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How Football Matches Affect Abnormal Returns of European Publicly Traded Football Teams

by

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Abstract

This paper applied a broader, more diverse dataset to investigate whether match results still lead to abnormal returns and to identify which match factors are the most influential. Abnormal returns were measured using the market model and event studies for 23 teams during the 2016-2019 seasons. We confirmed that victories result in positive abnormal returns of 0.39% and draws/losses lead to negative abnormal returns of -0.29% and -1.0% respectively. The degree of these abnormal returns varied depending on factors such as match location, team ranking within their league, whether teams were on a win streak, and betting odds. The greatest abnormal returns equaling 1.46% were observed when a team was victorious winning against betting odds, while the greatest negative abnormal return of -2.35% was observed when a team lost to a team of lower ranking within their league.

Keywords: Football stocks, Abnormal returns, Event study, Investor sentiment

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1. Introduction

1.1 Research Background

Football securities are a growing area of interest within the world of finance. Although they only became available on the public markets within the past few decades, the sport has been recognized worldwide for far longer. Older forms of the sport can be traced to ancient Greece, but the modern version we recognize was formalized in England in 1863, when the first football club was formed (Encyclopedia Britannica, 2020). Since then, the popularity of the sport has continued to grow alongside the considerable revenues the top clubs generate. For example, in 2020, FC Barcelona surpassed the €800 million mark (Deloitte, 2020). The STOXX Football Index has shown steady growth over the years (STOXX Europe Football, 2020) as can be seen appendix A table 1.0. An increased interest to drive athletic as well as financial performance led clubs go public for further funding. In 1983 the Tottenham Hotspurs, based out of England, was the first club to do so, trading on the London Stock Exchange. Duque and Ferreira (2005) noted a shift in clubs moving toward a profit-maximization model, which has brought some ethical challenges to how the sport is typically governed.

The introduction of football clubs to publicly traded stock markets has drawn the interest of analysts in addition to the fans of the sport. Although traditional firms offer infrequent signals to the market in the form of annual and quarterly reports, sporting teams have a unique characteristic in signaling their abilities through match outcomes. This paper seeks to expand on earlier work by examining the impact of winning streaks on average abnormal returns (henceforth referred to as $\overline{AR}$) and to what extent betting odds accurately predict match outcomes and may signal abnormal returns (henceforth referred to as AR). The comparison of home and away games has been included to serve as an additional baseline marker to earlier works; however, other factors such as goal difference and red card penalties have been omitted. We believe both these measure smaller changes in results, whereas the prime driver in $\overline{AR}$ differences will be the match outcome, and instead we focused on the new condition where teams play games while on a winning streak. Earlier research by Bakx (2013) showed a slight increase in $\overline{AR}$ for away victories only at a 10% significance level.

Football is the most popular sport globally, and because of the many ways it impacts the economy as well as spectators' moods, it is a justified area of study. Deloitte (2019) shows how the revenues of major football clubs in Europe continue to grow at a rapid rate. The Deloitte report further states the *Big Five* in European football, consisting of England, Italy, Germany, Spain, and France, brought in 15,590 million euros across the 2017-2018 season.

After the initial public offering (henceforth referred to as IPO) of the Tottenham Hotspurs in 1983, for the 1996-97 season, 12 more clubs transitioned to the public market (Renneboog & Vanbrabant, 2000). Since then it has not been uncommon to see clubs list and delist over the years, prompting the question of whether this change has brought positive changes to the club performances. Earlier research conducted by Bauer & Keating (2009) found that lower divisions' clubs benefitted from the transition, but not at a statistically significant level. In financial terms, Renneboog and Vanbrabant (2000) concluded that football stocks generally underperformed versus the market, making them a poor choice for investors. Oh (2019) found that teams initially performed better competitively after an IPO, but, delivering aside, key financial ratios do not improve by going public. A detailed source of listings and delisting is available in Table 2.0 of Appendix B.

FIFA (Fédération Internationale de Football Association) estimated that more than 3.5 billion people watched at least some of the 2018 World Cup (FIFA, 2020), meaning this event was experienced by nearly half the world's population. Whether the fans' team wins or loses an important match can have an immense effect on their mood. Previous studies (Edmans, Garcia & Norli, 2007) have showed changes in mood, well-being, self-esteem, lottery ticket sales and even suicide rates depending on a match outcome. Carrol, Ebrahim, Tilling, Macleod, and Smith (2002) discovered a 25% increase in heart-attack hospital admissions in England during the three-day period after the country's world cup loss to Argentina by penalty shoot-outs. Regardless, whether you attend each match day cheering from your couch for your favorite team, or whether you struggle to name three major football teams, it is undeniable that sports have a profound effect on society.

1.2 Purpose of the Study

As the market cap of publicly traded football clubs continues to grow, so does the necessity for performing financial analysis on this emerging subgroup of stocks. Given we found significant levels of $\overline{AR}$ present around match days, this may open a pathway to further research to evaluate whether an investing strategy may be centered around predicting the market reactions based on a team's performance. The primary value of interest was to see the change in $\overline{AR}$ between T_0 and T_{+1} as a response to the match outcome, and secondarily the shift from T_{-1} to T_0 may illuminate whether investors predict certain outcomes and prepare accordingly.

For the purposes of this research, we assume the Efficient Market Hypothesis (henceforth EMH) holds and that publicly traded football clubs' stock prices react to the information made available by match outcomes. We assume that any changes to share price resulting in abnormal returns are explained by the news of these events. The event study employed during the research tests whether the market reacts to the availability of this new information.

We found that significant abnormal returns occur the day after a publicly traded team wins or loses, but not so much when teams drew. Our research confirmed the presence of AR after match days. Victories resulted in 0.39% $\overline{AR}$, whereas draws and losses resulted in -0.29% and -1.0% respectively. Depending on specific match conditions outlined in section 3, the magnitude of $\overline{AR}$ varies, such as whether a team is favored to win or the match location.

The paper is structured as follows: section two covers the theoretical background to the research and literature review; section three states the hypothesis of the research paper; section four covers the data sample and methodology applied; section five discusses the findings.

2. Literature/Theoretical Review

Section two covers the theoretical background of the EMH and earlier research relating to the abnormal returns linked to football matches of publicly traded football clubs. Various time periods, clubs and methods were considered to cross-examine the impact match outcomes have on football club stock returns.

2.1 Efficient Market Hypothesis

The EMH traces back to early work by Bachelier (1900), who investigated price changes on La Bourse. He proposed the securities were independently and identically distributed, meaning there would be no way to predict their movement and thus they followed a “random walk”. The term EMH was coined by Fama (1965), stating that traded securities are fairly priced, and these prices fully reflect all the information available to the market. Despite coming under substantial criticism over the years, it remains a staple in the financial world when it comes to analyzing markets. The random walk refers to the characterization of how price series are a result of random changes from the previous days’ prices (Malkiel, 2003), and it was later developed further by Fama to divide it into three subcategories: weak form, semi-strong form and strong form efficiency (Fama, 1965, 1970).

