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The Football Performance Effect on Stock Returns

An Event Study of Publicly Listed Football Clubs

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Abstract

We study the relationship between sporting performance and abnormal returns in football stocks. Based on a sample of 2,146 matches from nine European football clubs during 2014 through 2018, we find a positive stock market response after wins and a negative response after draws and losses. Using betting odds to measure market expectations, we find that abnormal returns are more precisely explained by the degree of expected performance. Losing in the European tournaments results in an even more negative abnormal return, and positive abnormal returns are only realized after highly unexpected outcomes. We also find evidence of the home advantage, even when taking betting odds into account.

Furthermore, our results indicate that turnarounds in performance yield greater abnormal returns. This means that a more positive stock market response follows when performing above expectations after underperforming in the previous match, and vice versa. Positive abnormal returns are also related to consecutive wins, while consecutive losses result in negative abnormal returns, though weaker than after turnarounds in performance. Additionally, the size of the abnormal returns seems to be time-dependent and increasing throughout the season.

Preface

This master’s thesis concludes our master’s program in business administration at Oslo Business School (OsloMet). The purpose of the study is to investigate how sporting performances affect the stock price of publicly listed European football clubs. Our passion for both the stock market and the beautiful game of football has made it very interesting to study these topics.

We want to express our sincere gratitude to our supervisor, Einar Belsom, for his guidance, valuable academic knowledge and constructive feedback. We also want to thank Per Arne Tufte for his helpful inputs regarding statistical matters. Finally, we thank Ole Morten Bratberg and his colleagues at Norsk Tipping AS for providing match statistics and betting odds.

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1 Introduction

Since football in its current form emerged in England in the middle of the 19th century, it has grown to become the world's most popular sport. In the beginning, only a few national football teams existed, and football was for a long time a British phenomenon (Footballhistory.org, 2020). Today there are 211 national associations affiliated with the Fédération Internationale de Football Association, the international governing body of football (FIFA, 2020). This emphasizes that football has become globalized.

Through this tremendous growth in popularity across the world, football has developed in terms of financial aspects. One example of this is that the biggest football clubs nowadays are acting more like commercial companies in order to become more competitive. They have introduced professional marketing strategies, made substantial investments in players and large stadiums, and some of them have aspired to become publicly listed (Renneboog & Vanbrabant, 2000). From 1999 to 2003, the number of publicly listed football clubs peaked (Aglietta, Andreff and Drut, 2010) and has since stabilized at approximately 20 clubs in recent years.

When football clubs go public, they may attract interest from both supporters affiliated with the club and investors seeking profit maximization. Even though football clubs are acting more like professional companies, their main goal may be to maximize performance rather than shareholder profits. Investments like player signings can yield both improved performance and profits, where performance and results might be of the highest interest for the club and the emotionally attached supporters. The rational investors, on the other hand, might be more interested in positive returns on their investments over time.

With the changing business models in the football industry, we see a shift towards profit-seeking operations in the clubs. Skyrocketing revenues and wealthy investors are now becoming the new standard as income related to broadcast and commercial rights are increasing and the share of matchday income is gradually decreasing. In the most recent edition of Deloitte Football Money League, as shown in Table 1, the share of matchday revenue for Manchester United has decreased by 5 percentage points in the last 5 years and is now only 17% of the total revenue (Ajadi, Burton, Dwyer, Hammond & Ross, 2020). This is also a trend for other clubs.

Table 1 – Manchester United Revenue 2015-2019 (in € million)

Source	2015	2016	2017	2018	2019
Matchday	114	137	125	120	121
% of total	*22%*	*20%*	*18%*	*18%*	*17%*
Broadcast	142	188	226	230	274
% of total	*27%*	*27%*	*33%*	*35%*	*38%*
Commercial	264	364	325	316	317
% of total	*51%*	*53%*	*48%*	*47%*	*45%*
Total	**520**	**689**	**676**	**666**	**712**

Source: Ajadi et al., 2020, p. 15

The decreasing share of matchday income is due to the stadiums having more or less a fixed capacity, which means that the only ways to increase matchday income is by playing more games or increasing the prices. The other two revenue categories, broadcast and commercial rights, are scalable. As described by Wigmore (2019) and Blitz (2015), the prices of broadcasting rights in the Premier League will likely continue to rise in the coming years. Commercial rights like sponsorship and kit sales also have a very high potential and increase with a club's global popularity. From an investment perspective, long contracts on sponsorship and broadcasting rights will be important, while low and stable matchday revenues may not affect the company's value significantly. Clubs that have a high growth potential in these scalable income sources could yield the highest stock returns.

The financial operations for a high-level European football club is solid, just like a lot of publicly traded industries. As described by Stadtmann (2006), unexpected news regarding a company's operations cause changes in asset prices. Frequently available news regarding traditional firms is often difficult to turn into useful and quantifiable information. Football clubs are unlike traditional firms due to a steady news flow in terms of match results during the season. This could be easier to quantify when considering financial aspects. Since this frequent news flow is uncomplicated to categorize, we have a unique opportunity to study how sporting performance relates to abnormal returns of publicly traded football clubs.

Previous research find evidence of abnormal returns in football stocks, e.g., Renneboog and Vanbrabant (2000). Scholtens and Peenstra (2009) find a positive and statistically significant stock market response following victories. After defeats they find that the market response is negative and stronger. Edmans, García and Norli (2007) use international football results as a mood variable to investigate the stock market's reaction to sudden changes in investor mood and finds that a loss in the World Cup elimination stage leads to a next-day negative abnormal return.

The purpose of our thesis is to investigate whether the football clubs' performance in terms of match outcomes have an impact on the stock prices. In line with previous research, we will study the effect of a win, draw and loss. To adjust for the element of surprise, we use betting odds to calculate the probability of a match outcome. We also investigate potential effects of different tournaments and locations. Our sample includes nine European clubs from nine different countries with match results and stock returns from the beginning of 2014 to the end of 2018. Hence, our study includes a more recent and diverse sample than previous research.

We provide two novel forms of analysis within research on football stocks. Inspired by the momentum effect in stock markets, our first contribution will be to test if there is a potential performance effect in consecutive games. This includes analyzing both persistent performance and performance turnarounds, from match to match. Since most of the crucial matches are played towards the end of the season, our second contribution will be to study how abnormal returns varies throughout the season. To the best of our knowledge, these effects have not been studied before.

We conduct an event study and analyze our results through the ordinary least squares method. Our estimations will be based on heteroskedasticity-robust standard errors. To find the expected returns, the market model is usually applied in event studies. Making sure the market model is applicable, we consider three alternative ways of calculating the expected returns. Due to the high frequency of new information, we will use a short event window of one day.

In addition to a presentation and discussion about our main findings, we will analyze the robustness of our models. This includes testing clustered standard errors and the effect of removing outliers. We also take nonnormality into account through bootstrapping. Furthermore, we will conclude and compare our results with existing literature and discuss whether these can be generalized. Finally, we will highlight potential limitations of our thesis and give our recommendations for future research.

2 Literature Review

In this review, we will cover topics related to our thesis within the existing literature. In the first section, we discuss previous research on how sporting events affect football stocks and mood. Additionally, we consider other aspects that may affect the price of football stocks. Second, we discuss the theory of efficient markets. Third, different kind of investors and how they react to new information are covered. Finally, we investigate the Monday effect and the payout structure in European football tournaments.

2.1 Match Results and Stock Returns

As mentioned in the introduction, several studies have investigated the relation between match outcomes and football stock returns in the past. Renneboog and Vanbrabant (2000) investigate whether the stock prices of publicly listed football clubs are influenced by sporting performance. Their event study reveals that positive abnormal returns at 1% is expected the first trading day after a win, and negative abnormal returns at 0.6% and 1.4% after a draw or loss respectively. Accumulating the abnormal returns over the week, they find evidence that defeats and draws trigger abnormal losses of 2.5% and 1.7%. In promotion and relegation games they find an even greater effect, with abnormal returns of 3.2% after a win and -3.1% after a loss.

In another study, Zuber *et al.* (2005) consider the performance of 10 publicly traded clubs in the English Premier League from 1997 to 2000. As a surprise variable, they include subjective winning probabilities by converting betting odds into dummy variables for expected outcomes. This made it possible to measure whether the result was expected or not, but not by how much the actual result differed from what was expected. They find that the stock price of the football teams is insensitive to unexpected match outcomes. To explain this, they state that investors in such firms do not trade on financial information, but utility from mere ownership due to passion for their respective team.

Stadtmann (2006) applies the news model to the football industry to study whether sporting results can explain changes in the stock price of Borussia Dortmund. Incorporating betting odds, he controls for whether a match outcome was expected or not. He also finds support for positive and negative abnormal stock returns for a won or lost match respectively. Stadtmann finds no statistically significant evidence that games in European competitions influence stock returns to a larger extent, despite that the coefficient for matches played in the Champions League is larger compared to the German Bundesliga estimates. Furthermore, a reversed news model is applied to his research to check the robustness. He points out several other news that plays an important role to stock returns. A limitation in his study is that only one football team is included in the analysis, which means that generalizing the results is difficult.

A more recent study analyzing the effect of football matches on stock market returns is conducted by Scholtens and Peenstra (2009). Studying 1,274 matches of eight teams in the national and European competitions, they find that the stock market response is positive and negative after a victory and defeat respectively. An interesting finding in their study is that the response to a loss is larger than after a win. Furthermore, they find that the market reacts stronger to results in European competitions.

Common for the studies discussed above, except from Zuber *et al.* (2005), is the evidence of abnormal returns after a victory or defeat. Today, these studies consist of old data and some of the studies only include football teams from a limited geographical area. Hence, it might be problematic to generalize their conclusions to a more recent setting and across several clubs from different nations. None of the papers discussed in this section study a potential performance effect in consecutive games or how abnormal returns differ throughout the season.

2.1.1 Sporting Events' Emotional Impact

Motivated by the abundance of evidence showing that sports results have an effect on mood, Edmans *et al.* (2007) employ a mood variable, match results from national football teams, to investigate the effect of investor sentiment on asset prices. By including results and cross-sectional data from 39 countries, they find that losses have an economically and statistically significant negative effect on the losing country's stock exchange. An effect is also found for international cricket, rugby and basketball, but not as strong as the football effect.

Another study analyzing a sporting event's effect on another variable is Trovato (1998), who examine the Stanley Cup of Hockey playoffs' connection to suicides in Quebec. Mostly he finds no statistically significant results on whether a loss or win in the Stanley cup finals impacts the suicide rate in Quebec. One exception was that Montreal Canadiens' early elimination in the Stanley Cup may have increased the risk of suicide by young men in Quebec. Trovato also finds some controversial results;

> On the exact day when Montreal are ousted early from the finals of the Cup series, there are fewer female suicides than expected … But when Montreal lose the Stanley Cup finals, suicide incidence goes up one day prior to this. In the two days preceding a Stanley Cup victory, suicide appears to be more likely than usual among 15- to 34-year-old women. (Trovato, 1998, p. 117)

Except from these findings, the study finds no statistically evidence on whether a loss or win in the Stanley cup finals impacts the frequency of suicides in Quebec. In his regression table on page 114, he presents a low R^2. This does not imply that the events have no effect on suicides but indicates that there are several other variables that affects the suicide rates.

Based on the findings in Edmans *et al.* (2007) and Trovato (1998) it seems like sporting outcomes might have an emotional impact. Assuming that the mood of the investors affects investment decisions, we believe that this could be a contributing factor to the link between sporting events and stock price fluctuations.

