Season FE, whilst Club FE simultaneously controls for time-invariant club heterogeneity. In panel data models, however, error terms of each club are typically not independent over time, as time-varying club-specific shocks cause observations within a club to be correlated (Wooldridge, 2010). In the context of this study, this means that an excellent season of a club could influence the results of the following season. To correct for this within-club correlation, standard errors are clustered at the club level. According to Wooldridge (2010, pp. 134–135), clustered standard errors "allow the units within each cluster to be correlated […] [but] assume independence across clusters“. This means that within-club correlation across seasons is accounted for, whilst individual clubs are treated as independent of one another.

However, clustered standard errors only adjust for correlation within a club over time. A separate challenge is the correlation between different clubs. To address this, the CD test is conducted to identify shocks that affect more than one club but not the entire sample and therefore have not been absorbed by TWFE and are not corrected by clustered standard errors. These include, for example, player transfers between two clubs or shocks that affect only a specific league. These dependencies are referred to as cross-sectional dependencies (CSD) (Pesaran, 2021). CSD is present when a shock affecting one club also influences another club, and can be tested using the CD test (Pesaran, 2021). In this study, the CD test results in a *p*-value of .03 with $z = -2.17$, meaning that H_0 (no CSD) is rejected and implies that the error terms across clubs are correlated. As clustered standard errors do not correct for CSD, the presence of CSD represents a remaining limitation for this study, which is discussed further in Section 6.2.1.

The variables used in the empirical analysis are measured in different units. To ensure comparability, standardised betas are used (Cohen et al., 2003). The *z*-score is calculated by subtracting the mean of the variable and then dividing the result by the standard deviation ($z = \frac{x - \mu}{\sigma}$) (Cohen et al., 2003). Each variable then has a mean of 0 and a standard deviation of 1, implying that the variables are now comparable despite their originally different units (Cohen et al., 2003). The standardised betas indicate by how many standard deviations the dependent variable changes when the independent variable increases by one standard deviation. These are used to test H_1 and H_2.

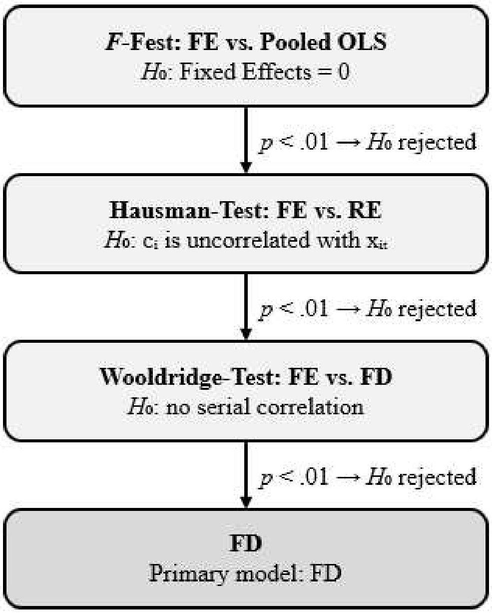
Based on the results of the specification test, TWFE with clustered standard errors at the club level is used as a robust estimator for Path b, as both club-specific and season-specific effects are empirically significant and time-varying club-specific observations are present.

4.2 Path a: Determinants of Squad Value (First Difference)

For Path a, three specification tests are carried out to determine the methodology of the empirical analysis. Figure 3 provides an overview of the individual tests and their respective results.

Figure 3

Specification Tests for Model Selection (Path a)



First, the F-test is used to determine whether FE or Pooled OLS is suitable for estimating the model. As in Path b, the F-test ($F = 24.01$) returns a p-value of $p < .01$, leading to the rejection of H_0 and confirming that unobservable, club-specific characteristics (c_i) influence not only sporting success but also squad value. Based on the F-test, FE is the preferred estimator over Pooled OLS. As Path a is based on the same data set as Path b, this result was to be expected.

Next, the Hausman test is conducted to determine whether FE or RE should be used. Again, H_0 is rejected ($\chi^2 = 26.06$, $p < .01$), meaning that FE is the appropriate method for Path a.

The Wooldridge Serial Correlation test is performed to determine whether c_i should be eliminated using FE (Within Demeaning) or FD. In contrast to Path b, H_0 is rejected for Path a ($\chi^2 = 62.11$, $p < .01$). This means that serial correlation is present in the FE residuals and that the error terms of a club in period t are correlated with the error terms of the same club in period t-1. FE (Within Demeaning) eliminates c_i by calculating the average of all observations for a club over the entire sample period and then subtracting this from the observation in period t (Wooldridge, 2010). This approach cannot eliminate serial correlation and is therefore not suitable as an estimator for the model in Path a. FD, on the other hand, measures changes from the previous period and is therefore more robust to serial correlation than FE (Wooldridge, 2010). The results of the Wooldridge Serial Correlation test are consistent with theoretical expectations. Squad values do not change randomly from season to season, but depend heavily on the previous season, as, for example, player contracts often have a duration of more than one year (Frick, 2011). Thus, a club that has a high squad value in one season is likely to have a high squad value in the following season. By measuring the change in squad value relative to the previous season, FD eliminates serial correlation.

As the Wooldridge Serial Correlation test has shown that FD is preferred over FE, the *F*-test (TWFE vs. Club FE) is no longer relevant.

Next, this model is tested for multicollinearity between the individual variables. The VIF is calculated based on manual FD variables and without an intercept. As in Path b, all VIF values are near 1 (transfer expenditures: 1.04, transfer revenues: 1.04, squad size: 1.76, average age: 1.67), meaning that all variables can be used together in the model without distorting the results. The warning in R Studio that VIF values are less reliable without an intercept is negligible given the clearly low VIF values.

The CD test is not performed for Path a, as both analyses are based on the same data, and therefore share the same cross-sectional structure. Given that CSD was already identified in Path b, it is assumed that the same limitation applies to Path a and should be considered when interpreting the results. Explicitly correcting for CSD would require additional methods which exceed the scope of this study and are therefore left for future research.

As in Path b, the model in Path a is estimated using clustered standard errors. Since the data is based on the same 15 clubs and 10 periods, it is assumed that time-varying club-specific events cause the values within a club to be correlated. Thus, for the final model for Path a, FD with clustered standard errors is used.

5. Results

Based on the models identified in Chapter 4, the following section reports the results of both empirical paths. Path b is presented first, as a significant positive influence of squad value on league points is required to estimate Path a.

5.1 Path b: Determinants of Sporting Success

Path b examines the determinants of sporting success measured in league points. The empirical analysis is based on five model specifications, with Table 5 showing the results for each model. The coefficients for each variable are listed in the table below. The corresponding standard errors are shown in parentheses below the coefficients. The significance levels are indicated by asterisks ($^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$). M1 and M2 are based on $N = 150$ observations, while M3 – M5 are based on $n = 149$ observations as one salary observation is missing (see Section 3.3). As outlined in Section 4.1, all models for Path b are estimated using TWFE (Club FE + Season FE) and clustered standard errors.

In total, five models (M1 – M5) are estimated, each progressively extending the previous one. M1 examines the influence of squad value on sporting success. This model isolates the core effect and directly addresses the research question. In M2, transfer expenditures are included in addition to squad value. This model tests whether investments in the form of transfer expenditures have a direct influence on sporting performance. In M3, the focus is on squad value and OpEx, by considering only squad value and total salary. In M4, both forms of investment are examined together. M5 represents the primary model, in which squad size and average age are added alongside squad value, transfer expenditures, and total salary. The variables added represent the control variables. By gradually expanding the model, it is tested whether the coefficients remain stable as additional variables are included. The coefficient of R^2 increases with each model specification, ranging from .155 in M1 to .233 in M5, indicating that each additional variable contributes to the model's explanatory power. The primary model

(M5) explains 23.3% of the within-club variance in league points. The coefficients of the individual variables are discussed in the following section.

Table 5

Determinants of Sporting Success

Determinants of Sporting Success (League Points)					
	Dependent Variable: League Points				
	(1)	(2)	(3)	(4)	(5)
Squad Value	0.033^{***}	0.038^{***}	0.036^{***}	0.040^{***}	0.041^{***}
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Transfer Expenditures		-0.029^{***}		-0.025^{**}	-0.024^{**}
		(0.011)		(0.011)	(0.010)
Total Salary			-0.048^{*}	-0.031	-0.041^{**}
			(0.025)	(0.024)	(0.020)
Squad Size					-0.044
					(0.192)
Average Age					1.438
					(1.467)
Observations	150	150	149	149	149
R^2	.155	.205	.184	.219	.233
Adjusted R^2	-.007	.044	.019	.052	.055
F-Statistic	22.916^{***}	15.961^{***}	13.912^{***}	11.390^{***}	7.307^{***}

Note: Two-way Fixed Effects: Club FE + Season FE. Standard errors clustered at the club level in parentheses. *, **, *** = $p < .10$, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Squad Value. Squad value represents one of the most important independent variables and is essential to answer the research question. M1 isolates the core effect by only testing the influence of squad value on sporting success. In this model, the variable has a coefficient of 0.033 and is highly significant ($p < .01$). This describes the baseline without considering additional variables or control variables. A β of 0.033 indicates that a EUR 100 million increase in squad value over a season leads to 3.3 additional league points. The coefficient increases with each additional model specification and remains highly significant in all models. After adding transfer expenditures in M2, the β remains stable and rises to 0.038. In M3, the coefficient (β = 0.036) falls slightly, but is still higher than in M1 (β = 0.033). This illustrates that squad value and total salary both measure player quality and thus slightly overlap. However, there is no underlying problem as there is only a minimal decline, the effect remains highly significant, and there is no multicollinearity (see Section 4.1). In M4 ($\beta = 0.040$) and M5 ($\beta = 0.041$), the coefficient for squad value increases further, and the effect remains highly significant ($p < .01$). This shows that the coefficients remain stable across all five models, implying that there is no indication of omitted variable bias. The narrow range of coefficients across the five models (0.033 – 0.041) reinforces the stability of the variable. Furthermore, the coefficient is positive in all five models, indicating that an increase in squad value has a positive effect on sporting success. In the primary model (M5), squad value reaches a coefficient of 0.041, meaning that a EUR 100 million increase in squad value is associated with 4.1 additional league points. Squad value is the only variable that is highly significant across all five models.

