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The Market's Matchday: Evaluating Stock reactions to Football Clubs performances in the UEFA Champions League

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22 May 2024

Foreword

The redaction of this Master thesis would not have been possible without the precious support of people we would like to acknowledge.

We first would like to thank our Master thesis supervisor, Pr. Leonardo Iania, for his availability and reactivity throughout the process of writing this thesis. The numerous calls full of invaluable advice and feedback allowed us to produce the best thesis possible.

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Additionally, we wanted to express our deep gratitude to two football clubs that have given us a passion for this wonderful sport, namely FC Barcelona and Standard de Liège. Despite their recent economic difficulties, these are two clubs that really breathe football, and who made us love it from an early age.

Lastly, we would like to thank each other for the nice collaboration while writing this thesis. Our complementarity and meticulousness drove us to the best and improved the quality of our work. Thanks to our great relationship, the hours devoted to working on the thesis were always spent in good mood.

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Abstract

At a time when the literature is focusing increasingly on the behavior of stocks over time, football club shares – thanks to their specific economic models – offer a very interesting opportunity to explore the mechanisms behind share price movements. That is why, for the purpose of this Master thesis, research has been carried out on the impact that match outcomes could have on stock prices exclusively in the UEFA Champions League, differing from other studies in this area focusing mainly on domestic competitions. To do so, four linear regressions – each offering an increasing level of detail on the influence of match outcomes – were run to assess the impact that a win, a loss, and a draw could have on the share prices of the associated football clubs. The results indicated that victories positively impact share prices more than defeats negatively affect them. Fans' deep attachment to their team could explain why defeats often have a less pronounced impact on share prices, as investors might be less inclined to sell even following unpleasant news like defeats. Moreover, draws are surprisingly perceived as even more detrimental than defeats as investors might prefer decisive outcomes. The results also suggested that the further a football club advances in the competition, the greater the impact on stock prices – illustrating the higher stakes involved in UEFA Champions League knockout matches. Finally, while certain elements, such as the significant market reactions following matches and the increasing magnitude of these reactions throughout the competition, align with the expectations of the Efficient Market Hypothesis (EMH), there is a growing belief that fan emotions significantly influence stock price movements after matches – due to an over-reaction after wins and under-reaction after losses – challenging the validity of the EMH.

Introduction

In 1983, Tottenham was the first football club ever to go public. Since then, some European football clubs followed the movement whereas others left the public market. Nowadays, several football clubs are quoted on public stocks. The most famous ones are Manchester United, Juventus, Borussia Dortmund, Sporting Lisbon, Porto, Olympique Lyonnais, FC Copenhagen, and Benfica. The combined market capitalization of all European publicly traded football clubs amounts to $5,34B (CompaniesMarketCap, 2023).

Although a market capitalization of $5,34B may be considered as small and is comparable to the market capitalization of a single company like *Asics*[1], these stocks have specific behavior that may be interesting to study. In this context, several research have already been conducted on the topic to understand the behavior of those specific stocks and their link with sportive outcomes. These studies all come to the same conclusion: the share prices of football clubs are linked to their sportive performance, i.e., they tend to increase following wins and decrease following losses.

However, most of the research on the subject has been carried out in the context of national championships. It might therefore be interesting, as part of this Master thesis, to focus the research on the results of European competitions and particularly on UEFA Champions League (UCL) matches. By working specifically on this prestigious tournament, this work could help to advance current research by providing new ideas on how to explain the behavior of football share prices after European matches. Furthermore, as the Champions League is the most prestigious football competition in Europe, its impact is important and deserves to be analyzed. Indeed, the tournament has a strong influence on various aspects of football clubs, ranging from visibility to the allocation of TV rights affecting financial health. Therefore, the first intuition suggests that the reaction is stronger after UCL matches than after national league matches. Going further, might be interesting to test whether this reaction is stronger depending on the stage of the competition at which the match takes place, given that the UCL is a knockout competition which could have an increasing impact on

[1] Asics Corporation has a market capitalization of $5,47B (Yahoo, n.d.).

investor reactions. Therefore, the refined research question that serves as the backbone of this thesis is the following one:

"*How do stock market valuations of European football clubs publicly traded on stock markets respond to their performance in UEFA Champions League matches, and to what extent can these responses be attributed to rational financial evaluation versus investor sentiment?*".

This research question is divided in two distinct parts. The first part concerns the link between the sportive performance of football clubs playing in the UEFA Champions League and their stock market valuation. It examines how on-field wins, losses, and draws impact clubs' share prices. The second part delves into the rationality of these market responses. The objective there is to evaluate whether these responses may be attributed to rational financial evaluation or are biased due to investors' sentiment towards football clubs. It is indeed crucial to understand the extent to which emotional factors, apart from financial fundamentals, affect investor decisions in the context of sports-related stocks.

Literature review

1. *Fundamentals of finance and stock market behavior*

Since the origin of financial markets and the introduction of stocks, the desire to understand the dynamics of stock price movements has captivated many. This interest is particularly triggered by the stark contrast between developed markets, which typically yield stable and substantial returns, and emerging markets, notorious for their volatility and unpredictable stock market behavior (Ruhani et al., 2018). Even in markets considered stable, one can observe significant day-to-day variations in stock exchange prices. This unpredictability is a pivotal concern for a range of stakeholders, including investors, risk managers, and policymakers, due to its significant implications on risk management, portfolio diversification, and hedging strategies.

Moreover, the global interconnection of markets amplifies the need for financial models capable of predicting stock behavior, as fluctuations in one market can directly influence another, thereby affecting anyone connected to the financial markets, directly or indirectly. This requirement underscores the importance of such models in grasping the wider economic picture, given the proven correlation between market trends and overall economic vitality, thus positioning it as a universal concern.

At present, we recognize three main schools of thought that explain how stock markets work: classical, behavioral, and the efficient market theory (Cho, 1980). In the classical view, the stock market is considered as a scale balancing supply and demand, where the settled price is the one where buyers and sellers agree to trade. At this balanced price point, there is no reason for anyone to push for a change because both buyers and sellers are satisfied. This balance is maintained through the Walrasian process, a sort of automatic price-tuning process that reduces or increases demand or supply until the balance is restored. According to this view, deals are made only when this fair price is found, ensuring the market stays steady and everyone is fairly treated (Ruhani et al., 2018).

The Efficient Market Hypothesis (EMH) posits that stock prices immediately and accurately reflect all available information in the market (Fama, 1970). The term "efficient market" was first introduced by Fama in a 1964 paper, where an efficient market was characterized as one where competitive forces ensure that new data about a stock's true value is swiftly and completely absorbed by the market, thereby reflected in the stock's price. According to this theory, it is therefore very difficult, if not impossible, for investors to take advantage of the new information available to them, as prices are supposed to immediately reflect this new data. As a result, there is no reason to believe that stocks are over- or under-valued. Indeed, Malkiel (2005) observed that, three decades following the introduction of the EMH, actively managed investment funds never achieved to significantly outperform passive index funds. As such, the theory suggests that consistently outperforming the market by leveraging new information is unlikely, since stock prices are thought to adjust to this information instantaneously, making stocks neither overpriced nor underpriced at any given moment. Indeed, EMH asserts that in an efficient market, it is impossible for any investor to achieve higher returns without accepting additional risk as they have no time to react before the market does. Therefore, deviations of actual returns from expected returns must be random and in general equal to zero and uncorrelated with information available online (Tease, 1993). Finally, three levels of EMH exist: weak form, semi-strong and strong form. Weak form version postulates that prices reflect all the information comprised in the last prices while semi strong form asserts that prices contain all the publicly available information. Lastly, the strongest form posits that stock prices also reflect inside information.

Developed independently in the 1960s by Jack Treynor, William Sharpe, John Lintner, and Jan Mossin, and based on the principles of the Efficient Market Hypothesis (EMH), the Capital Asset Pricing Model (CAPM) provides a framework for determining an investment's expected return by considering its risk relative to the overall market. This model emphasizes that an asset's total risk includes both systematic (cannot be mitigated through asset diversification) and unsystematic (or diversifiable) components. Within this framework, beta[2] plays a crucial role by measuring the relationship between an asset's returns and the market's returns, serving as a gauge for the asset's systematic risk contribution to a diversified portfolio's overall risk (Ruhani et al., 2018). Therefore, for investors to achieve higher returns, they must select assets with a beta greater than 1, indicating a higher sensitivity to market movements. Additionally, CAPM reveals that an ideally efficient portfolio, containing a mix of risky and risk-free assets, which will be considered by all investors (homogeneous

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[2] "Beta (β), primarily used in the capital asset pricing model (CAPM), is a measure of the volatility – or systematic risk – of a security or portfolio compared to the market as a whole"(Kenton, 2024).

expectations), is positioned at the tangent point where the Capital Market Line (CML)[3] meets the efficient frontier. Sharpe (1964) suggested this tangency point to represent the market portfolio itself, consistent with the EMH theory suggesting that investors are unable to systematically secure returns above the market average. Thus, at its core, CAPM asserts that the expected return on an asset should equal the risk-free rate plus a premium for risk, which is determined by the asset's beta (Womack et al., 2003). However, this model has been questioned several times for its testability and some doubts appeared (Ross, 1978). Indeed, a significant limitation of the CAPM is the assumption that market participants only consider the immediate future, ignoring longer-term investment horizons. Another limitation is the use of a single risk factor, beta, to account for differences in expected returns between different investments, which may not adequately reflect the complexities of financial markets (Miller, 1999).

Consequently, to address these limitations, renowned researchers Eugene Fama and Ken French have carried out extensive research in this field and identified two extra factors to explain more significantly the realized returns of publicly traded stocks. The first factor is Small Minus Big (SMB), capturing the historical trend where investments in companies with relatively small market capitalizations have yielded higher returns. The second factor is HML, which stands for High Minus Low, and represents the observed higher returns from stocks with high book-to-market values compared to those with low book-to-market values. Therefore, by incorporating the original market risk factor (i.e. the beta from CAPM) along with the two additional factors identified by Fama and French, namely Small Minus Big (SMB) and High Minus Low (HML), the widely adopted Fama-French Three Factors Model is derived. This more comprehensive model offers two distinct advantages. Initially, the Three Factors Model significantly enhances the understanding of the variations observed in realized returns, exhibiting R^2 values of 0.95 and above (while R^2 was equal to 0.8 for CAPM). Secondly, the model frequently reveals that a positive alpha seen in a CAPM analysis is often due to exposure to either HML or SMB factors, rather than genuine managerial skills (Womack et al., 2003).

[3] "The Capital Market Line (CML) represents portfolios that optimally combine risk and return." (Ganti, 2024)

Nonetheless, despite their robustness, models founded on the Efficient Market Hypothesis (EMH) exhibit certain limitations. Throughout the years, the EMH has increasingly been questioned by numerous financial economists. As suggested by Malkiel (2005), there seem to be several instances where market prices failed to reflect all available information. The technology-internet bubble of the late 1990s and early 2000s led many econometricians to reject the hypothesis of efficient market, suggesting instead that stock prices are more predictable than the hypothesis allows. During episodes of large-scale irrationality, there is an extent to which share prices are predictable based on their historic returns or on certain valuation metrics, including dividend yields and price-earnings ratios. Additionally, Lin (2023), rose three criticisms on the EMH. First, evidence demonstrates the existence of *momentum and reversal*. It refers to the tendency of stocks to follow persistent price trends and patterns, contrary to immediate information incorporation, as suggested by market efficiency. Second, the existence of *insider information and insider trading* challenges the assumption of equal access to information. It exposes information asymmetry and thereby undermines market efficiency. Finally, the author argues that the *influence of financial institutions* challenges the market efficiency hypothesis. Indeed, their market power and associated complexities introduces concerns about the EMH. Agency issues, herding behavior[4], and short-termism among financial institutions may compromise market efficiency.

In this context of limitations and concerns about the EMH, football shares are being analyzed and traded. The study of Ferreira et al. (2017) analyzes the clubs' returns in the light of the Efficient Market Hypothesis. The DFA (Detrended Fluctuation Analysis)[5] analysis highlights the presence of long-range dependence, challenging the validation of the EMH in its weak form. Theoretical frameworks suggest that financial markets have no memory, with return rates following a random pattern. However, the DFA exponents for football shares diverge from the expected random walk behavior, suggesting that investors might be able to predict the behavior of such stocks if additional information are present (i.e., match outcomes). Overall, football stocks show interesting features, notably low liquidity (which may

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[4] "Herding results from an obvious intent by investors to copy the behavior of other investors" (Bikhchandani & Sharma, 2000).

[5] The Detrended Fluctuation Analysis (DFA) is a technique used to analyze temporal dependence in time series, with the advantage of being used in the context of nonstationary time series (Ferreira et al., 2017).

incur trading costs for investors). Various elements, including significant game outcomes influence share prices. It underscores the deviation of football shares from the Efficient Market Hypothesis (Ferreira et al., 2017).

The theoretical financial models previously mentioned rely on the assumption that "persons and institutions are assumed to behave in a rational way" (Ruhani et al., 2018). However, more recently, researchers started to question this rationality assumption. In the 1990s, the focus of academic finance shifted away from econometric analyses towards the creation of models based on human psychology, with the objective of having a multidisciplinary approach that understands the financial behavior under the light of psychology, sociology and anthropology. This innovative approach, broadly referred to as "behavioral finance" seeks to incorporate the reasoning patterns of investors into financial models, from a human perspective (Ruhani et al., 2018). This shift to behavioral finance provides a clearer understanding of behaviors considered as non-rational in the stock market. Therefore, examining the dynamics of football club shares, and particularly the behavior of their abnormal returns, aligns with the behavioral finance theories arguing that investors are subject to feelings while making investment decisions (Palomino et al., 2009). According to Palomino et al. (2009), football results have a direct impact on investors' feelings, making them suitable for an analysis under the light of behavioral finance.

2. *The financial dynamics of European football*

As suggested by Ferreira et al. (2017), the share price of a firm is usually linked to its business model. In the context of professional football clubs, most of them concentrate their economic activity exclusively on football. Their revenues primarily derive from three sources: television broadcasting rights, ticket sales, and commercial activities, which include sponsorship and merchandising. On the expenditures side, the majority of the budget is allocated to salaries and player acquisitions (transfers) (Aglietta et al., 2010). Additionally, this categorization of football club revenues is confirmed by Deloitte in its renowned *Football Money League*[6] report. Indeed, the total revenue generated by the 20 wealthiest football clubs

[6] The Deloitte Football Money League is a ranking of football clubs by revenue generated from football operations (Deloitte, 2024).

amounted to €10.5bn in 2022/23. Money League clubs reported an average revenue exceeding €500m in 2023, with commercial revenue contributing to €222m (42%), broadcast revenues accounting to €213m (40%), and matchday revenue contributing to €93m (18%) (Deloitte, 2024).

Since main sources of revenue for football clubs come solely from football activities, the financial situation of football clubs is likely to be influenced by the on-field performance of the club. A well-performing team draws larger attendance to its games, leading to more frequent and popular television broadcasts. This, in turn, results in higher TV broadcasting rights and attracts more sponsors, boosting sales of club-related commercial products. On the contrary, if, for any reason, on-field results are to deteriorate, it is highly likely that the financial results would also decline, whereas salaries are not likely to drop that suddenly (Aglietta et al., 2010). The composition of clubs ranked 11th to 20th in the Money League also highlights the influence of on-field performance on financial revenues. For example, Eintracht Frankfurt climbed to 16th place in 2022/2023 from 22nd in the 2021/2022 season, due to its progression to the round of 16 of the UEFA Champions League for the first time ever[7] (Deloitte, 2024). In addition, Pinnuck and Potter (2006) suggest that attendance at football depends on the short-term and long-term success of the clubs involved. Additionally, the study highlights a strong relationship between match attendance and football success. Changes in membership are also a positive function of past success of the club, suggesting that the clubs' investments in the improvement of their football performance are justified. Furthermore, there is a positive correlation between the number of members membership and marketing-related expenditures made by clubs. Marketing revenues also exhibit a positive correlation with match attendance, indicating that clubs with higher popularity, attracting larger attendances, are more attractive to sponsors, potentially leading to increased marketing revenues (Pinnuck & Potter, 2006).

Moreover, European football has undergone significant transformations over the past two decades, driven by the emergence of major players who have reshaped the landscape through extensive trading and marketing efforts, resulting in substantial financial inflows. Among these shifts, the UEFA Champions League competition stands out as a pivotal change

[7] Eintracht Frankfurt lost to Napoli during the Round of 16 (UEFA.com, 2023).

in the sector, carrying profound implications for European football clubs in terms of revenue generation strategies. Indeed, established in 1955, the UEFA Champions League has evolved its format over time, expanding from 16 teams at its creation to accommodating 32 teams in its current format, with further plans to increase to 36 teams in the upcoming season. This strategy aims to enhance supporter engagement by providing more opportunities for fans to follow their teams, while also attracting sponsors and media attention. As a result, the UEFA Champions League has significantly increased its revenues, and in 2014 it even multiplied by ten the revenues it generated in 1994 (Dima, 2015).