According to Fama (1965) weak form EMH states that the current price is reflective of all information implied by previous prices. Should an agent be able to forecast security movements based on this limited information that is said to be a violation of the weak form EMH. The semi-strong form further adds that the prices are reflective of all publicly available information, which adds, for example, information taken from firms’ financial statements, announcements, or ongoing economic factors. For the semi-strong EMH to hold, we expect security prices to react to these news announcements. Lastly the strong form efficiency states that the price is reflective of information known by any participant in the market, including insider information as well.

In the early 21st century investors started questioning the validity of the EMH and discussions started to form whether market prices were predictable to an extent. Malkiel (2003) summarizes that for the EMH to hold, the stock prices cannot have what he described as a *long term memory*, i.e. the random walk is a result of the previous days' trading value. Lo and MacKinlay (1999), however, found evidence of short-term serial correlations, meaning sufficient trends in the same direction rebuke the true random walk theory. Lo and MacKinlay (2000) employed nonparametric statistical techniques to find *head and shoulders* and *double bottoms* which provides some ability to predict patterns in stock price movement.

2.2 Event Studies

Event studies are utilized by analysts to measure the impact of an event on the value of a firm or stock price. The first published study was done by James Dolley (1933 cited in MacKinlay, 1997), where he analyzed the change in stock price after splits. This foundation was improved upon later by several researchers by removing general stock market price movements and removing confounding events (MacKinlay 1997).

2.2.1 Limitations of Event Studies

The selection of sampling interval can heavily impact results. MacKinlay (1997) demonstrated that when using 50 securities the power of a five-percent test with daily values was 0.94, which then dropped to 0.35 when examining weekly values and further to 0.12 when the entire month was used. This was further reinforced by Morse (1984), strengthening the arguments to use daily intervals for the event studies. Accuracy can be improved further by adding multiple samples over the course of the day because of frequent trading; however, this creates its own set of difficulties. Because of the frequency of the football matches and for best power, this study utilizes a daily sampling of stock prices.

A second challenge mentioned by MacKinlay (1997) in this field of research is setting up the event studies is the assumptions regarding the event date. This refers to the timing of the event announcement or results, and whether it was done before or after the market closed for the day and had time to react. When it is uncertain, it is preferential to select the day prior as the event day, whereas if the announcement took place during trading hours the same day is considered the event day. A potential remedy to this is to extend the event window to two days, which seemed not to diminish the power of the study substantially. Ball and Torus (1988) used a maximum likelihood estimation to determine the difference in the two methods and found results to be similarly accurate as with the lengthier two-day window approach.

In order to analyze the $\overline{AR}$, there is an assumption that the returns are jointly normal and temporally independently and identically distributed, as this is necessary for the finite sample to hold (otherwise the results would be asymptotic). MacKinlay (1997) finds this is generally not an issue when conducting event studies given that the test statistics used converge rapidly to asymptotic distributions.

Additional challenges may arise from nonsynchronous trading, meaning assumptions are made regarding the time of stock trades when, in fact, it may vary. Because of this there may be issues with the measured variances and covariances of the observed stock as well as market prices, which in turn may bias our estimated beta used in the market model. A solution to this has been presented by Myron & Williams (1977) by introducing the assumption that the true return process is uncorrelated through time. They found that in the case of less frequently traded securities the adjusted beta could be 10-20% higher than its counterpart. This was contested by Jain in 1986, where he found this difference was minimal.

Lastly, the methodology implemented by MacKinlay (1997) may cause an upward bias when calculating the $\overline{AR}$ because of the rebalancing of equal weights when calculating the aggregate cumulative abnormal return (henceforth referred to as $\overline{CAR}$). as well as the transaction prices. These prices may be from the buyer or the seller side. Blume and Stambaugh (1983) found that in event studies using relatively lower market cap companies with wider bid-offer spreads that this bias could be remedied by instead using $\overline{CAR}$ to reflect the buy and hold strategies in these firms.

When conducting an event study, one must consider the possibility of confounding events playing a role in the findings. Football teams have certain unique factors which may skew team performance during a season and thus the $\overline{AR}$. The first is the addition or removal of coaching staff or key players. Changing a team coach midway through a season may improve performance in the short term due to a shock effect, however it is followed by a gradual worsening of performance (Peñas, 2011). Per football rules players may transition only between teams during winter and summer months, and domestic teams do not play during the summer months and there are very few, if any matches in December. As such we believe these factors will have a limited impact as a confounding event. Secondly, temporary player suspensions and injuries could be considered to play a role in deteriorating team performance over the short run. Professional football teams play with rosters of 25 players, which means that although a strong player may be absent because of temporary suspension, there is other talent that can replace him. Thus, we assume this effect will play a minor role, if any, in the performance aggregated over 23 teams and three seasons. Pertaining to injuries, it was found that for Spanish Division One football players, the average rate of injury was 41.7 per 1000 hours of competitive play, the majority of these injuries being muscular with a week's recovery time (Salces, Gomez-Carmona, Gracia-Marco, Moliner-Urdiales, Sillero-Quintana, 2014). We assume that, similar to the temporary suspensions, these infrequent injuries with short recovery times will not affect aggregated team performances and as such will not influence the $\overline{AR}$.

2.3 Previous Research

2.3.1 Sport Sentiment and Stock Return

The basis of this paper is examining the relation between stock prices and football match outcomes, which we believe to be connected by sport sentiment. Edmans, Garcia and Norli (2007) argue that a mood variable is responsible for changes in the stock prices. These authors conducted an extensive event study published in 2007 observing how football World Cup results affected the participating countries' stock returns. Their sample included 1,100 football game observations and an additional 1,500 observations in 4 other major sports. They found that losses resulted in AR of -49 basis points, and that this effect was more prevalent in smaller stocks as well as with more important matches. They did not find any cause to believe that wins had the opposite effect of causing positive AR.

Edmans, Garcia and Norli (2007) deemed that football match outcomes held enough importance to sway investors based on their mood. Football stood out above the other sports they examined such as cricket and rugby, based on viewership, game attendance, and merchandise sales. In their paper, they stated that a mood variable must drive mood, affect a significant portion of the population and be correlated across the sample group (Edmans, Garcia & Norli, 2007). This is further supported by Wann, Dolan, McGeorge and Allison (1994), which showed a positive connection to mood when sport fans' teams won, and a negative one when their teams lost.

Edmans, Garcia and Norli (2007) found stock prices reacted negatively to the news of a team's loss, but they recognized the possibility that this could be a result of economic effects as opposed to sports sentiment. A few of these consequences may include lower attendance in future games and a decrease in merchandise sales for the team in question. A truly rational investor would be expected to judge the match outcome based on the probability of a team winning based on game metrics as opposed to their personal beliefs. This is not always the case, however, because of the allegiance effect, which was showcased through a survey in England. At the time, 86% of fans thought they would beat Brazil in the quarter final, despite the latter being the no. 1-ranked team, whereas bookkeepers estimated England's chances of victory were 42% (Edmans, Garcia & Norli, 2007). Secondly, how the different stocks react is likely attributable to their size and hence their portfolio characteristics. A variety of earlier work points to a greater fraction of local ownership for small cap stocks because of the pricing challenges for international investors. Lastly the authors considered whether investors may be *hung over* after a game day, resulting in lower trading volume and hence decreasing the price of stocks. When comparing trading volume between match days and non-match days, there was not a significant difference.