Transfer Expenditures. Transfer expenditures are added to M2 as an independent variable. In M2, transfer expenditures are highly significant and have a β of -0.029. In M3, the variable is not included. In M4, the negative effect of transfer expenditures on league points is slightly weaker ($\beta = -0.025$) than in M2 ($\beta = -0.029$) but remains significant, despite not being highly significant. The same applies to M5. The negative effect weakens ($\beta = -0.024$), and the variable remains significant. An increase in transfer expenditures of EUR 100 million leads to 2.4 fewer league points. The coefficient is negative in all three models, which is consistent with the theoretical expectation that transfer expenditures do not directly improve sporting success and may have a negative direct effect when transfer expenditures are not efficiently converted into squad value (see Section 2.5).

Total Salary. Total salary is included in the models from M3 onwards. In M3, total salary has a coefficient of $\beta = -0.048$ and is significant at the 10% level. In M4, the negative effect becomes weaker ($\beta = -0.031$) but is no longer significant. By considering transfer expenditures and total salary together, both variables share part of the explained variance, causing the coefficient for total salary in M4 to be insignificant. After adding the control variables, the negative effect returns to strength (β = -0.041), and total salary leads to a decrease of 4.1 league points when it is increased by EUR 100 million. The effect is negative in all three models. The significance is not consistent across the three models (M3: $p < .10$, M4: $p > .10$, M5: $p < .05$).

Squad Size and Average Age. Squad size and average age are control variables and are only used in M5. Squad size has a coefficient of -0.044 and is not significant. Average age has a coefficient of 1.438 and is also not significant. Neither variable has a measurable influence on league points due to their lack of significance.

5.1.1 Standardised Beta Coefficients and Hypothesis Tests (H_1 & H_2)

The unstandardised beta coefficients provide an initial overview of the effects of the individual variables on sporting success. However, the unstandardised beta coefficients are not suitable for direct comparison between variables, as they are measured in different units. Squad value and transfer expenditures are measured in EUR million, total salary partly in EUR million and partly in GBP million, squad size in number of players, and average age in years. To ensure comparability between the effects, standardised beta coefficients are used. These are also employed to test hypotheses H_1 and H_2. Table 6 shows the standardised beta coefficients for models M2 – M5. M1 contains only the squad value, making a comparison between the coefficients infeasible, as determining standardised beta coefficients adds no value. All variables are z-standardised (mean = 0, standard deviation = 1). The coefficients indicate by how many standard deviations the dependent variable (league points) changes when the respective variable increases by one standard deviation.

Table 6

Determinants of Sporting Success (Standardised Beta Coefficients)

Standardised Beta Coefficients				
	Dependent Variable: League Points (standardised)			
	(2)	(3)	(4)	(5)
Squad Value	.787***	.747***	.814***	.835***
	(0.161)	(0.148)	(0.161)	(0.147)
Transfer Expenditures	-.208***		-.181**	-.174**
	(0.080)		(0.082)	(0.072)
Total Salary		-.284*	-.183	-.240**
		(0.148)	(0.140)	(0.118)
Squad Size				-.021
				(0.092)
Average Age				.109
				(0.111)
Observations	149	149	149	149
R^2	.210	.184	.219	.233
Adjusted R^2	.049	.019	.052	.055
F-Statistic	16.303***	13.912***	11.390***	7.307***

Note: Two-way Fixed Effects: Club FE + Season FE. All variables are *z*-standardised (mean = 0, SD = 1). Coefficients represent SD change in league points per SD change in predictor. Standard errors clustered at the club level in parentheses. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Squad value is the dominant variable in all models and the only one that remains consistently significant across all model specifications. In M5, squad value achieves a standardised beta coefficient of β = .835. This means that an increase of 1 standard deviation leads to .835 standard deviations more league points. The variable remains stable across all models and has a range of .747 – .835. Total salary has the second strongest effect on league points. In M5, the variable achieved a standardised beta coefficient of -.240 and is significant at the 5% level. The effect is significantly weaker than the influence of squad value. Similar results can be observed for transfer expenditures. As with total salary, the effect is negative (β = -.174) and significantly weaker than that of squad value. The standardised beta coefficients for squad size (β = -.021) and average age (β = .109) are very small and not significant. Overall, squad value exhibits the largest standardised effect on league points, with a coefficient approximately three times that of total salary and almost five times that of transfer expenditures.

Hypothesis H_1 tests whether the effect of squad value on league points is stronger than the effect of transfer expenditures on league points (|β_squad_value| > |β_transfer_expenditures). With a standardised beta coefficient of .835 for squad value in M5 and -.174 for transfer expenditures, H_1 is confirmed.

Hypothesis H_2 tests whether the effect of squad value on league points is stronger than the effect of total salary on league points (|β_squad_value| > |β_total_salary). With a standardised beta coefficient of .835 for squad value in M5 and -.240 for total salary, H_2 is also confirmed. Both hypotheses are thus supported by the results of the primary model (M5).

5.1.2 Robustness Checks

To test the robustness of the main results, five robustness checks are carried out. These include the use of an alternative dependent variable, a comparison of different estimators, the exclusion of individual clubs and seasons, and an endogeneity test.

Alternative Dependent Variable. To test whether the results depend on the operationalisation, an alternative dependent variable (league position) is used to estimate the models. League position is inverse, meaning that a negative value represents a higher league position, as a lower value indicates better sporting performance.

Table 7

Robustness Check: Alternative Dependent Variable (League Position)

Robustness Check: Alternative Dependent Variable (League Position)					
	Dependent Variable: League Position				
	(1)	(2)	(3)	(4)	(5)
Squad Value	-0.007***	-0.008***	-0.008***	-0.008***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Transfer Expenditures		0.006**		0.006*	0.006**
		(0.003)		(0.003)	(0.003)
Total Salary			0.007	0.003	0.004
			(0.005)	(0.004)	(0.005)
Squad Size					0.022
					(0.047)
Average Age					-0.237
					(0.236)
Observations	150	150	149	149	149
R^2	.144	.192	.164	.203	.216
Adjusted R^2	-.020	.029	-.006	.033	.033
F-Statistic	21.018***	14.756***	12.038***	10.331***	6.603***

Note: Two-way Fixed effects: Club FE + Season FE. Standard errors clustered at the club level in parentheses. League position is inverse: a negative coefficient equals a better performance. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Squad value has a negative coefficient in all five models and is consistently significant. In M5, squad value has a coefficient of -0.009 (p < .01), implying that an increase in squad value leads to an improvement in league position. Transfer expenditures and total salary each have a positive coefficient. When transfer expenditures or total salary increase, clubs achieve a weaker league position, which is consistent with the results from Path b and confirms that the main findings are robust to alternative operationalisations of sporting success.

Estimator Robustness. The estimator robustness check examines whether the main results depend on the chosen estimator. Section 4.1 has already provided empirical evidence that TWFE is methodologically the most accurate estimator. The estimator robustness check (see Appendix Table A7) now examines whether the results remain stable even when a different estimator is used. A total of three estimators are compared: TWFE, Club FE, and FD. Squad value is positive and highly significant in all three estimators. The coefficients vary slightly (TWFE: $\beta = 0.041$, Club FE: $\beta = 0.025$, FD: $\beta = 0.031$) but are consistent in terms of sign and significance. Transfer expenditures and total salary have negative coefficients in all three estimators. However, the significance is reduced and no longer present for the total salary when using the FD method. Although the Club FE and FD methods are not methodologically preferred, the consistent signs indicate that the results remain stable and thus do not depend on the choice of estimator.

Leave-One-Out. The Leave-One-Club-Out and Leave-One-Season-Out approaches are used to check whether individual clubs or seasons dominate the results, and to identify outliers. For these tests, one club or one season is excluded at a time. The model is then re-estimated using the reduced sample. Outliers are identified by values deviating significantly from the primary model (M5), suggesting that a particular club or season is dominating the results. The results show that the coefficients for squad value, after excluding a single club, range between 0.037 and 0.046 (see Appendix Table A8). Furthermore, the results are highly significant in all 15 iterations. The primary model (M5), with a β of 0.041, falls within the range. As the range deviates only minimally from the primary model (M5), no single club dominates the main results. Therefore, the Leave-One-Club-Out test confirms the stability of the main results. The same applies to the Leave-One-Season-Out test. The coefficients for squad value range from 0.038 to 0.047 and are highly significant in all 10 iterations (see Appendix Table A9). This means that no single season dominates the results and that the main results are stable. Thus, both checks confirm the stability of the main results.

Endogeneity. Lastly, the lagged (t-1) and the lead (t+1) tests are used to determine whether squad value is endogenous or whether reverse causality is present. To test this, two further models are estimated (lagged squad value (t-1) and lead squad value (t+1)). The results are displayed in Table 8.