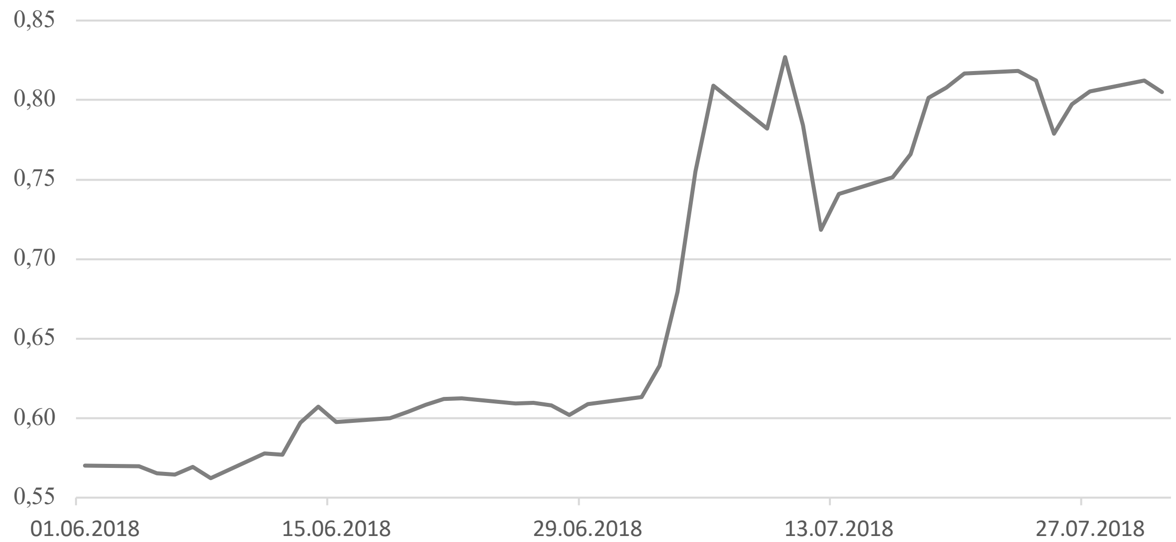
2.1.2 Other Aspects Affecting Football Stocks' Prices

Analyzing the results of existing literature, we see that match outcomes do not explain all of the price reactions when it comes to football stocks. As an example, Stadtmann (2006) consider the R^2 of 0.1606 as exceptionally high in a model including expected or unexpected match outcomes for the German Bundesliga, European cup and German national cup. He describes potential omitted explanatory variables such as overall ranking, meaning that the success of one team (Borussia Dortmund) is also influenced by the sporting success or failure of its major competitors. Furthermore, he points out some important events due to corporate governance-related information.

Another potential omitted variable is player transfers. These could be perceived as either positive or negative amongst investors and fans, depending on how they value the new player compared to the investment cost. Even though Stadtmann (2006) does not find coefficients significantly different from zero related to this, some player signings could still seem to affect share prices.

When Cristiano Ronaldo was sold from Real Madrid to Juventus in the summer of 2018, a lot of expectations came along with the player. Not only was he expected to improve Juventus from a sporting point of view but signing a player like Ronaldo also dramatically increases kit sales and other factors related to revenue for the club. In the first 24 hours after being announced as a Juventus player, Juventus sold 520,000 shirts compared to 850,000 for the whole 2016/17 season (Hess, 2018). In the same 24-hour time frame, Juventus also increased their social media followers by 2.2 million, and in the first 17 months following the signing, their Instagram account went from 9.8 to 33.5 million followers (Doyle, 2019). Clearly, this kind of signings are affecting a football club, a fact that is also taken into account by investors. In Figure 1, we see the direct impact from the signing of Ronaldo on the Juventus share price. As rumors of the potential move began to spread in the week before the signing was announced, Juventus experienced a 35% share price increase from 2 July to 10 July. On the day of the announcement, the price dropped, only to rise again a week later.

Figure 1 – Juventus Share Price June/July 2018



Based on previous research and the aspects presented above, it is clear that football stock prices are affected by a lot more than match results and performances. In this thesis, we only cover one kind of event affecting prices, and thus it is important to keep in mind that our models will, to a large extent, yield low explanatory power.

2.2 Market Efficiency

The theory of efficient markets was developed by Fama in 1970. This theory led to the efficient market hypothesis (EMH). According to the EMH, the market prices reflects all available information. Fama (1970) introduced three concepts about market efficiency depending on how much information that is available for the market participants; weak, semi-strong and strong form of efficiency. The weak form of market efficiency states that all historical information about prices are baked into today's price. The semi-strong states that share prices reflects all public information. The strong form states that prices reflect all public and private information.

To test whether new public information affects stock prices, event studies are normally used. If the results from the study show that prices reflect new information quickly, markets are semi-strong form efficient. An example is Ball and Brown (1968) that studied whether the accounting income numbers had an impact on the stock price. They found that the stock price is affected, but only if the numbers are surprisingly good or bad.

As described in our introduction, new information may occur more frequently for a football club than for other companies. This information in form of match results will become known at the same time for all stakeholders, since no one knows the result before the match is played. What is especially interesting about Ball and Brown's findings in relation to our study is whether a return on a football club's stock price will be larger or smaller if the win or loss was expected or not. We will get back to this in chapter 3 and 4.

2.3 Shareholders

Professor in sport economics, Harry Arne Solberg, states that if you are going to achieve return on your investments, you should not invest in football stocks (Nilsen and Normann, 2012). Further, he says that the football teams differ from an ordinary company, since their objective may not be to maximize the shareholders' return. This statement makes it interesting to investigate who the owners of these shares are.

Renneboog and Vanbrabant (2000) separates the shareholder structure of football clubs into three categories; controlling shareholders, institutional investors and many individual investors. They also state that the individual investors may often be fans who consider holding shares as a way of supporting their teams and think of potential profit as a bonus only.

Leach and Szymanski (2015) argued that many of the shareholders may invest in football clubs to increase their public profile and status. Further they refer to Sloane (1971) on how professional sporting teams in the United States are considered as profit-maximizing businesses, while European teams are considered as utility-maximizing. Studying 16 English football clubs that went public in the mid-1900s, Leach and Szymanski (2015) found no positive shift toward profit-maximizing behavior. This means that clubs in England did not change their behavior due to profit- or utility maximization after going public.

Based on existing literature, there seem to be evidence that investors in football stocks are both profit- and utility oriented. For a fan-shareholder, success on the pitch may be the most important objective. In addition to this, fan-shareholders could also be affected by allegiance bias. Allegiance bias can cause an unrealistic view on future performance (Markman & Hirt, 2002). This could cause irrational investors that impact fluctuation in stock prices. Additionally, if shareholders only care about supporting their respective clubs, they may not sell or buy stocks due to specific match outcomes.

2.4 Momentum Strategy & Investor Reactions

The momentum strategy in stock markets is well-documented in the literature. In practice, this means that buying past winners and selling past losers should yield an abnormal return. Several papers document the effect in different markets. Jegadeesh and Titman (1993, 2001) document a momentum effect on a 3- to 12-month period in the U.S. stock market but emphasizes that these returns are reversed in subsequent periods. This reversion is also documented further by Lee and Swaminathan (2000). Analyzing the markets in 12 European countries, Rouwenhorst (1998) arrives at similar results by finding higher returns for a portfolio consisting of previous winning stocks than for a portfolio of previous losing stocks.

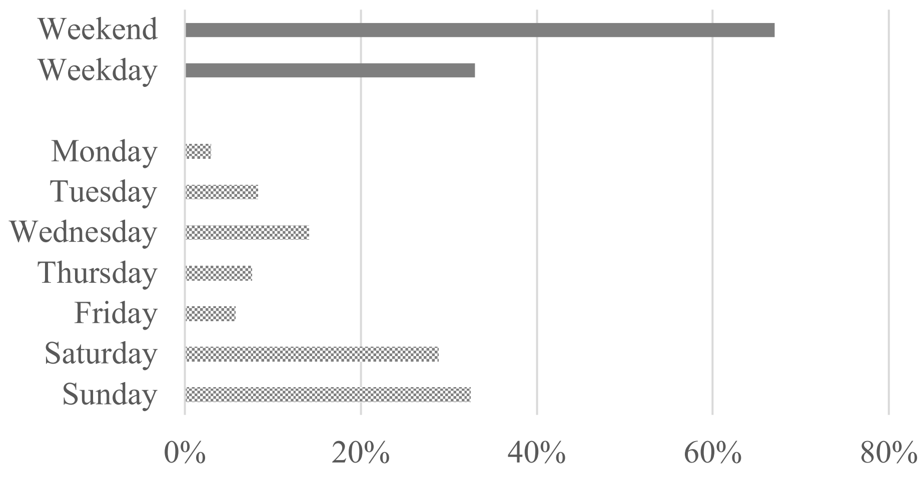
The momentum effect is not that straight forward though, as research done by the likes of De Bondt and Thaler (1985) show cases of how investors overreact to unexpected information. Because of this, portfolios with loser stocks are now outperforming winner portfolios in the long term. The momentum effect seems to be somewhat ambiguous, but still the strongest case can be made for winners to keep outperforming losers, at least in the medium term.

What makes this interesting in relation to football stocks is whether previous returns affect returns in the future on an event-to-event basis, and whether this potential effect can be related to match results. The utility of those that have invested in football clubs can reasonably be measured by direct returns, but also the feelings associated with the club winning or losing, assuming the investor is also a fan of the club. Thus, when analyzing a potential momentum effect, we must keep in mind that a loss in utility is often perceived as worse than a similar gain (Kahneman and Tversky, 1979). If both their findings and the momentum effect can be translated into football stocks, we should expect that losing matches and experiencing negative returns will cause even worse performances on the stock exchanges.

2.5 The Monday Effect

Football is usually played during weekends, and as illustrated in Table 2, our sample is no exception with 67% of the matches played on Friday, Saturday or Sunday. This brings up the weekend, or Monday, effect and whether we should take this into account in our research.

Table 2 – Matchday Distribution From the Sample



Through a meta-study, Pettengill (2003) gives an overview on how there is a range of different findings all supporting the Monday effect, that is that Mondays are characterized by negative or more negative returns than the preceding Friday. Statistical evidence of the

Monday effect came as early as the 1920s and 1930s, getting further backing in the 1970s and 1980s. Cross (1973) finds evidence that the number of stock price increases on Fridays are significantly higher than those on Mondays. Analyzing the S&P 500 Index, French (1980) finds persistent negative returns for Mondays. Jaffe, Westerfield and Ma (1989) find that the negative average returns on Mondays only occur when the market was already declining in the previous week, while Wang, Li and Erickson (1997) only find evidence of the Monday effect in the last two weeks in each month. We see that more recent research begins to cast doubt about the magnitude of the Monday effect, and as summarized by Pettengill (2003), it has been found that the effect disappeared or even became positive for large-firm securities, but not for small-firm securities.

Clearly there are ambiguous findings regarding the Monday effect and whether it is necessary to take it into account. Pettengill does further research on findings related to possible reasons for the Monday effect, not reaching any satisfactory conclusions as backing for, nor against, the effect. His conclusion is that the Monday effect either has to be based on the market not being efficient or that it is just rational responses to relevant information. Even though our sample might be affected by a Monday effect, we believe that this will not impact how sporting performance affects abnormal returns, only increase the amount of white noise. Thus, we will consider only relevant information from our events, without any adjustments for a potential Monday effect.

2.6 Prize Money and Its Effect on Cash Flows

A reason why stock prices fluctuate is investors' expectations of future cash flows. This raises the question of how prize money related to match and tournament outcomes affect stock prices of publicly listed football clubs. E.g., in the Premier League, prize money is distributed based on an equal share to all clubs, their league ranking and the TV income (Planet Football, 2019). This distribution of revenues in national leagues causes reduced cash flow effects from a single match perspective. In the European tournaments, on the other hand, we will see that each match potentially generates a higher future cash flow.

Stadtmann (2006) states that prize money from the European competitions should be considered when investigating how match outcomes affect stock prices. Participating in the European football tournaments arranged by Union of European Football Associations has a high standing among the top teams in Europe. Not only is the UEFA Champions League (UCL) and the Europa League (UEL) popular from a sporting point of view, but they are also a significant source of income. Prize money is based on participation in both the qualification, group and knockout stage. In addition to this, extra income is generated based on wins and draws in the group stage and the final, as well as a ten-year team ranking based on previous achievements. Finally, commercial income related to the TV market is split across the clubs from the different countries.