This remarkable growth underscores its growing importance in the global football landscape, especially when considering UEFA's policy of redistributing 75% of its profits, including those from both the Champions League and the Europa League[8], back to participating teams. Consequently, distributions to these teams have significantly evolved, increasing at an average rate of 12% annually over the last decade. The breakdown, reviewed a few years ago, is as follows: 25% of the total sum is allocated as a fixed reward for qualification, 30% depends on sporting results (points and/or matches won) and 15% is allocated to the market pool – a share of money distributed to clubs according to the size of their market, estimated from the value of TV broadcasting contracts in each country. In addition, a new element (accounting for 30% of the breakdown) has recently been introduced, based on teams' performance coefficients over the last decade and the historical number of European titles won (Sanchez, 2019). This new aspect further underscores the significance of teams' success in the tournament, as their performances now hold an even greater influence on the revenue they generate.

However, alongside the direct income received by the UEFA and the revenue generated from ticket sales for European matches, an indirect impact exists that is far more challenging to quantify yet arguably more crucial. Indeed, participating in the Champions League and performing well can also stimulate increased future commercial activities while simultaneously inflating the market value of the team's players. A successful season in the tournament can significantly boost the team's popularity, fan engagement (resulting in additional income from marketing activities), and consequently enhance the value for stock

[8] The effective structure of the Champions League was promptly embraced and implemented, using identical principles, by the second European inter-clubs competition, the UEFA Europa League (UEL), starting in 2009 (Dima, 2015).

market investors. Hence, this indirect aspect becomes even more critical for clubs with an income exceeding 100 million euros, as in many cases, their direct income remains relatively low (between 10 and 25% of their budget), while the indirect impact holds the potential to generate significantly more in the future. The situation may not be analogous for clubs with lower incomes, as the direct impact (comprising 40 to 60% of the budget) plays a pivotal role in enabling these clubs to expand their operations (Dantas et al., 2020). Conversely, football teams unable to qualify or facing poor results during the tournament are vulnerable to substantial financial losses due to the huge disappointments of their fans (Dima, 2015). This underscores the critical need for European football teams to secure qualification for the UEFA Champions League and strive for successful performance (in accordance with their standing), not only to compete for the most prestigious trophy in Europe but also to ensure the financial sustainability of the club.

Nevertheless, the above-depicted increased revenue induced by participation in a European competition must be considered carefully, especially for small clubs. In certain circumstances, the qualification to UCL or UEL affects the development of these clubs, with investments in both tangible and intangible assets, suggesting that the qualification has an impact on clubs' overall development. Yet, the financial benefit from such investments is not immediate. The general liquidity indicator of small Portuguese clubs[9] revealed treasury difficulties following participation, indicating that the direct impact of participation is insufficient for clubs to finance their activities in the short term. In some cases, the situation even led to technical bankruptcy. While participation to European competitions can be beneficial, it also induces significant financial risks (Dantas et al., 2020). Additionally, a study conducted at FC Barcelona identified a clear relationship between management strategies and the positive evolution of financial performance. As a conclusion, good and efficient management is key to the financial sustainability of football clubs participating in European competitions, especially for smaller clubs (Dantas et al., 2020).

[9] Vitória SC and FC Paços de Ferreira (Dantas et al., 2020)

3. The link between sportive performance and clubs' shares prices

"*While football results are not cash flows, they are expected to affect the share price of football clubs because winning games is likely to increase the club's subsequent cash flows and value via a number of routes*". This statement, from Bell et al. (2012), suggests that the share prices of football stocks are likely to be linked with the sportive results of football clubs and for this reason, good sportive performances might result in financial rewards (Floros, 2014). The *number of routes* represent the different previously mentioned aspects of a club's financing. Football clubs, particularly through their share prices, offer an interesting opportunity to explore alternative theories behind fluctuations in share price, diverging from the traditional business-related information that heavily influences research on equity pricing and market efficiency (Bell et al., 2012).

Furthermore, football outcomes represent an excellent type of information to analyze for multiple reasons. First, games are played during evenings and weekends, meaning that stock markets are closed when the information occurs. As a result, markets are expected to open at a new price reflecting the outcome of the match. Additionally, the high frequency of football matches increases the volume of available information, enriching the dataset for further analysis. Then, the information is quantified[10], available as soon as the final whistle blows, and instantly spread across media. Furthermore, the outcome of a game is not known to insiders before the game occurs, meaning there is no pre-release trading. Finally, betting odds may be used as market expectations for the result, enabling the surprise element of the information to be computed (Bell et al., 2012).

For all these reasons, numerous studies have already been conducted on the topic, with the objective to know whether stock prices of football clubs are dependent on team's performance or not. Most studies report that stock returns of football teams are significantly linked with the clubs' wins, losses or draws (Floros, 2014). Edmans et al. (2007) highlight the influence of losses on share prices whereas Kaplanski and Levy (2009) observe a robust link between FIFA World Cup results and stock market returns. Additionally, Floros (2014) suggests that stock prices fluctuate in response to various events[11] , showcasing shifts in the feelings of investors and supporters. Furthermore, the insights provided by Edmans et al. (2007) and

[10] Through goals and points.
[11] *e.g. positive/negative results, buy/sell a player, etc.* (Floros, 2014).

Ashton et al. (2011) studies give more theoretical details about the relationship between match results and stock returns. Besides those findings, Boido and Fasano (2007) analyze Italian football clubs and their shares behavior in the stock market to conclude that Italian investors react negatively to draws.

Given the ever-increasing amounts of money circulating in the world of football, Scholtens and Peenstra (2010) also wanted to analyze whether match results could have an impact on the market valuation of football clubs. This interest was further motivated by the observation that the unveiling of new information, such as football match results, correlates directly with expected future cash flows or, conversely, with a reduction in expected cash flows – following a loss. Therefore, investors can quickly interpret and assimilate this information in their reassessment of a football club's value, making match results highly significant in terms of their potential influence on the share price of listed clubs.

A new aspect of their research is the analysis of both European and national matches for a group of international teams. Using the study methodology event, they focused their research solely on the reaction of a stock to a specific event: the outcome of a football match, which can be a victory, a defeat, or a draw. Therefore, expected returns[12] have been settled, using an estimation period[13] of 250 trading days. This approach is in line with the methods used by Brown and Warner (1980, 1985) and Campbell et al. (1997). The 250 trading-day period is chosen because it covers the entire sample period, given the difficulty of identifying an estimation period that is unaffected by events likely to have an impact on returns. After the subtraction of the expected returns from the actual returns, the abnormal returns were identified, which represent the deviation from what was anticipated, highlighting the specific impact of the event on the stock's performance. Since the event period used in their study is a single day, i.e. the first trading day after the match, Scholtens and Peenstra (2010) assessed the impact of the outcome of a football match for this single event period, thus avoiding any event period overlap and hence any misinterpretation of the analysis result. This approach is not uncommon as it follows the suggestions of Dyckman et al. (1984) as well as Glascock et al.

[12] Expected returns are the returns that can be expected when the event has not taken place. They were calculated by the market model (Brown and Warner, 1980, 1985; Beaver, 1981; Dyckman et al., 1984).
[13] Estimation period is used to calibrate the parameter's model establishing a benchmark for what returns would have been had the event not taken place (Scholtens & Peenstra, 2010).

(1991) to use such short period to concentrate on the immediate and pure outcomes of an event.

Considering the detailed methodology used by Scholtens and Peenstra (2010), their findings offer persuasive insights on the influence of football match outcomes on stock market valuations. Firstly, it was established that stock markets generally react positively to victories and negatively to defeats. However, one of the key findings is that the market reaction is much stronger to defeats, underlining the idea that the public is generally much more sensitive to losses. In addition, Scholtens and Peenstra (2010) concluded that the stock market reacts more intensely to the results of European competitions than to those of domestic tournaments. Finally, the research determined that unexpected results in European matches lead to a stronger stock market reaction than expected results, whereas this is not the case in domestic competitions. These latest findings can be attributed to the greater likelihood of European competitions being accompanied by significant financial incentives, a factor which deeply influences market reactions to sporting results (Scholtens & Peenstra, 2010).

Finally, the study by Palomino et al. (2009) diverges in its conclusions and offers other perspectives. Convinced of the limited capacity of individuals to process information, they believe that people process news differently according to its perceived importance. Gilbert et al. (2007) support this view by revealing that investors' inattention, generated by this limited capacity to process information, strongly influences the overall stock market. Interesting conclusions can be drawn from this research. Indeed, the market appears to respond more quickly to positive news compared to negative news: while 60% of the three-day abnormal return[14] following a win is generated on the first day, only 28% of the return is explained on the first day after a loss for the same period. This result is similar to the studies carried out by Hong et al. (2000) and Chan (2003), highlighting the slower response of the stock market to unpleasant news. Moreover, contrary to Scholtens and Peenstra (2010) who confirm a stronger reaction in absolute terms in case of defeats, Palomino et al. (2009) characterize the market reactions to a victory and a defeat similar in magnitude over a three-day window. This finding is also in opposition with the results obtained by Brown and Hartzell (2001), who

[14] A three-day period is used to measure abnormal returns, to account for both the immediate market reaction and any delayed reaction as news spreads among investors (Palomino et al., 2009).

discovered that for US professional basketball games, the market's response to a defeat is significantly more pronounced than to a victory.

Additionally, Bell et al. (2012) provide other perspectives on the subject by adding additional variables in their model. The goal of this approach is to isolate the effect of match outcomes on financial markets, separating it from the impact of other variables. This provides a clearer understanding of how sports performances impact financial markets. Some of these extra variables turn to have a significant impact on share prices behavior. Specifically, the market index, the point surprises and lagged point surprises[15], the point surprises from home games, the goals ahead[16] factor and the variable representing unexpected outcomes all demonstrate significant impacts. This highlights the complex interconnection between factors and their role in explaining market dynamics, especially in the context of sports-related investments. On the other side, some variables appeared to exert little to no influence on financial returns. It turns out to be the case for the importance of the game[17], the goal surprises and lagged goal surprises[18], the match results and the expected outcomes. Surprisingly, Bell et al. (2012), point out that match outcomes account for only a small fraction of the variations in share prices. This finding diverges from conclusions of most studies in this area, paving the way for further research on the topic. Moreover, the conclusions drawn on expected and unexpected football results support the view that football results are price sensitive information and that there is no evidence against the notion that football stocks are semi-strong efficient (Bell et al., 2012). This information is interesting to highlight since it is in opposition with the findings of Ferreira et al. (2017), highlighting the presence of long-range dependence within football shares, challenging the validation of the EMH.

4. Investor psychology and its impact on club shares

In addition to the dependence of football shares on results, sports, and particularly football, are influenced by the feelings and passions of fans, which have the potential to

[15] Point surprises are calculated based on betting odds, suggesting the number of points expected to be earned by a specific club during a match (Bell et al., 2012).
[16] The goals ahead variable incorporates the goal difference between two teams during a match (Bell et al., 2012).
[17] The importance of the game is measured either in terms of the degree of rivalry between the two match competitors, or in terms of the closeness of the match to the end of the season (Bell et al., 2012).
[18] Goal surprises considers the actual goal difference of a match and compares to was anticipated before the match (Bell et al., 2012).

substantially affect their rational decision-making abilities (Ferreira et al., 2017). Furthermore, Duque and Ferreira (2005) state that "*shares of football companies have the interesting characteristic of being traded based on two possible reasons: the irrational esteem of their supporters and the economic rational of any investment*". In summary, the fans' irrational sentiments towards football clubs combined with the influence of match outcomes on clubs' financials, as previously outlined, pave the way for abnormal returns. Consequently, this section aims to analyze abnormal returns exhibited by football shares under the light of *behavioral finance*.

As discussed above, the goal of behavioral finance is to explain and understand the reasoning patterns of investors, including their emotional states and the extent to which they affect their decision-making process. It attempts to provide a human-centered explanation of the what, the why, and the how of finance investing. Behavioral finance studies financial markets as well as provides explanations to stock market anomalies, speculative market bubbles, and crashes[19]. Finally, it investigates the sociological and psychological factors influencing the decision-making processes of individuals and groups. Behavioral finance is an evolving area that continues to grow thanks to the wide range of academic papers bringing new perspectives on the topic (Ricciardi & Simon, 2000).

Under the light of behavioral finance, many psychological research confirms the tangible impact of sports results on mood. For example, Wann et al. (1994) suggest that fans exhibit positive emotional responses to their teams' successes, suggesting that these outcomes can increase or decrease their self-esteem and broadly affect their overall life satisfaction. Schwarz et al (1987) show that the results of two German matches in the 1982 World Cup considerably altered people's perception of their well-being and their opinions on national issues. Hirt et al. (1992) found that Indiana University college students were more confident in their own performance after seeing their fellow students win a basketball match. Moreover, some other studies claim that changes in mood directly affect economic behavior. For instance, Arkes et al. (1988) show that there was an increase of lottery tickets in Ohio State in the period that followed the victory of the Ohio State University football team.

[19] Such as the January effect (for market anomalies), the internet bubble, and crashes of 1929 and 1987 (Ricciardi & Simon, 2000).

However, the impact of sports outcomes extends well beyond mere fluctuations in mood and can even affect people's health. Carroll et al. (2002) show that there was a 25% increase in heart attack admissions immediately after England lost the World Cup final to Argentina in a penalty shoot-out. Further, White (1989) reports a notable rise in homicides in cities following their teams' elimination from the U.S. National Football League playoffs. Moreover, Trovato (1998) show a significant rise in suicides among Canadians when the Montreal Canadians are eliminated early from the Stanley Cup playoffs.

Although a clear relationship between sporting events and human behavior has been demonstrated, a large amount of evidence suggests that football in particular is an important part of people's lives. For example, World Cup 2022-related content was viewed over 262 billion times, including likes, shares, replies and clicks, and the final between Argentina and France alone attracted over 1.5 billion viewers (FIFA, 2023). Furthermore, in countries like Brazil, Argentina, and Mexico, where living standards are often regarded as modest, it is estimated that many individuals allocate more of their average expenditures to football matches than to other essential consumer goods (Boido, 2006).

In 2007, Edmans et al. used the results of international football matches as a significant factor in analyzing their effects on stock market returns, as they knew they could have a profound impact on public mood. While they show that a loss has a significant negative effect on the losing country's stock market[20], they also demonstrate that market reactions following a loss are more likely to be driven by investor mood rather than by rational responses to new information, in line with the EMH approach. Edmans et al. (2007) found that the negative effect of a highly anticipated loss is not correctly assessed in advance. Indeed, the market's reaction does not correspond to a rational adjustment to the anticipated economic impacts (i.e. the negative effect of a loss) that a rational investor would have correctly assessed prior to the event. Furthermore, since the observed impact is more pronounced in countries with a deep cultural affinity for football, it suggests that these market responses are more closely tied to emotional responses rather than economic considerations. Lastly, the effect of football losses is more pronounced in small-capitalization stocks, which are known to be more sensitive to investor sentiment. Indeed, owners are often locals who are much more easily

[20] For example, the elimination of a major international football competition is correlated with an average drop of 38 basis points in the national stock market index the following day. (Edmans et al., 2007).

influenced by the performance of the national team, once again supporting the mood-based explanation over the efficient market theory approach.

In addition, as suggested by Baker and Wurgler (2006) and Edmans et al. (2007), smaller club stocks are supposed to be more strongly influenced by investor mood as they attract less media attention. Therefore, if the hypothesis of an overreaction caused by investor mood is verified, football results of smaller clubs are supposed to generate stronger price reactions. Palomino et al. (2009) tested this hypothesis by partitioning their club sample in two subsamples based on the companies' market evaluations. The results suggest the presence of overreaction due to investor sentiment, contrary to the Efficient Market Hypothesis. Indeed, the average abnormal return for small clubs is twice as strong as that for large clubs, in the case of both victories and defeats[21]. Moreover, if football shares follow the Efficient Market Hypothesis, investors should price the expected outcome before the occurrence of a match (Palomino et al., 2009). Consequently, the higher the likelihood of wins, the weaker the market reaction should be. The analysis of Palomino et al. (2009) demonstrates that the magnitude of market responses to victories increases as the likelihood of winning increases[22]. This indicates investors usually overreact to wins, especially when the outcome is strongly expected, challenging the validation of the EMH.

However, the research conducted by Bernile et al. (2011) demonstrates that the market is capable of efficiently processing information, such as match outcomes, in a manner that aligns with the principles of the Efficient Market Hypothesis. They observed that pre-match stock prices often did not match predicted outcomes, suggesting that investors' expectations were skewed. Yet, following the matches, stock prices appeared to realign, effectively assimilating the actual outcomes of the matches into their valuations. This approach reveals that despite biased expectations on football games[23], the market's reactions to the match are not irrational and seem to be valuing the shares fairly. Consequently, Bernie et al (2011) conclude that while investors tend to react emotionally in the short term, which

[21] The average abnormal return is equal to 1.2% for small clubs and equals 0.6% for large clubs, in the case of a win. Following losses, the average abnormal return for small clubs equals -1.3% whereas it equals -0.6% for large clubs (Palomino et al., 2009).

[22] The average abnormal return after a victory amount to 1% when the win was strongly expected, compared to 0.5% for matches where the team was highly expected to lose (Palomino et al., 2009).

[23] Investors tend to be overly optimistic about their teams' chances, leading to disappointment when outcomes do not align with these expectations, which in turn affects stock prices negatively (Bernile et al., 2011).

goes against the EMH approach, the market tends to adjust in the long term to effectively reflect the actual outcome of the match.