Table 8

Robustness Check: Endogeneity Test (Squad Value)

Robustness Check: Endogeneity - Lagged & Placebo Test		
	Dependent Variable: League Points	
	Lagged (t-1)	Placebo (t+1)
Squad Value (t-1)	-0.002	
	(0.008)	
Squad Value (t+1)		0.033***
		(0.006)
Transfer Expenditures	-0.017	-0.015
	(0.013)	(0.010)
Total Salary	0.025	-0.029
	(0.023)	(0.018)
Squad Size	-0.106	0.208
	(0.240)	(0.264)
Average Age	-0.298	2.274
	(1.527)	(1.737)
Observations	134	134
R^2	.020	.151
Adjusted R^2	-.229	-.065
F-Statistic	0.438	3.778***

Note: Two-way Fixed Effects: Club FE + Season FE. Standard errors clustered at the club level in parentheses. Lagged: squad value from the previous season ($_{t-1}$). Placebo: squad value from the following season ($_{t+1}$). *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Squad value is not significant in the lagged test and yields a coefficient of -0.002. This suggests that the past squad value (t-1) has no significant influence on current league points. All other variables and the entire model are also not significant (R^2 = .020, F = 0.438, p > .10). The future squad value (t+1), on the other hand, is highly significant (β = 0.033, p < .01). This suggests that the future squad value might be related to current league points, indicating potential reverse causality. This finding and the related limitations are discussed in Section 6.2.

5.2 Path a: Determinants of Squad Value

Path a examines the determinants of squad value. Table 9 shows the results of the two model specifications estimated for this path. The coefficients for each variable are listed in the table. The corresponding standard errors are shown in parentheses below the coefficients. The significance levels are indicated by asterisks ($^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$). As outlined in Section 4.2, both models for Path a are estimated using FD and clustered standard errors. The models are based on $n = 135$ observations, as one observation per club is missing due to the FD approach.

Table 9

Determinants of Squad Value

Determinants of Squad Value		
	Dependent Variable: Δ Squad Value	
	(1)	(2)
Δ Transfer Expenditures	0.279***	0.323***
	(0.055)	(0.070)
Δ Transfer Revenues		-0.134
		(0.125)
Δ Average Age		9.505
		(24.475)
Δ Squad Size		4.836
		(3.091)
Constant	43.164***	40.854***
	(6.946)	(7.330)
Observations	135	135
R^2	.050	.109
Adjusted R^2	.043	.082
F-Statistic	7.000***	3.992***

Note: First difference estimator (FD). Standard errors clustered at the club level in parentheses. *, **, *** = $p < .10, .05, .01$. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

M1 examines the effect of Δ transfer expenditures on Δ squad value exclusively. M2 is extended by including control variables and tests whether the effect of Δ transfer expenditures remains stable after incorporating the control variables. M2 represents the primary model for Path a.

Δ Transfer Expenditures. Δ Transfer expenditures are highly significant in both models ($p < .01$). In M1, the variable yields a coefficient of β = 0.279. After adding the control variables, the coefficient rises to β = 0.323. In both models, the effect of Δ transfer expenditures is positive, meaning that a EUR 100 million increase in transfer expenditures leads to a EUR 32.3 million increase in squad value.

Control variables. The control variables (transfer revenues, squad size, and average age) are incorporated exclusively in M2. None of the three variables is significant. Δ Transfer revenues (β = -0.134) has a negative impact on Δ squad value, whilst Δ squad size (β = 4.836) and Δ average age (β = 9.505) have a positive effect on Δ squad value.

Hypothesis Test (*H_3*). Hypothesis *H_3* (β_transfer_expenditures > 0) is tested using a one-tailed *t*-test based on the primary model (M2). In M2, Δ transfer expenditures have a coefficient of 0.323. The one-tailed *t*-test yields a *p*-value of $p < .01$ and is therefore highly significant. Thus, β_transfer_expenditures > 0 and *H_3* is confirmed. This result confirms that transfer expenditures have a significant positive effect on the seasonal change in squad value.

5.2.1 Robustness Checks

To test the robustness of the main results in Path a, three robustness checks are carried out. These consist of the estimator robustness check and two Leave-One-Out checks. Tests for endogeneity and for the use of an alternative variable are not conducted. As the endogeneity test has already been performed in Path b and suggests that endogeneity is present, it is assumed that endogeneity is also present in Path a, as clubs with higher squad values may systematically invest more. Testing this would require additional methodological steps that exceed the scope of this study. Testing for an alternative dependent variable is equally omitted, as no comparable variable to squad value can be obtained within the scope of this study.

Estimator Robustness. As outlined in Section 4.2, the most accurate estimator for Path a is FD. To test whether the main results remain stable, FD is compared to two alternative estimators (TWFE and Club FE). The coefficients of the individual variables under the use of the different estimators are shown in the Appendix in Table A10. The independent variable (transfer expenditures) remains positive and highly significant ($p < .01$) in all three estimators. Although the coefficients vary strongly (FD: $\beta = 0.323$, Club FE: $\beta = 0.516$, TWFE: $\beta = 0.387$), their significance remains consistent. This demonstrates the robustness and stability of the variable regardless of the choice of estimator. Transfer revenues and average age are not significant in any of the three estimators ($p > .10$) and reverse across estimators. Transfer revenues have a negative coefficient under FD and a positive coefficient under Club FE and TWFE. Average age has a positive coefficient under FD and a negative coefficient under Club FE and TWFE. However, these changes in sign are not critical due to the lack of significance. Squad size is positive in all three estimators but is only significant at the 1% level in the Club FE model. As this variable serves only as a control variable and is not relevant to H_3, this observation can be disregarded. The estimator robustness check shows that the independent variable (transfer expenditures) remains stable across all three estimators, meaning that the results of the empirical analysis for Path a do not depend on the chosen estimator.

Leave-One-Out. For Path a, the Leave-One-Club-Out and Leave-One-Season-Out tests are carried out. The Leave-One-Club-Out test examines whether individual clubs dominate the main results. Each club is excluded once before the primary model (M2) is estimated for the remaining 14 clubs ($n = 126$). Δ Transfer expenditures are significant in all 15 iterations ($p < .05$), and the coefficients range from 0.287 to 0.369 (see Appendix Table A11). The coefficient in the primary model ($\beta = 0.323$) falls within this range. The small deviation from the primary model confirms that no single club dominates the results. The Leave-One-Season-Out test examines whether individual seasons distort the main results. Each season is excluded once before the primary model is estimated on the remaining eight seasons ($n = 120$). Δ Transfer expenditures are significant in all nine iterations ($p < .05$) and range between 0.286 and 0.425 (see Appendix Table A12). M2 falls within the range ($\beta = 0.323$). Thus, the Leave-One-Season-Out test confirms that no single season dominates the main results. All three robustness checks confirm the stability of the results used for H_3. Transfer expenditures remain consistently significant and positive in all tests.

6. Discussion

The following section interprets the findings in the context of the theoretical background and existing literature. Furthermore, limitations and suggestions for further research are discussed.

6.1 Interpretation of Main Findings

The empirical results provide strong support for the conceptual framework, confirming that squad value acts as a mediator between transfer expenditures and sporting success. The main findings of Path b are discussed first, followed by Path a, and the relationship between the two paths.

6.1.1 Interpretation of Main Findings of Path b

Squad Value. The results of the empirical analysis confirm the positive influence of squad value on league points (M5: unstandardised $\beta = 0.041$, $p < .01$), thereby supporting H_1 (|β_squad_value| > |β_transfer_expenditures|) and H_2 (|β_squad_value| > |β_total_salary|). These results can be explained by Becker's (1993) human capital theory. Squad value represents a club's aggregated human capital and suggests that a higher squad value leads to more league points. This is consistent with the fundamental concept of human capital theory, stating that investments in human capital increase future productivity (Becker, 1993). According to the RBV theory by Barney (1991), the results suggest that squad value meets the criteria of a strategic resource (valuable, rare, inimitable, and non-substitutable) and thus leads to a competitive advantage for the club. Furthermore, the findings are supported by existing literature. Lepschy et al. (2020) argue that a higher squad value of the starting lineup positively influences sporting success, and Gómez & Amat (2025) found that squad value strongly correlated with league points. The results of this study present the same findings and are supported by the existing literature.

Transfer Expenditures. The results of the empirical analysis show a negative effect of transfer expenditures on league points (unstandardised $\beta = -0.024$, $p < .05$). This negative effect can be explained by the existing literature (see Chapter 2). Possible explanations relate to the time-delayed effect in the capital stock (see Section 2.3), human capital theory (see Section 2.2), and transfer market efficiency (see Section 2.4). Hall & Jorgenson (1967) argue that the capital stock K reacts to investments with a time lag. By applying this theory to the results of this study, this could mean that transfer expenditures immediately increase squad value, but sporting performance only improves after a temporal delay. This delay could arise, for example, because newly signed players need time to integrate into the team. In the short term, this could weaken a potential direct positive effect of transfer expenditures on league points or even result in a negative effect. Whether a time-lagged effect is present in the following period was tested using the Lagged Transfer Expenditure Test, in which transfer expenditures are replaced by the lagged value (t-1) (see Appendix Table A13). The test shows that the lagged coefficient is not significant ($p > .10$), suggesting that a pure time-lag effect does not explain the negative direct effect. Therefore, further explanations are needed to explain the direct negative effect of transfer expenditures on league points.