Based on the revenues as stated by football-coefficient.eu (2020), we have summarized the European football prize money paid by UEFA to the nine clubs in our sample in the 2018/19 season. Ajax, Borussia Dortmund, Juventus, Lyon, Manchester United and Porto all participated in both the group and knockout stage of the UCL. Copenhagen participated in the group stage of the UEL, while Celtic played both in the group and knockout stage. Galatasaray started in the UCL group stage but did only qualify for the UEL knockout stage. This resulted in revenues as summarized in Table 3 below.

Table 3 – European Football Prize Money 2018/19

Club	European Prize Money*	No. of Matches	Prize Money / Match
FC Porto	€ 78,458,000	10	€ 7,845,800
Juventus	€ 75,966,000	10	€ 7,596,600
Manchester United FC	€ 75,274,000	10	€ 7,527,400
Borussia Dortmund	€ 58,610,000	8	€ 7,326,250
Olympique Lyonnais	€ 53,002,000	8	€ 6,625,250
AFC Ajax	€ 77,266,000	12	€ 6,438,833
Galatasaray SK	€ 29,322,000	8	€ 3,665,250
FC Copenhagen	€ 7,078,620	6	€ 1,179,770
Celtic FC	€ 9,315,760	8	€ 1,164,470

**Prize money from both the UEFA Champions League and Europa League for the 2018/19 season*

Source: https://www.football-coefficient.eu/money/

In the UCL, the prize money is higher than in the UEL. All clubs that got to at least the UCL knockout stage received a minimum of €6.4 million per match, with an average of €7.2 million per match. Prize money decreased drastically for those not participating in the UCL knockout stage with a maximum of €3.7 million per match and an average of €2.0 million per match. These 3 teams (Galatasaray, Copenhagen and Celtic) registered fewer wins and draws in the group stages than the other 6 teams, which also contributed to the lower revenues.

It is clear that participating, and winning matches, in the European competitions generates a substantial source of income for the clubs. Compared to their national leagues, a win in the UCL or UEL will most likely lead to a higher revenue per match.

As one of the most commercial leagues, the Premier League is associated with high payouts to the clubs. In the 2018/19 season, Liverpool received a total of £149 million from the Premier League (Planet Football, 2019). This was the highest payout in that Premier League season. Using an exchange rate of 1.5 EUR/GBP, this is equivalent to €4.5 million per match. This is €1.0 million less than the average European payout for all our nine clubs listed in Table 3, and €2.7 million less than for those that played in the UCL knockout stage. Keep in mind that these numbers are per match. In total, on the other hand, prize money will be larger in the leagues than in the European tournaments, at least in the Premier League. Winning matches and participating in the UCL or UEL should be considered as more exclusive moneywise than the national leagues when analyzing the effect of each single match.

3 Data & Methodology

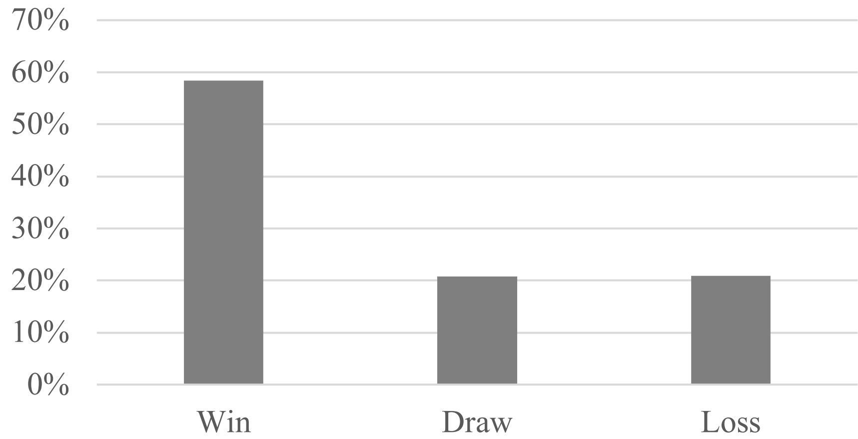
In this chapter, we will give a detailed description on how we construct our sample, how we gather data and which methodology we apply. In our sample selection we investigate which football clubs and matches to include. Next, we present our data sources and the selection of stock indices. Finally, we give a thorough review on how we conduct our event study, step by step.

3.1 Sample Selection

To select which football clubs to include, we made some assumptions; the club must be listed today and also have participated in either the UEFA Champions League or UEFA Europa League in the time period. One potential limitation we face by making these assumptions is the possibility of survivorship bias. “Survivorship bias is the tendency to view the performance of existing stocks in the market as a representative comprehensive sample without regarding those that have gone bust” (Chen, 2019). We notice that the number of listed football clubs was higher some years ago than it is now, which means that the clubs that are still listed today could be better performing clubs than those that have been delisted in recent years. We believe that this will not be a major threat to our research, and thus, including clubs that have not been listed within the whole sample period will not be taken into account.

Another potential disadvantage comes from the assumption of participation in the European tournaments. By only adding these clubs, we include clubs that on average win more than they lose or draw, as they are the best clubs in their respective national leagues. Our data sample consists of matches with a 58%-win rate and draw and lose rates of 21% each, as shown in Table 4. This could cause bias in our estimates, but we do not see this as a major threat because we account for this problem by including betting odds in our model. Betting odds solve this issue by accounting for the relative strength between the opponents, and thus, it will be easier to measure relative performance.

Table 4 – Win-, Draw-, Loss Rate From the Sample



Based on previous research and web pages such as KPMG Football Benchmark (2017) and finance.yahoo.com we found 16 clubs matching our criteria. These are listed in Appendix I. The 16 clubs are split across nine countries. Since we want to have a broad view on European football, we choose to set a limit of maximum one club from each country. Stock & Watson (2015) state that having a sample with overrepresentation of one part of the population can cause sampling bias. Thus, we believe that more than one club from a country could lead to sampling bias in our sample, as clubs from countries with more than one publicly listed football team would be overrepresented. Another potential issue could be cross correlation if two clubs from the same country are both affected by country specific events. Hence, we choose to include one club from each of the nine countries.

We introduce a rating system, currency adjusted relative volume (CARV), to help us choose the nine clubs. CARV is the trading volume for a specific time period related to the club's stock price when converted to a common currency, in this case EUR. Based on a liquidity preference, we include the club from each country with the highest CARV, as presented in Appendix I. This gives the following nine clubs: Galatasaray SK (Turkey), Juventus (Italy), Borussia Dortmund (Germany), FC Porto (Portugal), Olympique Lyonnais (France), Manchester United FC (England), F.C. Copenhagen (Denmark), AFC Ajax (Netherlands) and Celtic FC (Scotland).

Appendix I shows that trading occurs much more frequently in Turkey and Italy, than in the Netherlands and Scotland. Even though Ajax and Copenhagen only have a CARV which is almost just a tenth of Manchester United, and Celtic is just almost a tenth of that again, we still include them as we believe this will strengthen our sample by diversifying with both heavily and thinly traded clubs. Among the infrequently traded stocks we see that especially Celtic FC has a large amount, 91%, of zero returns first trading day after a game. This could be a potential problem for our analysis. We will consider this issue in section 4.6.

3.2 Data Sources

We received a dataset containing historic odds and results from the Norwegian lottery and betting company Norsk Tipping AS. They did an excerpt of results and odds from 27 November 2012 to 25 May 2019 for the clubs listed in Appendix I. We are aware of differences between odds from different bookmakers. However, we do not see using only one bookmaker as opposed to a market average as a threat to our research since we remove the bookmaker's mark-up, as we show in section 3.3.4. We would also like to point out that odds from different betting companies usually are quite similar, because the bookmakers want to prevent arbitrage betting.

Daily stock prices and returns are downloaded from Thomson Reuters Eikon. We downloaded data from 1 November 2012 to 31 July 2019 to match the data from Norsk Tipping. All the clubs in Appendix I were included, and in addition we downloaded the same information for the following all share indices based on where the different clubs are listed; BIST All Shares Index (Turkey), FTSE Italia All-Share Index (Italy), DAX Composite Index (Germany), PSI All Share Gross Return Index (Portugal), CAC All Share Index (France), NYSE Composite Index (USA, Manchester United), OMX Copenhagen GI (Denmark), AEX All Share Index (Netherlands) and FTSE All Share Index (England, Celtic). STOXX Europe Football Index was also downloaded for the same period.

We also tried to do the calculation of abnormal returns using the main indices for the same countries; BIST 100 (Turkey), FTSE MIB (Italy), DAX (Germany), PSI 20 (Portugal), CAC 40 (France), NYSE Index (USA, Manchester United), OMX Copenhagen 20 (Denmark), AEX (Netherlands) and FTSE 100 Index (England, Celtic). Those are indices including only the largest companies in the respective countries. Despite statistically significant and similar results as when using all share indices, we choose to keep using the all share indices due to the fact that a football club usually is smaller and different from the largest companies in each country.

3.3 Methodology

We study our research topics by conducting an event study. An overview of this methodology is given in Brown and Warner (1980, 1985), Bowman (1983), Dyckman, Philbrick and Stephan (1984) and MacKinlay (1997). One purpose of this method is to measure the impact of a specific event on a firm's value.

Bowman (1983) describes five steps to follow when conducting an event study:

1. *Identify the event of interest.*
2. *Model the security price reaction.*
3. *Estimate the excess return.*
4. *Organize and group the excess returns.*
5. *Analyze the results.*

Our event of interest is any football match played by the nine clubs in the European tournaments and their national leagues and cups. This means that we will observe quite frequent events throughout the year, except between the seasons. Our sample will consist of 35-60 events for each club per calendar year. As described by Brown and Warner (1980), having a precise definition of the event date is important. In our case, this is not a major problem as our events, the matches, all have a specific date. Since the outcomes cannot be known in advance, unless facing the problem of match fixing, we see no reason to start our event window before the match itself. Further, our return of interest is limited to the first trading day after the match is played. Thus, our event window lasts from matchday to the following trading day, with the matchday being day 0. If a club plays two matches between two trading days, both matches are removed from our sample. This is because the first trading day will be affected by both outcomes and it will be difficult to separate the effects. Hence, our sample is reduced by 50 observations.

To aggregate daily abnormal returns, event studies often use cumulative abnormal returns (CAR) or buy-and-hold abnormal returns (BHAR). As a consequence of the high frequency of events, we do not see it as preferable to use neither CAR, nor BHAR, in our study. Hence, we maintain our conclusion about using a very short event window.

Another issue could be confounding events such as player signings or earnings announcements within the event window. Based on the number of events we observe each year, and the ambiguous effects of events such as player signings, we believe that removing matches with confounding events will not add enough value compared to the downside, which is the reduced number of events and time consumption. However, we will still examine potential problematic outliers in our robustness chapter.

When choosing our period of examination, we prioritize based on the following criteria: *1) Recent data*, and *2) Sufficient number of observations.* Existing studies on this topic are based on older samples, and thus we want to find results based on more recent information. As described by Edmans *et al.* (2007), one of the main disadvantages of event studies is that the number of observations is usually quite low. To prevent this disadvantage, our period of examination will start at 1 January 2014 and end at 31 December 2018, which leads to a sample of 2,146 football matches. This is 1,046 more than used by Edmans *et al.* (2007). By starting our examination period 1 January 2014, we make sure that we have gathered enough data for our estimation period. The estimation period will be discussed in section 3.3.1.

To model the security price reaction, we define the actual return for all stocks and indices. Using discrete returns, we define $R_{j,t}$ as:

$$R_{j,t} = \frac{P_{j,t}}{P_{j,t-1}} - 1$$

Where $P_{j,t}$ is the price of club *j* at the end of period *t* adjusted for dividends and stock splits and $P_{j,t-1}$ is the price of club *j* at the end of period t – 1 adjusted for dividends and stock splits.