Moreover, Palomino et al. (2009) analyzed the time persistence of market reactions following football matches to assess their rationality. In the case of an overreaction to match results, the market reaction is expected to be transitory and to disappear after a few days. Nonetheless, abnormal returns after wins are stronger over a five-day window than over a two- or three-day window. This implies that abnormal returns following matches show a tendency to persist over time. Besides, the sign of the abnormal return on the first trading day following a match is not reversed during the following days, suggesting that the reactions from the investors are not transitory. These findings do not support the hypothesis of an overreaction of football investors, aligning with the hypothesis of an efficient market (Palomino et al., 2009). Furthermore, it is presumed that investor mood has stronger influence on the prices of shares held by individual investors than on those held by institutional investors. Therefore, Palomino et al. (2009) divided their club sample into two subsamples depending on the nature of their ownership[24]. According to overreaction theories, clubs with institutional investors – who are presumed to be more rational in their decision-making than individuals – among their shareholders should experience weaker price reactions to matches. However, it appears that clubs without institutional investors within their shareholder base show weaker market reactions. This discovery contradicts the overreaction hypothesis (Palomnio et al., 2009). Finally, as described above, investors are expected to integrate the anticipated result in their share price before the occurrence of a match in the case of an efficient market. Therefore, market reactions to losses should be weaker, the higher the probability of this result. Indeed, it is proven by Palomino et al. (2009) that the market reactions to a defeat become less important as its anticipated probability increases[25]. This finding corroborates the hypothesis that markets are, indeed, efficient.

In conclusion, while some studies suggest the existence of market overreaction in the context of football values, it is very difficult to really prove it due to the existence of counter-arguments, as explained above. However, a very plausible explanation for this possible

[24] "*The first group consists of seven teams whose blockholders (i.e. shareholders with at least a 3% stake) include at least one large institutional investor. The second group consists of nine teams without such an institutional major shareholder*" (Palomino et al., 2009).

[25] The average abnormal return after a defeat is equal to -1.3% when the team was strongly expected to win, compared to -0.6% for matches the team was highly expected to lose (Palomino et al., 2009).

overreaction could lie in investors' loyalty to their clubs. Indeed, it may be reflected in a reduction in the number of shares sold following negative events (e.g. a defeat) (Palomino et al., 2009).

Objectives and hypotheses

1. Objectives

As suggested by numerous academic papers and studies, there are evidence of a significant link between match outcomes and share prices of publicly quoted football clubs. However, these findings are mainly centered on domestic leagues. While some studies focus European leagues as well, the findings remain solely on the analysis of a significant difference between results in domestic leagues and in European leagues. Therefore, it may be interesting to have a closer look at the impact of the biggest European competition, and the evolution of football clubs within this tournament. Based on this, this Master thesis will focus on the effect of football matches played in the UEFA Champions League on clubs' returns and analyze the impact of a club's progression within the various stages of the competition, seeking to identify significant differences between the rounds.

For the purposes of this analysis, four linear regression models will be applied in the context of the UEFA Champions League, each designed to examine club returns at an increasingly detailed level. First, the initial model aims to verify whether matches outcomes have an impact on clubs' returns. The second model has a different purpose since it analyzes the returns of football clubs depending on the type of outcomes, i.e. victories, defeats, or draws. Indeed, a distinction is made between wins, draws, and defeats for matches played in the competition to examine how each outcome affects share price distinctly. Additionally, the third model delves into more details within the competition as it checks the significant differences of returns related to matches played in the group stage of the competition in comparison with the ones played in the knockout phase, unveiling the financial importance of the two different competition phases. Finally, the last model offers the largest level of details to the analysis presented in this thesis. Indeed, the goal of this model is to distinguish matches played at each stage of the competition (group stage, round of 16, quarterfinals, and semifinals) and analyze their impact on the stocks' prices.

2. *Hypotheses*

After discussing the main objectives, the four models with their own assumptions were identified and used as the basis for the linear regressions. Here is *Figure 1* helping to identify the abbreviations of the indexes used in the hypotheses:

Abbreviation	Name
Rst	Result
W	Win
L	Loss
GS	Group Stage
KO	Knockout
16	Round of 16
4	Quarterfinal
2	Semifinal

Figure 1 - Table of the indexes used in the hypotheses

Model 1: One independent variable

Linear regression predicting the abnormal return of European quoted football clubs – the dependent variable – based on one independent variable representing the outcome of matches in the Champions League competition (i.e., a win, a draw, or a defeat). While this linear regression is useful to determine whether the result of a match has an impact on stock prices, it does not isolate the impact that a win could have over a loss or a draw.

H$_0$: $\beta_{Rst} = 0$

The null hypothesis asserts that the result of Champions League matches does not influence the share price of listed European football clubs, which would be evidenced by a coefficient equal to zero for the "Result" variable in the regression analysis.

H$_1$: $\beta_{Rst} \neq 0$

The alternative hypothesis asserts that the result of Champions League matches does influence the share price of listed European football clubs, which would be evidenced by a coefficient significantly different from zero for the "Result" variable in the regression analysis.

Model 2: Two independent variables

Linear regression model predicting the abnormal returns of European quoted football clubs using two independent dummy variables[26]: one for the victory outcomes in Champions League matches, and another for defeats, while draws are counted in the intercept. It differs from model 1 as model 2 isolates the impact that a win, a loss, and a draw would have on share prices.

H0: $\beta_W, \beta_L = 0$

The null hypotheses suggest that wins or losses have no impact on the share prices of publicly traded European football clubs, as demonstrated by a zero coefficient for both variables in the regression analysis.

H0: $\beta_W, \beta_L \neq 0$

The alternative hypotheses suggest that wins or losses have an impact on the share prices of publicly traded European football clubs, as demonstrated by coefficients that would be significantly different from zero for both variables in the regression analysis.

Model 3: Four independent variables

Linear regression model designed to analyze the abnormal returns of publicly traded European football clubs, using four independent variables to distinguish group stage matches and knockout matches. Each category uses two variables to represent a win or a loss. This approach enables an evaluation of whether the impact of winning or losing differs significantly between group stage (GS) matches and knockout (KO) matches.

H0: $\beta_{W^{GS}}, \beta_{L^{GS}}, \beta_{W^{KO}}, \beta_{L^{KO}} = 0$

[26] A dummy variable in linear regressions is a variable taking 0 or 1 as value to represent subgroups of the sample in an analysis.

The null hypotheses suggest that the results of wins or losses in group stage and knockout matches have no impact on the share prices of listed European football clubs, as demonstrated by a zero coefficient for the four variables in the regression analysis. This suggests that the phase of the competition (group stage vs. knockout stage) does not have a statistically significant impact on the stock price reactions to match outcomes.

H$_1$: $\beta_{W^{GS}}, \beta_{L^{GS}}, \beta_{W^{KO}}, \beta_{L^{KO}} \neq 0$

The alternative hypotheses propose that the results of wins or losses in group stage and knockout matches have an impact on the share prices of listed European football clubs, as demonstrated by a coefficient significantly different from zero for the four variables in the regression analysis. This suggests that the phase of the competition (group stage vs. knockout stage) has a statistically significant impact on the stock price reactions to match outcomes.

Model 4: Eight independent variables

Linear regression model designed to analyze abnormal returns of publicly traded European football clubs, using eight independent variables to distinguish all the different stages (expect the finals) in the UEFA Champions League. Each category (group stage, round of 16, quarterfinals, and semifinals) uses two dummy variables to represent either a win or a loss, with the basic scenario of the draw outcome being implicitly incorporated into the model's intercept. This approach enables an evaluation of whether the impact of winning or losing differs significantly across the various, distinct phases of the tournament, from the initial group rounds through the increasingly competitive knockout stages, including the round of 16, the quarterfinals, and the semifinals.

H$_0$: $\beta_{W^{GS}}, \beta_{L^{GS}}, \beta_{W^{16}}, \beta_{L^{16}}, \beta_{W^{4}}, \beta_{L^{2}}, \beta_{W^{2}}, \beta_{L^{2}} \ = 0$

The null hypotheses suggest that the outcomes of win or loss have no impact on the share prices of publicly traded European football clubs in all stages of the European Competition, as demonstrated by a zero coefficient for the eight variables in the regression analysis. This suggests that the phase of the competition (group stage, round of 16, quarterfinals and semifinals) does not have a statistically significant impact on the stock price reactions to match outcomes.

H₁: $\beta_{W^{GS}}, \beta_{L^{GS}}, \beta_{W^{16}}, \beta_{L^{16}}, \beta_{W^{4}}, \beta_{L^{2}}, \beta_{W^{2}}, \beta_{L^{2}} \neq 0$

The alternative hypotheses suggest that the outcomes of win or loss have an impact on the share prices of publicly traded European football clubs in all stages of the European competition, as demonstrated by coefficient different from 0 for the eight variables in the regression analysis. This suggests that the phase of the competition (group stage, round of 16, quarterfinals and semifinals) has a statistically significant impact on the stock price reactions to match outcomes.

Methodology and data

The approach used in the Master thesis primarily focuses on calculating abnormal returns, which serve as the dependent variable for each of the models mentioned above. These returns represent the part of a stock's performance that diverges from expected market trends and that is directly associated with the event under study, i.e. the outcome of a Champions League match. As suggested by Scholtens and Peenstra (2010), the use of the study's methodological event and abnormal returns allow to precisely define the impact that the outcome of a Champions League match can have on stock prices. Moreover, for accurate use and full analysis of these abnormal returns, it was imperative to meticulously extract and process the relevant data. This section is therefore twofold: firstly, it details the precise sequence of steps followed to calculate abnormal returns and their subsequent incorporation into our four linear regression models; secondly, it describes in more details the approach used to extract and transform the data – divided into three sections: football data, financial data and joined data (which is the combination of the two).

1. Methodology

Computing the Abnormal Returns

The first step to calculate the abnormal returns is to compute the expected returns for all the European listed football clubs participating in the Champions League during the selected period. These returns represent how the stock should have performed if no particular event took place, i.e., a UEFA Champions League football match. Given all the criticisms about the Capital Asset Pricing Model (CAPM) in the literature, the Fama-French model has been identified as the most suitable model for this objective. Indeed, while CAPM focuses only on market risk (beta), the Fama-French model includes two additional factors – size (SMB: Small Minus Big) and value (HML: High Minus Low) – which gives a broader view of what drives stock returns. This holds particularly true for football clubs, which, while not strictly following broader market trends, might also be impacted by their book-to-market values and their overall size.

To accomplish this, it was necessary to extract data related to the Fama-French factors (Market Risk Premium, Small Minus Big, and High Minus Low) as well as the actual returns of football clubs. The actual returns, once adjusted by the risk-free rate, constitute the dependent variable for the initial linear regression employed in this Master thesis. Leveraging data from the last five seasons, this initial linear regression – employing actual returns adjusted by the risk-free rate as the dependent variable and the Fama-French model factors as explanatory variables – generated coefficients for each of the explanatory variable of the Fama-French model for a single season, which are critical to estimating the expected returns. Here is the linear regression followed by a table (*Figure 2* - Table of the Fama-French regression variables) helping to identify the variables and the indexes:

$$(AtR_t^i - rf_t) \sim \beta_{0,s} + \beta_{1,s} \times SMB_t + \beta_{2,s} \times HML_t + \beta_{3,s} \times MrP_t$$

Abbreviation	Name	Description
Dependent variable		
AtR_t^i	Actual returns	Actual returns that are observed on Bloomberg on day t for football club i.
rf_t	Risk-free rate	Risk-free rate observed on day t (retrieved from *Kenneth* data library).
Independent variables		
SMB_t	Small Minus Big factor	Small Minus Big factor observed in Europe on day t (retrieved from *Kenneth* data library).
HML_t	High Minus Low factor	High Minus Low factor observed in Europe on day t (retrieved from *Kenneth* data library).
MrP_t	Market Risk Premium	Market Risk Premium observed in Europe on day t (retrieved from *Kenneth* data library).
Indexes		
i	Football club	Index representing each of the football clubs analyzed.

t	Period	Index representing the specific time period at which the analysis is conducted, where t = 1 corresponds to one day.
s	Season	Index representing each of the different seasons analyzed throughout the Master Thesis (from 2003 to 2023).

Figure 2 - Table of the Fama-French regression variables

This linear regression was therefore run for each distinct season based on the data from the five previous seasons to find the corresponding coefficients. Obviously, as the Master thesis investigates the direct effect of game outcomes on the stock market performance of football clubs on the subsequent opening market day, data extraction for the Fama-French model and the actual returns were intentionally confined to daily values.

Upon obtaining the coefficients for the Fama-French model's three factors – SMB, HML, and the market risk premium – these were then used in conjunction with the corresponding daily Fama-French factor values. By multiplying the daily factor values by their respective coefficients and then remove the risk-free rate[27], the expected return for each day could be calculated. This figure represents the daily return expected for all the listed football clubs as a whole playing in the Champions League solely from the market and size/value factors, without any external events affecting stock prices. Finally, to calculate the abnormal returns, these expected returns were subtracted from the actual returns observed. This is the final stage, and identifies the returns that deviate from market expectations, potentially due to football match results or other club-specific information.

Exploring the Various Models: A Comprehensive Overview

As explained in the previous section, the Master thesis is structured around four models, each offering an increasingly detailed examination of the impact of match results. These models deepen the analysis by taking into account the stage of the competition in which matches are played, in order to assess the effects in greater depth. Indeed, although the four models share the same dependent variable – abnormal returns, each one uniquely analyzes the impact of match outcomes in the Champions League. They differ in the number of dummy

[27] Removing the risk-free rate is necessary as the dependent variable of this linear regression is equal to the expected return plus the risk-free rate.

variables introduced, which represent the outcome of the match and the various stages of the tournament, allowing a nuanced assessment of how each phase influences market reactions. To avoid multicollinearity – a situation in which two or more independent variables in a linear regression are highly linearly correlated – the choice was made to exclude the dummy variables representing the result of the draw. In this way, the sum of the dummy variables can be different from 1, which allows the avoidance of the dummy variable trap[28]. This situation implies that the intercept represents the result of the draw and captures the base level of abnormal returns when all other variables are equal to zero. If this precaution had not been taken, multicollinearity would have distorted the estimation of the coefficients and could have made the results unreliable.

Additionally, the models do not take account of competition finals, for two main reasons. Firstly, the analysis, which covers the 2003 to 2023 seasons, does not have sufficient data on finals to accurately assess their impact on share price trends. Indeed, the rarity of listed teams reaching the finals during this period limits the reliability of this data (only three listed European football clubs have reached finals from 2003 to 2023). It would therefore have been unreasonable to use this limited data to conclude what influence a Champions League final might have on share prices. Secondly, the unique nature of the finals, characterized by heightened media attention, distorts the impact clubs' financial. The high level of exposure means that reaching the finals is an achievement in itself, and a defeat may not affect share prices as it does in previous phases. Consequently, finals have been excluded to maintain consistency in match analyses.

Lastly, before diving precisely into the four models, here is a table (*Figure 3* - Table of variables used in the regression models
) to help identify the different variables used:

[28] The dummy variable trap is a scenario in regression analysis where the inclusion of a dummy variable for each category of a categorical variable leads to perfect multicollinearity, making the coefficients of the model indeterminate and the estimates unreliable.

Abbreviation	Name	Description
Dependent variable		
AR	Abnormal returns	Returns representing the part of a stock's performance diverging from market trends and directly associated to Champions League matches outcomes.
Independent variables		
Rst	Result	Variable taking 1 as value for a match ending in a win, 0 for a draw, and -1 for a loss for the analyzed club (only used in the first model).
W	Win	Dummy variable equal to 1 if the football club won the match, 0 otherwise.
L	Loss	Dummy variable equal to 1 if the football club lost the match, 0 otherwise.
Indexes		
GS	Group Stage	Index specifying when a match is played in the group stage of the competition.
KO	Knockout	Index specifying when a match is played in the knockout phase of the competition.
16	Round of 16	Index specifying when a match is played during the round of 16.
4	Quarterfinal	Index specifying when a match is played during quarterfinals.
2	Semifinal	Index specifying when a match is played during semifinals.
i	Football club	Index representing each of the football clubs analyzed.
t	Period	Index representing the specific time period at which the analysis is conducted, where t = 1 corresponds to one day.

Figure 3 - Table of variables used in the regression models

Model 1: Basic Outcome-Based Model

$$AR_t^i \sim \beta_0 + \beta_1 \times Rst_{t-1}^i$$

Model 1 is designed to globally assess the influence of Champions League matches on share prices, irrespective of the outcome of the match (win, loss, or draw) or the stage of the competition. The variable "Results" is a mixed measure encoding all possible outcomes of a match into a single variable. It simplifies the model by combining the outcomes into three levels: -1 for a defeat, 0 for a draw, and 1 for a victory. β_0 represents the baseline level of abnormal returns when the result of the game is a draw (as the draw outcome has been encoded as 0). Therefore, β_1 indicates the changes that happen in the abnormal returns for a win or a loss relative to a draw. The primary aim of this model is to determine whether match results – no matter the outcome – have a financial impact, which can then be studied in greater detail in the subsequent models. To achieve this goal, the data have been combined into a comprehensive dataset representing the results of Champions League matches for all European football clubs listed between 2003 and 2023. This complete dataset, explained in more details later, forms the basis of the "Results" variable, which reflects the result of the corresponding matching.