Another possible explanation for the direct negative effect is derived from Becker's (1993) human capital theory (see Section 2.2). This theory states that new players contribute general human capital, but firm-specific human capital must first be developed (Becker, 1993). Consequently, the effect of transfer expenditures on league points would not be visible in the short term but would only have an effect at a later period. In contrast to the time-delayed effect from the previous explanation, an explanatory approach based on firm-specific human capital cannot determine whether and when the effect will occur, as the effect depends on the quality of integration. Due to this uncertainty, it is not possible within the scope of this study to empirically test whether the accumulation of firm-specific capital is the reason for the negative direct effect of transfer expenditures on league points. However, it does represent a possible explanation.

A third possible explanation is based on transfer market efficiency (see Section 2.4). Shynkevich (2022) demonstrates in his study that the transfer market is a semi-efficient market. This means that transfer prices are based on historical and publicly available information, but insider knowledge does not influence the price (Fama, 1970; Mondello, 2013). Furthermore, emotional or non-performance-related factors such as popularity or media presence can inflate the transfer price, thereby exceeding a player's actual sporting value (Fűrész & Rappai, 2022). This hyperinflation could mean that transfer expenditures do not necessarily reflect a player's quality, and explains why transfer expenditures have a negative impact on league points in this study. Clubs with higher transfer expenditures may be paying for a player's popularity rather than their sporting quality. Furthermore, transfer expenditures are controlled for alongside squad value in the models. Both variables partially capture the same underlying dimension of player quality. Despite uncritical VIF values, a partial overlap between the two variables cannot be ruled out. Therefore, high transfer expenditures are not a reliable indicator of sporting success and, as outlined in the conceptual framework, can only indirectly influence sporting success as a mediator through squad value.

Overall, the negative direct effect of transfer expenditures on league points is supported by existing literature, as all three explanations suggest that transfer expenditures operate indirectly through squad value rather than directly on sporting success. This indirect relationship is discussed in further detail in Section 6.1.3.

Total Salary. Total salary has a negative effect on league points in all three models (M3 – M5), but the significance is inconsistent. In M3 ($p < .10$) and M5 ($p < .05$), the variable is significant, whilst in M4 ($p > .10$), it is not significant. These results suggest that total salary is a weaker predictor than squad value, as squad value remains significant in all five models. The inconsistent significance could be related to the overlap in content with other variables, as high-quality players tend to have high salaries, as discussed in Section 2.2. Furthermore, total salary, squad value, and transfer expenditures all capture player quality, meaning that the variance is distributed across the variables. Squad value is the only variable that is stable and significant in all models, suggesting that this variable accounts for the largest proportion of the variation. Additionally, in Section 2.3.1, salaries were defined as OpEx, which, according to IAS 38, cannot be capitalised as an asset and therefore have no direct impact on K. As squad value is the primary mediator between investments and league points, no direct effect of total salary on league points was to be expected. The empirical results confirm this. The negative coefficient supports Frick's (2011) theory that moral hazard exists in professional football. He argues that players have fewer incentives to improve their performance after signing a long-term contract and that salaries thereby do not necessarily reflect sporting performance (Frick, 2011). The results of the empirical analysis are consistent with this approach, as the negative coefficients suggest that high salary expenditures do not lead to more league points. As expected, total salary is therefore not a reliable direct predictor of sporting success. For club management, this suggests that salary expenditures should be critically evaluated, as no direct link can be established between salary and sporting success.

Squad Size and Average Age. Squad size has no significant influence on league points ($p > .10$), confirming that the quality of the squad is more important than its size. Average age also has no significant effect on league points ($p > .10$), meaning that the theory developed by Poli et al. (2018) that a player's optimal age is 26.5 years cannot be confirmed. This may be due to the selected sample, as the average age of the individual clubs in the sample ranges between 22.2 and 27.7 years, and deviates only slightly from the optimal age presented by Poli et al. (2018). Thus, the effect might not be visible in this study because of the small variation within the sample. As neither of the control variables has a significant influence on sporting success, this confirms the assumption that financial indicators, such as squad value, transfer expenditures, or total salary, have a stronger influence on sporting success than structural characteristics of the squad.

6.1.2 Interpretation of Main Findings of Path a

The results from Path a are used to test H_3 (β_transfer_expenditures > 0).

Δ **Transfer Expenditures.** The results show that Δ transfer expenditures have a significant positive impact on squad value ($p < .01$). In the primary model of Path a (M2), this is the only variable with a significant impact. Transfer expenditures are thus the only significant determinant of seasonal squad development in this model, and support the assumption by Rohde & Breuer (2016) that transfer expenditures are a key driver of squad value. Furthermore, the results are consistent with the existing literature by Jorgenson (1963) and Matesanz et al. (2018). As outlined in Section 2.3.1, transfer expenditures represent CapEx that directly increases K. The results indicate that transfer expenditures increase squad value, thereby confirming Jorgenson's (1963) investment theory. Furthermore, Matesanz et al. (2018) distinguish between internally and externally developed human capital. The positive impact of transfer expenditures on squad value confirms that externally developed human capital increases squad value. This result supports the assumption made by Matesanz et al. (2018).

An unstandardised β of 0.323 in M2 means that the squad value increases by EUR 32.3 million when transfer expenditures rise by EUR 100 million. This implies that only 32.3% of transfer expenditures are reflected in squad value, suggesting that an increase in transfer expenditures is not converted 1:1 into squad value ($\beta < 1$). Possible explanations include the hyperinflation discussed in Section 6.1.1 and the structural composition of the squad value. Due to the hyperinflation, the transfer price may be higher than the actual sporting value of a player due to non-performance-related factors (Fűrész & Rappai, 2022). Squad value, on the other hand, represents solely the sporting value of all players, which could explain the low coefficient. Another possible explanation for the low coefficient is the composition of the squad value, which consists of existing players and newly acquired players (see Section 2.3.1). Thus, transfer expenditures explain only part of the seasonal development in squad value. The remaining part is explained by the internal development of players (see Section 2.2.1). As outlined in Section 2.2.1, internal human capital can be built up through successful training and directly increases K. A coefficient of $\beta < 1$ was therefore to be expected. Overall, the results of Path a show that transfer expenditures are a significant driver of seasonal squad development, even if the effect is not passed on 1:1. Moreover, the findings are supported by the existing literature, and H_3 is confirmed by the empirical analysis.

Control variables. None of the three control variables (transfer revenues, squad size, and average age) has a significant influence on squad value ($p > .10$). Transfer revenues have a negative coefficient (unstandardised $\beta = - 0.134$), which is reasonable, as transfers represent divestments that reduce K. However, as transfer revenues have no significant influence on squad value, the variable is not interpreted further. Squad size has a positive coefficient (unstandardised $\beta = 4.836$), meaning that more players increase the squad value. However, as this variable is not significant in the model ($p > .10$), this assumption cannot be confirmed. This finding supports the interpretation in Section 6.1.1 that the quality of the squad is more important than the quantity. Average age is also not significant ($p > .10$) and thus cannot be interpreted meaningfully.

6.1.3 Relationship between Path a and Path b

The results of both empirical analyses confirm the mediator structure outlined in the conceptual framework (see Section 2.5). Transfer expenditures significantly increase squad value (Path a, H_3: unstandardised $\beta = 0.323$, $p < .01$), which in turn has a significant positive effect on league points (Path b, H_1 & H_2: standardised $\beta = .835$, $p < .01$). All three hypotheses are therefore confirmed by the empirical analyses and provide the foundation for the mediator structure.

The results of the empirical analysis suggest that squad value acts as a mediator between transfer expenditures and sporting success. Path b indicates that transfer expenditures negatively affect league points when the direct effect is analysed. Furthermore, Path b shows that squad value is the main determinant of league points. After Path a has been executed, the mediator structure is clearly visible. Path a shows that transfer expenditures significantly increase squad value, which supports the assumption that the effect is indirect (transfer expenditures → squad value → league points). The indirect effect implies that the quality of the squad is more important for sporting success than the amount of transfer expenditures. Clubs that spend large amounts but fail to build up a proportionally valuable squad are penalised by the negative direct effect from Path b. Clubs should therefore ensure they carefully target their player purchases and integrate them successfully into the team to use the potential human capital efficiently and convert it into sporting success. However, hyperinflation can weaken the indirect effect due to overpriced transfers (see Section 2.4.1). Although the indirect effect is evident from the two analyses, it cannot be statistically confirmed within the scope of this study as no mediator analysis was conducted.

The conceptual framework is therefore supported by the empirical analyses and confirms that squad value acts as a mediator in converting investment into sporting success. Furthermore, the two analyses show that direct investment is not a reliable determinant of sporting success and must be channelled through squad value to result in sporting success.

6.2 Limitations

Despite robust findings and several robustness checks, this study faces limitations in terms of methodology, sample size, and content. These limitations restrict the interpretation and ability to generalise the findings. The limitations of this study are divided into three parts: methodological limitations, sample limitations, and content-related limitations.

6.2.1 Methodological Limitations

As outlined in Section 5.1.2, the lead robustness check indicates that reverse causality could be present, meaning that squad value is not only a determinant of sporting success but also a result of sporting success. The findings on reverse causality suggest that high transfer expenditures lead to a higher squad value, which in turn leads to sporting success, which then leads to increased revenue and consequently to potentially higher transfer expenditures. This phenomenon is already recognised in the literature. Chapter 2 describes the relationship between sporting and financial success by referring to the dual market. The results of this study illustrate the statistical relationship between variables. However, due to reverse causality, they should not be interpreted as causal effects. It is therefore not possible to clearly state whether a higher squad value leads to more league points or whether sporting success increases the squad value.