3.3.1 The Market Model

To calculate the abnormal, or excess, return we also need to establish expected returns. The expected return is the estimated return if no event occurs. We use the market model discussed in Brown and Warner (1985) and Dyckman *et al.* (1984) as our main model to calculate the expected returns. The difference between the actual and expected return is the abnormal return. Three other possible models for abnormal returns will be discussed later in this chapter. We also discussed using the Capital Asset Pricing Model (CAPM) instead of the market model, but since the market model is considered as superior to the CAPM (MacKinlay, 1997), our decision is to stick to the market model.

We follow the approach used and suggested by Scholtens and Peenstra (2009) and Brown and Warner (1985) and use an estimation period of 250 trading days. We thus have a rolling estimation period that moves for each match, so that there is a 250 trading days estimation period before each event. The expected return using the market model is defined as;

$$\hat{R}_{j,t}^{MM} = \hat{\alpha}_j + \hat{\beta}_j R_{m,t}$$

Where $R_{m,t}$ is the return of the market index at day t, $\hat{\alpha}_j$ and $\hat{\beta}_j$ are the OLS regression estimates when regressing the index returns on the stock returns using the estimation period of 250 trading days. The beta $\hat{\beta}_j$ is an estimate of the shares' risk compared to the stock market. The $\hat{\alpha}_j$ is the intercept from the regression line.

We notice that some of the stocks included in our thesis are thinly traded. Brown and Warner (1985) show that this could lead to inconsistent and downward biased β-estimates. They also state that "by construction, OLS residuals for a security sum to zero in the estimation period, so that a bias in the β-estimates is compensated by a bias in α" (Brown and Warner, 1985, p. 16). Even though biased β-estimates not necessarily imply misspecification in an event study, we tried to calculate an industry beta for all the stocks. This β-estimate was calculated using the median OLS beta estimate for the football clubs included in the sample. Using this, the beta for the highly traded stocks got an unfavorable reduction of the beta compared to the increase in beta for the thinly traded stocks. Thus, we did not proceed with this estimation.

We also calculated β_j using weekly returns, which often improves the estimations for thinly traded stocks. These estimations did not differ substantially from when using daily data. In theory it should have reduced the downward bias in β-estimates, but since there are several weeks without trading on some of the thinly traded stocks, we did not find any more reliable estimations. Hence, we use daily stock returns in our market model estimations.

The abnormal return $AR_{j,t}$ is defined as;

$$AR_{j,t} = R_{j,t} - \hat{R}_{j,t}^{MM}$$

which is the difference between the actual and expected return using the market model.

3.3.2 The STOXX Europe Football Index

An alternative way of calculating the abnormal return is using the returns on the STOXX Europe Football index, assuming β_j equals 1, as an indicator of the expected return;

$$\hat{R}_{j,t}^{STOXX} = R_t^{STOXX}$$

This index gives a description of which market conditions the clubs operate in, and accurately represents the breadth and depth of the European football industry. STOXX Europe Football index covers all 22 publicly listed football clubs on European stock exchanges including all teams but Manchester United from our sample. Based on this, it is reasonable to believe that the clubs we have chosen has a large impact on the return on this sector index as a whole. Assumed that winning a football match has a positive impact on the stock's return, a possible issue occurs when a large amount of the clubs in the index win at the same time, which is not unlikely based on Table 4 and the fact that they often play on the same day. This could lead to underestimated abnormal returns since $\hat{R}_{j,t}^{STOXX}$, to a larger extent, will follow the clubs returns compared to a broad market index. The following formula is used to calculate the abnormal returns using STOXX Europe Football index as an alternative for the market model;

$$AR_{j,t}^{STOXX} = R_{j,t} - \hat{R}_{j,t}^{STOXX}$$

3.3.3 Direct and Mean Adjusted Returns

Finding abnormal returns could also be done without risk adjustments. The most basic way of doing this is by using the unadjusted procedure as explained by Bowman (1983). This method assumes that each club's realized return is the excess return, which in turn leads to

$$\hat{R}_{j,t}^{U.A.} = 0$$

The unadjusted abnormal return is thus defined by:

$$AR_{j,t}^{U.A.} = R_{j,t} - \hat{R}_{j,t}^{U.A.} = R_{j,t}$$

The mean adjusted procedure used by Brown and Warner (1980) is another way to find abnormal returns without adjusting for risk. This method is based on CAPM with constant systematic risk and a stationary efficient frontier. Thus, the expected return is the mean return for a given time period in advance. As with other time periods, we use 250 trading days here as well. Thus;

$$\hat{R}_{j,t}^{M.A.} = \frac{1}{250} \sum_{t=-250}^{0} R_{j,t}$$

This gives the mean adjusted abnormal return:

$$AR_{j,t}^{M.A.} = R_{j,t} - \hat{R}_{j,t}^{M.A.}$$

3.3.4 Measuring Performance

To find whether a result was expected or not we incorporate betting odds into our model. This allows us to account for expectations related to the match outcome. We will base our calculations on the method described by Stadtmann (2006) to make sure we maintain all information from the betting odds, compared to using a noncontinuous variable like Zuber *et al.* (2005).

As described by Stadtmann (2006), any betting company has a mark-up for every match which prevents risk-free profits from betting on the three possible outcomes of a football match. In the match between Manchester United and Southampton on 19 August 2016, the odds were 1.42, 4.10 and 6.10 for home, draw and away respectively. If someone wants to lock in a NOK 100 payout, they will have to place three bets:

$$\frac{100}{1.42} = 70.42$$

$$\frac{100}{4.10} = 24.39$$

$$\frac{100}{6.10} = 16.39$$

That means they will have to pay NOK 111.20 for a NOK 100 payout after the match. Norsk Tipping therefore had a mark-up of 11.2% in this case. This can also be found by summing the inverse of the odds:

$$\left(\frac{1}{1.42} + \frac{1}{4.10} + \frac{1}{6.10}\right) - 1 = 1.112 - 1 = 11.20\%$$

We are interested in using this to find the probabilities of the different outcomes implied by the betting odds and the mark-up. Stadtmann (2006) calculates an average mark-up to use for all the matches. To avoid doing this, we can instead take the inverse of the specific odds for each single match and divide this by the sum of all three inverse quotes. By doing this, we find the probabilities:

$$\frac{\frac{1}{1.42}}{\frac{1}{1.42}+\frac{1}{4.10}+\frac{1}{6.10}} = 63\%$$

$$\frac{\frac{1}{4.10}}{\frac{1}{1.42}+\frac{1}{4.10}+\frac{1}{6.10}} = 22\%$$

$$\frac{\frac{1}{6.10}}{\frac{1}{1.42}+\frac{1}{4.10}+\frac{1}{6.10}} = 15\%$$

Thus, there was a 63% chance of a Manchester United win, a 22% chance of a draw and a 15% chance of a Southampton win.

In any league or group game of football, a win yields 3 points, a draw 1 point and a loss 0 points. Even though a knock-out game in the national cups or European competitions does not give points, we maintain the point system as it still allows us to test the effect of expectations. In our example, the expected points for Manchester United was therefore $(3 \times 63\%) + (1 \times 22\%) = 2.12$ points. Next, we can use this to measure performance vs. expected performance. Manchester United won the game and exceeded their expected points by $(3 - 2.12) = 0.88$. On the other hand, Southampton had $(3 \times 15\%) + (1 \times 22\%) = 0.67$ expected points, and thus an underperformance of -0.67 points due to their loss.

If the value of performance vs. expected performance is close to 3, this would indicate the most surprising result. A value of 0, on the other hand, indicates performance as expected. By using this continuous scale to measure performance, similar to Stadtmann (2006), we maintain more of the information obtained from betting odds compared to using only categories of expected results, as in Zuber *et al.* (2005).

3.3.5 Season Progression

To measure how abnormal returns varies throughout the season, we created a season progression variable. Since each club neither have exactly the same number of days in every season, nor the same number of matches, we need to create a comparable scale. Counting the number of days between the first and last match for each club, and in each season, we can measure the season progression in percentages by counting the number of days for each match from the first matchday and dividing this by the total number of days in the season. This creates an interval between 0 and 1 where 0 is before the season has started, and 1 is when the final match has been played.

We provide an example using the 2014/15 season for Ajax. This season lasted 280 calendar days and contains 44 matches. It started on 10 August, and match number 10 was played on 5 October. Since there are 56 calendar days between these dates, Ajax had played $\frac{56}{280} = 20\%$ of the season at this stage. Hence, we can now easily compare the progression across the different clubs and seasons. We will calculate the season progression for the 2014/15, 2015/16, 2016/17 and 2017/18 seasons.

To take into account whether the first and last match in each season is a league, cup or European match, we could have created three progression variables for each club in each season. This way we would measure more accurately when each tournament started and when it finished. We tested this on Ajax, but the regression output was similar to the one with only one progression variable. Due to time consumption, we thus decided not to create these additional variables.

4 Results & Discussions

In this chapter we will present and discuss our results. First, we analyze the win-, draw-, loss- and performance effects. Second, we investigate to which extent these effects are maintained in different tournaments and locations. Third, the results from the turnaround model are presented, before we include a season progression variable. Finally, we conduct different robustness tests for our results.

We run all of our regressions as OLS regressions. In addition, since we believe that all data samples to a certain degree will face problems related to heteroskedasticity, we run all regressions with robust standard errors as this method will not harm our results in the special case of homoskedasticity. This is recommended by MacKinlay (1997). Regression coefficients described in our results will be marked with "***", "**" or "*" depending on whether they are statistically significant at the 1%-, 5%- or 10%-level respectively.

To check whether there is any notable difference between the four different abnormal return models presented in chapter 3, we first run some of the regressions with all four models. This way, we check whether any of the models differ substantially from the others. We will keep the market model as our preferred model in line with previous research, should they not differ substantially. We emphasize that the abnormal returns in the direct model by definition is only its discrete returns. For the sake of simplicity, we will still describe each regression with abnormal returns as the dependent variable.

4.1 WDL Model

Our first model (Table 5) presents the win-, draw-, loss effect (WDL), where we run the following regression:

$$AR = \alpha + \beta_1 D_W + \beta_2 D_D + \varepsilon$$

Where AR is the abnormal return for any given model, D_W is a dummy variable for a win, D_D is a dummy variable for a draw, α is the intercept and thus the interpretation for a loss, ε is the error term and β_1 and β_2 is the regression coefficients. The coefficients and intercept are taken into account when presenting the results in Table 5 and Table 7. This means that the stated win- and draw coefficients is the regression coefficients adjusted for the intercept.

Table 5 – The Win-, Draw-, Loss Effect

	Win	Draw	Loss
Market Model	0.348***	-0.355**	-0.865***
N = 2146	(6.58)	(-2.37)	(-5.37)
STOXX Model	0.367***	-0.389**	-0.839***
N = 2146	(6.61)	(-2.10)	(-5.31)
Direct Model	0.440***	-0.303**	-0.837***
N = 2146	(6.77)	(-2.43)	(-5.05)
Mean Model	0.353***	-0.384**	-0.918***
N = 2146	(6.70)	(-2.43)	(-5.50)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are respective t-values for each coefficient.*

The effect across all models is that a win yields a positive abnormal return, a draw yields a negative abnormal return and a loss yields a negative abnormal return that is more than double of the positive win effect. For the market model, a win is associated with a 0.348*** percentage point increase in abnormal returns, while a draw and loss are associated with a 0.355** and 0.865*** percentage point decrease in abnormal return respectively.

In total, we see that the market model does not differ substantially from the other models. Based on t-values, all models yield approximately the same statistical significance level, but there are some differences in how strong the effects are across the models. For example, the Direct Model gives a 0.092 percentage point higher effect on abnormal returns after a win than the market model.

4.2 Performance model

In Table 6, we illustrate how an over- or underperformance affects abnormal returns. We have established a variable, $Performance$, that measures the difference between actual points gained and the expected points. Further definition of this can be found in section 3.3.4. This gives the following regression:

$$AR = \alpha + \beta_1 Performance + \varepsilon$$

Where $Performance$ measures an overperformance when positive and an underperformance when negative, α is the intercept, ε is the error term and β_1 is the regression coefficient.