Model 2: Unified Outcome Analysis Model

$$AR_t^i \sim \beta_0 + \beta_1 \times W_{t-1} + \beta_2 \times L_{t-1}$$

Model 2 is designed to differentiate the effects of wins and losses on abnormal stock market returns, allowing separate analysis of each outcome. This approach differs from Model 1, whose objective was to determine the overall financial effect of match results. In this model, precision is essential: the aim is to delimit the specific effect of victories and defeats on the share prices of European football clubs participating in the Champions League. To this end, two distinct categorical variables are introduced. The "W" variable is assigned to 1 for victories, while "L" is associated to 1 for defeats, with both defaulting to 0 otherwise. Draws are not represented by a separate variable; instead, their effect is inferred when the values "W" and "L" are both equal to 0, the basic impact on abnormal returns being represented by the intercept, β_0. As this model does not take into consideration the stage in which the match is played, it can only estimate the influence of a win and a loss in general in the context of the UEFA Champions League. To accomplish this objective, a detailed dataset similar to Model 1 has been compiled, with the key distinction being the inclusion of two dummy variables to distinctly represent wins and losses.

Model 3: Stage-Specific Outcome Evaluation Model

$$AR_t^i \sim \beta_0 + \beta_1 \times W_{t-1}^{GS,i} + \beta_2 \times L_{t-1}^{GS,i} + \beta_3 \times W_{t-1}^{KO,i} + \beta_4 \times L_{t-1}^{KO,i}$$

The third model incorporates more precision than its predecessors, distinguishing between matches in the group stage and matches in the knockout phase. It aims to rigorously assess the differential impact of match outcomes on stock prices during the group and knockout phases. It is postulated that the financial implications of match results may vary by tournament phase due to different levels of stakes and investor sentiment. In this model, draws are also embedded in the intercept. Therefore, β_0 would indicate the abnormal performance when matches end in a draw, both in the group phase and in the knockout phase. It serves as a benchmark for comparing the effects of wins and losses. The dataset used to achieve the objective is again similar to the first model, but with the inclusion of four dummy variables to distinguish between wins or losses in the group stage or knockout stage.

Model 4: Comprehensive Stage Analysis Model

$$AR_t^i \sim \beta_0 + \beta_1 \times W_{t-1}^{GS,i} + \beta_2 \times L_{t-1}^{GS,i} + \beta_3 \times W_{t-1}^{16,i} + \beta_4 \times L_{t-1}^{16,i} + \beta_5 \times W_{t-1}^{4,i} + \beta_6 \times L_{t-1}^{4,i} + \beta_7 \times W_{t-1}^{2,i} + \beta_8 \times L_{t-1}^{2,i}$$

Model 4 is the final and most detailed model presented in this thesis, offering an in-depth analysis with a wide range of variables. As the previous models already analyze the influence of match results on stock prices and distinguish matches between the group phase and knockout matches, Model 4 aims to examine the different impact that match results can have on abnormal returns in the different phases of the tournament. Indeed, the results of this model allow the interpretation of the influence that matches outcomes in the group stage, round of 16, quarterfinals, and semifinals have individually on share price movements. The results of draws are also incorporated into the significance of the intercept, which indicates abnormal returns when matches end in a draw, for each phase of the competition. Logically, the dataset used is also the most detailed, incorporating eight dummy variables representing each of the different phases of the UEFA Champions League, taking the value 1 when the match result is the one they represent and 0 otherwise.

2. *Data*

Having clearly explained the models in the section above, along with their independent and explanatory variables, the present section examines the data extraction and transformation to make these models viable. First, it explains how Champions League matches data was processed to create a table in Excel with all Champions League matches from 2003 to 2023 and the corresponding dummy variables. Next, it describes how the financial data (i.e. the share prices of listed European football clubs) were extracted and processed. Finally, it details how the data were merged to run the four linear regressions – representing the four models explained above.

Football data

In order to extract key insights from the Champions League matches impact on listed European football clubs, the first step needed is to retrieve historical data from UCL matches. Therefore, the data from match outcomes have been retrieved from *Kaggle*[29] databases. Those datasets provide information on UEFA Champions League games from the creation of the competition (season 1955-56) to the season 2015-16. Since the data retrieved from the Internet only covered matches until the 2015-16 season, the information from the more recent seasons have been retrieved and encoded manually. This has been done thanks to the football results available on the website of the French sport newspaper, *L'EQUIPE*. Nevertheless, this study only focuses on the "new" format of the UCL, starting during the 2003-04 season. Consequently, match outcomes from 1955-56 until 2002-03 were useless for the sake of this analysis and have therefore not been used for this Master thesis.

The choice of only focusing on the new format of the Champions League has been made for several reasons. First, the new format of the competition offers a uniform structure that has been stable over the past years. This stability allows the data to be comparable across different seasons. This consistency within the data is required for the empirical analysis. Additionally, as suggested in the literature, the expansion of the competition from 16 to 32 teams drastically increased the revenue generated by the UEFA Champions League.

[29] *Kaggle* is a shared online platform for data science and machine learning projects, with thousands of datasets widely available, on a wide variety of subjects.

Consequently, the financial impact for clubs of participating in Europe's most prestigious tournament became more important. Therefore, the financial management of football clubs is more comparable by focusing solely on matches played after 2003.

As the data from the *Kaggle* database were in a raw.csv format some preparation was needed to be carried out on them to make them suitable for further analyses. Excel Power Query have mainly been used for this purpose. The first queries concerned the conversion of the data from the .csv format to an Excel format (.xlsx), and the separation between the relevant columns. *Figure 4* shows the database format prior to any preparation. It was also necessary to remove columns that were not pertinent to this analysis, such as the half-time scores of the matches for example. Afterwards, queries were run to erase the rows related to the qualifying rounds of the competition, as they are not the focus of this thesis since their impact and importance are not comparable with those of the competition rounds. Additionally, some steps were needed to separate the score columns. Indeed, the scores related to matches were incorporate in the same column, without any distinction between home and away teams. For the analysis carried out later, it was necessary to separate those columns between the goals scored by each team. Therefore, extra columns have been created, incorporating the different scores of the home team and the away team separately. There are three "score" columns that have been divided using Excel Power Query: final score, aggregate score (for second leg matches), and penalties (for the relevant second leg matches).

```
Stage,Round,Group,Date,Team 1,FT,HT,Team 2,∑FT,ET,P,Comments
Qualifying,Qual. Round 1 | Leg 1,,(Tue) 30 Jun 2015 (W26),Crusaders › NIR (1),0-0,0-0,Levadia › EST (1),,,,
Qualifying,Qual. Round 1 | Leg 1,,(Tue) 30 Jun 2015 (W26),Lincoln Red Imps › GIB (1),0-0,0-0,FC Santa Coloma › AND (1),,,,
Qualifying,Qual. Round 1 | Leg 1,,(Tue) 30 Jun 2015 (W26),Pyunik › ARM (1),2-1,0-0,S.S. Folgore Falciano Calcio › SMR (1),,,,
Qualifying,Qual. Round 1 | Leg 1,,(Wed) 1 Jul 2015 (W26),B36 Torshavn › FRO (1),1-2,0-0,The New Saints › WAL (1),,,,
Qualifying,Qual. Round 1 | Leg 2,,(Tue) 7 Jul 2015 (W27),Levadia › EST (2),1-1,0-0,Crusaders › NIR (2),(a) 1-1 (agg.),,,Away Goals (2)
Qualifying,Qual. Round 1 | Leg 2,,(Tue) 7 Jul 2015 (W27),The New Saints › WAL (2),4-1,0-0,B36 Torshavn › FRO (2),6-2 (agg.),,,
Qualifying,Qual. Round 1 | Leg 2,,(Tue) 7 Jul 2015 (W27),FC Santa Coloma › AND (2),1-2,0-0,Lincoln Red Imps › GIB (2),1-2 (agg.),,,
Qualifying,Qual. Round 1 | Leg 2,,(Tue) 7 Jul 2015 (W27),S.S. Folgore Falciano Calcio › SMR (2),1-2,0-0,Pyunik › ARM (2),2-4 (agg.),,,
```

Figure 4 - Example of raw outcomes from the .csv file (2015-16)

So far, the data represents the score of the games and the involved teams but does not explicitly identify the winning and losing teams for each match. To do so, conditional columns have been created using Excel Power Query. Three columns per team per round of the competition (i.e., group stage, round of 16, quarterfinals, semifinals) have been created to represent the outcome of the game depending on the stage of the competition in which it takes place. Those said columns all contain binary values (0 or 1) representing the outcome of the match. The first column represents the "Win" variable, indicating 1 if the team won the game and 0 if the team did not win. The second column is the "Loss" variable, indicating 1 if the team lost the match and 0 if it did not lose it. Lastly, the third column represents the "Draw" variable, indicating 1 if the match ended in a draw and 0 otherwise. As explained above, the distinction between the stages has been made thanks to conditional columns. The conditions were first to identify the stage of the game to indicate the outcome in the corresponding columns. Afterwards, the queries compared the goals scored by the two teams, to identify the winner of the match. For second leg matches, it was more challenging to identify the winner of the game. Indeed, a team may have lost the second leg but still qualify for the next round thanks to the score of the first leg (the opposite scenario is also possible). Therefore, the queries had to look at the aggregate score[30] for the second leg matches to determine the winner of the two legs (i.e., the team qualified for the next round). When matches go to extra-time, the aggregate score indicates a draw (since both teams scored the same number of goals), which is not possible for second leg matches. In those cases, the queries investigated the extra-time score to determine the qualified teams. A draw is still possible after extra-time. Therefore, in those (rare) cases, the queries looked at the after-penalty score to determine the winner. These conditions suggest that the team considered to be the winner of a second leg match is the team who is qualified for the next round, as it is more consistent with the expected share price moves. *Figure 5*Figure 5 shows an example of conditional column query.

```
  #"Colonne personnalisée ajoutée 5" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonnes renommées 3", "HWin_16", each
if [Round] = "Round of 16 | Leg 1" and [H Team FT] > [A Team FT.1] then 1 else
if [Round] = "Round of 16 | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HWin_16", Int64.Type}}),
```

Figure 5 - Conditional column query

[30] The aggregate score is the sum of the scores in the two legs.

So far, there is one row per match. However, to run more easily the different models that are explained in the next section, it is more relevant to have one row per club per match. Therefore, the rows have been duplicated and the match results variables have been slightly changed to represent the corresponding outcomes for each team. The above-mentioned steps have been operated separately for each season, before merging all the seasons analyzed together in one Excel file, with one worksheet per season. More details about the queries ran on Excel Power Query can be found in *appendix 1.*

After all the modification and data preparation for football matches data, 17 columns have been identified for each matches and clubs: Stage, Round, Group, Date, Team, Win_GS, Loss_GS, Draw_GS, Win_16, Loss_16, Draw_16, Win_Quarter, Loss_Quarter, Draw_Quarter, Win_Semi, Loss_Semi, and Draw_Semi. *Figure 6* shows an example of football data after preparation (taking for instance the finals into account), illustrating Juventus' journey to defeat in the 2014/15 Champions League final.

Stage	Round	Group	Date.4	H Team	Win_GS	Loss_GS	Draw_GS	Win_16	Loss_16
Group	Matchday ?	A	16/09/14	Juventus	1	0	0	0	0
Group	Matchday ?	A	1/10/14	Juventus	0	1	0	0	0
Group	Matchday ?	A	22/10/14	Juventus	0	1	0	0	0
Group	Matchday ?	A	4/11/14	Juventus	1	0	0	0	0
Group	Matchday ?	A	26/11/14	Juventus	1	0	0	0	0
Group	Matchday ?	A	9/12/14	Juventus	0	0	1	0	0
Knockout	Round of 16 | Leg 1		24/02/15	Juventus	0	0	0	1	0
Knockout	Round of 16 | Leg 2		18/03/15	Juventus	0	0	0	1	0
Knockout	Quarterfinals | Leg 1		14/04/15	Juventus	0	0	0	0	0
Knockout	Quarterfinals | Leg 2		22/04/15	Juventus	0	0	0	0	0
Knockout	Semifinals | Leg 1		5/05/15	Juventus	0	0	0	0	0
Knockout	Semifinals | Leg 2		13/05/15	Juventus	0	0	0	0	0
Knockout	Final		6/06/15	Juventus	0	0	0	0	0

Draw_16	Win_Quarter	Loss_Quarter	Draw_Quarter	Win_Semi	Loss_Semi	Draw_Semi	Win_Final	Loss_Final
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0	0
0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	0	1

Figure 6 - Example of football data from season 2014-15

Moreover, to make the understanding of what the data from the four models relate to easier, *Figure 7* provides an overview of all the matches and clubs analyzed throughout the

Master thesis. As it can be seen, there are 1071 football matches that are being analyzed for the sake of this research. The table highlights the number of matches played by each of the 17 clubs analyzed. From there, it is shown that FC Porto and Juventus are the clubs with the most records in the analyzed time window, with both 142 matches played in the competition. It is interesting to note that FC Porto played the most frequently during the 20 seasons (with 18 participations), whereas Juventus participated in 16 Champions League during the time window analyzed. However, since the two clubs have played the same number of matches, it therefore means that, in general, Juventus went further in the competition. This is confirmed by the data representing the number of games in the different stages in this table. Indeed, Juventus played 46 of their 142 matches[31] in the knockout phase whereas FC Porto only played 36 matches in the knockout phase[32].

Club/Round	Group stage	Round of 16	Quarterfinals	Semifinals	Final	TOTAL
AFC Ajax	78	6	2	2	0	**88**
AS Roma	54	14	6	2	0	**76**
Beşiktaş İstanbul JK	35	2	0	0	0	**37**
Borussia Dortmund	66	15	8	2	1	**92**
Celtic FC	60	6	0	0	0	**66**
FC Porto	106	24	9	2	1	**142**
Fenerbahçe İstanbul SK	24	2	2	0	0	**28**
Galatasaray İstanbul AŞ	48	4	2	0	0	**54**
Juventus	96	26	14	4	2	**142**
Kobenhavn	30	2	0	0	0	**32**
Manchester United FC	42	10	4	0	0	**56**
Olympique Lyon	54	14	3	3	0	**74**
SL Benfica	78	10	8	0	0	**96**
Sporting CP	48	4	0	0	0	**52**
SS Lazio	18	2	0	0	0	**20**
Tottenham Hotspur FC	6	2	2	0	0	**10**
Trabzonspor AŞ	6	0	0	0	0	**6**
TOTAL	**849**	**143**	**60**	**15**	**4**	**1071**

Figure 7 - Table of matches per club per round of the UCL

[31] 26 in the round of 16, 14 in quarterfinals, 4 in semifinals, and 2 in finals.
[32] 24 in the round of 16, 9 in quarterfinals (one match has been removed from the data, since the next trading day was too far from the match day), 2 in semifinals, and 1 in final.

Lastly, *Figure 8* illustrates the number of victories, defeats, and draws per listed football clubs participating in the Champions League from 2003 to 2023. Juventus and FC Porto are the listed teams who have won the most games over this period: a statistic that can be explained by the fact that – as explained above – these are the two teams who have played the most games in this competition over this period. Juventus' greater number of victories explains why they have reached more quarterfinals, semi-finals and finals over the years than FC Porto.

Football clubs	Number of Victories	Number of Defeats	Number of Draws	TOTAL
AFC Ajax	33	36	19	**88**
AS Roma	29	34	13	**76**
Beşiktaş İstanbul JK	9	20	8	**37**
Borussia Dortmund	44	32	16	**92**
Celtic FC	15	39	12	**66**
FC Porto	65	46	31	**142**
Fenerbahçe İstanbul SK	9	14	5	**28**
Galatasaray İstanbul AŞ	11	31	12	**54**
Juventus	75	42	25	**142**
Kobenhavn	8	15	9	**32**
Manchester United FC	26	19	11	**56**
Olympique Lyon	29	24	21	**74**
SL Benfica	35	42	19	**96**
Sporting CP	17	29	6	**52**
SS Lazio	4	8	8	**20**
Tottenham Hotspur FC	5	3	2	**10**
Trabzonspor AŞ	1	1	4	**6**
TOTAL	**415**	**435**	**221**	**1071**

Figure 8 - Number of defeats, victories, and draws per club

Financial data

The second primary dataset in this market thesis encompasses stock market figures of publicly listed European football clubs. Share price histories, spanning 25 seasons from 1998-

99 to 2022-23[33], were sourced from Bloomberg and compiled into Excel spreadsheets. This period saw 17 such clubs trading publicly while competing in the UEFA Champions League. Details of these clubs are presented in the subsequent table (*Figure 9*).

	Country	Entry	Number of participations while being listed (between 2003 and 2023)
AFC Ajax	Netherlands	1998	13
AS Roma	Italy	2000	9
Beşiktaş İstanbul JK	Turkey	2002	6
Borussia Dortmund	Germany	2000	11
Celtic FC	Scotland	1995	10
FC Porto	Portugal	1995	18
Fenerbahçe İstanbul SK	Turkey	2004	4
Galatasaray İstanbul AŞ	Turkey	2002	8
Juventus	Italy	2001	16
Kobenhavn	Denmark	2000	5
Manchester United FC	England	2012	7
Olympique Lyon	France	2007	9
SL Benfica	Portugal	2007	13
Sporting CP	Portugal	2000	8
SS Lazio	Italy	1998	3
Tottenham Hotspur FC	England	1983	1
Trabzonspor AŞ	Turkey	2005	1

Figure 9 - Table of publicly traded Champions League clubs

For the sake of consistency, financial data have been restated in euros. This provides a harmonized set of data eliminating any potential discrepancies that could arise when dealing with multiple currencies. Indeed, when all returns are denominated in euros, it is easier to compare the performance of stocks without any additional conversions or adjustments. Furthermore, using a consistent currency base helps to keep the integrity of the statistical analysis meaning that all findings or patterns observed are due to the variables of interest rather than currency differences.