Edmans, Garcia and Norli (2007) found significant losses exceeding 7% monthly for football stocks; however, a positive counter reaction was not discovered for winning matches. They believe this is rooted in sport sentiment, especially because these effects were more profound in countries where football spirit is more predominant as well as in the smaller stocks with local ownership. From an investor standpoint, they believe there is not enough justification to set up a portfolio strategy based on these findings; however, it furthers the research into the field of linking investor mood to asset pricing.

2.3.2 Share Price Reaction to Sporting Performance

Renneboog and Vanbrabant (2000) were among the first researchers to examine the effects of sporting results on football club stocks after the influx of publicly traded teams in 1997. Over their research period, only two of the traded clubs out of 22 were non-British (Lazio and Ajax). The authors examined these 22 clubs from their first day of trading through the end of 1998. Stock data was taken from the London Stock Exchange (LSE) and Alternative Investment Market (AIM). The Capital Asset Pricing Model was used to calculate the expected returns over the estimation windows, and AR were the difference between the logarithmic realized returns and the logarithmic expected returns, and an estimation window of six months prior to the first event was used to calculate the estimated betas.

Renneboog and Vanbrabant (2000) utilized a five-day period as most games took place on weekends and matches were played once a week. If a game took place on, for instance, a Wednesday, a three-day period would be used instead. The match events were taken from the 3 seasons spanning 1995-1998, totaling 840 observations. Their research was conducted in order to draw further inferences into the following categories: 1) Sorting the matches depending on the outcome; 2) Separating matches based on leagues (English/Scottish/European); 3) promotion and relegation games; and 4) separating teams depending whether they traded on the LSE or the AIM.

When analyzing match outcomes, Renneboog and Vanbrabant (2000) found that victories resulted in next-day jumps of nearly 1% in stock prices and 1.3% over the course of the week. Losses however resulted in a 1.4% drop after the event, and a negative $\overline{CAR}$ of 2.5% over the following days. Draws similarly lead to 1.7% decreases over the following week. In terms of promotion/relegation games, victories resulted in a higher increase of 3.2% next-day and up to 4% over the course of the week, whereas a defeat resulted in a decrease of $\overline{AR}$ equal to 3.1% and 2.1% over the following days. The relegation matches produced even greater results, with victories resulting in 5.8% increases the first day and 10.4% cumulative returns over the coming week, and defeats noted a 6.5% decrease over the first day and the $\overline{CAR}$ resulted in 13.8%. Draws influenced the prices to swing down three days after matches. Gils (2016) found similar results when conducting an event study over the period of 2000-2015 while examining 30 publicly traded football clubs. After examining 10,915 match results, he concluded victories resulted in 0.48% $\overline{AR}$ whereas draws and losses resulted in -0.59% and -1.02% respectively.

Lastly, Renneboog and Vanbrabant (2000) examined the potential seasonal effects of their study and the impact of Manchester United as an outlier. For their three-season period, the first one consisted of only Tottenham, Celtic and Manchester United as publicly listed teams whereas the last one included all 17 publicly traded teams at the time. Manchester United was one of the most dominant teams at the time both in terms of match results and in regard to stock performance, which was evidenced by their weekly $\overline{CAR}$ post-victory increase of 2% compared to 1.3%, and defeats showed a decrease of 1.5% compared to the 2.5% decline other teams suffered.

To summarize Renneboog and Vanbrabant's findings, victories in regular matches resulted in a 1% increase in $\overline{AR}$ whereas defeats and draws resulted in decreases of 1.4% and 0.6%. The pattern was evident across all 3 geographic subregions that were examined. Additionally, relegation games had the most drastic effects on $\overline{AR}$, followed by promotion games. Although a few standout teams from this research period saw significant gains in their stock price, Jensen's Alpha and the Sharpe Ratio of an equally weighted portfolio of these clubs would have underperformed versus the market.

2.3.3 Football Betting Market

Palomino, Renneboog and Zhang (2008) further investigated how investor sentiment is affected by information salience, particularly as it pertains to the football betting market. They argue that although investors are reactive to information as it becomes available, they are limited firstly to the degree of how much information they can process and secondly by the salience, i.e. how prevalent or "loud" it is. The aim of their research was to determine the degree of difference in stock market price reactions when comparing the announcements. The characteristics of these announcements differ greatly; however, the area of specific interest is how the odds are limited to specific websites whereas game outcomes are flooded across a variety of news mediums. The authors focused on 4 areas of research: 1) do match outcomes affect stock prices, 2) are market reactions rational or do they overact because of investor sentiment/salience, 3) does the release of betting odds trigger stock price changes, and 4) can betting odds be used to predict stock returns?

At the time of their research 20 clubs were publicly listed, but because of restrictions in the amount of data or trading frequency, only 16 of them were included. Dummy variables were used to capture the varying degrees of certainty produced by the betting odds of wins/losses for a team. Palomino, Renneboog and Zhang (2008) found results which agreed with earlier work in the field, as it was reaffirmed that victories led to an increase in $\overline{AR}$ whereas losses and draws had the opposite effect. Interestingly, in the case of victories there was no evidence of $\overline{CAR}$ the following days, but losses did have the detrimental effect in the form of negative $\overline{CAR}$. Furthermore, results showed that increases were greater when teams were expected to win; however, the reaction was weaker in the face of a loss the more likely the ex-ante probability. Lastly, Palomino, Renneboog and Zhang (2008) found that in terms of betting odds' ability to predict stock movement the only statistically significant $\overline{CAR}$ was present when teams were strongly expected to win. This illustrates that salience alone cannot explain the results, and that investor sentiment is likely the dominant force in driving these price changes.

2.3.4 European Expansion

Saraç and Zeren (2013) sought to expand on the established consensus regarding team performance and stock reactions by examining the three most popular Turkish teams: Beşiktaş, Galatasaray and Fenerbahçe. Matches took place between 2005-2012. In addition to being located in a region other than the UK, these Turkish teams went public post 2000, offering a newer sample of data as compared to previous work. Saraç and Zeren confirm Edmans, Garcia and Norli (2007) that these small to mid-cap football stocks react to match performance as they are held by fans, extending upon the notion that this is attributable to the fanaticism often seen in sports fans (Klein, Zwergel & Heiden, 2009).

The conditions examined in Saraç and Zeren's (2013) work included the type of match played, the betting odds prior to the match, whether the match was played home or away and the lag between the match date and market opening date. The empirical model consisted of 8 explanatory variables to draw inferences how the stock return is affected by the various match conditions. Although the complete models were all found to be statistically significant in explaining the individual securities' returns, the only variable which was significant across all three teams was goal difference. Saraç and Zeren further noted that Besiktas had a substantially more significant value than the two other examined clubs, which they attribute to a beta value of 0.72 compared to 0.32 and 0.29. Further, it was noted that match importance (Europe or Champions league games) had a negative effect on the stock return. When observing these teams' performance in the major leagues over the observed period they did not perform well, which explains the negative correlation.

3. Hypothesis

The aim of the paper is to continue previous research in the realm of football match outcomes and the impact on their respective share prices. Twenty-two publicly traded teams on the STOXX Football Index plus Manchester United were analyzed to determine whether current conditions produce the same results pertaining to $\overline{AR}$ as previous work, as well as exploring the impact of momentum in sports and whether betting odds can significantly determine $\overline{AR}$ on the market after a match.