A greater absolute value of the performance variable is consistent with a larger deviation from the expected performance. Due to the fact that a club never has a 100% chance of winning or losing a match, the expected points can never be 3 or 0. Hence, our performance measure can never take values of exactly 3 or –3, and will thus lie in the interval $\langle -3, 3 \rangle$. The performance measure can become exactly 0 if the expected points are 1 and the match outcome is a draw. This happened on 26 February 2014 when Galatasaray drew at home to Chelsea in the Champions League and the odds from Norsk Tipping implied an expected point of exactly 1 for Galatasaray.

Table 6 – The Performance Effect

	Performance	Intercept
Market Model	0.487***	-0.077
N = 2146	(8.04)	(-1.12)
STOXX Model	0.493***	-0.070
N = 2146	(8.11)	(-0.98)
Direct Model	0.508***	-0.007
N = 2146	(8.25)	(-0.10)
Mean Model	0.508***	-0.092
N = 2146	(8.24)	(-1.32)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are respective t-values for each coefficient.*

Consistent with the WDL effect presented in Table 5, we find evidence of increased abnormal returns with a good performance and vice versa for a bad performance. Based on the market model, every point above expected yields a 0.487*** percentage point increase in abnormal returns. Also consistent with our findings in section 4.1, we see that each return models' performance coefficients are quite similar to each other. Based on these findings, as well as previous research and theories, we do not see any disadvantages with basing our final conclusions on the market model.

The performance effect when using the market model yields an adjusted R^2 of 0.0287. This is 28% higher than the adjusted R^2 for the WDL effect, which is 0.0224. Thus, by implementing betting odds, the performance model explains more of the variation in abnormal returns than when using only match outcomes in the WDL model. R^2 in each model is quite low, 0.0233 and 0.0292 for the WDL and performance effect respectively. As discussed in section 2.1.1 and 2.1.2 this should not be a problem, as looking at specific events affecting abnormal returns often yields a low explanatory power.

4.3 Tournament & Location

As discussed in the literature review, different tournaments may impact how match outcomes affect investors and abnormal returns. Additionally, we want to check if there are any differences between playing at home or away. We study these aspects both with the WDL and the performance model.

4.3.1 WDL Model

To check the WDL effect for different tournaments and locations (Table 7), we run 5 different regressions based on the market model. The regression equation is as presented in section 4.1, but each sample is now reduced to only include matches from the respective tournaments or locations.

Table 7 – The WDL Effect for Tournaments & Locations

	Win	Draw	Loss
Market Model	0.348***	-0.355**	-0.865***
N = 2146	(6.58)	(-2.37)	(-5.37)
Tournament			
National League	0.429***	-0.335**	-0.836***
N = 1570	(5.86)	(-1.96)	(-4.40)
National Cup	0.347	-0.886	0.370
N = 220	(0.03)	(-1.61)	(0.54)
European Cup	-0.215***	-0.193**	-1.332***
N = 356	(-2.77)	(-2.56)	(-4.35)
Match Location			
Home	0.242***	-0.631	-1.073***
N = 1074	(4.04)	(-1.30)	(-3.54)
Away	0.495***	-0.142**	-0.771***
N = 1072	(5.39)	(-2.16)	(-4.07)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are respective t-values for each coefficient.*

Table 7 shows that for national leagues, we find consistent results compared to the whole sample using the market model. This indicates that the WDL effects discussed in section 4.1 is transferable to matches played in the national leagues. National cups, on the other hand, yield no statistically significant results on a 10%-level. We believe that this can be explained by the potential lack of importance of national cups, both in sporting and financial aspects. For the matches in the Champions League and the Europa League we find an even stronger loss effect, statistically significant at the 1%-level, than in the national league. The most interesting result though, is the fact that we find that a win decreases the abnormal return by 0.215 percentage points, statistically significant at the 1%-level. This is a somewhat surprising result; however, the effect of a win is significantly less negative than from a defeat, which is consistent with the national league estimates. One possible explanation may be that a win in some of the last games in the group stages, as well as the second games in each knock-out round, may not have a positive impact for the club. Another possible explanation is the fact that most of the clubs included in our sample face high expectations of winning, especially in the group stage. Thus, it may be reasonable to believe that winning will not, on average, cause positive abnormal returns.

When analyzing home and away matches, we have to take into account that a home win is more common than an away win, and that a home loss is less common than an away loss. Thus, it is not unexpected that we find a stronger win effect for away games, as well as a stronger loss effect for home games. An away win, will according to our results, yield a 0.253 percentage point higher abnormal return than a home win, while a home loss yields a 0.302 percentage point lower abnormal return than an away loss. These home and away results are both statistically significant at the 1%-level. For home games we do not find a statistically significant effect at the 10%-level for a draw, while a draw in away games still have a 5%-level statistically significant negative effect on returns.

4.3.2 Performance model

As with the WDL model, we wanted to check the performance effect for each tournament and location. The regression equation is as presented in section 4.2.

Table 8 shows that we find consistent results for national leagues compared to the whole sample with the market model. This means that a good performance in a national league match is associated with a positive abnormal return, statistically significant at the 1%-level. For national cups, we find a weaker performance effect, which is not statistically significant at the 10%-level. Matches played in European cups yield a notable higher abnormal return when our performance measure increases by 1, compared to matches in the national leagues. We believe that this can be explained by a higher share of important matches, both in financial and sporting aspects, as described in section 2.6.

Table 8 – The Performance Effect for Tournaments & Locations

	Performance	Intercept
Market Model	0.487***	-0.077
N = 2145	(8.04)	(-1.12)
Tournament		
National League	0.495***	0.011
N = 1570	(6.93)	(0.13)
National Cup	0.215	0.107
N = 220	(1.04)	(0.48)
European Cup	0.557***	-0.564***
N = 356	(4.37)	(-3.36)
Match Location		
Home	0.488***	-0.163*
N = 1074	(5.44)	(-1.70)
Away	0.496***	0.009
N = 1072	(6.03)	(0.09)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are respective t-values for each coefficient.*

What is interesting about the results for the European cups, is that we find an intercept that is statistically significant at the 1%-level and that has about the same impact as when the performance measure is 1, only in the opposite direction. This means that if the difference between actual and expected points is 0, the predicted abnormal return will be negative. Hence, a performance as expected in the European cups is associated with a negative abnormal return. Furthermore, an underperformance in Europe seems to predict, on average, a more negative abnormal return than in the national leagues.

The negative intercept also means that it will take a much larger overperformance to yield positive abnormal returns, than in the other tournaments. Since our sample mostly consists of top performing European clubs, they will often face a higher chance of winning matches, as described in section 3.1. A higher chance of winning means that achieving a higher performance score becomes harder, as the odds reflect the winning chances. Hence, it could make sense that we observe a large and negative intercept, since the clubs often have to outperform the expectations by a lot to achieve abnormal returns.

Through our performance measure, we take betting odds into account. This means that the home advantage that we found evidence for in the WDL model, should be controlled for in our performance model. Still, there seems to be a stronger effect in an overachievement when playing away, than when playing at home. Taking intercepts into account, a performance measure of 1 at home yields an increase at about 0.3 percentage points in abnormal returns, while the same performance away yields an increase at about 0.5 percentage points.

4.4 The Turnaround Effect

As in previous research on this subject, all of our models in section 4.1-4.3 study the effect of one match at a time. To test the effect of the last match's outcome on the next event's abnormal return, we created a lagged variable of the abnormal return. Based on the theory of efficient markets, we believe that abnormal returns contain both the effects from our events as well as omitted variables. We also considered using a lagged variable of performance instead, but since this is considered old information after the previous event, it seemed likely that it would not improve our model. Our suspicions were confirmed by trying this out.

Based on the findings presented in section 4.2, we can assume that a positive abnormal return is related to a good performance. Hence, a positive lagged abnormal return should be consistent with a good performance in the last match. Including a secondary lagged abnormal return (t–2) was also tested, but due to a very high p-value we chose not to go any further with this variable.

When running this regression, we only add one more variable compared to the one we ran in section 4.2. This is, AR_{t-1}, which is the abnormal return for each club after the previous match. We therefore also get another regression coefficient, β_2. This gives the following regression equation:

$$AR = \alpha + \beta_1 Performance + \beta_2 AR_{t-1} + \varepsilon$$

The other variables are explained in section 4.2.

To make sure that we still do not find any substantial differences between our different models for abnormal returns, we run this regression for each model as presented in Table 9.

Table 9 – The Turnaround Effect

	Performance	AR_{t-1} (%)	Intercept
Market Model	0.490***	-0.136***	-0.078
N = 2145	(8.14)	(-2.78)	(-1.15)
STOXX Model	0.494***	-0.146***	-0.067
N = 2145	(8.17)	(-3.15)	(-0.98)
Direct Model	0.511***	-0.150***	0.002
N = 2145	(8.39)	(-3.22)	(0.03)
Mean Model	0.511***	-0.152***	-0.096
N = 2145	(8.38)	(-3.26)	(-1.39)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively.*
Numbers in parentheses are respective t-values for each coefficient.

As in the results presented earlier, we observe roughly the same performance coefficients across the different models for abnormal returns. There are some differences for the lagged abnormal return coefficients, though all are statistically significant at the 1%-level. We believe that these differences are not sufficient for us to reconsider our decision to base our final conclusions on the market model.

When studying the results for the market model, we see that the performance effect is nearly identical as in previous models. In this case we get a coefficient of 0.490***, compared to 0.486*** in the performance model. Based on this we can say that our performance measure does not lose any explanatory power when including the lagged abnormal return. Through the coefficient for the lagged abnormal return, we find that a positive abnormal return of 1% after the previous match is related to a 0.136*** percentage point lower abnormal return after the most recent match, statistically significant at the 1%-level. To a certain extent, these coefficients state that a good performance, combined with a negative abnormal return from the previous match, will predict an even more positive abnormal return for this event. Based on our sample, the average absolute performance is 1.03, while the average absolute abnormal return is 1.73%. We emphasize again that a positive performance measure is related to an overachievement, and vice versa for a negative number. Based on this and using the average values, our model would predict the following (Table 10):

Table 10 – Estimations of the Turnaround Effect		Most Recent Match	
		Overperformance	Underperformance
Previous Match	Overperformance	**0.19%**	**-0.82%**
	Underperformance	**0.66%**	**-0.35%**

Calculated using the regression results for the market model in Table 9.

Whether the previous match was an over- or underperformance is determined by whether the lagged abnormal return was positive or negative, based on our results in section 4.2. For the most recent match, over- or underperformance is determined by the sign of our performance measure. Hence, as an example, 0.19% is calculated using a positive lagged abnormal return and a positive performance measure, 1.73% and 1.03 respectively.

First, we notice evidence of a potential momentum effect. This is because two similar performances in a row still yields a positive/negative effect on abnormal returns, in line with our assumptions in section 2.4. The predicted abnormal return is now less than when only considering the most recent match result. This could be explained by the mean reversion effect, as a correction could be expected after a recent abnormal return. What is more interesting, is the effect when a club experiences a turnaround in match results. An overperformance in the most recent match yields a higher abnormal return when the club comes from a performance below expectations, assumed that a negative abnormal return is associated with an underperformance. This is an indication that turnarounds in match results could yield higher abnormal returns. We therefore name these findings as "the turnaround effect".

The turnaround effect indicates that abnormal returns are related to whether a team is in form or not. If a team is in form, they will have had several good performances in a row, and thus it is often expected that this will continue. The opposite is true if the team is not in form. Hence, it seems reasonable that overperforming two matches in a row causes less positive abnormal returns than an unexpected change in form. Likewise, underperforming after an overperformance is related to more negative abnormal returns than two underperformances in a row.