[33] The 1998 to 2002 seasons were also used to calculate the coefficients of the Fama-French models in order to calculate expected yields, as they were based on data from the previous 5 seasons, as explained in the Methodology section.

After having been retrieved, the share prices of those clubs have been merged in a common worksheet. From there, it was possible to compute the daily returns of football clubs by using the following formula:

$$Return_{stock} = \frac{Price_{t+1} - Price_t}{Price_t}$$

Additionally, the historical data from the Fama-French 3 factors estimators have been retrieved on the *Kenneth* data library, that contains the Fama-French factors from several countries. From the website, the data from the daily European 3 factors (Market Minus risk-free rate, Small Minus Big, and High Minus Low) model from 1998 to 2023 have been retrieved and exported to an Excel file. Those data will serve as a basis for the computation of the Fama French OLS estimators for European football clubs, useful for the calculation of expected returns.

Joined/Combined data

The last steps of the data preparation prior to the linear regressions have been made using Excel Visual Basic for Applications (VBA). Indeed, it was needed to cross the information from the football data and the financial data for the sake of the further analyses.

This first VBA codes were meant to check for correspondences between match outcomes and financial returns season by season. Consequently, all rows related to non-listed football club matches have been removed from the analyzed data and the Excel file only contains information from UCL matches of listed clubs (*appendix 2*). Additionally, it was needed to link the outcomes data with the returns computed. For this purpose, VBA codes were also run, adding the financial return of the day following the occurrence of a game to the football match rows (*appendix 3*). When the code fails to find a return value for the day following a match, it leaves the cell empty. The returns for these rare instances are manually retrieved based on the next available return, with a verification for any league games played in the meantime, to keep the effect of European matches isolated. Thanks to these codes, football data were combined with the actual returns following football matches.

Additionally, prior to the linear regression predicting the OLS estimators of the Fama-French factors for European football clubs, a VBA code (script in *appendix* 4) was run to link the returns of football clubs with the 3 Fama-French factors from 1998 (5 years before the first analyzed season) to 2023. From there, it was possible to run this first regression using *RStudio* (script in *appendix 5*). Below is a sample of the coefficients derived from the linear regression:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.10095687	0.03476504	-2.9039768	3.69E-03
SMB	0.15783747	0.05396713	2.9246963	3.46E-03
HML	-0.02666076	0.06375469	-0.4181772	6.76E-01
Mkt-RF	0.24708855	0.0450449	5.4853838	4.25E-08

Figure 10 - Coefficients of the season 2003/04 derived from the linear regression based on the 5 preceding seasons (1998/99 to 2002/03)

From these season-specific coefficients, different for each season, it was possible to compute the daily expected returns of football clubs, from September to June as it is the typical duration of a Champions League season. Therefore, as outlined in the *methodology*, a five-years window was used for this analysis. Once all the expected returns have been calculated, other VBA codes were executed to incorporate these expected returns into the primary Excel worksheet, containing match outcomes data and the actual returns (*appendix 6*). Again, the expected returns from the day following the occurrence of a game have been used, for a sake of consistency.

The last step before obtaining all the variables necessary to the linear regressions involves the calculation of the abnormal returns, using the following formula:

$$Abnormal\ Return = Actual\ Return - Expected\ Return$$

Once the abnormal returns have been computed for every football match analyzed, it was possible to execute the 4 linear regression models above-mentioned. These regressions have also been run on RStudio and the scripts can be found in *appendix 7, 8, 9, and 10.*

Results

This section delves into the outcomes of the models and concentrates on the interpretations. It is structured into three distinct parts. Firstly, a detailed analysis of the results of the Fama-French model used to calculate expected returns is carried out. This is followed by the explanation the results of the four main models that are subject of interpretations, representing the core of this Master thesis. Finally, connections with the literature are established in order to position the work in relation to the various publications.

1. *Fama-French model's results*

This section is devoted to analyzing the results of the coefficients found to calculate expected returns using the Fama-French model. The results can be observed in *appendix 11*.

As shown by the figures in *appendix 11*, the HML factor is not statistically significant for 15 of the 20 seasons analyzed (i.e. seasons 1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17 – see *appendix 11*) as their p-values are greater than 0.05, which is represented by the absence of an asterisk next to the figures. As a reminder, High Minus Low (HML) factor captures the excess returns of value stocks over growth stocks. The insignificance found in the results shows that football clubs do not adhere to the value growth dynamics described by the HML factor in the Fama-French model. HML is therefore irrelevant in explaining football clubs' stock market returns, which are therefore maybe better explained by other factors more suited to the world of football.

This can be explained by the way people value football clubs. Valuing a football club requires careful examination of intangible assets, which have a significant impact on the share price. However, these assets are often difficult to identify for football clubs and might also be undervalued. For example, the value of a club's brand, often overlooked, can secure lucrative sponsorship deals and drive merchandise sales, increasing the club's revenues beyond its book value. In addition, the intrinsic talent of players is another essential intangible element. The market value of a club's players may not be fully reflected in the club's financial records. In particular, outstanding performances by key players in major competitions such as the Champions League can boost revenues through increased tickets and merchandising sales, thus influencing the club's share price without correspondingly altering the book-to-market value ratio. As a result, these intangible assets are not properly accounted by book-to-market ratios, compromising the effectiveness of the High-Minus-Low (HML) model in predicting football club returns.

The non-effectiveness of the HML factor also illustrates the fact that the market itself – at least this more traditional factor – does not explain alone the stock prices fluctuations but is also dictated by other variables such as feelings and passions of fans following news concerning their clubs. Ferreira et al. (2017) emphasize on the importance of behavioral finance in understanding the phenomenon, highlighting that feelings can greatly influence rational decision-making among investors. Consequently, as their mood is impacted by new events, they modify their decisions, which could also partly explain the stock price fluctuations observed after matches.

In contrast to the HML factor, the SMB factor is statistically significant in 15 of the 20 seasons analyzed (i.e. seasons 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13, 14, 18, 19 – see *appendix 11*). SMB, which stands for 'Small Minus Big,' represents the excess returns of small-capitalization stocks over big-capitalization stocks. Given that this factor is significant in most seasons, it suggests that the size of European quoted football clubs as a whole is an important variable in explaining stock returns during the studied period. More precisely, it implies that the size of football clubs (in terms of market capitalization) makes them react differently by following different financial dynamics compared to other types of companies.

As suggested by Edmans et al. (2007), small capitalization stocks - which are more sensitive to investor sentiment - suffer more from the impact of losses. This is consistent with our findings on the SMB factor, which corroborate the fact that small companies react more strongly. According to Edmans et al. (2007), this increased reaction can be attributed to the local ownership of these companies, whose decision-making is strongly influenced by the performance of the national team. This confirms that stock market movements can be explained by mood, which questions the market efficiency hypothesis.z

Finally, the market risk factor (Rm-Rf) proved statistically significant for each season, illustrating the dependence of football club stock returns on overall market movements. As this factor captures the market movements as a whole, it suggests that the market is a key aspect in determining the evolution of stock market returns. Furthermore, this finding suggests that the market for football club shares exhibits some degree of efficiency in pricing individual shares in response to overall market movements, which is consistent with the principles of the Efficient Market Hypothesis. Hence, the significance of the factor therefore underlines the importance of overall market movements in football club share price fluctuations, and illustrates that even in the world of football, general market dynamism has its role to play, as does fan sentiments.

Analysis of the returns derived from the Fama-French model

Round:	All matches	Group stage	Round of 16	Quarterfinals	Semifinals	Finals
Actual returns	-0,6830	-0,5725	-1,0961	-0,4632	-2,8155	-4,6703
Expected returns	-0,0053	-0,0111	0,0053	0,0622	-0,0793	0,1251
Abnormal returns	-0,6778	-0,5614	-1,1014	-0,5254	-2,7362	-4,7954

Figure 11 - Table of average returns

From the OLS estimators found for the Fama-French 3 factors of each season, it was possible to compute the expected returns from the market on the days following football matches. *Figure 11* highlights the average actual, expected, and abnormal returns of football clubs during the analyzed time window. From this table, expected returns seem to be relatively low on average. Since abnormal returns are the result of the difference between actual and expected returns, the low expected returns induce a small variability between actual and abnormal returns. This suggests that the theoretical returns derived from the market fail to correctly assess football share prices' behavior since the expected returns are low compared to the actual returns observed. Therefore, the returns of football clubs seem to be influenced by external factors that are not incorporated into the Fama-French factors. This observation further supports the hypothesis that match outcomes indeed seem to exert an influence on football club shares' returns.

2. Linear regressions' results

The core of this Master thesis lies in the interpretation of the four models previously mentioned. This section describes the interpretation of the linear regressions outcomes that enables to assess the potential impact of Champions League matches on football clubs share prices. Additionally, it allows the evaluation of whether the evolution of a quoted club within the competition exert an influence on its share price.

Model 1

Figure 12 (more details can be found in *appendix 12*) exhibits the coefficients of the first linear regression. As a reminder, this model is the one with the smallest level of detail. This regression aims to analyze the impact of football matches on abnormal returns, without yet differentiating the individual impact of wins and losses.

Model 1				
Coefficients				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-0.6594	0.1104	-5.975	3.13E-09***
Rst_{t-1}^{i}	0.9853	0.1239	7.954	4.58E-15***
Diagnostic Measures				
Residual standard error	3.611 on 1069 degrees of freedom			
Multiple R-squared	0.05587	**Adjusted R-squared**	0.05499	
F-statistic	63.26 on 1 and 1069 DF	**p-value**	4.581E-15	

Figure 12 - Results of the first model

The results of this linear regression provide evidence that match results indeed exert an influence on stocks behavior. The values found suggest that the null hypothesis of this model must be rejected. Indeed, the p-value of the *Result* variable equals 4.58e-15. It therefore means that β_{Result} is significantly different from zero. The value of the coefficient is equal to 0.9853, suggesting that a victory has a positive influence on a club's share price (as victories are incorporated in the *Result* variable with a value of 1). Conversely, this value suggests that defeats exert a negative influence on a club share price since it corresponds to a *Result* value of -1.

While the *Result* variable incorporates wins and losses, the effect of draws on football clubs share prices is captured by the intercept. Indeed, when a match finishes without winner, the value of the *Result* variable equals 0. Therefore, the effects of draws are depicted by the intercept. In this model, the intercept is statistically significant (p-value = 3.13e-09) and has a value of -0.6594. This suggests that matches ending in a draw in the UEFA Champions League have a negative effect on football clubs share prices.

Additionally, the adjusted R-squared of this model has a value of 0.05499, indicating that the model explains 5.5499% of the abnormal returns' variability. It paves the way for additional models, with a larger level of detail, that have the potential to explain a larger percentage of the dependent variable's variability.

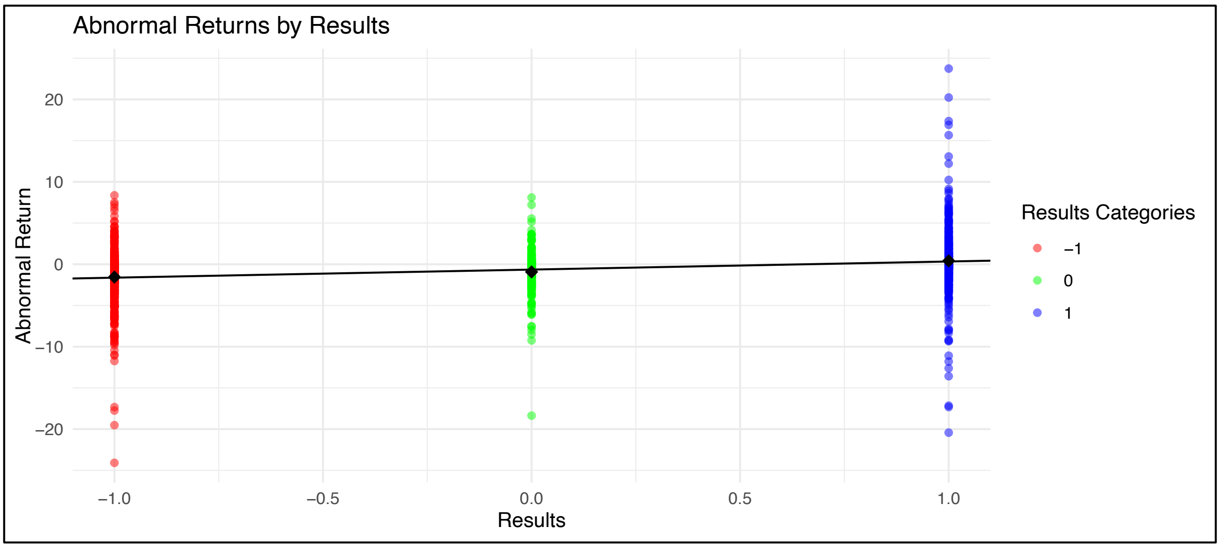

Figure 13 - Graph of abnormal returns by outcome

Figure 13 provides an additional overview of model 1 regression's outcomes. The graph represents the three types of outcomes analyzed on the x-axis (i.e., -1 refers to defeats, 0 to draws, and 1 to victories), and the abnormal returns for each match on the y-axis. The black diamond for each type of outcome represents the average abnormal return for this specific outcome. This graph highlights the presence of a higher level of variability in the abnormal returns related to victories. This may suggest that, in general, the impact of wins is greater on the abnormal returns. Concerning defeats and draws, it is more challenging to draw new insights based on this graph. Therefore, it also underlines the need for additional models that offer an increased degree of precision to further analyze impact of football matches.

In general, this first model is interesting to observe as it provides an initial overview on the influence of football matches and checks whether they actually impact the financial returns or not. However, it does not offer the opportunity to separately interpret the impact of victories and defeats, since the three outcomes are incorporated into the same variable. From the interpretation of this model, it is not possible to know whether victories exert a stronger influence on the returns than defeats, or the other way around. Therefore, it highlights the usefulness of additional models that incorporates more detail within the variables.

Model 2

The second model of this Master thesis distinguishes the effect of wins and losses separately, allowing a separate interpretation of the effect of these outcomes on football clubs share prices.

Model 2				
Coefficients				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-0.9579	0.2425	-3.950	8.32e-05 ***
W	1.3808	0.3000	4.603	4.66E-06 ***
L	-0.5965	0.2979	-2.002	0.0455 *
Diagnostic Measures				
Residual standard error	3.597 on 1064 degrees of freedom			
Multiple R-squared	0.05827	**Adjusted R-squared**	0.0565	
F-statistic	32.92 on 2 and 1064 DF	**p-value**	1.345E-14	

Figure 14 - Results of the second model

The results of this linear regression are in line with the first model's results (*Figure 14*, more details in *appendix 13*). Indeed, wins are considered to have a positive impact on abnormal returns, with a coefficient value of 1.3808. The p-value related to this variable (4.66e-06) makes this OLS estimator statistically significant as it rejects the null hypothesis and allows its right interpretation. On the other side, losses appear to exert a negative impact on football clubs' abnormal returns. Indeed, on the UCL football matches analyzed, the coefficient representing losses have a negative value of -0.5965, with a slightly significant p-value of 0.0455 (also rejecting the null hypothesis). Those results are in line with the initial intuitions of this Master thesis, suggesting that winning matches have a positive impact on clubs' share prices whereas losing matches exert a negative impact. However, the coefficients suggest that victories induce a stronger reaction from investors compared to defeats, implying a stronger impact on stock prices following wins than losses. In comparison with the results obtained in Model 1, this model exhibits stronger reactions when the outcomes are considered separately. Indeed, following wins, the size of effect is larger (1.3808 > 0.9853). Conversely, the market reaction following losses is less strong using this model (-0.5965 > -0.9853).

Additionally, the impact of draws, represented by the intercept, appears to be negative. Indeed, the coefficient of the intercept is negative, statistically significant (p-value = 8.32e-05) and equals -0.9579, implying a negative reaction of the market following wins in the UEFA Champions League. The magnitude of this effect is more pronounced than the one observed in the first model. It suggests that the market reacts even more negatively to draws than previously anticipated. Intriguingly, in this model, draws are perceived even more negatively that defeats. This may suggest that investors potentially prefer decisive outcomes. Nevertheless, this intriguing result underscores the need for more detailed models, allowing a deeper interpretation of the coefficients. Moreover, it is shown that, using this model, the value of the adjusted R-squared slightly increased and equals now 0.0565, paving the way for additional models with a greater level of details, potentially increasing the percentage of variability explained by the model.

<u>Model 3</u>

Figure 15 (more details can be found in *appendix 14)* shows the results of the third model of the Master thesis. This model is more detailed than the previous one and aims to provide a more targeted interpretation.