CSD represents a further limitation. The CD test ($z = -2.17$, $p = .030$) has shown that CSD is present and that the clubs are correlated with one another. Clustered standard errors were used to address the within-club correlation. However, this does not resolve the CSD limitation and should be considered when interpreting the results. Furthermore, the small number of clusters limits the reliability of clustered standard errors. With only 15 clubs, the number of clusters falls below the recommended threshold of 20 to 50 clusters suggested by Colin Cameron & Miller (2015), which could lead to standard errors being underestimated and *p*-values being too small.

The use of the FD methodology in Path a results in a loss of one observation per club, meaning that the results are based on $n = 135$ instead of $N = 150$. This further reduces the already small sample size and limits the statistical power of the empirical analysis. Despite this limitation, the FD method is the most suitable approach for estimating the model (see Section

4.2). In future studies, a longer time period could be considered to minimise the relative percentage of data loss due to FD.

Both models display low adjusted R^2 values (Path a: $R^2 = .082$, Path b: $R^2 = .055$), meaning that the models can explain only a portion of the variance in league points and squad value. These values suggest that other factors, which are not considered in the model, influence sporting success and squad value development. This is typical in sports economics studies, as many random components influence the data (Hägglund et al., 2013). Furthermore, the mediator structure is only justified by the results of Path a and Path b. To empirically confirm the relationship between transfer expenditures, squad value, and league points, a mediator analysis needs to be conducted. The results of this study suggest a mediator structure, but should be interpreted carefully due to the lack of mediator analysis.

The variables in the empirical analysis are measured in different units. Data on total salary are predominantly reported in EUR. For Premier League clubs, however, these are stated in GBP. Moreover, exchange rate fluctuations and inflation are disregarded in this study. Standardised betas address the unit problem by allowing coefficients to be compared independently of scale, but exchange rate fluctuations and inflation remain uncontrolled. Standardised betas should therefore be used to ensure the comparability of the coefficients.

6.2.2 Sample Limitations

The study is based on a sample of 15 UEFA Champions League clubs, which are observed over a period of ten seasons (2015/16 – 2024/25). This leads to $N = 150$ observations in Path b and $n = 135$ observations in Path a. For a panel dataset, this sample size is relatively small, which could mean that some effects are not visible. Furthermore, the sample consists exclusively of UEFA Champions League clubs, meaning that the study is based on a homogenous sample. Only clubs that regularly participate in the UEFA Champions League were selected, which could result in successful clubs being overrepresented. Clubs that are less successful or play in lower leagues might achieve different results than this sample. The low variation within the sample could limit the explanatory power of the models and should therefore be interpreted with caution. Furthermore, the sample consists exclusively of European clubs, implying that the results may not be transferable to clubs from other continents. Moreover, due to limited data availability, the sample lacks a salary value for RB Leipzig for the 2015/16 season. The number of observations in M3 - M5 of Path b is reduced from $N = 150$ to $n = 149$. However, as only one observation is omitted, the impact on the results should be minimal.

Another limitation of the sample relates to the observation period. A total of ten seasons that have been shaped by structural changes, which are not controlled for in the model, are analysed. These include, for example, the restructuring of the UEFA Champions League format, the COVID-19 pandemic, and the introduction of new rules. From the 2024/25 season onwards, 36 clubs instead of the original 32 clubs participate in the UEFA Champions League. The addition of four extra clubs could cause some teams to meet the sample selection criteria solely because of the new rules, and thus be included in the sample, potentially distorting the results. Similarly, COVID-19 represents a structural change. The 2019/20 and 2020/21 seasons in particular were heavily affected by the pandemic (Bond et al., 2022). Clubs were subject to stricter hygiene and quarantine regulations, and the majority of matches took place without spectators. These particular circumstances could influence the club's sporting performance. But, as the Leave-One-Season-Out test has been used to check whether individual seasons dominate the results, and as the test did not reveal any anomalies, it can be assumed that COVID-19 does not represent a limitation for this study. Another limitation is the introduction of new regulations. In 2009, UEFA introduced the Financial Fair Play (FFP) rules (Martín-Magdalena et al., 2024). These state that clubs may not spend more than they earn and are intended to protect clubs against high levels of debt (Martín-Magdalena et al., 2024). During the period under consideration (2015/16 – 2024/25), these regulations have changed in some respects (Martín-Magdalena et al., 2024). In 2022, the FFP regulations were replaced by the UEFA Financial Sustainability Regulations (FSR), meaning that clubs are now subject to stricter controls (Martín-Magdalena et al., 2024). The introduction of these new regulations mainly affects the variables transfer expenditures, transfer revenues, and total salary, as clubs can no longer invest without limit (Martín-Magdalena et al., 2024). As this study does not explicitly control for these structural changes, these regulations could restrict transfer activity and thereby distort the study's results.

6.2.3 Content-related Limitations

As this study focuses on financial determinants of sporting success, several non-financial factors, such as coach quality, club culture, and injury rates, are not controlled for in the empirical analysis. Although Frick and Simmons (2008) demonstrate that coach quality influences sporting success, Bryson et al. (2024) argue that changes in coaching staff do not have a significant impact on sporting performance. Furthermore, the quality of the coach is difficult to quantify objectively, which could lead to inaccurate results. Therefore, this variable is not included in this study, as the focus is on the financial determinants of sporting success. The same applies to club culture. Similarly, the injury rate of players is disregarded. Hägglund et al. (2013) argue that a higher injury rate leads to fewer points. However, as the data is not publicly available and the sample only contains top clubs with large squads, this variable is not considered further in the study.

A further limitation is the use of the season as the basis for the empirical analysis. In this study, individual seasons are compared with one another, and no distinction is made between winter and summer transfers. If transfers are to have a different impact on the team's sporting performance, this is not captured in this study. The literature suggests that firm-specific human capital takes time to develop (see Section 2.2). This could mean that a winter transfer has a different effect on sporting success than a summer transfer, as the time a player has to integrate into the team is shorter. This study refers to annual transfer expenditures only. Thus, no conclusions can be drawn regarding the effects of different transfer timings.

As outlined in Section 3.1, squad value data are based on Transfermarkt.de data. The data are estimated by the community and do not constitute official figures. Herm et al. (2014), Müller et al. (2017), and Prockl & Frick (2018) confirm that the community-estimated values are almost identical to actual transfer market prices. Nevertheless, subjective components cannot be completely eliminated. This could lead to measurement uncertainties and distort the data. Therefore, the use of Transfermarkt.de data represents a limitation. However, due to its widespread use in the literature and the values being almost identical to actual transfer market data, the community-estimated data is sufficiently accurate for this study.

Another limitation is the dependent variable in Path b. League points per club and season are used to measure sporting success. This means that sporting performance in other national or international competitions is not included. If sporting performance across all competitions were included, the results might differ from those presented in this study. However, the robustness check for Path b shows that the results remain robust even when using league position as the dependent variable. This suggests that the results should not change significantly even when all competitions are considered. However, as this has not been tested, the choice of dependent variable in Path b represents a limitation.

6.3 Further Research

The study serves as a foundation for identifying financial factors that influence sporting success in professional football. To ensure the findings can be applied to other leagues and clubs and to increase the statistical power of the model, further studies should be conducted. This would require extending the observation period to ensure that the results remain robust across different time periods. By including additional seasons, the statistical power of the model would be increased, and the relative loss of data caused by the FD method would be reduced.

Furthermore, with a larger data set, structural changes can be better controlled or isolated by including more periods both before and after the period of change. Moreover, this study includes only clubs that frequently participate in the UEFA Champions League. Future studies could include more clubs in the sample to allow the results to be generalised and applied to other clubs. Additionally, a comparison could be made between different leagues. Studies could focus on potential differences between European and non-European leagues or on differences between the various leagues within a single country. This would enable testing whether the findings from this study can be applied to clubs in lower leagues, which consequently have fewer financial resources. Furthermore, including non-European clubs would allow for a comparison between different continents. As outlined in Chapter 1, European football accounts for more than 80% of transfer expenditures in global professional football. Further studies should be conducted on a global sample to test whether the findings are shaped by the financial structures in Europe or whether they hold globally.

This study utilises league points and league position to measure sporting success. Both variables relate to national performance, as only matches in the club's own league are considered. Sporting performance in other competitions, such as national cup competitions or the UEFA Champions League, is disregarded. To capture the overall performance of clubs, further studies should include sporting performance across all competitions in which the club participates. This would provide a more comprehensive understanding of the relationship between investment and sporting success, as sporting performance across all competitions would be considered, rather than relying on a single competition.

Furthermore, the study could be extended to non-financial factors. Further studies could analyse which financial and non-financial factors influence sporting success. Variables relating to coaching quality, club culture or injury rate could be included to improve the model's explanatory power. In addition, the financial variables could be divided further to provide more detailed information. Transfer expenditures could be divided into summer and winter transfer expenditures to analyse whether the different transfer windows have a different effect on sporting success. Players acquired during the winter transfer window play for the club for only half a season. This shortens the integration period and could reduce the impact on sporting success due to the delayed effect of transfer expenditures on squad value (see Section 6.1.1). Further studies could investigate whether the findings of this study remain stable when differentiating between winter and summer transfers.

In this study, the mediator effect is addressed only in terms of content and not tested empirically. Further studies could conduct a mediator analysis to test whether the effect is empirically verifiable. Moreover, further studies should address endogeneity and CSD. The lead test indicates that endogeneity might be present, meaning that it cannot be clearly determined whether squad value impacts sporting success or whether sporting success drives squad value. Whilst this finding is mentioned in this study, it is not explored further. Further studies should employ methods to correct for reverse causality. Additionally, the CD test shows that the error terms of the individual clubs are correlated, suggesting that individual shocks affect several, but not all, clubs within the sample. Despite clustered standard errors, CSD cannot be completely eliminated. Thus, further studies should apply methods that explicitly correct for CSD.