The adjusted R^2 for the turnaround effect is 0.0470. This is 64% higher than the adjusted R^2 for the performance effect presented in section 4.2, and 110% higher than for the WDL effect. Hence, including a lagged variable seems to better explain the variation in abnormal returns compared to only including match outcomes or the performance measure.

4.4.1 The Turnaround Effect in Different Tournaments and Locations

We also test the turnaround effect for the different tournaments and locations. For the results presented in Table 11, the regression equation is the same as in section 4.4.

Table 11 – The Turnaround Effect in Tournaments and Locations

	Performance	AR_{t-1} (%)	Intercept
Market Model	0.490***	-0.136***	-0.078
N = 2145	(8.14)	(-2.78)	(-1.15)
Tournament			
National League	0.500***	-0.150***	-0.003
N = 1570	(7.13)	(-2.68)	(-0.04)
National Cup	0.251	0.061	0.138
N = 219	(1.45)	(0.43)	(0.63)
European Cup	0.612***	-0.230**	-0.537***
N = 356	(4.58)	(-2.01)	(-3.22)
Match Location			
Home	0.491***	-0.153**	-0.154
N = 1073	(5.45)	(-2.28)	(-1.62)
Away	0.498***	-0.119*	-0.002
N = 1072	(6.10)	(-1.67)	(-0.01)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are the respective t-values for each coefficient.*

Once again, we do not see any substantial differences when comparing the market model results as a whole with the national league sample. The estimates for matches played in national cups are not statistically significant at the 10%-level. For European matches the performance effect is somewhat stronger, with an offsetting intercept. The turnaround effect in the European tournaments is significantly stronger than in national leagues.

As explained before, achieving positive abnormal returns through winning in the European tournaments is harder, and a loss often seems to result in more negative abnormal returns. This seems to be the case also for the turnaround effect if the club underperforms in Europe when coming from an overperformance, as this relates to an even more negative abnormal return. Should they overperform in the European tournament when coming from an underperformance, the turnaround effect will predict a positive effect on abnormal returns. The total predicted abnormal return though, will still be less than in a similar scenario in the national league, consistent with our previous findings regarding wins in the European tournaments.

For matches played at home, the turnaround effect is stronger and statistically significant at the 5%-level. Away-matches yield a weaker turnaround effect than the market model as a whole but is only statistically significant at the 10%-level. Since the coefficients do not differ substantially from the full sample, we do not see any reason to investigate this variation further.

4.5 The Season Progression Effect

As for the turnaround effect, no published papers to the best of our knowledge have studied how abnormal returns are affected by the season progression. It is well known that matches played late in the season may be more important as they decide both league titles and relegations, as well as the fact that tournament finals are played at this stage of the season. Hence, the importance of matches varies throughout the season.

To check if this is reflected in the abnormal returns, we created a season progression variable as described in section 3.3.5. First, we extract the residuals from the turnaround model, and convert these to absolute values. This is to make sure that we measure the changes in abnormal returns regardless of direction. Next, we regress the season progression variable on the absolute residuals. This means running the following regression;

$$Turnaround\ Model_{Absolute\ Residuals} = \alpha + \beta_1 Progression + \varepsilon$$

Where $Progression$ measures the completed part of the season at a match-to-match level, α is the intercept, ε is the error term and β_1 is the regression coefficient. The results from this regression is presented in Table 12.

Table 12 – The Season Progression Effect

	Progression	Intercept
Turnaround Model Residuals	0.721***	1.381***
N = 1699	(3.23)	(10.58)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are the respective t-values for each coefficient.*

Analyzing the season progression coefficient, we observe a potential positive relation between the size of the turnaround model residuals and the time of the season, statistically significant at the 1%-level. Hence, it seems like the unexplained part of the abnormal returns increases throughout the season, which also indicates that the abnormal returns themselves increase. These findings are consistent with the distribution of important matches throughout the season, if we assume that more important matches are also related to higher abnormal returns. We emphasize that this applies to both positive and negative abnormal returns, which means that the clubs both can gain or lose more towards the end of the season, both in form of direct revenue and stock price fluctuations.

To showcase the impact of the progression variable we will present an example. The average progression from match to match is only 0.02. This means that in our sample, one additional match played will on average increase the season progression by two percentage points. Using this average value, we find that each additional match played only yields a $0.721 \times 0.02 = 0.014$ percentage point increase in the residuals from the turnaround model.

We also extracted the absolute residuals from the turnaround model with respect to national leagues, national cups and European tournaments, and regressed the season progression variable on these residuals. The season progression coefficient with regards to the national leagues marginally decreased to 0.714***, while for national cups it decreased to 0.661***. For the matches played in Champions League and Europa League, the season progression effect became somewhat greater, increasing to 0.780***. An explanation why we observe a higher coefficient for the European tournaments could be that this tournament is perceived as more important from an investment perspective, since matches later in the season seem to be related to more positive or negative abnormal returns. To achieve a high season progression value, the clubs have to reach the latter stages of the tournament, which again implies more important matches. The observed coefficients also indicate that the national league is more important than the national cup from an investment perspective, as the abnormal returns after league matches seem to increase more throughout the season than after cup matches.

4.6 Robustness

To test the robustness in relation to being able to generalize our results across clubs, we run several tests. First, we conduct a regression for the turnaround effect with respect to each club. Second, we tried removing Celtic from the sample due to a high amount of trading days with zero returns, as stated in section 3.1. Third, since our sample consists of panel data, we may face some problems due to autocorrelation within each club over time. We deal with this potential problem by testing clustered standard errors, as described by Stock and Watson (2015). These standard errors allow for autocorrelation within each club while retaining the heteroskedasticity robust standard errors as we initially applied.

These three robustness tests improve the possibility to generalize our results. Additionally, as discussed in section 4.2, our methods of calculating the abnormal returns yield results that are not substantially different from each other. Hence, we conclude that our findings are robust with respect to the estimation procedure of abnormal returns. Further consideration of robustness will include investigating the impact of excluding outliers, as well as discussing the case of nonnormality.

4.6.1 Robustness Across Clubs

To be able to generalize the turnaround effect, we will have to investigate whether results for each club is consistent with our general findings. The turnaround effect using samples for each club is presented in Appendix II. In general, the results seem to follow the same pattern, at least the ones with statistically significance at the 1, 5 or 10%-level. We highlight Celtic and Manchester United as their results differ substantially from the rest.

For Celtic, both the performance effect and the lagged abnormal return coefficient is close to zero and not statistically significant at the 10%-level. A potential reason for this could be the thin trading volume. Based on this, we wanted to check whether the turnaround effect in total is robust with respect to excluding Celtic. As shown in Table 13, we can see that the estimates remain at about the same levels as before. Hence, including Celtic in our sample may not be problematic, but it may increase the amount of white noise.

Table 13 – The Turnaround Effect Excluding Celtic

	Performance	AR_{t-1} (%)	Intercept
Market Model	0.490***	-0.136***	-0.078
N = 2145	(8.14)	(-2.78)	(-1.15)
Excluding Celtic	0.535***	-0.138***	-0.096
N = 1887	(8.07)	(-2.78)	(-1.24)

****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively. Numbers in parentheses are the respective t-values for each coefficient.*

For Manchester United, the regression coefficients presented in Appendix II have the opposite signs compared to the others, as well as having quite low t-values. Thus, it seems like it could be difficult to generalize our results for Manchester United. One potential reason for this may be that the club is listed on the New York Stock Exchange. This means that during some matches, the stock exchange will be open. Hence, analyzing returns on the next trading day might be wrong as the price already reflects information from the event. This is a potential weakness in our study. Despite this, as with Celtic, we do not get substantially different results when excluding Manchester United from our sample. Hence, including Manchester United seems to only increase white noise.

After running a Durbin-Watson test (Durbin, 1950, 1951), we find, for the whole sample, no statistical evidence that the error terms are autocorrelated (d = 1.97). When running the same test for each club, there is some evidence of positive serial correlation. Since this test assumes strictly exogenous regressors, we also run Durbin's alternative test for serial correlation (Durbin, 1970) because this test does not have the same assumption of exogeneity. This test does not show the same tendency of positive serial correlation when investigating each club. Despite this, we tried running our regressions with clustered standard errors. When using clustered standard errors with respect to clubs in our regressions, we do not find any problematic differences.

Through our investigations of Celtic, Manchester United and clustering, we do not find any major limitations that need further assessment in our thesis. This does not mean that the issues presented should be neglected, but due to little or no impact on our estimations, we choose not to go any further on these matters.

4.6.2 Outliers

Based on the turnaround model, we made a leverage-versus-squared-residual plot (L-R plot) to find potential problematic outliers. This plot can be found in Appendix III. The purpose of this is to find the observations which both deviates the most from our predictions and also have the highest leverage. The three most problematic outliers are observation 612, 1212 and 1224. One of these observations was a match played by Galatasaray in May 2015. This was the second leg of the semifinal in the Turkish cup, which they lost. They still advanced to the final due to winning on aggregate result. Based on that, we observed a high positive abnormal return, but a low performance score due to the loss. Hence, we consider this observation as not a part of our population and that it should be removed from the sample.

The other two problematic outliers were two consecutive matches played by Porto in November/December 2016. In this period, we observe a sharp increase in the stock price which is reversed by an equally sharp decline shortly after. Based on our general findings, the match outcomes and the lack of public relevant information we believe that these observations also are not a part of our population. This means that we remove these outliers as well.

After running our regressions again, without these potential problematic observations, we see no major differences. Thus, our results are robust with respect to outliers, which is not surprising since only 3 out of 2,145 observations are problematic.

4.6.3 Nonnormality

To check whether our residuals are normally distributed, we created histograms and plots based on residuals and fitted values. In Appendix IV, we present the histogram and plot for the turnaround model. Histograms for our other models had similar distributions, while plots for the other models do not make sense due to having only noncontinuous variables in the regressions. Based on the histogram in Appendix IV, we believe to have the case of nonnormality. The distribution seems to be somewhere near leptokurtic, which is often the case for daily returns. The distribution of daily returns is proven to be leptokurtic by Fama

(1976), while Brown and Warner (1985) gives further indication of leptokurtic daily excess returns. As for the plot, we do not observe any concerning obvious patterns, but still the case of normality is not that strong.

To supplement our eye test, we run a skewness and kurtosis test for normality available in Stata. Through the command *sktest* we perform a test that is similar to the Jarque-Bera test of normality (Jarque and Bera, 1987) but with two adjustments to the sample size. More details about this test can be found in Stata manuals (Stata, 2020). As we suspected from our eye test, the skewness and kurtosis test for normality also provides evidence of nonnormality in our residuals.

Based on existing literature, finding evidence of nonnormality is not that surprising. The question now is what kind of implications this has on the robustness of our results. Brown and Warner (1985) find that nonnormality in the case of daily returns does not significantly reduce the power of, nor the impact on, an event study. Dyckman *et al.* (1984) find no problems when applying the t-test on portfolios in the case of nonnormality. Finally, Saens and Sandoval (2005) find no problems in the case of nonnormality at the 5% significance level, but the null hypothesis is rejected too often at the 1%-level. Based on this, we believe that our case of a near leptokurtic distribution should not be that problematic or worsen our robustness. Despite this, we decided to perform bootstrap sampling and estimation to make sure that our estimates are robust even though they are not normally distributed.

Using the built-in bootstrap command in Stata, we performed sampling and estimations for each of our regressions with the market model. This means testing both win, draw, loss, performance and turnaround effects. Each bootstrap had 10,000 repetitions and a similar sample size as the original sample. Using this sample size is the most common procedure in machine learning (Brownlee, 2019). Each bootstrap sample is created by drawing a similar amount of observations than in the original sample and replacing the observation in the original sample after each drawing. Hence, the estimations will still be done with the same original sample size, but some matches may be represented several times, or not at all, in each bootstrap sample. For each coefficient, we ran the bootstrap estimations 5 times with different initial values for the random-number seeds used by the random-number function in Stata. This means that we have done 50,000 simulations of each coefficient, which are summarized in Appendix V. An excerpt containing the bootstrap for the turnaround model is shown in Table 14.