3.1 Hypothesis H_1: Abnormal Returns Match Outcome

The first hypothesis acts as a benchmark to previous research within the field: Match results have a significant impact on the share prices of publicly traded football teams. Winning matches will result in positive $\overline{AR}$, whereas draws and losses will result in negative $\overline{AR}$. The earlier studies were done by Renneboog and Vanbrabant in 2000 and later confirmed by Duque and Ferreira in 2008. Our study includes all currently publicly listed football teams through 2016-2019 to confirm the continued truth of this hypothesis.

H_1: Winning matches will result in positive AR while losing/drawing matches will result in negative AR.

3.2 Hypothesis H_2: Abnormal Returns Home Versus Away Matches

With the second hypothesis we will measure the effect of match location on the fluctuation in stock prices: “Home game victories will have a lesser $\overline{AR}$ than away victories, whereas draws and losses at home will have a greater negative $\overline{AR}$ than draws and losses away.” We speculate that the investors will be more surprised by a victory away, and as such the next trading day will have a more enthusiastic response in terms of higher $\overline{AR}$. Similarly a loss at home will have a greater impact because of the passionate nature of the sport. Investors will have a stronger reaction to these home games, as seen in earlier work conducted by Palomino et al. in 2008. This may be because a large portion of these stocks are held by fans of the team (Renneboog & Vanbrabant, 2000).

H_2: Home game victories will have a lesser $\overline{AR}$ than away victories, whereas draws and losses at home will have a greater negative $\overline{AR}$ than draws and losses away.

3.3 Hypothesis H_3: Abnormal Returns Two-Game Win Streak

The third hypothesis examines the role of momentum in sports and how it changes the reaction to match outcomes as seen in stock prices. Sports psychologists define momentum as "a positive or negative change in cognition, physiology, affect, and behavior caused by a precipitating event or series of events that will result in a shift in performance" (Taylor & Demick, 1994). As teams begin to build confidence in momentum, we predict their performance will be expected by investors. We believe teams that go on winning-streaks will result in expected future wins, resulting in lesser positive $\overline{AR}$ as compared to regular wins. Negative $\overline{AR}$ will be greater, however, than a regular loss because of the unexpected outcome by investors.

H_3: When teams play a match following two consecutive wins, a winning outcome will result in lesser positive $\overline{AR}$ as compared to regular wins, and greater negative $\overline{AR}$ in the case of losses/draws.

3.4 Hypothesis H_4: Abnormal Returns League Standing

The fourth hypothesis examines the role of team standing within their league starting at the series. This serves as an auxiliary signal alongside the betting odds, that earlier performance within the league should serve as an indicator of future performance. We expect the stock prices to react differently should a perceived superior team win as opposed to an underdog team securing a win. This ties into the markets' perception of expected and unexpected outcomes and probabilities of success. Defeating a higher ranked team is a more significant feat, and as such the markets' reaction will be stronger than in the case of a regular win, whereas losses are expected and as such the negative $\overline{AR}$ will not be as significant.

H_4: When a team beats a higher-ranked team, that victory will produce a higher $\overline{AR}$ than winning against a lower-ranked team. Further, losses and draws against a stronger opponent will not have such a drastic negative $\overline{AR}$ as against weaker teams. When a team wins against a weaker opponent, the positive $\overline{AR}$ will be smaller, while draws and losses will produce a greater negative $\overline{AR}$.

3.5 Hypothesis H_5: Abnormal Returns Betting Odds

The betting market operates alongside the sporting side of publicly traded clubs and offers early signaling in the form of betting odds. The final hypothesis addresses the impact of these predictions in relation to the $\overline{AR}$ after a match day. Based on these odds we can determine whether an outcome is expected or unexpected. If the match outcome aligns with the betting odds, it is considered an expected outcome, whereas if either of the two alternative outcomes take place against the odds it is considered unexpected. We expect the market to consider the betting odds as predictions, and should the outcome deviate from this prediction, the market reaction will be greater.

H_5: In the case of expected wins and losses, the absolute $\overline{AR}$ will be less than the absolute $\overline{AR}$ of unexpected wins and losses.

4. Data & Methodology

Section 4 covers the data sources and methodology used to investigate the abnormal returns of publicly traded football clubs in Europe. Additional descriptive statistics are provided for an overview of the results from the football matches.

4.1 Data and Sample Selection

Match and stock data were selected for the 23 publicly listed European football clubs which were active during the 2016-2019 seasons. Most of these clubs participate in their domestic top leagues, except for FK Teteks which played the 2016-17 season in the second division. Ruch Chorzow played 2017-18 in division 1 and 2018-19 in Division Two. Silkeborg played the 2018-19 season in Division One. Further, betting odds were not available for FK Teteks nor the secondary leagues for Ruch Chorzow and Silkeborg, and as such hypothesis five works with fewer observations as compared to the other hypotheses. The clubs examined may be found in table 2.1 in Appendix B.

Match results and betting odds from the 2016-2019 season were gathered from football-data.co.uk. FK Teteks match results were entered manually from macedonianfootball.com (2019). Ruch Chorzow and Silkeborg scores from lower divisions were taken from flashscore.com (2019). Teteks betting data was not available, as applies to two seasons for Ruch Chorzow and one season for Silkeborg. Share price data for the publicly traded clubs as well as the MSCI World Mid Cap Index was collected from the Bloomberg terminal.

4.2 Event Studies

In order to test the hypothesis listed in section three, multiple event studies were conducted on each team's matches over the course of the three-year research period. This was done to determine the effect of match outcomes on the share prices, and to measure whether $\overline{AR}$ were present. As discussed in the background chapter, the strong form of the Efficient Market Hypothesis states that share prices are a result of all available information on the market (Fama, 1970).

The methodology which is employed by this thesis closely resembles the model used by Fama, Fisher, Jensen and Roll (1969). Our study utilizes closing prices of football clubs' stock, meaning these may have been taken at varying times throughout the day. By using the market model to estimate AR we are taking the general trend of the market into consideration. Our sample consists of 23 teams of which 2 are British (Manchester United and Celtic).

We examined three-day $\overline{CAR}$ to measure the $\overline{AR}$ on the football clubs' stock, thus the three days of the event period need to be defined. We considered the football match to be the event date, which generally took place over weekends when the markets were closed. Day 0 is then the date of the most recent market close, day -1 is the prior listed stock price and day +1 is the market day following the match and captures the markets' reaction. In the event of consecutive match days or matches taking place within the same three-day observation window, the earlier occurring match was omitted in order not to overlap with other event windows. Although MacKinlay (1997) recommends setting up additional criteria for firm selection such as market cap and industry, the comparatively small sample of publicly traded football clubs removed the necessity of setting additional parameters for selection. For the purposes of this study we selected a 120-day estimation window per MacKinlay, which took place prior to the first match of the 2016 season. The same estimation window for each team was used across all seasons.

4.2.1 Procedure for an Event Study

The evaluation of the event's impact requires a measure of the AR. The AR is defined as the difference seen in actual return of the security versus the expected return of the stock over the event window, where the normal return is the expected return without conditioning on the event taking place. For company i and event date τ the AR is:

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau) \tag{1}$$

where $AR_{it}, R_{i\tau}$ and $ER_{i\tau}$ are the abnormal, actual, and normal returns respectively for the time period τ. X_τ is the conditioning information for the normal return model.