Model 3				
Coefficients				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-0.9579	0.2418	-3.962	7.93E-05 ***
$W_{t-1}^{GS,i}$	1.2601	0.3101	4.063	5.19E-05 ***
$L_{t-1}^{GS,i}$	-0.3352	0.3149	-1.065	0.28726
$W_{t-1}^{KO,i}$	1.9370	0.4819	4.020	6.24E-05 ***
$L_{t-1}^{KO,i}$	-1.3080	0.4115	-3.179	0.00152 **
Diagnostic Measures				
Residual standard error	3.586 on 1062 degrees of freedom			
Multiple R-squared	0.06567	**Adjusted R-squared**	0.06215	
F-statistic	18.66 on 4 and 1062 DF	**p-value**	7.772E-15	

Figure 15 - Results of the third model

The current findings indicate that victories have a more substantial positive impact on stock prices than losses have a negative impact. Additionally, draws are generally viewed unfavorably by the markets. Intrigued by these outcomes, the analysis was extended to examine potential variations in market reactions based on both the results of the matches and the phase of the competition. Consequently, four dummy variables were introduced in the linear regression model to differentiate between group stage (GS) matches and knockout (KO) stage matches. Thanks to the higher level of detail in this model, the adjusted R-squared rose to 0.06215, meaning that 6.215% of the variability of abnormal returns is explained by the model.

The augmented analysis supports the initial hypothesis: financial market reactions are more pronounced for matches in the knockout stages, reflecting the heightened stakes of these contests. Indeed, as illustrated in *Figure 15*, the estimated coefficients for the knockout matches are larger in terms of impact for both wins and losses compared to the ones for group stage matches[34]. Specifically, the data reveals that the positive impact on stock prices of a victory in a knockout match is nearly double that of a victory in a group stage match. This disparity is even more pronounced in case of defeats as a loss in a knockout stage match incurs

[34] The estimated coefficient for a win in the group stage stands at 1.2601, whereas for a win in the knockout phase, it rises to 1.9370. Furthermore, the absolute value of the estimated coefficient for a loss in the group stage is 0.3352, while for a loss in the knockout phase, it increases to 1.3080.

a negative impact on stock prices that is nearly fourfold greater than a loss in a group stage match.

Furthermore, the results suggest that victories generally have a greater impact on share price movements than defeats. Whether in the group phase or the knockout phase, victories have a larger impact than defeats. Specifically, victories in the group phase have a coefficient of 1.2601, compared to -0.3352 for defeats. In the knockout phase, victories have a coefficient of 1.9370, while defeats have a coefficient of -1.3080. Even if the difference in terms of impact decreases for the knockout phase, the gap remains significant and clearly demonstrates a greater reaction after victories.

However, regarding the impact of defeats, the analysis reveals that the coefficient for losses in group stage matches is not statistically significant, given that its p-value exceeds the 0.05 threshold[35]. This observation requires considerable caution in the interpretation of this coefficient. The insignificance of the loss coefficient in this context suggests that financial markets may not respond as sensitively, or in a statistically predictable way, to defeats during the initial stages of the competition. Therefore, the outcomes of Model 3 does not justify rejecting the null hypothesis for this coefficient, thus lacking statistical evidence that losing in the group phase negatively impacts share prices.

As a result, three of the four null hypotheses can be rejected (given the p-values smaller than 0.05), indicating that the coefficients for group stage and knockout stage victories, and group stage defeats are significatively different from zero.

Additionally, upon closer inspection of the intercept value, it is evident that draws generally result in a negative impact on share prices. This could be attributed to fans' disappointment when their club settles for a draw in such a prestigious competition like the UEFA Champions League. Since this analysis does not allow an examination of draw impacts based on the match stage, only a general trend regarding matches ending in a draw can be discerned.

[35] The p-value of losses in the group stage equals 0.28726.

Finally, these results underline above all the crucial importance of the results of knockout matches, suggesting that investors place much greater weight on these high stakes matches when assessing the value of listed football clubs.

Model 4

As a reminder, Model 4 is the most detailed since it distinguishes between all stages of the competition (except the final – as explained in the *methodology and data* section) and the outcome of the games. *Figure 16* (more details can be found in *appendix 15*) exhibits the results of this last model.

Model 4				
Coefficients				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-0.9579	0.2404	-3.984	7.23E-05 ***
$W_{t-1}^{GS,i}$	1.2601	0.3084	4.086	4.72E-05 ***
$L_{t-1}^{GS,i}$	-0.3352	0.3131	-1.071	0.284582
$W_{t-1}^{16,i}$	1.5208	0.5542	2.744	0.006172 **
$L_{t-1}^{16,i}$	-1.2045	0.4894	-2.461	0.014002 *
$W_{t-1}^{4,i}$	3.2966	0.9516	3.464	0.000553 ***
$L_{t-1}^{4,i}$	-0.7350	0.6130	-1.199	0.230766
$W_{t-1}^{2,i}$	2.0415	1.2835	1.591	0.112016
$L_{t-1}^{2,i}$	-6.3363	1.4756	-4.294	1.91E-05 ***
Diagnostic Measures				
Residual standard error	3.566 on 1058 degrees of freedom			
Multiple R-squared	0.07951	**Adjusted R-squared**		0.07255
F-statistic	11.42 on 8 and 1058 DF	**p-value**		1.243E-15

Figure 16 - Results of the fourth model

As explained in the previous sections, two additional dummy variables were introduced for each stage of the competition (group stage, round of 16, quarterfinals, and semifinals). This was done to investigate if the impact on stock prices varied with the competition's progression and the stakes involved in each match. As now the model incorporates all the stages and gives a higher level of details, the Adjusted R-squared rose to

0.07255, which means that 7.255% of the variability of abnormal returns is explained by the model.

The initial hypothesis suggested that financial market reactions would intensify at each subsequent stage, reflecting the escalating significance of match outcomes. The findings largely support the hypothesis. Indeed, the estimated coefficients reveal a clear trend: as a club progresses further in the tournament, the coefficients increase, indicating a greater impact at the more advanced stages. This can be demonstrated by comparing the estimated coefficients for losses in two different stages: losses in the group stage have an absolute value of approximately 0.3352, whereas losses in semifinals significantly increase to an absolute value of 6.3363. The same trend can be identified for wins: wins in the group stage have a value of 1.2601, whereas wins in semifinals increase to 2.0415.

However, there is one notable exception: the quarterfinals matches**.** Contrary to expectations, victories in the quarterfinals appear to exert a greater impact on stock prices than those in semifinals. Moreover, stock prices seem to be less negatively influenced following a loss in the quarterfinals than in the round of 16, which contradicts the initial hypothesis. These anomalies suggest that the market's expectations might be lower for success in the quarterfinals, leading to stronger positive reactions when victories occur (with an impact coefficient around 3.3) and less severe negative reactions to defeats as it was more expected by the fans. Therefore, reaching quarterfinals can already be seen as a real success for most of the clubs, leading to lower dissatisfaction if the next round is no longer an option.

Additionally, the same interpretation concerning draws (that are embedded in the intercept) can be made for this final linear regression. Indeed, with the estimated coefficient being negative and equal to -0.9579, draws generally have a negative impact on stock prices. It can therefore be concluded that investors consider draws unfavorably, perhaps in the same way as they do of defeats. However, as explained in Model 3, the value of -0.9579 represents the value of the abnormal return when all other variables are equal to zero. It is therefore impossible to analyze what the effects of a draw would be according to the phase of the competition in which the match takes place.

However, this linear regression analysis encounters a challenge as three coefficients are not statistically significant: losses in group stage, losses in quarterfinals, and wins in semifinals[36]. Therefore, the results derived from this analysis should be approached with caution. Nevertheless, there is still a noticeable tendency across the coefficients that allows an interpretation.

3. Comparison with the literature

The results of the four models are consistent with the work of Scholtens and Peenstra (2010) on one key point: stock markets react positively to wins and negatively to losses. However, contrary to their conclusions, our research presents a divergent perspective on a crucial point: they postulated that the market reacts more strongly to defeats, on the assumption that the public is more sensitive to losses. In contrast, our data reveals a more pronounced market reaction to wins, challenging the expected norm of greater sensitivity to negative outcomes. This difference can be explained by the scope of our Master thesis which focuses exclusively on the Champions League competition, whereas the work of Scholtens and Peenstra (2010) also focuses on domestic matches in national competitions. Indeed, as discussed in the literature section, the UEFA Champions League offers substantial monetary rewards to football teams winning games and progressing through the rounds, as well as financial incentives for clubs with strong past performances (Sanchez, 2019). This influx of funds could further explain why investors might view victories in Champions League as significant opportunities for a club's future prosperity, thereby having a more pronounced impact for wins on the stock market. However, the less pronounced market response to defeats also corroborates the findings of Gilbert et al. (2007). They established that the market reacts more slowly to defeats, which explains why markets value defeats less strongly than victories in our work, as our conclusions are drawn from the short-term (1 day) following matches. Gilbert et al. (2007) support this view by revealing that investors' inattention, due to their limited capacity to process information, strongly influences the overall stock market. Their research concludes that the market responds more rapidly to positive news compared to negative news: while 60% of the three-day abnormal return following a win is generated

[36] The p-value of losses in the group stage equals 0.284582, for losses in quarterfinals, it equals 0.230766 whereas the p-value of wins during semi-finals is equal to 0.112016.

on the first day, only 28% of the return is explained on the first day after a loss for the same period. These findings suggest that the slower market reaction to defeats can lead to a less pronounced market response in the short-term, as observed in our study. Furthermore, the impact of a win on share prices, which intensifies at later stages of the competition, can be attributed to the progressively higher prize money that clubs receive as they advance through the tournament. In addition, the lower impact on stock prices of defeats can be explained by the loyalty of football fans investors towards their club. Indeed, this type of investors may be less likely to sell their shares after defeats, resulting in a fewer amount of shares being traded following negative outcomes, in line with Palomino et al. (2009) findings. Lastly, our analysis of the effect of draws – observed to have a negative impact on share prices, probably because investors prefer clear outcomes – corroborates with the findings of Boido and Fasano (2007). Indeed, having examined Italian football clubs and the performance of their shares on the stock market, the latter noted that Italian investors tend to react unfavorably to draws.

Additionally, Palomino et al. (2009) suggest that the magnitude of market responses following wins increases as the likelihood of winning increases. It explains why investors tend to overreact to wins, especially when the outcome is strongly expected. According to the same study, the market reactions following defeats become less important as its anticipated probability increases. These findings particularly corroborate with the insights drawn by our group stage matches analysis as matches tend to be more predictable. Indeed, *Figure 17* represents the percentage of exits from the group stage of the analyzed clubs on the 20 seasons considered. It shows that the majority of the clubs failed to qualify for the knockout phase more than half the time. Out of 15 clubs (Tottenham Hotspur FC and Trabzonspor AŞ are removed from this analysis, since those clubs only participated once in the Champions League while being publicly traded during the time window), 9 of them (60%) show an exit percentage smaller than 40% (with 7 clubs being below 30%) – even though the percentage of chance to qualify for the round of 16 for a club participating in the group stage is equal to 50%[37]. This shows that most of the clubs analyzed show tendency not to qualify for the knockout phase, and therefore show more predictability concerning their match outcomes. In line with Palomino et al. (2009) findings, the group stage results of the different models

[37] There are four teams composing each group, and the two first teams in the group ranking qualify for the round of 16.

previously mentioned show an overreaction to wins as well as an underreaction to defeats. As explained above, the outcomes of matches in the group stage are considered as predictable and are therefore similar to Palomino et al. (2009) conclusions in a sense that victories show a larger magnitude stock prices impact than defats thanks to their increased predictability in group stage.

Club:	AFC Ajax	AS Roma	Beşiktaş İstanbul JK	Borussia Dortmund	Celtic FC	FC Porto	Fenerbahçe İstanbul SK	Galatasaray İstanbul AŞ	Juventus	Kobenhavn	Manchester United FC	Olympique Lyon	SL Benfica	Sporting CP	SS Lazio	Tottenham Hotspur FC	Trabzonspor AŞ
Percentage of exits from the group stage	23,08%	77,78%	16,67%	72,73%	30,00%	66,67%	25,00%	25,00%	81,25%	20,00%	71,43%	77,78%	38,46%	25,00%	33,33%	100,00%	0,00%

Figure 17 - Table representing the percentage of exits from the group stage of the analyzed clubs

Conclusion

In conclusion, while several football clubs are publicly traded on stock markets, the behavior of their share prices following matches remain incompletely understood. Previous research primarily focused on the effect of domestic league games, occasionally extending to matches in European football competitions. Nevertheless, a notable gap persists in these studies. Indeed, none of them focused solely on Europe's most prestigious football competition, the UEFA Champions League. Given the significant revenues associated with the participation in this competition, it deserves a closer look. Therefore, this study contributes to fulfill this gap by analyzing the impact of UEFA Champions League matches on the share prices of football clubs. Additionally, it analyzes how a club's progression within the competition influences its share price behavior.

To achieve this, several linear regressions were conducted using abnormal returns as dependent variables. One of the key elements of abnormal returns resides in the computation of expected returns, which were calculated using the Fama French 3 factors method, allowing robust estimations of football clubs' expected returns. Fama French estimators have been computed for each season, based on the data from the 5 previous seasons to accurately capture the variability in returns. Some coefficients, particularly the HML (High Minus Low) were not statistically significant, paving the ways for potential abnormal returns. Once abnormal returns were computed thanks to these coefficients, four linear regression models have been run, each with increasing levels of details to illustrate the trends in football shares returns.

The analysis of these four models leads to several key conclusions. Firstly, the share prices of listed football clubs generally rise after a UEFA Champions League victory, while defeats lead to a fall in share prices. Notably, the positive market reaction is more pronounced after victories, suggesting that investors react more strongly to a team's successful performance. In addition, the data indicates that draws are poorly perceived by the market, probably because investors prefer clear results.

Furthermore, the analysis reveals that the further a team progresses in the tournament, the greater the impact of its match results on its share price. Indeed, even if the quarterfinals seem to be the only exception to the hypothesis, stock market reactions to matches increase gradually depending on the stage of the competition in which the match is played. This indicates that, for instance, a victory in semifinal positively influences the stock market price of a listed football club more significantly than a win in the group stage does. Conversely, a defeat in semifinal negatively affects the team's stock market price more severely than a loss in the group stage. However, no interpretation could be made for the draws as these are directly incorporated into the intercept. It was therefore impossible to analyze the individual effect that a tie might have had depending on the stage of the tournament.

Additionally, fans' emotions play a key role in investment decisions relating to football club shares. The enduring loyalty that fans often show to their clubs influence their shares on the stock market in a way that differs considerably from what one would expect from a rational investor. This deep attachment explains why defeats often have a less pronounced impact on share prices; fans who are also investors may be more reluctant to sell their shares in response to unfavorable results, such as a Champions League defeat. The interaction between fan loyalty and market dynamics in sports-related investments is highlighted by this emotional attachment, which contrasts with the rapid sales generally seen in other sectors. Therefore, the findings of this Master thesis reveal a complex relationship between fan-driven investment behaviors and the Efficient Market Hypothesis as, interestingly, some aspects also suggest an alignment with the EMH. Notably, the significant presence of market reactions following matches aligns with the hypothesis as match results are seen as new information integrated by the market into the stock prices of football clubs. Furthermore, the increasing magnitude of the reactions throughout the competition aligns with the EMH expectations as matches at a further stage involve more important stakes and have larger financial implications for clubs, represented by the larger magnitudes of stock price movements in the analysis. Conversely, the presence of over- and under- reactions following UCL matches is not in line with the EMH principles. Indeed, non-financial indicators such as fans loyalty and sentiment seem to exert an influence on stock prices, inconsistent with market efficiency. Additionally, the impact of draws, while not fully incorporated in this analysis due to multicollinearity issues, also suggests inconsistencies with EMH theories as draws appear to exert a stronger negative influence on returns than defeats. In summary, although the returns of football club shares display some patterns that could be interpreted as rational, the overall findings point to deviations from the strict rationality posited by the EMH.

Limitations

There are some limitations that should not be overlooked when reading this Master thesis. Indeed, while other studies such as those by Bernie et al. (2011) and Palomino et al. (2009) tend to opt for a long-term approach in analyzing the match outcomes to assess the time persistence of the market reactions, this work only focuses on short-term reactions – as the share price considered is the closing price on the first trading day after the market reopens. This considerably limits the analysis of reactions to the results of Champions League matches, as the behavior of share prices following a match result is not fully captured. Another limitation concerns the interpretation of the draws. To avoid multicollinearity, draws were incorporated into the intercept in all four linear regression models. As a result, this approach prevented a detailed analysis of how stock prices react to the draws at different stages of the competition. Potential further research could be focused on the draws specifically and analyze what could be their market reactions throughout the competition. Lastly, another significant limitation is the exclusion of finals from the analysis due to insufficient data. Indeed, it would have been preferable to analyze the UEFA Champions League as a whole to see if there is any consistency in the conclusions about the increasing impact of results on share prices. Once again, this could constitute additional research by incorporating more finals into the set of data.