Table 14 – Excerpt of Bootstrap

Turnaround Model	Observed Coef.	Bootstrap Std. Err.	z	P > |z|	Normal-based [95% Conf. Interval]	
Performance						
	0.0049004	0.0005984	8.19	0.000	0.0037275	0.0060733
	0.0049004	0.0005999	8.17	0.000	0.0037245	0.0060763
	0.0049004	0.0006018	8.14	0.000	0.0037209	0.0060799
	0.0049004	0.0005996	8.17	0.000	0.0037252	0.0060756
	0.0049004	0.0006003	8.16	0.000	0.0037238	0.0060770
AR_{t-1}						
	-0.1362188	0.0495904	-2.75	0.006	-0.2334142	-0.0390235
	-0.1362188	0.0486284	-2.80	0.005	-0.2315288	-0.0409089
	-0.1362188	0.0488988	-2.79	0.005	-0.2320586	-0.0403790
	-0.1362188	0.0488455	-2.79	0.005	-0.2319542	-0.0404834
	-0.1362188	0.0491257	-2.77	0.006	-0.2325034	-0.0399342

Each bootstrap was run with 10,000 repetitions. Full table can be found in Appendix V.

We find consistent standard errors both throughout the different bootstrap estimations and when comparing with our original results. Thus, we believe that our results are robust with respect to nonnormality.

5 Conclusions, Limitations and Future Research

This master thesis investigates the link between the sporting performance of football clubs and their abnormal returns. In the following, we will present our main conclusions and the limitations of our thesis. We will also give our recommendations to future research.

5.1 Conclusions

We document a positive relation between winning a football match and the abnormal return of the winning club's stock. Draws and losses seem to cause negative abnormal returns. In absolute terms, the observed loss effect predicts an impact twice as strong on the abnormal returns than the impact from a win or draw. These findings are in line with previous research, e.g., Scholtens and Peenstra (2009).

The first conclusion is transferable to our findings when taking into account whether the match outcome was expected or not. Performing above expectation relates to a positive abnormal return, whereas the reverse applies for an underperformance. While these findings support previous research, e.g., Stadtmann (2006), it also contradicts Zuber *et al.* (2005) which find that the stock price of a football team is insensitive to unexpected match outcomes. With our recent and broader sample, we generalize both Scholtens and Peenstra (2009) and Stadtmann (2006) to an even broader international setting in our two first conclusions.

Our main contribution to existing research is the conclusion that abnormal returns is higher when a club experiences a turnaround in performance, i.e., more positive when overperforming after an underperformance and vice versa. Positive abnormal returns are also related to consecutive wins, while consecutive losses result in negative abnormal returns. We emphasize that the greatest excess returns are obtained after a change in form.

In our second contribution, we find evidence of increasing abnormal returns throughout the season, which means that more important matches are related to greater abnormal returns. This is in line with Renneboog and Vanbrabant (2000), who found that promotion and relegation matches yielded more positive and negative abnormal returns respectively.

All our main conclusions are transferable to matches played in the national leagues. Most of our findings related to national cups are inconsistent and not statistically significant at the 10%-level. Thus, we believe not to have found any relation between performance in national cup matches and abnormal returns. When investigating results from European tournaments, our findings differ from our main conclusions. First, we observe a stronger negative impact on abnormal returns from a loss. Even though a win yields less negative abnormal returns than a loss, as in our main findings, the predicted abnormal return is still negative. Second, it seems like positive abnormal returns can only be obtained from more extreme overperformances. Third, we find a stronger turnaround effect for matches played in European tournaments. Our finding with regards to losses in the European tournaments is in line with Scholtens and Peenstra (2009). Also similar to our results, they observe a weaker win effect in the European tournaments, but not quite as controversial as our negative and statistically significant coefficient.

The win-, draw-, loss model gives evidence of the home advantage. A home win yields less positive abnormal returns than an away win, while a loss at home yields more negative abnormal returns than a loss away. Even though the home advantage should be controlled for when taking betting odds into account, playing at home or away still makes an impact on the abnormal returns when considering expected performance. Thus, the home advantage still seems to influence the match outcomes' impact on the stock returns. Additionally, we find a somewhat stronger and weaker turnaround effect for matches played at home and away respectively.

5.2 Limitations and Future Research

A thesis like this will obviously have several limitations and issues which have not been taken into consideration. In this final section, we will cover what we believe to be the most essential limitations and give our recommendations to future research.

Before gathering data, we decided to have a more diverse sample than previous research on football stocks. By doing this, we were able to have a broader overview of a potential link between abnormal returns and sporting performance. We thought this would make us able to generalize the results across more clubs from multiple countries. However, we did not obtain the generalization possibilities that we hoped for. Our sample may be affected by increased white noise from the thinly traded stocks, as well as the special cases of Porto with a high proportion of the outliers and Manchester United listed on a stock exchange which may be open during matches. We believe that this could cause some difficulties when trying to generalize our results to other publicly listed football clubs. Despite this, the arguments about generalization in the conclusion could still be valid for clubs included in our sample. A recommendation for future research is to provide further discussions related to the issues from a diverse sample.

Further limitations related to our data sample could be the length of the sample period, which could have been extended in both directions. In addition to this, a case could have been made to include more clubs that match our selection criteria. As an attempt to prevent the possibility of survivorship bias, as described in section 3.1, we could have been less selective by including clubs that are now delisted but have been listed within the sample period. The sample could also include more than one club from each country. Despite our sample being broader and more diverse than in previous research, we still recommend future research to consider an even broader and less restrictive sample.

We used a short event window of one day. The disadvantage with this is that we do not take any potential expectations before the event, or any prevailing effects after the event, into account. This could have been done by using an event window over the week, like in Renneboog and Vanbrabant (2000). Alternatively, an event window shorter than one day could have been used by investigating intraday movements. Even though we have confidence in our choice of event window length, we recommend that future research does a further consideration of the trade-off between using different event windows.

The case of omitted variable bias is another potential limitation. As discussed in our literature review, a possible omitted variable is player signings. Some player signings will cause no effect on investor expectations, while other signings might be seen as game changers. We considered finding and controlling for these, but the amount of time required, in combination with the potential reduction of our sample, caused us to not proceed with this. In any case, determining which signings that matter would be a difficult, if not impossible, task. In addition to this, rumors about transfers could cause uncertainties about when exactly the stock prices reflect this information. That said, we believe that since regression models are built to deal with random disturbances, our results would not be substantially different should we control for player signings. Furthermore, player signings mostly occur during transfer windows outside the season, which makes transfers less likely to happen at the same time as a match result. Thus, the potential problems when omitting this variable might be limited. Despite this, considering player signings, or other possible omitted variables, could be an interesting topic for future research.

Choosing to keep all matches in national cups and European tournaments in our sample is another limitation. Since the outcome of some matches in these tournaments does not affect whether a club proceeds to the next stage, it is reasonable to believe that the match outcome does not impact the financials of the club and thus not the stock price. Hence, we assume that these matches may cause biases in the national and European cup findings. We recommend taking this into account in future research.

Another recommendation is to take into account that different national league matches will have different degrees of importance. Even though we have implemented betting odds and a season progression variable, we have not considered neither the isolated importance of each match nor whether the abnormal returns was affected by other matches in the same league. Our recommendation to future research is to create a variable based on match importance and league position.

Finally, we hope that future research can develop our turnaround model. One limitation to this contribution is that we assume that the abnormal return after the previous match reflects the performance in the previous match. Since using historical prices to predict future fluctuations in theory should not be possible due to the random walk, it would be interesting to see if the turnaround model can get further backing through other calculations.

6 References

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7 Appendices

APPENDIX I – Currency Adjusted Relative Value

Club	Country	IPO Date	Vol 14 Jan 2020	Avg. Price 14 Jan 2020	Currency	Volume / Price	Convert Rate	Conv. Price	Vol / C.Price
Galatasaray SK	Turkey	20.02.2002	176 796 486	2,23	TRY	79 280 935	0,15	0,33	528 539 570
Trabzonspor	Turkey	10.04.2005	184 984 599	2,57	TRY	71 978 443	0,15	0,39	479 856 288
Besiktas JK	Turkey	25.02.2002	37 755 697	2,60	TRY	14 521 422	0,15	0,39	96 809 479
Juventus	Italy	20.12.2001	17 457 541	1,26	EUR	13 877 219	1,00	1,26	13 877 219
AS Roma	Italy	17.05.2000	1 461 931	0,63	EUR	2 309 528	1,00	0,63	2 309 528
Fenerbahce SK	Turkey	20.02.2004	1 734 794	15,48	TRY	112 067	0,15	2,32	747 112
SS Lazio	Italy	01.03.1998	1 033 198	1,57	EUR	660 190	1,00	1,57	660 190
Borussia Dortmund	Germany	25.02.2008	1 619 264	8,53	EUR	189 832	1,00	8,53	189 832
FC Porto	Portugal	01.06.1998	17 970	0,65	EUR	27 646	1,00	0,65	27 646
Sporting CP	Portugal	02.06.1998	6 773	0,80	EUR	8 466	1,00	0,80	8 466
Olympique Lyonnais	France	08.02.2007	9 383	3,07	EUR	3 056	1,00	3,07	3 056
Manchester United FC	England	10.08.2012	50 275	20,21	USD	2 488	0,90	18,19	2 764
FC Copenhagen	Denmark	11.11.1997	4 689	101,90	DKK	46	0,13	13,25	354
AFC Ajax	Netherlands	06.05.1998	7 090	21,00	EUR	338	1,00	21,00	338
SL Benfica	Portugal	22.05.2007	1 338	4,67	EUR	287	1,00	4,67	287
Celtic FC	Scotland	22.12.2005	6 112	151,00	GBP	40	1,17	176,67	35

Appendix I – This rating system, CARV, is used to choose which club from each country that is included in our sample.

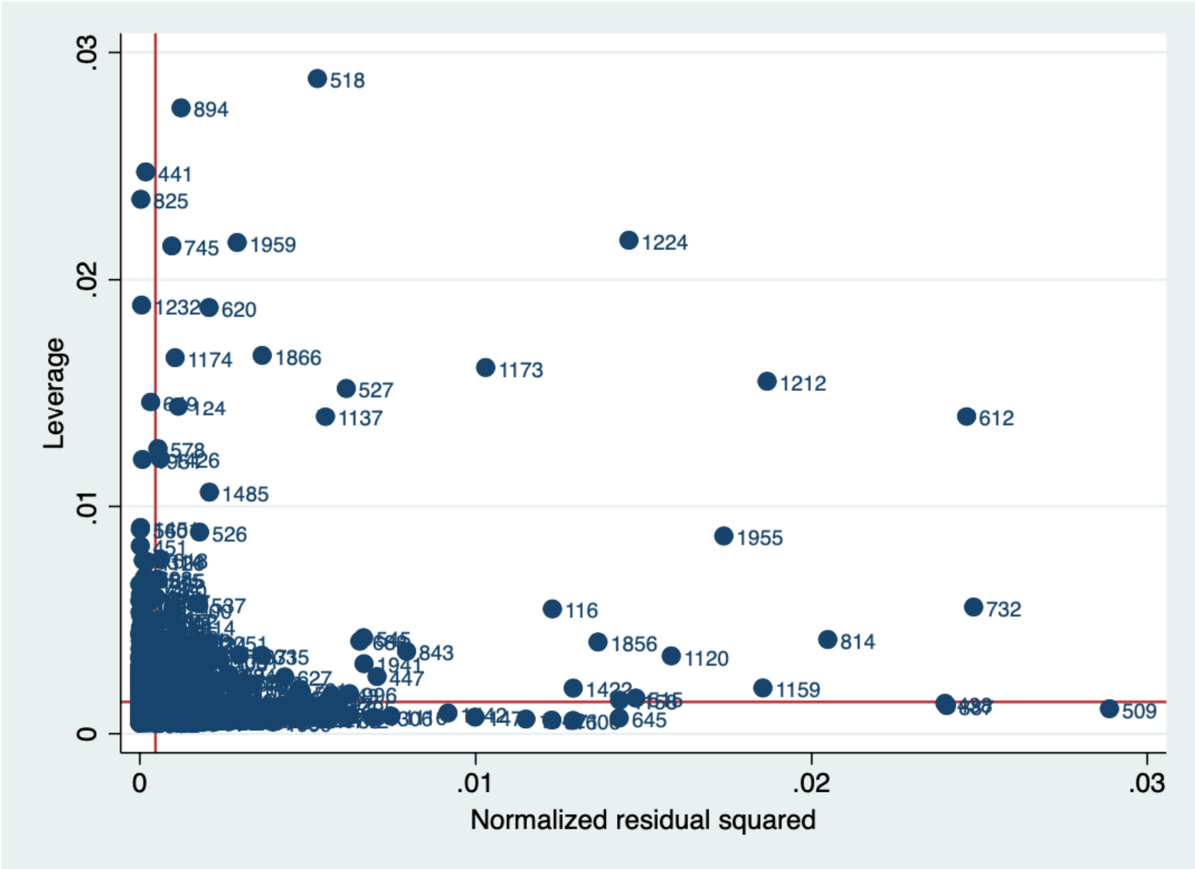
APPENDIX II – The Turnaround Effect for Each Club