In order to model the normal returns, we used the market model where X_τ is the market return. In this model, the MSCI World Mid Cap Index is used as market return as we believe this best captures the characteristics of football-club stock in terms of value and trading. When using this model, we assume a stable linear relation between the market return and the return of the examined firm model. For any security i the market model may be written as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$
$$E(\varepsilon_{it} = 0) \qquad var(\varepsilon_{it}) = \sigma_\varepsilon^2 \tag{2}$$

where R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term. α_i, β_i and σ_ε^2 are parameters of the market model.

4.2.2 Analyzing Abnormal Returns

This research centers around measuring the changes in AR around football matches. T = 0 is considered the event date, $T = T_1 + 1$ to $T = T+2$ is the event window, and $T = T_0 + 1$ to $T = T_1$ is the estimation window. $L_1 = T_1 – T_0$ is the length of the estimation window and $L_2 = T_2 – T_1$ is the length of the event window. When conducting event studies, it is paramount for the estimation and event window not to overlap, as such certain matches were omitted: the most recent match was preserved in this case to capture the most recent response and sentiment in investors. Furthermore, this is done to prevent the event impact from affecting the normal return measure because the model requires impact to be captured by the AR.

4.2.3 Estimation of the Market Model

Under general assumptions, ordinary least squares (OLS) is a consistent estimation method when evaluating the market model parameters above and hence efficient. For the i^{th} company in event time, the OLS estimators of the market model parameters for our estimation window of observations are:

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1} * (R_{m\tau} - \hat{\mu}_m)^2} \tag{3}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i \hat{\mu}_m \tag{4}$$

$$\hat{\sigma}^2_{\varepsilon_i} = \frac{1}{L_1 - 2} \sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i \hat{\mu}_{m\tau})^2 \qquad (5)$$

where

$$\hat{\mu}_i = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{i\tau}$$

and

$$\hat{\mu}_m = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{m\tau}.$$

Given the market model parameter estimates obtained using OLS, we can analyze the AR. Using the market model to measure the normal return, the sample AR is:

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau} \qquad (6)$$

where $AR_{i\tau}$ represents the sample of L_2 AR for firm i during the event window. Under the null hypothesis and conditional on the event-window market returns, we expect AR to be jointly normally distributed with a zero conditional mean and conditional variance $\sigma^2(AR_{i\tau})$, where

$$\sigma^2(AR_{i\tau}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right] \qquad (7)$$

From (8), the conditional variance has two components: the disturbance variance σ^2_ε from (2) and also the additional variance due to the sampling error in α_i and β_i.

Under the null hypothesis, H_0, that the event has no impact on the behavior of returns (mean or variance) the distributional properties of the AR can be used to draw inferences over any period within the event window. Under H_0 the distribution of the sample AR of a given observation in the event window is:

$$AR_{i\tau} \sim N(0, \sigma^2(AR_{i\tau})) \tag{8}$$

4.2.4 Aggregation of Abnormal Returns

To state an overall conclusion for the event window, the AR observations must be aggregated. The aggregation is along two dimensions, through time and across securities. To accommodate a multiple-event window, it is necessary to explain the term of cumulative abnormal return (henceforth referred to as CAR). The CAR from τ_1 to τ_2 is the sum of the included AR:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}. \tag{9}$$

Asymptotically, as L1 increases, the variance of CAR_i is:

$$\sigma_i^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1)\sigma_{\varepsilon_i}^2 \tag{10}$$

The distribution of the CAR under H_0 is:

$$CAR(\tau_1, \tau_2) \sim N(0, \sigma_i^2(\tau_1, \tau_2)) \tag{11}$$

Given the null distributions of the AR and the CAR, tests of the null hypothesis can be performed. For each security, the AR were aggregated from (7) for each event period, which given N events the formula for period τ is:

$$\overline{AR_\tau} = \frac{1}{N^2}\sum_{i=1}^{N} AR_{i\tau} \tag{12}$$

consequently, the variance is:

$$var(\overline{AR_\tau}) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2 \tag{13}$$

The $\overline{AR}$ for any event period can be evaluated using these estimates.

Then, the $\overline{CAR}$ can be aggregated over the event window using the same procedure as that used to obtain the CAR for each security i. For any interval in the event window:

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR_\tau} \tag{14}$$

$$var\left(\overline{CAR}(\tau_1, \tau_2)\right) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR_\tau}) \tag{15}$$

where the variance of the $\overline{CAR}$ (15) is the sum of all variances of the $\overline{AR}$ over the event window.

Inferences about the $\overline{CAR}$ can be obtained using:

$$\overline{CAR}(\tau_1, \tau_2) \sim N\ [0, var\left(\overline{CAR}(\tau_1, \tau_2)\right)] \tag{16}$$

Finally, the null hypothesis that the $\overline{AR}$ are zero can be tested using

$$\theta_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{var\left(\overline{CAR}(\tau_1, \tau_2)\right)^{1/2}} \sim N(0,1) \tag{17}$$

4.3 Descriptive Statistics

Table 4.1

Total Matches

The table shows an overview of the total sample size of all matches and the different subsamples used to conduct the research. The European publicly traded teams played a total of 2325 matches, resulting 1304 victories, 499 draws, and 522 defeats. Based on the descriptive statistics, it is evident the publicly traded teams perform better than average, as seen for example by the 1304 victories compared to only 522 defeats. This is because the publicly traded teams sampled are generally the best teams of their respective leagues. For that same reason, the sample size of teams that win as expected per betting odds is large. As we can see, the subsample of betting odds presents fewer observations because betting odds for some of the teams playing in inferior divisions could not be obtained. For individual team match performance refer to table 3.0 in appendix C.

	Victory (%)	**Draw (%)**	**Defeat (%)**	**Total**
Total Sample	1304 (56%)	499 (21%)	522 (22%)	2325
Two game win streak	443 (62%)	152 (21%)	114 (16%)	709
Home	739 (63%)	224 (19%)	202 (17%)	1165
Away	565 (49%)	275 (24%)	320 (28%)	1160
Better team	56 (30%)	44 (24%)	86 (46%)	186
Worse team	587 (65%)	178 (20%)	145 (16%)	910
Expected betting odds	1132 (86%)	-	190 (14%)	1322
Unexpected betting odds	108 (27%)	-	287 (73%)	395

5. Results

Section 5 discusses the observed results from hypothesis 1 through 5 individually and concludes with an overall results discussion.