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Appendix

Appendix 1:

```
let
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  #"Type de colonne changé" = Table.TransformColumnTypes(Source, {{"Column1", type
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{"Column5", type text}, {"Column6", type text}, {"Column7", type text}, {"Column8",
type text}, {"Column9", type text}, {"Column10", type text}, {"Column11", type
text}, {"Column12", type text}}, "fr"),
  #"En-têtes promus" = Table.PromoteHeaders(#"Type de colonne changé",
[PromoteAllScalars = true]),
  #"Type de colonne changé 1" = Table.TransformColumnTypes(#"En-têtes promus",
{{"Stage", type text}, {"Round", type text}, {"Group", type text}, {"Date", type
text}, {"Team 1", type text}, {"FT", type text}, {"HT", type text}, {"Team 2", type
text}, {"∑FT", type text}, {"ET", type text}, {"P", type text}, {"Comments", type
text}}, "fr"),
  #"Diviser la colonne par délimiteur" = Table.SplitColumn(#"Type de colonne changé
1", "FT", Splitter.SplitTextByDelimiter("-"), {"FT.1", "FT.2"}),
  #"Colonnes renommées" = Table.RenameColumns(#"Diviser la colonne par délimiteur",
{{"FT.1", "Team 1 FT"}, {"FT.2", "Team 2 FT"}}),
  #"Colonnes supprimées" = Table.RemoveColumns(#"Colonnes renommées", {"HT"}),
  #"Diviser la colonne par délimiteur 1" = Table.SplitColumn(#"Colonnes
supprimées", "Team 1", Splitter.SplitTextByDelimiter(" ›"), {"Team 1.1", "Team
1.2"}),
  #"Colonnes supprimées 1" = Table.RemoveColumns(#"Diviser la colonne par
délimiteur 1", {"Team 1.2"}),
  #"Diviser la colonne par délimiteur 2" = Table.SplitColumn(#"Colonnes supprimées
1", "Team 2", Splitter.SplitTextByDelimiter(" ›"), {"Team 2.1", "Team 2.2"}),
  #"Colonnes supprimées 3" = Table.RemoveColumns(#"Diviser la colonne par
délimiteur 2", {"Team 2.2"}),
  #"Premières lignes supprimées" = Table.Skip(#"Colonnes supprimées 3", 90),
  #"Type de colonne changé 2" = Table.TransformColumnTypes(#"Premières lignes
supprimées", {{"Team 1.1", type text}, {"Team 1 FT", Int64.Type}, {"Team 2 FT",
type text}, {"Team 2.1", type text}}, "fr"),
  #"Colonnes renommées 1" = Table.RenameColumns(#"Type de colonne changé 2",
{{"Team 1.1", "H Team"}, {"Team 1 FT", "H Team FT"}, {"Team 2 FT", "A Team FT"},
{"Team 2.1", "A Team"}}),
  #"Diviser la colonne par délimiteur 3" = Table.SplitColumn(#"Colonnes renommées
1", "Date", Splitter.SplitTextByDelimiter(") "), {"Date.1", "Date.2", "Date.3"}),
  #"Diviser la colonne par délimiteur 4" = Table.SplitColumn(#"Diviser la colonne
par délimiteur 3", "Date.2", Splitter.SplitTextByDelimiter(" ("), {"Date.4",
"Date.5"}),
  #"Type de colonne changé 3" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 4", {{"Date.1", type text}, {"Date.4", type date}, {"Date.5", type
text}, {"Date.3", type text}}, "fr"),
```

```
  #"Colonnes supprimées 2" = Table.RemoveColumns(#"Type de colonne changé 3",
{"Date.1", "Date.5", "Date.3"}),
  #"Diviser la colonne par délimiteur 5" = Table.SplitColumn(#"Colonnes supprimées
2", "A Team FT", Splitter.SplitTextByDelimiter(" ("), {"A Team FT.1", "A Team
FT.2"}),
  #"Type de colonne changé 4" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 5", {{"A Team FT.1", Int64.Type}, {"A Team FT.2", type text}}, "fr"),
  #"Colonnes supprimées 4" = Table.RemoveColumns(#"Type de colonne changé 4", {"A
Team FT.2"}),
  #"Diviser la colonne par délimiteur 6" = Table.SplitColumn(#"Colonnes supprimées
4", "∑FT", Splitter.SplitTextByDelimiter(" ("), {"∑FT.1", "∑FT.2"}),
  #"Type de colonne changé 5" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 6", {{"∑FT.1", type text}, {"∑FT.2", type text}}, "fr"),
  #"Colonnes supprimées 5" = Table.RemoveColumns(#"Type de colonne changé 5",
{"∑FT.2"}),
  #"Diviser la colonne par délimiteur 7" = Table.SplitColumn(#"Colonnes supprimées
5", "∑FT.1", Splitter.SplitTextByDelimiter("-"), {"∑FT.2", "∑FT.3"}),
  #"Type de colonne changé 6" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 7", {{"∑FT.2", type text}, {"∑FT.3", Int64.Type}}, "fr"),
  #"Colonnes renommées 2" = Table.RenameColumns(#"Type de colonne changé 6",
{{"∑FT.2", "∑FT H"}, {"∑FT.3", "∑FT A"}}),
  #"Diviser la colonne par délimiteur 8" = Table.SplitColumn(#"Colonnes renommées
2", "ET", Splitter.SplitTextByDelimiter("-"), {"ET.1", "ET.2"}),
  #"Colonne personnalisée ajoutée" = Table.AddColumn(#"Diviser la colonne par
délimiteur 8", "HWin_GS", each if [Stage] = "Group" and [H Team FT] > [A Team FT.1]
then 1 else 0),
  #"Colonne personnalisée ajoutée 1" = Table.AddColumn(#"Colonne personnalisée
ajoutée", "HLoss_GS", each if [Stage] = "Group" and [H Team FT] < [A Team FT.1]
then 1 else 0),
  #"Colonne personnalisée ajoutée 2" = Table.AddColumn(#"Colonne personnalisée
ajoutée 1", "Draw_GS", each if [Stage] = "Group" and [H Team FT] = [A Team FT.1]
then 1 else 0),
  #"Type de colonne changé 7" = Table.TransformColumnTypes(#"Colonne personnalisée
ajoutée 2", {{"ET.1", Int64.Type}, {"ET.2", type text}}, "fr"),
  #"Diviser la colonne par délimiteur 9" = Table.SplitColumn(#"Type de colonne
changé 7", "ET.2", Splitter.SplitTextByDelimiter(" "), {"ET.3", "ET.4"}),
  #"Type de colonne changé 8" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 9", {{"ET.3", Int64.Type}, {"ET.4", type text}}, "fr"),
  #"Colonnes supprimées 6" = Table.RemoveColumns(#"Type de colonne changé 8",
{"ET.4"}),
  #"Diviser la colonne par délimiteur 10" = Table.SplitColumn(#"Colonnes supprimées
6", "P", Splitter.SplitTextByDelimiter("-"), {"P.1", "P.2"}),
  #"Type de colonne changé 9" = Table.TransformColumnTypes(#"Diviser la colonne par
délimiteur 10", {{"P.1", Int64.Type}, {"P.2", type text}}, "fr"),
  #"Diviser la colonne par délimiteur 11" = Table.SplitColumn(#"Type de colonne
changé 9", "P.2", Splitter.SplitTextByDelimiter(" "), {"P.3", "P.4"}),
  #"Type de colonne changé 10" = Table.TransformColumnTypes(#"Diviser la colonne
par délimiteur 11", {{"P.3", Int64.Type}, {"P.4", type text}}, "fr"),
  #"Colonnes supprimées 7" = Table.RemoveColumns(#"Type de colonne changé 10",
{"P.4"}),
```

```
  #"Colonne personnalisée ajoutée 3" = Table.AddColumn(#"Colonnes supprimées 7",
"AWin_GS", each if [Stage] = "Group" and [H Team FT] < [A Team FT.1] then 1 else
0),
  #"Type de colonne changé 11" = Table.TransformColumnTypes(#"Colonne personnalisée
ajoutée 3", {{"HWin_GS", Int64.Type}, {"HLoss_GS", Int64.Type}, {"Draw_GS",
Int64.Type}, {"AWin_GS", Int64.Type}}),
  #"Colonne personnalisée ajoutée 4" =
Table.TransformColumnTypes(Table.AddColumn(#"Type de colonne changé 11",
"ALoss_GS", each if [Stage] = "Group" and [H Team FT] > [A Team FT.1] then 1 else
0), {{"ALoss_GS", Int64.Type}}),
  #"Valeur remplacée" = Table.ReplaceValue(#"Colonne personnalisée ajoutée 4", "(a)
", "", Replacer.ReplaceText, {"∑FT H"}),
  #"Type de colonne changé 12" = Table.TransformColumnTypes(#"Valeur remplacée",
{{"∑FT H", Int64.Type}}),
  #"Colonnes renommées 3" = Table.RenameColumns(#"Type de colonne changé 12",
{{"∑FT H", "AggH"}, {"∑FT A", "AggA"}}),
  #"Colonne personnalisée ajoutée 5" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonnes renommées 3", "HWin_16", each
if [Round] = "Round of 16 | Leg 1" and [H Team FT] > [A Team FT.1] then 1 else
if [Round] = "Round of 16 | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HWin_16", Int64.Type}}),
  #"Colonne personnalisée ajoutée 6" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 5",
"HLoss_16", each if [Round] = "Round of 16 | Leg 1" and [H Team FT] < [A Team FT.1]
then 1 else
if [Round] = "Round of 16 | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HLoss_16", Int64.Type}}),
  #"Colonne personnalisée ajoutée 7" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 6",
"Draw_16", each if [Round] = "Round of 16 | Leg 1" and [H Team FT] = [A Team FT.1]
then 1 else 0), {{"Draw_16", Int64.Type}}),
  #"Colonne personnalisée ajoutée 8" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 7",
"AWin_16", each if [Round] = "Round of 16 | Leg 1" and [H Team FT] < [A Team FT.1]
then 1 else
```

```
if [Round] = "Round of 16 | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"AWin_16", Int64.Type}}),
  #"Colonne personnalisée ajoutée 9" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 8",
"ALoss_16", each if [Round] = "Round of 16 | Leg 1" and [H Team FT] > [A Team FT.1]
then 1 else
if [Round] = "Round of 16 | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"ALoss_16", Int64.Type}}),
  #"Colonne personnalisée ajoutée 10" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 9",
"HWin_Quarter", each if [Round] = "Quarterfinals | Leg 1" and [H Team FT] > [A Team
FT.1] then 1 else
if [Round] = "Quarterfinals | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HWin_Quarter", Int64.Type}}),
  #"Colonne personnalisée ajoutée 11" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 10",
"HLoss_Quarter", each if [Round] = "Quarterfinals | Leg 1" and [H Team FT] < [A
Team FT.1] then 1 else
if [Round] = "Quarterfinals | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
```

```
else 0), {{"HLoss_Quarter", Int64.Type}}),
  #"Colonne personnalisée ajoutée 12" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 11",
"Draw_Quarter", each if [Round] = "Quarterfinals | Leg 1" and [H Team FT] = [A Team
FT.1] then 1 else 0), {{"Draw_Quarter", Int64.Type}}),
  #"Colonne personnalisée ajoutée 13" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 12",
"AWin_Quarter", each if [Round] = "Quarterfinals | Leg 1" and [H Team FT] < [A Team
FT.1] then 1 else
if [Round] = "Quarterfinals | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"AWin_Quarter", Int64.Type}}),
  #"Colonne personnalisée ajoutée 14" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 13",
"ALoss_Quarter", each if [Round] = "Quarterfinals | Leg 1" and [H Team FT] > [A
Team FT.1] then 1 else
if [Round] = "Quarterfinals | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"ALoss_Quarter", Int64.Type}}),
  #"Colonne personnalisée ajoutée 15" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 14",
"HWin_Semi", each if [Round] = "Semifinals | Leg 1" and [H Team FT] > [A Team FT.1]
then 1 else
if [Round] = "Semifinals | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HWin_Semi", Int64.Type}}),
  #"Colonne personnalisée ajoutée 16" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 15",
"HLoss_Semi", each if [Round] = "Semifinals | Leg 1" and [H Team FT] < [A Team
FT.1] then 1 else
```

```
if [Round] = "Semifinals | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HLoss_Semi", Int64.Type}}),
  #"Colonne personnalisée ajoutée 17" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 16",
"Draw_Semi", each if [Round] = "Semifinals | Leg 1" and [H Team FT] = [A Team FT.1]
then 1 else 0), {{"Draw_Semi", Int64.Type}}),
  #"Colonne personnalisée ajoutée 18" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 17",
"AWin_Semi", each if [Round] = "Semifinals | Leg 1" and [H Team FT] < [A Team FT.1]
then 1 else
if [Round] = "Semifinals | Leg 2" then
    if [AggH] < [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"AWin_Semi", Int64.Type}}),
  #"Colonne personnalisée ajoutée 19" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 18",
"ALoss_Semi", each if [Round] = "Semifinals | Leg 1" and [H Team FT] > [A Team
FT.1] then 1 else
if [Round] = "Semifinals | Leg 2" then
    if [AggH] > [AggA] then 1
    else if [AggH] = [AggA] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"ALoss_Semi", Int64.Type}}),
  #"Colonne personnalisée ajoutée 20" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 19",
"HWin_Final", each if [Round] = "Final" then
    if [H Team FT] > [A Team FT.1] then 1
    else if [H Team FT] = [A Team FT.1] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
```

```
        else 0
    else 0
else 0), {{"HWin_Final", Int64.Type}}),
  #"Colonne personnalisée ajoutée 21" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 20",
"HLoss_Final", each if [Round] = "Final" then
    if [H Team FT] < [A Team FT.1] then 1
    else if [H Team FT] = [A Team FT.1] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"HLoss_Final", Int64.Type}}),
  #"Colonne personnalisée ajoutée 22" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 21",
"AWin_Final", each if [Round] = "Final" then
    if [H Team FT] < [A Team FT.1] then 1
    else if [H Team FT] = [A Team FT.1] then
        if [ET.1] < [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] < [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"AWin_Final", Int64.Type}}),
  #"Colonne personnalisée ajoutée 23" =
Table.TransformColumnTypes(Table.AddColumn(#"Colonne personnalisée ajoutée 22",
"ALoss_Final", each if [Round] = "Final" then
    if [H Team FT] > [A Team FT.1] then 1
    else if [H Team FT] = [A Team FT.1] then
        if [ET.1] > [ET.3] then 1
        else if [ET.1] = [ET.3] then
            if [P.1] > [P.3] then 1
            else 0
        else 0
    else 0
else 0), {{"ALoss_Final", Int64.Type}})
in
  #"Colonne personnalisée ajoutée 23"
```

Appendix 1 – Excel Power Queries (2014-15)

Appendix 2:

```
Sub SupprimerLignesNonCorrespondantes()
    Dim FeuillePrincipale As Worksheet
    Dim FeuilleEntreprisesUtiles As Worksheet
    Dim DerniereLignePrincipale As Long
    Dim DerniereLigneUtiles As Long
    Dim Trouve As Range
    Dim i As Long

    ' Noms exacts des feuilles
    Set FeuillePrincipale = ThisWorkbook.Sheets("2003-04")
    Set FeuilleEntreprisesUtiles = ThisWorkbook.Sheets("Public")

    ' Trouver la dernière ligne de chaque feuille
    DerniereLignePrincipale = FeuillePrincipale.Cells(FeuillePrincipale.Rows.Count,
  "E").End(xlUp).Row ' Ajusté pour la colonne E
    DerniereLigneUtiles =
    FeuilleEntreprisesUtiles.Cells(FeuilleEntreprisesUtiles.Rows.Count,
  "A").End(xlUp).Row ' Ajusté pour la colonne A

    ' Boucle à rebours pour supprimer les lignes non correspondantes
    For i = DerniereLignePrincipale To 2 Step -1
        Set Trouve = FeuilleEntreprisesUtiles.Range("A1:A" &
DerniereLigneUtiles).Find(What:=FeuillePrincipale.Cells(i, "E").Value, _
            LookIn:=xlValues, LookAt:=xlWhole) ' Ajusté pour les colonnes E et A

        ' Si l'entreprise n'est pas trouvée dans la liste utile, supprimer la ligne
        If Trouve Is Nothing Then
        FeuillePrincipale.Rows(i).Delete
        End If
    Next i
End Sub
```

Appendix 2 – VBA code removing non-listed clubs (2003-04)

Appendix 3:

```
Sub InsérerSharePriceDuLendemain()
    Dim wsPrincipal As Worksheet
    Dim wsSecondaire As Worksheet
    Dim DerniereLignePrincipale As Long, DerniereLigneSecondaire As Long
    Dim i As Long, j As Long
    Dim DateCherchee As Date
    Dim Trouve As Boolean

    ' Nom des feuilles
    Set wsPrincipal = ThisWorkbook.Sheets("2013-14")
    Set wsSecondaire = ThisWorkbook.Sheets("Returns")

    DerniereLignePrincipale = wsPrincipal.Cells(wsPrincipal.Rows.Count,
"E").End(xlUp).Row
    DerniereLigneSecondaire = wsSecondaire.Cells(wsSecondaire.Rows.Count,
"A").End(xlUp).Row

    ' Parcourir chaque ligne du tableau principal
    For i = 2 To DerniereLignePrincipale
        DateCherchee = wsPrincipal.Cells(i, "D").Value + 1 ' Date du lendemain
        Trouve = False

        ' Parcourir le tableau secondaire pour trouver une correspondance
        For j = 2 To DerniereLigneSecondaire
            If wsPrincipal.Cells(i, "E").Value = wsSecondaire.Cells(j, "A").Value
And _
               wsSecondaire.Cells(j, "B").Value = DateCherchee Then
                ' Si correspondance trouvée, insérer le share price dans le tableau
principal
                wsPrincipal.Cells(i, "T").Value = wsSecondaire.Cells(j, "D").Value
                Trouve = True
                Exit For
            End If
        Next j

        ' Si aucune valeur trouvée pour le lendemain, laisse la cellule vide
        If Not Trouve Then
            wsPrincipal.Cells(i, "T").Value = ""
        End If
    Next i
End Sub
```