7. Conclusion

Due to increasing financial investment in professional football, the relationship between capital investments and sporting success remains a central topic for both academic research and club management. This study focuses on identifying financial factors that determine sporting success by examining the extent to which capital investments and squad value determine the sporting success of UEFA Champions League clubs. The study is based on a panel data set of 15 clubs observed over ten seasons (2015/16 – 2024/25). The empirical analysis is divided into two paths. Path a analyses the determinants of squad value using FD, whilst Path b identifies the determinants of sporting success using TWFE.

The results from Path b identify squad value as the main predictor of sporting success. With a standardised beta of .835 ($p < .01$), squad value is the strongest determinant of sporting success. The results are consistent with Becker's (1993) human capital theory and Barney's (1991) RBV theory. Squad value represents aggregate human capital, and the findings show that this results directly in sporting success. The positive influence of squad value on sporting success supports Barney's (1991) RBV theory, which claims that valuable, rare, inimitable, and non-substitutable resources lead to a competitive advantage in the long term. Furthermore, the results are consistent with the existing literature. Lepschy et al. (2020) and Gómez & Amat (2025) found that squad value has a significant positive effect on sporting success. The results of this study support these theories.

Transfer expenditures have a negative direct impact on sporting success (standardised $\beta = -.174$, $p < .05$). Although this may seem counterintuitive at first, this finding is consistent with the literature. Hall & Jorgenson (1967) argue that the capital stock reacts to investment with a time lag, meaning that the acquisition of new players does not have an immediate effect within the current season. The effect may occur with a time lag and cannot be measured within the scope of this study. Furthermore, Becker (1993) argues that firm-specific human capital must first be built up when acquiring new players before it can be transformed into sporting success. Additionally, Fűrész & Rappai (2022) state that, due to hyperinflation, transfer fees might exceed a player's actual value, thereby negatively impacting the direct influence of transfer expenditures on sporting success.

Total salary also has a negative impact on sporting success. As Frick (2011) notes that player performance depends on the type of contract, this was to be expected. Frick (2011) claims that player performance declines after a contract is signed and increases shortly before contract renewal. The level of salary, therefore, has less influence on sporting success, which is supported by the results of the empirical study.

In Path a, transfer expenditures are the only significant driver of squad value (unstandardised $\beta = 0.323$, $p < .01$). This finding is supported by the research of Matesanz et al. (2018) and Jorgenson (1963), who argue that externally acquired human capital increases the capital stock. However, the effect is not passed on 1:1, as the development of home-grown players also increases squad value.

The combination of both empirical analyses shows that transfer expenditures have no direct positive influence on sporting success but rather have an indirect effect through squad value. This indirect effect confirms the mediator structure and demonstrates that the quality of investments is more important than the quantity of transfer expenditures. Clubs should therefore invest strategically in players to increase squad value in the long term, rather than aiming for maximum transfer expenditures. Inefficient transfer decisions are penalised by the direct negative effect and should be carried out with careful consideration. New players should be strategically integrated into the team to develop human capital efficiently and rapidly transform it into squad value.

Despite stable results across several robustness checks, this study faces limitations. The lead test suggests that reverse causality may be present, meaning it cannot be clearly stated whether squad value influences sporting success or whether sporting success influences squad value. Furthermore, the relatively small and homogeneous sample of 15 UEFA Champions League clubs limits the statistical power and generalisability of the results. Further studies should address these limitations and include non-financial factors. Additionally, a mediation analysis should be conducted to empirically demonstrate the indirect effect of transfer expenditures on sporting success.

The study provides empirical evidence that squad value is the main predictor of sporting success, whilst transfer expenditures and total salary have no direct positive influence on sporting performance. The mediator structure suggests that transfer expenditures have an indirect effect and that the quality of investments is more important than the quantity of expenditures. Clubs should therefore prioritise the quality of players and their successful integration into the team to efficiently transform human capital into a competitive advantage.

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Appendix A

Supplementary Tables

Table A1

UEFA Champions League Club Sample Selection

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
FC Barcelona	La Liga	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Atlético de Madrid	La Liga	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Real Madrid	La Liga	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Bayern Munich	Bundesliga	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Paris Saint-Germain	Ligue 1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Manchester City FC	Premier League	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
Borussia Dortmund	Bundesliga	x	✓	✓	✓	✓	✓	✓	✓	✓	✓	9
SL Benfica	Liga Portugal	✓	✓	✓	✓	✓	x	✓	✓	✓	✓	9
Juventus FC	Serie A	✓	✓	✓	✓	✓	✓	✓	✓	x	✓	9
FC Porto	Liga Portugal	✓	✓	✓	✓	x	✓	✓	✓	✓	x	8

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
Shakhtar Donezk	Ukrainian Premier League	✓	x	✓	✓	✓	✓	✓	✓	✓	✓	9
Liverpool FC	Premier League	x	x	✓	✓	✓	✓	✓	✓	x	✓	7
Inter Milan	Serie A	x	x	x	✓	✓	✓	✓	✓	✓	✓	7
Club Brugge	Pro League (Belgium)	x	✓	x	✓	✓	✓	✓	✓	x	✓	7
RB Leipzig	Bundesliga	x	x	✓	x	✓	✓	✓	✓	✓	✓	7
Sevilla FC	La Liga	✓	✓	✓	x	x	✓	✓	✓	✓	x	7
FC Red Bull Salzburg	Austrian Bundesliga	x	x	x	x	✓	✓	✓	✓	✓	✓	6
Manchester United	Premier League	✓	x	✓	✓	x	✓	✓	x	✓	x	6
SSC Napoli	Serie A	x	✓	✓	✓	✓	x	x	✓	✓	x	6
Chelsea FC	Premier League	✓	x	✓	x	✓	✓	✓	✓	x	x	6
Bayer Leverkusen	Bundesliga	✓	✓	x	x	✓	x	x	✓	x	✓	5
PSV Eindhoven	Eredivisie	✓	✓	x	✓	x	x	x	x	✓	✓	5
Celtic FC	Scottish Premiership	x	✓	✓	x	x	x	x	✓	✓	✓	5
Ajax Amsterdam	Eredivisie	x	x	x	✓	✓	✓	✓	✓	x	x	5
Tottenham Hotspur	Premier League	x	✓	✓	✓	✓	x	x	✓	x	x	5
Arsenal FC	Premier League	✓	✓	x	x	x	x	x	x	✓	✓	4
Atalanta BC	Serie A	x	x	x	x	✓	✓	✓	x	x	✓	4

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
AC Milan	Serie A	x	x	x	x	x	x	✓	✓	✓	✓	4
AS Monaco	Ligue 1	x	✓	✓	✓	x	x	x	x	x	✓	4
Red Star Belgrade	Serbian SuperLiga	x	x	x	✓	✓	x	x	x	✓	✓	4
Young Boys	Swiss Super League	x	x	x	✓	x	x	✓	x	✓	✓	4
Galatasaray SK	Süper Lig (Turkey)	✓	x	x	✓	✓	x	x	x	✓	x	4
Sporting CP	Liga Portugal	x	✓	✓	x	x	x	✓	✓	x	✓	5
Dinamo Zagreb	HNL (Croatia)	✓	✓	x	x	✓	x	x	✓	x	✓	5
Dynamo Kyiv	Ukrainian Premier League	✓	✓	x	x	x	✓	✓	x	x	x	4
Zenit St. Petersburg	Russian Premier League	✓	x	x	x	✓	✓	✓	x	x	x	4
Olympiacos FC	Greek Super League	✓	x	✓	x	✓	✓	x	x	x	x	4
Lyon	Ligue 1	✓	✓	x	✓	✓	x	x	x	x	x	4
CSKA Moscow	Russian Premier League	✓	✓	✓	✓	x	x	x	x	x	x	4
LOSC Lille	Ligue 1	x	x	x	x	✓	x	✓	x	x	✓	3
Feyenoord	Eredivisie	x	x	✓	x	x	x	x	x	✓	✓	3
FC Copenhagen	Danish Superliga	x	✓	x	x	x	x	x	✓	✓	x	3

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
Beşiktaş JK	Süper Lig (Turkey)	x	✓	✓	x	x	x	✓	x	x	x	3
Lokomotiv Moscow	Russian Premier League	x	x	x	✓	✓	✓	x	x	x	x	3
Borussia Mönchengladbach	Bundesliga	✓	✓	x	x	x	✓	x	x	x	x	3
Valencia CF	La Liga	✓	x	x	✓	✓	x	x	x	x	x	3
AS Roma	Serie A	✓	x	✓	✓	x	x	x	x	x	x	3
SS Lazio	Serie A	x	x	x	x	x	✓	x	x	✓	x	2
Viktoria Plzeň	Czech First League	x	x	x	✓	x	x	x	✓	x	x	2
Olympique de Marseille	Ligue 1	x	x	x	x	x	✓	x	✓	x	x	2
VfL Wolfsburg	Bundesliga	✓	x	x	x	x	x	✓	x	x	x	2
Malmö FF	Allsvenskan (Sweden)	✓	x	x	x	x	x	✓	x	x	x	2
FC Basel	Swiss Super League	x	✓	✓	x	x	x	x	x	x	x	2
Aston Villa	Premier League	x	x	x	x	x	x	x	x	x	✓	1
Stade Brest	Ligue 1	x	x	x	x	x	x	x	x	x	✓	1
VfB Stuttgart	Bundesliga	x	x	x	x	x	x	x	x	x	✓	1
Bologna FC	Serie A	x	x	x	x	x	x	x	x	x	✓	1
Sturm Graz	Austrian Bundesliga	x	x	x	x	x	x	x	x	x	✓	1