5.1 Results Hypothesis H_1: Abnormal Returns Match Outcome

Table 5.1

Abnormal Returns Match Outcome

This table displays the $\overline{AR}$ of all games played by the listed football clubs in the dataset. $\overline{AR}$ are split by wins, draws and losses. $\overline{\text{CAR}}$ for the three-day event windows are also shown, as well as the total number of observations. Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	0.00048	1.159		0.00705	16.418	***	0.00048	1.113	
0	0.00331	3.856	***	-0.0005	-0.581		0.00173	2.015	**
1	0.00390	3.027	***	-0.00289	-2.241	**	-0.01099	-8.529	***
N	1304			499			522		
$\overline{\boldsymbol{CAR}}$ **(3-day)**	0.00790	6.132	***	-0.00024	-0.187		-0.01193	-9.259	***

According to hypothesis H_1 Winning matches will result in positive $\overline{AR}$, whereas draws and losses will result in negative $\overline{AR}$. The results we found line up with all examined earlier research: Wins lead to positive $\overline{AR}$ whereas losses display the highest absolute negative $\overline{AR}$, followed by draws (Renneboog & Vanbrabrant, 2000). In the cases of victories, it can be inferred that the market anticipates the outcome as seen by the increase in $\overline{AR}$ from T_{-1} to T_0 for wins and with draws a strong $\overline{AR}$ at T_{-1} is followed by a negative return of -0.05% for T_0. Losses, however, do not seem to display this anticipatory characteristic as positive $\overline{AR}$ increase from T_{-1} to T_0, insinuating the market does not foresee the outcome. Although Palomino et al. (2008) was unable to find positive $\overline{CAR}$ for victories, based on our significant results we found this to be present.

5.2 Results Hypothesis H_2: Abnormal Returns Home Versus Away Matches

Table 5.2

Abnormal Returns Home Versus Away Matches

This table displays the $\overline{AR}$ of all games played by the listed football clubs in the dataset, split into categories of whether the game was a home or an away game. $\overline{AR}$ are split by wins, draws and losses. $\overline{\text{CAR}}$ for the three-day event windows are also shown, as well as the total number of observations. Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

Panel A: Home									
	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	0.00036	0.833		0.00411	9.559	***	0.00237	5.522	***
0	0.00356	4.142	***	0.00168	1.957	*	-0.00171	-1.998	**
1	0.00302	2.339	**	-0.00788	-6.11	***	-0.01728	-13.406	***
N	739			224			202		
$\overline{CAR}$ **(3-day)**	0.00714	5.537	***	-0.00213	-1.655	*	-0.01546	-12.001	***
Panel B: Away									
	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	0.00052	1.207		0.00343	7.978	***	0.00181	4.214	
0	0.00314	3.653	***	0.00568	6.614	***	0.00155	1.803	
1	0.00476	3.693	***	-0.00701	-5.435	***	-0.01408	-10.928	
N	565			275			320		
$\overline{CAR}$ **(3-day)**	0.00911	7.067	***	0.0021	1.633		-0.01083	-8.3991	

According to hypothesis H_2 the home games will produce a lower $\overline{AR}$ when compared to away games, whereas draws and losses at home will have a greater negative $\overline{AR}$ when compared to away games.

When examining victories, away games experience a slightly higher $\overline{CAR}$ as compared to away victories. Victories experience similar trends with modest gains at T_{-1}, and then hover rather constant from T_0 to T_{+1}. The location of a match has the most striking effect on games that end in a draw, as for home games this results in a three-day $\overline{CAR}$ of -0.21% whereas the same circumstance for an away game results in a 0.21% three-day $\overline{CAR}$. Although days T_{-1} and T_{+1} have similar values in both locations, it is interesting to observe that for home games T_0 $\overline{AR}$ are 0.17% but for away games the same day holds 0.57% $\overline{AR}$. When a team plays an away game, the market seems to be far more optimistic about the outcome; however, in both instances there is a trend that succeeds in predicting the outcome of the match. In the event of a defeat we see the largest discrepancy in reactions for the three outcomes under H_2. At home, a defeat leads to a three-day $\overline{CAR}$ of -1.55% whereas the same outcome away yields -1.08%. This largely stems from the negative trend observed at T_0 for home matches, suggesting the market is cautious toward these perceived negative potential outcomes.

Our findings support H_2 that there is a discrepancy between the $\overline{AR}$ depending on whether the game is played at home or away. Away victories $\overline{AR}$ were significant at the 1% level whereas for home games wins were significant at the 5% level. Away defeats did not show any statistically significant returns whereas home defeats were significant at all time intervals at the 1% level. This contrasts Bakx (2013) where day T_{+1} $\overline{AR}$ for victories were not statistically significant; however, defeats were. From the results we can determine that the market reacts more favorably toward victories when teams play away because of the perception that it is less likely for them to win, and the perception of losses at home have more impact at home. This is supported by the notion that these smaller football club stocks are held by local fans of a team (Edmans, Garcia & Norli, 2007), who would be in attendance at these home games, and as such the defeat would have greater salience in reaching the investors.

5.3 Results Hypothesis H_3: Abnormal Returns Two-Game Win Streak

Table 5.3

Abnormal Returns Two-game Win Streak

This table displays the $\overline{AR}$ of all games played by the listed football clubs in the dataset which were coming off a two-game win streak prior to the match observed. $\overline{AR}$ are split by wins, draws and losses. $\overline{\text{CAR}}$ for the three-day event windows are also shown, as well as the total number of observations. Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	-0.0025	-5.82	***	0.00263	6.111	***	-0.0009	-2.128	**
0	0.00529	6.154	***	0.0032	3.724	***	-0.00402	-4.679	***
1	0.00435	3.373	***	-0.0097	-7.51	***	-0.00843	-6.542	***
N	443			152			114		
$\overline{\boldsymbol{CAR}}$ **(3-day)**	0.00618	4.791	***	-0.0036	-2.823	***	-0.01329	-10.31	***

According to hypothesis H_3, when teams play a match following two consecutive wins, a winning outcome will result in lesser positive $\overline{AR}$ as compared to regular wins, and lesser negative $\overline{AR}$ in the case of losses/draws.

H_3 examines whether outcomes coming from two-game win streaks affect $\overline{AR}$ differently from regular outcomes. In the case of victories, three-day $\overline{CAR}$ for regular wins is only moderately higher than those for teams on a win streak. For win streaks, the market reacts negatively at T_{-1}, sees the strongest positive gain of the three-day window at T_0 with an $\overline{AR}$ of 0.53%. We can note that the win-streak scenario sees stronger $\overline{AR}$ at T_0 and T_{+1} as compared to the base case. When a draw occurs, the three-day $\overline{CAR}$ for the team on a win streak is weaker by roughly -0.30%, which is true for the loss scenario as well. At day T_{+1} we see the largest variance, where for teams on a win streak, the negative $\overline{AR}$ is nearly three times that of a usual draw. At day T_0, teams on a win streak still see a positive $\overline{AR}$ of 0.32% as compared to a negative value for usual draws, suggesting investors are still optimistic that past performance may predict future performance. We can see that $\overline{AR}$ after match days are greater for these teams that are on a win-streak whereas losses and draws do not cause the same degree of negative $\overline{AR}$ as compared to the base case. Although there is no earlier work conducted on this specific match circumstance, we can infer that investor sentiment can explain this deviance from the predicted outcome. Investors overreact to victories that were expected and underreact to unexpected losses, suggesting the local shareholders favor their preferred teams and fail to rationally evaluate the value of the stocks.