Appendix II – The Turnaround Effect for Each Club

	Performance	AR_{t-1} (%)	Intercept
Market Model	0.490***	-0.136***	-0.078
N = 2145	(8.14)	(-2.78)	(-1.15)
Football Club			
Ajax	0.118	-0.099	-0.015
N = 213	(0.81)	(-1.04)	(-0.10)
Borussia Dortmund	0.825***	-0.046	-0.168
N = 240	(7.46)	(-0.68)	(-1.43)
Celtic FC	0.064	0.030	0.047
N = 258	(1.42)	(0.41)	(0.84)
FC Copenhagen	0.442***	-0.160**	-0.112
N = 207	(3.78)	(-2.24)	(-0.86)
FC Porto	0.932**	-0.269***	-0.059
N = 231	(2.27)	(-3.32)	(-0.14)
Galatasaray	0.405	0.096	0.036
N = 215	(1.58)	(0.66)	(0.14)
Juventus	0.686***	-0.041	-0.331*
N = 267	(4.24)	(-0.58)	(-1.78)
Manchester United	-0.020	0.027	-0.150
N = 262	(-0.21)	(0.38)	(-1.56)
Olympique Lyon	0.855***	-0.014	0.058
N = 252	(6.08)	(-0.11)	(0.37)

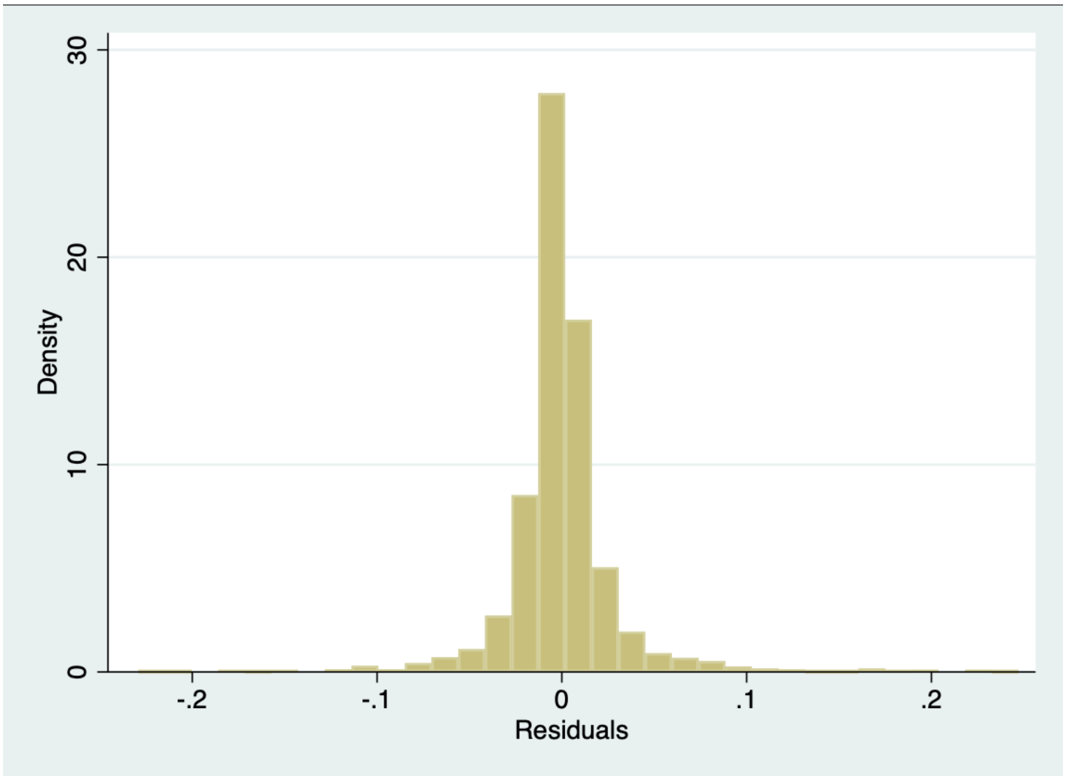
****, ** and * indicate statistical significance at the 1, 5 and 10%-levels respectively.*
Numbers in parentheses are the respective t-values for each coefficient.

APPENDIX III – Leverage-Versus-Squared-Residual Plot

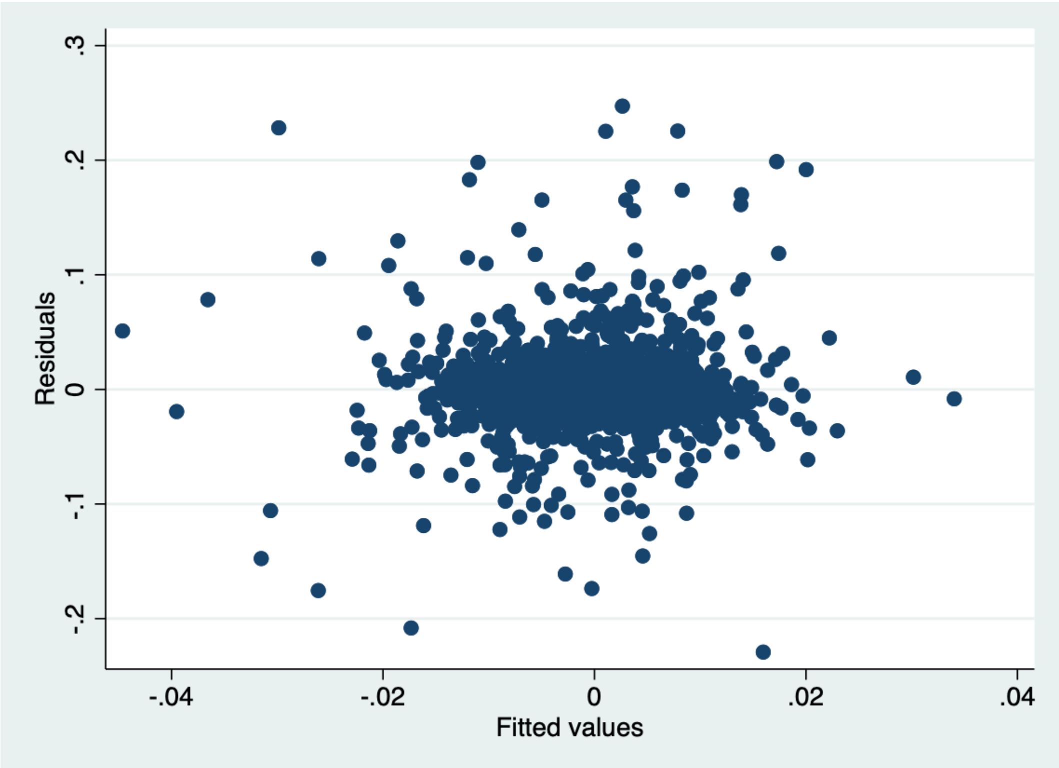


Appendix III – L-R plot based on the turnaround model. Used to find problematic outliers in the upper right corner.

APPENDIX IV – Residual Histogram and Plot



Appendix IV, Histogram – Based on residuals from the turnaround model.



Appendix IV, Plot – Based on residuals and fitted values from the turnaround model.

Appendix V – Bootstrap Results

Bootstrap Table

WDL-model	Observed Coef.	Bootstrap Std. Err.	z	P > |z|	Normal-based [95% Conf.	Interval]	Seed No.
Win							
	0.0121293	0.0018368	6.60	0.000	0.0085292	0.0157294	1071938054
	0.0121293	0.0018385	6.60	0.000	0.0085259	0.0157326	678209990
	0.0121293	0.0018514	6.55	0.000	0.0085006	0.0157579	647049224
	0.0121293	0.0018166	6.68	0.000	0.0085689	0.0156897	1523142091
	0.0121293	0.0018443	6.58	0.000	0.0085145	0.0157440	632144767
Draw							
	0.0050982	0.002125	2.40	0.016	0.0009334	0.0092631	2042361894
	0.0050982	0.0021537	2.37	0.018	0.0008771	0.0093194	1398080684
	0.0050982	0.0021548	2.37	0.018	0.0008749	0.0093215	1563698608
	0.0050982	0.0021665	2.35	0.019	0.0008519	0.0093445	432498915
	0.0050982	0.0021518	2.37	0.018	0.0008809	0.0093156	1274977303
Loss							
	-0.0050982	0.0021323	-2.39	0.017	-0.0092775	-0.0009189	1547495053
	-0.0050982	0.0021721	-2.35	0.019	-0.0093554	-0.0008410	2032172207
	-0.0050982	0.0021555	-2.37	0.018	-0.0093229	-0.0008735	414790344
	-0.0050982	0.0021365	-2.39	0.017	-0.0092858	-0.0009107	441048355
	-0.0050982	0.0021255	-2.40	0.016	-0.0092641	-0.0009324	1878749624

Performance Model	Observed Coef.	Bootstrap Std. Err.	z	P > |z|	Normal-based [95% Conf.	Interval]	Seed No.
Performance							
	0.0048653	0.0006023	8.08	0.000	0.0036848	0.0060458	654526731
	0.0048653	0.0006075	8.01	0.000	0.0036747	0.0060559	1732552939
	0.0048653	0.0006058	8.03	0.000	0.0036779	0.0060527	421320115
	0.0048653	0.0006055	8.03	0.000	0.0036785	0.0060521	446228821
	0.0048653	0.0006097	7.98	0.000	0.0036703	0.0060603	518703130

Turnaround Model	Observed Coef.	Bootstrap Std. Err.	z	P > |z|	Normal-based [95% Conf.	Interval]	Seed No.
Performance							
	0.0049004	0.0005984	8.19	0.000	0.0037275	0.0060733	2028347948
	0.0049004	0.0005999	8.17	0.000	0.0037245	0.0060763	61423661
	0.0049004	0.0006018	8.14	0.000	0.0037209	0.0060799	575985305
	0.0049004	0.0005996	8.17	0.000	0.0037252	0.0060756	1016483772
	0.0049004	0.0006003	8.16	0.000	0.0037238	0.0060770	363526112
AR_{t-1}							
	-0.1362188	0.0495904	-2.75	0.006	-0.2334142	-0.0390235	1277565223
	-0.1362188	0.0486284	-2.80	0.005	-0.2315288	-0.0409089	1319783570
	-0.1362188	0.0488988	-2.79	0.005	-0.2320586	-0.0403790	149223604
	-0.1362188	0.0488455	-2.79	0.005	-0.2319542	-0.0404834	1376600183
	-0.1362188	0.0491257	-2.77	0.006	-0.2325034	-0.0399342	1744015261

Each bootstrap was run with 10,000 repetitions.

Seed No. is the initial value of the random-number seed used by the random-number functions in Stata.