Appendix 3 – VBA code adding financial returns to the football data (2013-14)

Appendix 4:

```
Sub CopierDonneesFamaFrench()
    Dim wsPrincipal As Worksheet
    Dim wsSecondaire As Worksheet
    Dim DerniereLignePrincipale As Long, DerniereLigneSecondaire As Long
    Dim i As Long, j As Long
    Dim DateCherchee As Date
    Dim Trouve As Boolean

    ' Noms des feuilles
    Set wsPrincipal = ThisWorkbook.Sheets("Returns + Fama3f")
    Set wsSecondaire = ThisWorkbook.Sheets("Fama 3f")

    ' Trouver la dernière ligne de données pour chaque feuille
    DerniereLignePrincipale = wsPrincipal.Cells(wsPrincipal.Rows.Count,
"B").End(xlUp).Row
    DerniereLigneSecondaire = wsSecondaire.Cells(wsSecondaire.Rows.Count,
"A").End(xlUp).Row

    ' Parcourir chaque ligne du tableau principal
    For i = 2 To DerniereLignePrincipale
        DateCherchee = wsPrincipal.Cells(i, "B").Value
        Trouve = False

        ' Parcourir le tableau secondaire pour trouver une correspondance
        For j = 2 To DerniereLigneSecondaire
            If wsSecondaire.Cells(j, "A").Value = DateCherchee Then
                ' Si une correspondance de date est trouvée, copier les valeurs
correspondantes
                wsPrincipal.Cells(i, "E").Value = wsSecondaire.Cells(j, "B").Value
' Mkt-Rf
                wsPrincipal.Cells(i, "F").Value = wsSecondaire.Cells(j, "C").Value
' SMB
                wsPrincipal.Cells(i, "G").Value = wsSecondaire.Cells(j, "D").Value
' HML
                wsPrincipal.Cells(i, "H").Value = wsSecondaire.Cells(j, "E").Value
' RF
                Trouve = True
                Exit For ' Sortie immédiate de la boucle après avoir trouvé la
correspondance
            End If
        Next j

        ' Si aucune correspondance n'est trouvée, les cellules restent vides (pas
nécessaire de le faire explicitement dans ce script)
    Next i
End Sub
```

Appendix 4 – VBA code matching actual returns and historical Fama French factors

Appendix 5:

```
#install.packages("readxl")
library(readxl)
dataS_4 <- read_excel("Returns (1).xlsx", "Season -4")
dataS_3 <- read_excel("Returns (1).xlsx","Season -3")
dataS_2 <- read_excel("Returns (1).xlsx","Season -2")
dataS_1 <- read_excel("Returns (1).xlsx","Season -1")
dataS0 <- read_excel("Returns (1).xlsx","Season 0")


#install.packages("dplyr")
library(dplyr)
combined_data <- bind_rows(dataS_4, dataS_3, dataS_2, dataS_1, dataS0)

names(combined_data)[names(combined_data) == "Daily return - RF"] <-
"DailyReturnRF"
names(combined_data)[names(combined_data) == "Mkt - RF"] <- "MktRF"


model1 <- lm(formula = DailyReturnRF ~ SMB + HML + MktRF, data = combined_data)

summary(model1)

coefficients_df1 <- as.data.frame(coef(summary(model1)))
View(coefficients_df1)
```

Appendix 5 – R Script of the Fama French regression

Appendix 6:

```
Sub InsérerSharePriceDuLendemain()
    Dim wsPrincipal As Worksheet
    Dim wsSecondaire As Worksheet
    Dim DerniereLignePrincipale As Long, DerniereLigneSecondaire As Long
    Dim i As Long, j As Long
    Dim DateCherchee As Date
    Dim Trouve As Boolean

    ' Noms des feuilles
    Set wsPrincipal = ThisWorkbook.Sheets("2022-23")
    Set wsSecondaire = ThisWorkbook.Sheets("Expected returns")

    DerniereLignePrincipale = wsPrincipal.Cells(wsPrincipal.Rows.Count,
"E").End(xlUp).Row
    DerniereLigneSecondaire = wsSecondaire.Cells(wsSecondaire.Rows.Count,
"A").End(xlUp).Row

    ' Parcourir chaque ligne du tableau principal
    For i = 2 To DerniereLignePrincipale
        DateCherchee = wsPrincipal.Cells(i, "D").Value + 1 ' Date du lendemain
        Trouve = False

        ' Parcourir le tableau secondaire pour trouver une correspondance
        For j = 2 To DerniereLigneSecondaire
            If wsPrincipal.Cells(i, "E").Value = wsSecondaire.Cells(j, "A").Value
And _
               wsSecondaire.Cells(j, "B").Value = DateCherchee Then
                ' Si correspondance trouvée, insérer le share price dans le tableau
principal
                wsPrincipal.Cells(i, "U").Value = wsSecondaire.Cells(j, "C").Value
                Trouve = True
                Exit For
            End If
        Next j

        ' Si aucune valeur trouvée pour le lendemain, laisse la cellule vide
        If Not Trouve Then
            wsPrincipal.Cells(i, "U").Value = ""
        End If
    Next i
End Sub
```

Appendix 6 – VBA code adding expected returns to the football and financial data (2022-23)

Appendix 7:

```
library(readxl)
dataModel1 <- read_excel("Master Excel.xlsx","1 variable")

names(dataModel1)[names(dataModel1) == "Abnormal return"] <- "AbnormalReturn"
model4 <- lm(formula = AbnormalReturn ~ Outcome, data = dataModel1)
summary(model1)

#plot
coefficients <- coef(model1)
View(coefficients)
library(ggplot2)
ggplot(dataModel4, aes(x = Outcome, y = AbnormalReturn)) +
  geom_point(aes(color = as.factor(Outcome)), alpha = 0.5) +
  geom_abline(intercept = coefficients[1], slope = coefficients[2], color = 
"black") +  # Ajoutez 'aes(group = 1)' si nécessaire
  stat_summary(fun.y = mean, geom = "point", shape = 18, size = 3, color = "black", 
aes(group = 1)) +
  labs(title = "Abnormal Returns by Outcome", x = "Outcome", y = "Abnormal Return") 
+
  theme_minimal() +
  scale_color_manual(values = c("-1" = "red", "0" = "green", "1" = "blue"), name = 
"Outcome Categories")
```

Appendix 7 – R script for model 1

Appendix 8:

```
library(readxl)
dataModel2 <- read_excel("Master Excel without stage.xlsx","Without stages and 
final")

names(dataModel2)[names(dataModel2) == "Abnormal return"] <- "AbnormalReturn"

model2 <- lm(formula = AbnormalReturn ~ Win + Loss, data = dataModel2)
summary(model2)
```

Appendix 8 – R script for model 2

Appendix 9:

```
library(readxl)
dataModel3 <- read_excel("Master Excel without stage.xlsx","Distinction GS KO 
without final")

names(dataModel3)[names(dataModel3) == "Abnormal return"] <- "AbnormalReturn"

model3 <- lm(formula = AbnormalReturn ~ Win_GS + Loss_GS + Win_KO + Loss_KO, data = 
dataModel3)
summary(model3)
```

Appendix 9 – R script for model 3

Appendix 10:

```
library(readxl)
dataModel1 <- read_excel("Master Excel without stage.xlsx","All S and stages
without final")

library(dplyr)


names(dataModel1)[names(dataModel1) == "Abnormal return"] <- "AbnormalReturn"

model1 <- lm(formula = AbnormalReturn ~ Win_GS + Loss_GS
                + Win_16 + Loss_16 + Win_Quarter + Loss_Quarter
                + Win_Semi + Loss_Semi
                , data = dataModel1)
summary(model1)
```

Appendix 10 – R script for model 4

Appendix 11:

	Estimate	Std. Error	t value	Pr(>|t|)
Season 2003-2004				
(Intercept)	-0,10095687	0,03476504	-2,9039768	3,69E-03**
SMB	0,15783747	0,05396713	2,9246963	3,46E-03**
HML	-0,02666076	0,06375469	-0,4181772	6,76E-01
MktRF	0,24708855	0,0450449	5,4853838	4,25E-08***
Season 2004-2005				
(Intercept)	-0,09683	0,032259	-3,00158	2,69E-03**
SMB	0,139998	0,051421	2,722602	6,49E-03**
HML	-0,00214	0,060277	-0,03554	9,72E-01
MktRF	0,223846	0,040004	5,595606	2,26E-08***
Season 2005-2006				
(Intercept)	-0,0850479	0,029811	-2,85292	4,34E-03**
SMB	0,16680151	0,052727	3,163487	1,56E-03**
HML	0,01885279	0,07027	0,268291	7,88E-01
MktRF	0,24900463	0,03906	6,374925	1,91E-10***
Season 2006-2007				
(Intercept)	-0,08999275	0,028218	-3,18923	1,43E-03**
SMB	0,23365178	0,052503	4,450231	8,66E-06***
HML	0,14431667	0,105238	1,371337	1,70E-01
MktRF	0,30116795	0,037358	8,061777	8,26E-16***
Season 2007-2008				
(Intercept)	-0,04064211	0,024968	-1,62777	1,04E-01
SMB	0,13866825	0,051323	2,701889	6,90E-03**
HML	0,26886025	0,113526	2,368272	1,79E-02*
MktRF	0,22749179	0,03513	6,475781	9,79E-11***
Season 2008-2009				
(Intercept)	-0,01638275	0,022269	-0,73569	4,62E-01

SMB	0,09569335	0,059841	1,599131	1,10E-01
HML	0,13617614	0,104729	1,300271	1,94E-01
MktRF	0,26495297	0,027576	9,608094	8,71E-22***
Season 2009-2010				
(Intercept)	-0,01853612	0,022793	-0,81323	4,16E-01
SMB	0,19399777	0,048437	4,005171	6,23E-05***
HML	0,0418224	0,053615	0,780045	4,35E-01
MktRF	0,36847874	0,02132	17,28289	3,16E-66***
Season 2010-2011				
(Intercept)	-0,0198404	0,023884	-0,8307	4,06E-01
SMB	0,24051197	0,05047	4,765438	1,90E-06***
HML	0,03380653	0,048572	0,696008	4,86E-01
MktRF	0,37208806	0,022138	16,80779	8,59E-63***
Season 2011-2012				
(Intercept)	-0,00601	0,025104	-0,23936	8,11E-01
SMB	0,189177	0,055016	3,438546	5,86E-04***
HML	0,014167	0,050512	0,28046	7,79E-01
MktRF	0,350488	0,02365	14,82007	2,48E-49***
Season 2012-2013				
(Intercept)	-0,02069	0,027825	-0,7435	4,57E-01
SMB	0,230858	0,059747	3,86392	1,12E-04***
HML	0,001519	0,052733	0,028799	9,77E-01
MktRF	0,34814	0,025335	13,7414	1,05E-42***
Season 2013-2014				
(Intercept)	-0,02543	0,030718	-0,82769	4,08E-01
SMB	0,308116	0,069806	4,413869	1,02E-05***
HML	0,014222	0,057504	0,247325	8,05E-01
MktRF	0,359314	0,030161	11,91311	1,43E-32***
Season 2014-2015				
(Intercept)	0,011582	0,031532	0,367316	7,13E-01
SMB	0,425104	0,098365	4,321702	1,56E-05***
HML	0,203196	0,08179	2,484358	1,30E-02*
MktRF	0,275977	0,042385	6,511249	7,69E-11***
Season 2015-2016				
(Intercept)	0,024392	0,031692	0,769662	4,42E-01
SMB	0,206584	0,09679	2,134348	3,28E-02*
HML	0,013935	0,084988	0,163962	8,70E-01
MktRF	0,263361	0,042197	6,241226	4,46E-10***
Season 2016-2017				
(Intercept)	0,039217	0,032114	1,221183	2,22E-01
SMB	0,184814	0,089643	2,06167	3,93E-02*
HML	0,019505	0,077333	0,252216	8,01E-01
MktRF	0,315864	0,042787	7,382307	1,64E-13***
Season 2017-2018				

(Intercept)	0,06373094	0,03009325	2,1177815	3,42E-02*
SMB	0,12067147	0,08722914	1,3833848	1,67E-01
HML	0,01254902	0,07257681	0,1729068	8,63E-01
MktRF	0,35216261	0,04701961	7,4896972	7,29E-14***
Season 2018-2019				
(Intercept)	0,053224	0,028017	1,899739	5,75E-02
SMB	0,023578	0,079309	0,297298	7,66E-01
HML	0,054495	0,068812	0,791942	4,28E-01
MktRF	0,403158	0,042079	9,580984	1,11E-21***
Season 2019-2020				
(Intercept)	0,030415	0,026156	1,162824	2,45E-01
SMB	0,05034	0,072643	0,692978	4,88E-01
HML	-0,03493	0,062904	-0,55528	5,79E-01
MktRF	0,428273	0,037183	11,51808	1,44E-30***
Season 2020-2021				
(Intercept)	0,040832	0,027276	1,496986	1,34E-01
SMB	0,282757	0,077283	3,6587	2,54E-04***
HML	0,12554	0,063249	1,984853	4,72E-02*
MktRF	0,598288	0,037036	16,15406	3,51E-58***
Season 2021-2022				
(Intercept)	0,02040326	0,02721943	0,7495844	4,54E-01
SMB	0,17295001	0,08276897	2,0895513	3,67E-02*
HML	0,250621	0,05264879	4,7602426	1,95E-06***
MktRF	0,53531774	0,0344444	15,5415032	5,04E-54***
Season 2021-2022				
(Intercept)	0,008350731	0,028465	0,293365	7,69E-01
SMB	0,164854542	0,084152	1,959016	5,01E-02
HML	0,278666164	0,047597	5,854664	4,89E-09***
MktRF	0,538668094	0,030032	17,93634	3,73E-71***

Appendix 11 – Fama French coefficients

Appendix 12:

```
Call:
lm(formula = AbnormalReturn ~ Outcome, data = dataModel4)

Residuals:
     Min       1Q   Median       3Q      Max
-22.4465  -1.3490   0.0773   1.5801  23.4174

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.6594     0.1104  -5.975 3.13e-09 ***
Outcome       0.9853     0.1239   7.954 4.58e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.611 on 1069 degrees of freedom
Multiple R-squared:  0.05587,   Adjusted R-squared:  0.05499
F-statistic: 63.26 on 1 and 1069 DF,  p-value: 4.581e-15
```

Appendix 12 – R output of Model 1

Appendix 13:

```
Call:
lm(formula = AbnormalReturn ~ Win + Loss, data = dataAllSeasons)

Residuals:
     Min       1Q   Median       3Q      Max
-22.5368  -1.2926   0.0757   1.5245  23.3204

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.9579     0.2425  -3.950 8.32e-05 ***
Win           1.3808     0.3000   4.603 4.66e-06 ***
Loss         -0.5965     0.2979  -2.002   0.0455 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.597 on 1064 degrees of freedom
Multiple R-squared:  0.05827,   Adjusted R-squared:  0.0565
F-statistic: 32.92 on 2 and 1064 DF,  p-value: 1.345e-14
```

Appendix 13 – R output of Model 2

Appendix 14:

```
Call:
lm(formula = AbnormalReturn ~ Win_GS + Loss_GS + Win_KO + Loss_KO,
    data = dataAllSeasonsbis)

Residuals:
     Min       1Q   Median       3Q      Max
-22.7980  -1.3090   0.1308   1.5205  22.7642

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.9579     0.2418  -3.962 7.93e-05 ***
Win_GS        1.2601     0.3101   4.063 5.19e-05 ***
Loss_GS      -0.3352     0.3149  -1.065  0.28726
Win_KO        1.9370     0.4819   4.020 6.24e-05 ***
Loss_KO      -1.3080     0.4115  -3.179  0.00152 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.586 on 1062 degrees of freedom
Multiple R-squared:  0.06567,   Adjusted R-squared:  0.06215
F-statistic: 18.66 on 4 and 1062 DF,  p-value: 7.772e-15
```

Appendix 14 – R output of Model 3

Appendix 15:

```
Call:
lm(formula = AbnormalReturn ~ Win_GS + Loss_GS + Win_16 + Loss_16 +
    Win_Quarter + Loss_Quarter + Win_Semi + Loss_Semi, data = dataModel1)

Residuals:
    Min      1Q  Median      3Q     Max
-22.798  -1.309   0.124   1.521  21.405

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   -0.9579     0.2404  -3.984 7.23e-05 ***
Win_GS         1.2601     0.3084   4.086 4.72e-05 ***
Loss_GS       -0.3352     0.3131  -1.071 0.284582
Win_16         1.5208     0.5542   2.744 0.006172 **
Loss_16       -1.2045     0.4894  -2.461 0.014002 *
Win_Quarter    3.2966     0.9516   3.464 0.000553 ***
Loss_Quarter  -0.7350     0.6130  -1.199 0.230766
Win_Semi       2.0415     1.2835   1.591 0.112016
Loss_Semi     -6.3363     1.4756  -4.294 1.91e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.566 on 1058 degrees of freedom
Multiple R-squared:  0.07951,	Adjusted R-squared:  0.07255
F-statistic: 11.42 on 8 and 1058 DF,  p-value: 1.243e-15
```

Appendix 15 – R output of Model 4