5.4 Results Hypothesis H_4: Abnormal Returns League Standing

Table 5.4

Abnormal Returns League Standing

This table displays the $\overline{AR}$ of all games played by the listed football clubs in the dataset, split into categories of whether the team faced a higher or lower ranked team as determined by league ranking. $\overline{AR}$ are split by wins, draws and losses. $\overline{\text{CAR}}$ for the three-day event windows are also shown, as well as the total number of observations. Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

Panel A: Higher ranked									
	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	0.00771	17.94	***	0.00800	18.608	***	-0.00492	-11.449	***
0	0.00193	2.248	**	-0.00085	-0.994		-0.00410	-4.768	***
1	0.00752	5.832	***	-0.00783	-6.072	***	-0.01863	-14.454	***
N	55			44			86		
$\overline{\boldsymbol{CAR}}$ **(3-day)**	0.01716	13.310	***	-0.00069	-0.532		-0.02289	-17.761	***

Panel B: Lower ranked									
	Victories			Draws			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	-0.00078	-1.82	*	0.00342	7.952	***	0.00861	20.035	***
0	0.00540	6.289	***	0.00543	6.315	***	0.00587	6.83	***
1	0.00349	2.71	***	-0.01248	-9.678	***	-0.02355	-18.269	***
N	587			178			145		
$\overline{\boldsymbol{CAR}}$ **(3-day)**	0.00664	5.148	***	-0.00369	-2.859	***	-0.00882	-6.845	***

According to hypothesis $H_{4,}$ in the event of an expected outcome as determined by league standing, $\overline{AR}$ will fluctuate less as compared to unexpected outcomes. When examining victories under the different conditions, facing a stronger team displayed the highest returns, followed by the base case and lastly beating a lower ranked team. Should a draw occur, this is perceived more negatively when the opposing team is of lower rank, which aligns with our findings in the win-streak hypothesis. Defeats were the most interesting situation to consider, where contrary to H_4 we found that losing to a higher ranked team had a substantially greater negative three-day $\overline{CAR}$ as compared to losing to a lower ranked team. Although day T_{-1} displays the most drastic negative $\overline{AR}$ of -2.35% for defeats against lower ranked teams, we can observe prior to this the security shows positive $\overline{AR}$ values as the market assumes a victory against the opposing team. Competing against a higher ranked team meanwhile is accommodated by negative $\overline{AR}$ throughout the entire event window.

Our findings are in line with other hypotheses that unexpected outcomes affect $\overline{AR}$ to a greater extent than their baseline counterparts. We can thus conclude that league standing as two teams face one another is a significant condition when predicting the degree of abnormal returns an investor would expect from the next trading day.

5.5 Results Hypothesis H_5: Abnormal Returns Betting Odds

Table 5.5

Abnormal Returns Betting Odds

This table displays the $\overline{AR}$ of all games played by the listed football clubs in the dataset, split into categories of whether the outcome was expected or not as per betting odds. $\overline{AR}$ are split by victories and defeats. $\overline{\text{CAR}}$ for the three-day event windows are also shown, as well as the total number of observations. Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

Panel A: Expected						
	Victories			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	0.00482	11.22	***	-0.00434	-10.105	***
0	0.00348	4.052	***	0.00048	0.556	
1	0.00298	2.314	**	-0.0142	-11.014	***
N	1132			190		
$\overline{CAR}$ **(3-day)**	0.01142	8.861	***	-0.01852	-14.369	***
Panel B: Unexpected						
	Victories			Defeats		
Day	$\overline{AR}$	t-stat		$\overline{AR}$	t-stat	
-1	-0.0024	-5.59	***	0.00434	10.111	***
0	0.00129	1.5		0.00312	3.632	***
1	0.01455	11.29	***	-0.01715	-13.306	***
N	108			287		
$\overline{CAR}$ **(3-day)**	0.01344	10.43	***	-0.00961	-7.456	***

According to hypothesis H_5 in the event of an expected outcome as determined by betting odds, $\overline{AR}$ will fluctuate less as compared to unexpected outcomes.

When examining victorious conditions, H_5 is correct in assuming unexpected victories have a stronger effect on $\overline{AR}$ as evidenced by the difference of 1.14% and 2.28% respectively. These results are largely attributable to the spike observed in the unexpected case where $\overline{AR}$ at T_{-1} is 1.30%, which is significantly higher than the expected results counterpart. The unexpected victory only had a greater T_{+1} $\overline{AR}$ of 0.11%, which leads us to believe the match outcome in this case did not significantly determine the three-day $\overline{CAR}$ for the study. Furthermore, the relatively stable $\overline{AR}$ over all event days in the expected case suggests that investors are predicting the victorious condition, whereas in the unexpected case the $\overline{AR}$ for T_0 is only 0.14%.

For teams that experience a defeat, we observe some contrast in the findings. As predicted, the unexpected defeat does have a greater absolute $\overline{AR}$ at T_{+1} in the unexpected case, as values are -1.72% compared to -1.42%, suggesting that investors are more shocked by this news and thus reflected in the $\overline{AR}$. In terms of the three-day $\overline{CAR}$, the expected defeat has a more profound effect, however, which can be linked to the negative $\overline{AR}$ at T_{-1} and low value at T_0. In the unexpected case, the market is quite optimistic, showing stable positive $\overline{AR}$ over the event days prior to the match. We can conclude from these findings that the investors aptly brace themselves prior to the match day anticipating the outcome and the return of the stock at T_{+1}. Significant day T_{+1} results were found for all conditions; however, expected victories were only statistically significant at the 5% level.

In the case of victories and defeats, our assumptions were correct in that unexpected results had a greater impact on $\overline{AR}$ as compared to expected results. This reaffirms our conclusions from the other hypothesis that sport sentiment leads to an overreaction in investors and hence drives $\overline{AR}$ beyond expected counterparts. When an unexpected win occurs, this leads the investor to overestimate a team's performance and drive up $\overline{AR}$ whereas the shock of an unexpected defeat causes greater negative $\overline{AR}$. Similar to the case of expected/unexpected outcomes as related to league standing, the betting odds serve as an additional variable to predict the magnitude of AR based on the match conditions.

5.6 Overall Results

Table 4.0 in appendix D displays the $\overline{AR}_{T+1}$ for all hypotheses and possible match outcomes. The data clearly illustrates how victories bring the greatest positive $\overline{AR}$ and losses the largest absolute negative $\overline{AR}$, with some mixed cases pertaining to draws and loses in terms of ranking. Under victorious conditions $\overline{AR}$ were significant at the 1% level for all hypotheses, whereas the same was true for losses with the exception of H_2 where significant abnormal returns were not found for away losses. Draws are largely not statistically significant, except for draws on home turf and draws facing lower ranked teams based on league standing.

For victories, the forerunner is H_5 with unexpected wins showing 1.46% $\overline{AR}$, followed by away-wins and win-streak wins with 0.48% and 0.43% respectively. In terms of defeats, the most detrimental outcome to $\overline{AR}$ is when losing to a lower ranked team, followed by losses to higher ranked teams and losses at home. $\overline{AR}$ are respectively -2.35%, -1.86% and -1.73%. The $\overline{AR}$ seem to conform to a trend: Surprising victories see a larger increase in $\overline{AR}$ than regular wins, whereas losses incur greater absolute negative returns when they occur at home or when facing lower-ranked teams within their league. These findings suggest that the emotions within sport sentiment drive the magnitude of $\overline{AR}$ a security will show after certain match outcomes and conditions.