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
Sparta Prague	Czech First League	x	x	x	x	x	x	x	x	x	✓	1
Girona FC	La Liga	x	x	x	x	x	x	x	x	x	✓	1
Slovan Bratislava	Nike Liga (Slovakia)	x	x	x	x	x	x	x	x	x	✓	1
RC Lens	Ligue 1	x	x	x	x	x	x	x	x	✓	x	1
SC Braga	Liga Portugal	x	x	x	x	x	x	x	x	✓	x	1
Union Berlin	Bundesliga	x	x	x	x	x	x	x	x	✓	x	1
Real Sociedad	La Liga	x	x	x	x	x	x	x	x	✓	x	1
Newcastle United	Premier League	x	x	x	x	x	x	x	x	✓	x	1
Royal Antwerp FC	Pro League (Belgium)	x	x	x	x	x	x	x	x	✓	x	1
Rangers FC	Scottish Premiership	x	x	x	x	x	x	x	✓	x	x	1
Eintracht Frankfurt	Bundesliga	x	x	x	x	x	x	x	✓	x	x	1
Maccabi Haifa	Israeli Premier League	x	x	x	x	x	x	x	✓	x	x	1
FC Sheriff Tiraspol	Moldovan Super Liga	x	x	x	x	x	x	✓	x	x	x	1
Villarreal CF	La Liga	x	x	x	x	x	x	✓	x	x	x	1
FC Midtjylland	Danish Superliga	x	x	x	x	x	✓	x	x	x	x	1

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
FC Krasnodar	Russian Premier League	x	x	x	x	x	✓	x	x	x	x	1
Stade Rennais	Ligue 1	x	x	x	x	x	✓	x	x	x	x	1
Ferencváros TC	Nemzeti Bajnokság I (Hungary)	x	x	x	x	x	✓	x	x	x	x	1
Istanbul Başakşehir FK	Süper Lig (Turkey)	x	x	x	x	x	✓	x	x	x	x	1
KRC Genk	Pro League (Belgium)	x	x	x	x	✓	x	x	x	x	x	1
SK Slavia Prague	Czech First League	x	x	x	x	✓	x	x	x	x	x	1
Schalke 04	2. Bundesliga (Germany)	x	x	x	✓	x	x	x	x	x	x	1
AEK Athens	Greek Super League	x	x	x	✓	x	x	x	x	x	x	1
TSG Hoffenheim	Bundesliga	x	x	x	✓	x	x	x	x	x	x	1
RSC Anderlecht	Pro League (Belgium)	x	x	✓	x	x	x	x	x	x	x	1
Qarabağ FK	Azerbaijan Premier League	x	x	✓	x	x	x	x	x	x	x	1
Spartak Moscow	Russian Premier League	x	x	✓	x	x	x	x	x	x	x	1

Team	League	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23	2023/24	2024/25	Champions League Participation
NK Maribor	Slovenian PrvaLiga	x	x	✓	x	x	x	x	x	x	x	1
APOEL FC	Cypriot First Division	x	x	✓	x	x	x	x	x	x	x	1
Ludogorets Razgrad	Bulgarian First League	x	✓	x	x	x	x	x	x	x	x	1
FC Rostov	Russian Premier League	x	✓	x	x	x	x	x	x	x	x	1
Legia Warsaw	Ekstraklasa (Poland)	x	✓	x	x	x	x	x	x	x	x	1
Leicester City	Premier League	x	✓	x	x	x	x	x	x	x	x	1
FC Astana	Kazakhstan Premier League	✓	x	x	x	x	x	x	x	x	x	1
BATE Borisov	Vysheyshaya Liha (Belarus)	✓	x	x	x	x	x	x	x	x	x	1
Maccabi Tel Aviv	Israeli Premier League	✓	x	x	x	x	x	x	x	x	x	1
KAA Gent	Pro League (Belgium)	✓	x	x	x	x	x	x	x	x	x	1

Table A2

Descriptive Statistics: Club Overview: Minimums

Club Overview: Minimums								
Team	**League**	**Season**	**Points**	**Squad Value**	**Salary**	**Transfer Expenditures**	**Squad Size**	**Age**
Sevilla FC	LaLiga	10	41	183.9	34.2	20.0	33	25.2
Manchester United	Premier League	10	42	439.9	123.3	82.7	35	24.0
Chelsea FC	Premier League	10	44	553.5	98.6	45.0	36	22.2
RB Leipzig	Bundesliga	10	51	41.0	27.6	26.1	28	23.0
SSC Napoli	Serie A	10	53	321.9	52.2	24.4	31	24.8
Borussia Dortmund	Bundesliga	10	55	353.0	57.5	20.0	30	24.1
Liverpool FC	Premier League	10	60	375.2	90.5	10.4	35	23.8
Inter Milan	Serie A	10	62	294.3	59.3	42.5	34	24.5
Juventus FC	Serie A	10	62	440.0	88.8	95.4	33	24.6
Manchester City FC	Premier League	10	66	499.4	127.0	78.6	32	24.6
Paris Saint-Germain	Ligue 1	10	68	436.3	108.0	62.0	34	23.6
Real Madrid	LaLiga	10	68	714.3	151.8	0.0	29	24.4
Atlético de Madrid	LaLiga	10	70	418.5	73.0	29.5	30	24.7
Bayern Munich	Bundesliga	10	71	562.5	134.6	14.0	32	24.2
FC Barcelona	LaLiga	10	73	726.0	179.7	33.4	32	23.3

Note: Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25. Salary in EUR / GBP million depending on club nationality.

Table A3

Descriptive Statistics: Club Overview: Averages

Club Overview: Averages								
Team	**League**	**Season**	**Points**	**Squad Value**	**Salary**	**Transfer**	**Squad Size**	**Age**
FC Barcelona	LaLiga	10	85.6	905.4	264.8	144.3	37.5	25.2
Manchester City FC	Premier League	10	85.3	1034.6	164.0	196.1	37.6	25.6
Paris Saint-Germain	Ligue 1	10	84.8	847.1	233.7	185.6	38.2	25.2
Real Madrid	LaLiga	10	84.1	925.4	270.4	101.8	34.8	25.5
Juventus FC	Serie A	10	80.1	601.5	165.1	176.5	41.6	25.8
Liverpool FC	Premier League	10	80.1	843.5	126.6	111.1	42.3	24.7
Bayern Munich	Bundesliga	10	79.4	804.9	214.8	103.7	37.6	25.4
SSC Napoli	Serie A	10	78.1	508.6	86.1	95.7	37.0	26.3
Atlético de Madrid	LaLiga	10	77.7	630.5	151.6	116.0	37.9	25.7
Inter Milan	Serie A	10	77.4	552.1	115.0	107.9	40.4	26.3
Chelsea FC	Premier League	10	66.8	899.9	152.7	248.9	46.5	24.8
Borussia Dortmund	Bundesliga	10	66.6	537.3	103.6	88.6	35.9	25.1
Manchester United	Premier League	10	65.7	730.9	178.8	178.5	42.5	25.2
RB Leipzig	Bundesliga	10	62.4	426.0	74.2	91.4	32.8	24.2
Sevilla FC	LaLiga	10	58.9	280.3	71.3	67.2	39.7	26.3

Note: Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25. Salary in EUR / GBP million depending on club nationality.

Table A4

Descriptive Statistics: Club Overview: Maximums

Club Overview: Maximums								
Team	**League**	**Season**	**Points**	**Squad Value**	**Salary**	**Transfer Expenditures**	**Squad Size**	**Age**
Manchester City FC	Premier League	10	100	1460.0	226.3	317.5	47	26.9
Liverpool FC	Premier League	10	99	1170.0	170.8	192.2	56	25.6
Paris Saint-Germain	Ligue 1	10	96	1140.0	386.3	454.5	45	26.2
Juventus FC	Serie A	10	95	871.0	259.6	261.8	59	27.2
Real Madrid	LaLiga	10	95	1350.0	352.4	361.3	42	26.3
Inter Milan	Serie A	10	94	741.9	156.2	192.9	60	27.7
Chelsea FC	Premier League	10	93	1190.0	226.6	630.2	58	26.2
FC Barcelona	LaLiga	10	93	1160.0	357.0	388.1	47	26.8
SSC Napoli	Serie A	10	91	654.1	105.6	217.1	54	27.3
Atlético de Madrid	LaLiga	10	88	969.7	202.8	247.3	43	26.9
Bayern Munich	Bundesliga	10	88	965.1	285.4	187.5	45	26.6
Manchester United	Premier League	10	81	849.5	242.2	246.3	49	26.6
Borussia Dortmund	Bundesliga	10	78	654.0	131.0	148.5	44	25.6
Sevilla FC	LaLiga	10	77	418.2	84.8	188.7	49	27.0
RB Leipzig	Bundesliga	10	67	575.0	107.7	187.2	38	26.0

Note: Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25. Salary in EUR / GBP million depending on club nationality.