6. Conclusion

The aim of our research was to examine how stock prices react to football match outcomes. We applied a broader, more diverse dataset than did previous researchers. We found that those earlier results still held true, with further findings relative to the effect of wins. Our baseline hypothesis showed $\overline{AR}$ of 0.39% for wins and -1.19% for losses. We found statistically significant results for wins as well as losses, which contradicts earlier studies where this was only true for losses. Results for H_3 tested a condition new to the field of research, where we discovered a greater impact for victories of teams on a win-streak. The reverse was surprising as we expected losses under these conditions to have a greater impact, but we found the stock price did not decline as much. This suggests sentiment for the teams on a win-streak, as a rational investor would find the unexpected loss more upsetting.

Our findings also line up with earlier research around football teams' stock $\overline{AR}$, and we confirm this applies to a broader range of nationalities within Europe as well. With this in mind, investors holding stock in publicly traded football teams should diligently check match outcomes when these teams play as inferences can be made as to how the price will fluctuate when markets open. Although it would be interesting to measure the extent to which this applies to other sporting teams, at this time researchers are limited by the quantity of publicly traded sports teams. Including more advanced regression methods to account for the low trading volume of some of the teams would further the validity of the research. Due to the limited amount of sample data within the field, future research should investigate whether investment strategies centered around these $\overline{AR}$ can be implemented to outperform market returns. To answer such questions additional focus would need to be turned towards predicting match outcomes along with stock price reactions.

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Appendix

Appendix A

Table 1.0: STOXX Football Index performance

Appendix B

Table 2.0: Club Listing and Delisting Dates

Club Name	Country	Division (2020)	Listing Date	Delisting Date
Aalborg	Denmark	Den1	14.09.1998	
Aberdeen	United Kingdom	Sco1	01.02.2000	01.08.2003
AGF	Denmark	Den1	15.03.2000	
AIK	Sweden	Swe1	31.07.2006	
Ajax	Netherlands	Ned1	11.05.1998	
Arsenal	United Kingdom	Premier League	09.08.2002	26.29.2018
Aston Villa	United Kingdom	Premier League	06.05.1997	1.08.2006
Benfica	Portugal	Por1	21.05.2007	
Besiktas	Turkey	Tur1	19.02.2002	
Birmingham	United Kingdom	Eng1	01.04.1997	14.10.2009
Bolton	United Kingdom	Eng1	01.04.1997	30.06.2002
Bradford	United Kingdom	Eng3	14.05.2002	17.05.2002
Brondby	Denmark	Den1	01.01.1987	
Celtic	United Kingdom	Sco1	01.09.1995	
Charlton	United Kingdom	Eng2	20.03.1997	21.09.2006
Chelsea	United Kingdom	Premier League	29.03.1996	22.08.2003
Copenhagen	Denmark	Den1	01.12.1997	
Dortmund	Germany	Bundesliga	30.10.2000	
Fenerbahce	Turkey	Tur1	17.09.2004	
Galatasaray	Turkey	Tur1	19.02.2002	
Juventus	Italy	Serie A	19.12.2001	
Lazio	Italy	Serie A	06.05.1998	
Leeds	United Kingdom	Eng2	01.08.1996	28.04.2004
Leicester	United Kingdom	Eng2	22.04.1997	25.11.2002
Lyon	France	Fra1	08.02.1997	
Manchester City	United Kingdom	Premier League	26.02.2002	06.07.2007
Manchester United	United Kingdom	Premier League	07.06.1991	

Millwall	United Kingdom	Eng2	01.10.1998	19.12.2011
Newcastle	United Kingdom	Eng1	01.04.1997	06.07.2007
Nottingham Forest	United Kingdom	Eng2	01.10.1997	16.04.2002
Porto	Portugal	Por1	01.06.1998	
Preston	United Kingdom	Eng2	01.09.1995	28.09.2010
QPR	United Kingdom	Eng1	01.06.1995	01.05.2003
Roma	Italy	Serie A	22.05.2000	
Ruch Chorzow	Poland	III Liga	01.03.2010	
Sheffield United	United Kingdom	Eng2	01.12.1996	07.20.2001
Silkeborg	Denmark	Den1	11.06.2005	
Southampton	United Kingdom	Eng2	21.04.1994	08.04.2009
Sporting Lisbon	Portugal	Por1	21.05.2007	
Sunderland	United Kingdom	Eng1	01.12.1996	05.08.2004
Tottenham	United Kingdom	Eng1	01.12.1996	05.08.2004
Teteks	Macedonia	North Macedonia	01.06.2001	
Trabzonspor	Turkey	Tur1	15.05.2005	
Watford	United Kingdom	Eng2	01.08.2001	01.06.2011
West Brom	United Kingdom	Premier League	01.02.1998	11.01.2005

Table 2.1: Clubs Examined

Club Name	Country
Aalborg	Denmark
AGF	Denmark
AIK	Denmark
Ajax	Netherlands
Benfica	Portugal
Besiktas	Turkey
Brondby	Denmark
Celtic	United Kingdom
Copenhagen	Denmark
Borussia Dortmund	Germany
Fenerbahce	Turkey
Galatasaray	Turkey
Juventus	Italy
Lazio	Italy
Lyon	France
Manchester United	United Kingdom
Porto	Portugal
Roma	Italy
Ruch Chorzaw	Poland
Silkeborg	Denmark
Sporting Lisbon	Portugal
Teteks	Macedonia
Trabzonspor	Turkey

Appendix C

Table 3.0: Football Club Scores

Club Name	Victories	Draws	Defeats	Total Matches
Manchester United	59	26	22	107
Juventus	86	15	12	113
Roma	69	23	21	113
Lazio	57	24	31	112
Lyon	64	22	27	113
Porto	75	17	7	99
Sporting Lisbon	65	18	16	99
Benfica	76	15	9	100
Besiktas	60	24	15	99
Fenerbahce	50	31	20	101
Galatasaray	63	16	22	101
Borussia Dortmund	57	27	18	102
Ajax	76	12	12	100
Trabzonspor	46	27	27	100
Celtic	82	20	8	110
Ruch Chorzaw	19	15	43	77
Brondby	55	23	26	104
Silkeborg	34	23	39	96
Copenhagen	68	19	20	107
Teteks	28	16	37	81
AGF	39	29	39	107
Aalborg	29	32	41	102
AIK	47	25	10	82

Appendix D

Table 4.0: Match outcomes and conditions ranked by $\overline{AR}_{T+1}$

Statistically significance at the 1%, 5% and 10% level is noted by ***, **, * respectively.

Hypothesis	AAR (percentage)	Significance
H_5 Win unexpected	1.46%	***
H_2 Win away	0.48%	***
H_3 Win	0.43%	***
H_1 Win	0.39%	***
H_4 Win lower ranked team	0.35%	***
H_2 Win Home	0.30%	***
H_5 Win expected	0.30%	***
H_4 Win higher ranked team	-0.08%	***
H_1 Draw	-0.29%	
H_2 Draw away	-0.70%	
H_4 Draw higher ranked team	-0.78%	
H_2 Draw Home	-0.79%	*
H_3 Loss	-0.84%	***
H_3 Draw	-0.97%	***
H_1 Loss	-1.10%	***
H_4 Draw lower ranked team	-1.25%	***
H_2 Loss away	-1.41%	
H_5 Loss expected	-1.42%	***
H_5 Loss unexpected	-1.72%	***
H_2 Loss Home	-1.73%	***
H_4 Loss higher ranked team	-1.86%	***
H_4Loss lower ranked team	-2.35%	***