Table A5

Correlation with League Points

Correlations with League Points			
Variable	***N***	***r***	***p***
Squad Value	150	$.170^{*}$	.0378
Total Salary	149	-.124	.1315
Transfer Expenditures	150	-.132	.1083
Transfer Revenues	150	-.089	.2761
Squad Size	150	-.115	.1602
Average Age	150	.108	.1877

Note: Correlation based on within-club demeaning variables. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Table A6

Correlation with Squad Value

Correlations with Δ Squad Value			
Variable	***N***	***r***	***p***
Δ Transfer Expenditures	135	$.224^{***}$	.0091
Δ Transfer Revenues	135	-.060	.4897
Δ Squad Size	135	$.193^{**}$	.0249
Δ Average Age	135	-.066	.4443

Note: Correlation based on within-club demeaning variables. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Table A7

Robustness Check: Estimator Comparison

Robustness Check: Estimator Comparison			
	Dependent Variable: League Points		
	Two-Way FE	Club FE	First Difference
Squad Value	0.041***	0.025***	0.031***
	(0.007)	(0.006)	(0.006)
Transfer Expenditures	-0.024**	-0.020**	-0.020*
	(0.010)	(0.009)	(0.011)
Total Salary	-0.041**	-0.071***	-0.011
	(0.020)	(0.019)	(0.040)
Squad Size	-0.044	-0.053	-0.134
	(0.192)	(0.229)	(0.233)
Average Age	1.438	2.582**	-0.788
	-1.467	-1.176	-1.416
Constant			-1.687***
			(0.606)
Observations	149	149	134
R^2	.233	.170	.116
Adjusted R^2	.055	.047	.082
F-Statistic	7.307***	5.271***	3.366***

Note: Two-way Fixed Effects: Club FE + Season FE. Club FE: within-demeaning on club dimension. FD: dependent variable and regressors are first-differenced. Standard errors clustered at the club level in parentheses. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Table A8

Robustness Check: Leave-One-Club-Out (Path b)

Robustness Check: Leave-One-Club-Out (Path b)				
Excluded Club	***N***	**β Squad Value**	***SE***	***p***
Atlético de Madrid	139	0.046^{***}	0.007	< .01
Bayern Munich	139	0.041^{***}	0.007	< .01
Borussia Dortmund	139	0.042^{***}	0.007	< .01
Chelsea FC	139	0.039^{***}	0.007	< .01
FC Barcelona	139	0.041^{***}	0.007	< .01
Inter Milan	139	0.038^{***}	0.007	< .01
Juventus FC	139	0.038^{***}	0.007	< .01
Liverpool FC	139	0.037^{***}	0.007	< .01
Manchester City FC	139	0.044^{***}	0.009	< .01
Manchester United	139	0.04^{***}	0.007	< .01
Paris Saint-Germain	139	0.043^{***}	0.007	< .01
RB Leipzig	140	0.041^{***}	0.007	< .01
Real Madrid	139	0.044^{***}	0.008	< .01
Sevilla FC	139	0.039^{***}	0.007	< .01
SSC Napoli	139	0.04^{***}	0.007	< .01

Note: Based on the primary model (M5). Re-estimating the model by excluding one club at a time (n = 139 per iteration). β = coefficient of squad value. Standard errors at the club level. *, **, *** = p < .10, .05, .01.

Table A9

Robustness Check: Leave-One-Season-Out (Path b)

Robustness Check: Leave-One-Season-Out (Path b)				
Excluded Season	***N***	**β Squad Value**	***SE***	***p***
2015/16	135	0.038^{***}	0.009	< .01
2016/17	134	0.04^{***}	0.008	< .01
2017/18	134	0.041^{***}	0.007	< .01
2018/19	134	0.039^{***}	0.008	< .01
2019/20	134	0.043^{***}	0.007	< .01
2020/21	134	0.041^{***}	0.008	< .01
2021/22	134	0.041^{***}	0.007	< .01
2022/23	134	0.038^{***}	0.007	< .01
2023/24	134	0.04^{***}	0.007	< .01
2024/25	134	0.047^{***}	0.007	< .01

Note: Based on the primary model (M5). Re-estimating the model by excluding one season at a time (n = 135 or n = 134 per iteration). β = coefficient of squad value. Standard errors at the club level. *, **, *** = p < .10, .05, .01.

Table A10

Robustness Check: Estimator Comparison

Robustness Check: Estimator Comparison			
	Dependent Variable: Squad Value		
	FD	Club FE	TWFE
Transfer Expenditures	0.323***	0.516***	0.387***
	(0.070)	(0.100)	(0.098)
Transfer Revenues	-0.134	0.340	0.014
	(0.125)	(0.285)	(0.231)
Average Age	9.505	-10.539	-7.516
	-24.475	-24.008	-22.995
Squad Size	4.836	7.924***	0.090
	-3.091	-2.474	-3.129
Constant	40.854***		
	-7.330		
Observations	135	150	150
R^2	.109	.162	.071
Adjusted R^2	.082	.047	-.135
F-Statistic	3.992***	6.341***	2.318*

Note: FD: dependent variable and regressors are first-differenced. Club FE: within-demeaning on club dimension. TWFE: Club FE + Season FE. Standard errors clustered at the club level in parentheses. *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Table A11

Robustness Check: Leave-One-Club-Out (Path a)

Robustness Check: Leave-One-Club-Out (Path a)				
Excluded Club	***N***	**β Transfer Expenditures**	***SE***	***p***
Atlético de Madrid	126	0.313^{***}	0.071	< .01
Bayern Munich	126	0.326^{***}	0.077	< .01
Borussia Dortmund	126	0.334^{***}	0.074	< .01
Chelsea FC	126	0.329^{***}	0.099	< .01
FC Barcelona	126	0.339^{***}	0.085	< .01
Inter Milan	126	0.332^{***}	0.077	< .01
Juventus FC	126	0.307^{***}	0.066	< .01
Liverpool FC	126	0.287^{***}	0.057	< .01
Manchester City FC	126	0.314^{***}	0.077	< .01
Manchester United	126	0.369^{***}	0.062	< .01
Paris Saint-Germain	126	0.303^{***}	0.074	< .01
RB Leipzig	126	0.331^{***}	0.073	< .01
Real Madrid	126	0.346^{***}	0.080	< .01
Sevilla FC	126	0.331^{***}	0.073	< .01
SSC Napoli	126	0.341^{***}	0.073	< .01

Note: Based on the primary model (M2). Re-estimating the model by excluding one club at a time ($n = 126$ per iteration). β = coefficient of transfer expenditures. Standard errors at the club level. *, **, *** = $p < .10, .05, .01$.

Table A12

Robustness Check: Leave-One-Season-Out (Path a)

Robustness Check: Leave-One-Season-Out (Path a)				
Excluded Season	***N***	**β Transfer Expenditures**	***SE***	***p***
2016/17	120	0.372^{***}	0.077	< .01
2017/18	120	0.298^{**}	0.134	.029
2018/19	120	0.320^{***}	0.081	< .01
2019/20	120	0.414^{***}	0.131	< .01
2020/21	120	0.387^{***}	0.063	< .01
2021/22	120	0.349^{***}	0.095	< .01
2022/23	120	0.425^{***}	0.092	< .01
2023/24	120	0.286^{***}	0.090	< .01
2024/25	120	0.382^{***}	0.085	< .01

Note: Based on the primary model (M2). Re-estimating the model by excluding one season at a time ($n = 120$ per iteration). The season 2015/16 is excluded from the Leave-One-Season-Out test, as FD eliminates the initial observation for each club. β = coefficient of transfer expenditures. Standard errors at the club level. *, **, *** = $p < .10, .05, .01$.

Table A13

Robustness Check: Endogeneity Test (Transfer Expenditures)

Robustness Check: Lagged Transfer Expenditure		
	Dependent Variable: League Points	
	M5 (primary)	M5 (lagged transfer)
Squad Value	0.041***	0.034***
	(0.007)	(0.008)
Transfer Expenditure (t)	-0.024**	
	(0.010)	
Transfer Expenditure (t-1)		0.005
		(0.009)
Total Salary	-0.041**	-0.039
	(0.020)	(0.027)
Squad Size	-0.044	0.016
	(0.192)	(0.207)
Average Age	1.438	1.449
	(1.467)	(1.749)
Observations	149	134
R^2	.233	.156
Adjusted R^2	.055	-.059
F-Statistic	7.307***	3.915***

Note: Two-way Fixed Effects: Club FE + Season FE. Standard errors clustered at the club level in parentheses. Lagged: transfer expenditures from the previous season ($_{t-1}$). *, **, *** = p < .10, .05, .01. Sample: 15 UEFA Champions League clubs, seasons 2015/16 – 2024/25.

Appendix B

AI Declaration

I hereby declare that I, Lilly Burholt (581218), have written this thesis independently and using only the sources and tools indicated. I am aware that, even when using generative artificial intelligence (AI), I alone bear responsibility for the academic quality and subject-matter accuracy of this work. I affirm that I am aware of the opportunities, risks, and challenges associated with the use of generative AI in academic work. I am aware that AI-generated content may be incorrect. I therefore assure that I have used AI tools solely as aids and have carefully verified the accuracy of the content. I take full responsibility for the adaptation of any AI-generated content I have used. I hereby confirm that all tools used, along with their respective areas of application, are listed in the table below.

Overview of the Tools Used

Tools	Areas of Use
Claude AI	Summarisation of theoretical frameworks for an initial thematic overview
	Structural organisation of section content
	Support in the development of R Studio code (in particular, error diagnosis and debugging)
	Stylistic revision and refinement of the text sections
	Translation of the Abstract from English to Italian
DeepL	Translation and linguistic refinement of selected text sections
Grammarly	Grammatical and linguistic proofreading of text sections

Pavia, 24.06.2026

Place, Date

L. Burholt

Student's Signature