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ALL STOCKS ARE EQUAL, BUT SOME STOCKS ARE MORE EQUAL THAN OTHERS: ABNORMAL RETURNS OF FOOTBALL CLUBS

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Introduction

Brand distortions can be easily observed in everyday life (Aaker, 1991). The owner of a well-known brand name can benefit from a premium pricing strategy compared to the owner of unbranded products, as consumers believe that a product with a well-known name is better than products with less well-known names (Leuthesser, Kohli & Harich, 1995). But are such distortions also present in financial markets, where theoretically only firms' cash flows should affect their stock price?

The purpose of this work is to investigate if stock prices of firms are subject to distortions because of their brand.

Understanding whether a particular brand can create distortions in financial markets through its effect on mood and choices of investors, can be extremely useful for a professional investors, who can be able to take advantage of this distortions to make profit.

Therefore, analyzing how strong is the relationship that ties brand power and investors' mood and behaviour is extremely useful for a professional investor who wants to create an efficient portfolio or to realize profitable trading strategies.

To answer the question if stock prices of firms are subject to distortions because of their brand, I decided to analyze the relationship between soccer match results and stock returns of listed European soccer teams in order to understand if the stock market of football clubs is efficient or if it is characterized by these distortions.

Football clubs are probably one of the best setting of analysis because they present all the characteristics that, according to Young & Rubicam, one of the leading global marketing communications, distinguish a powerful brand: differentiation, relevance, esteem, knowledge.

Each football club is a brand (Cayolla and Louriero, 2014) and is able to influence the behaviour of actual and potential fans (Gladden and Funk, 2001). A strong passion for a football team can affect the emotional state and the relevant behavioural factors of individuals (Cirillo & Cantone, 2015): after a win supporters generally feel euphoric, while they can face a wave of pessimism because of a loss.

Since sports results are able to influence people's mood and behavior (Wann & Dolan, 1994; Schwarz, Strack, Kommer & Wagner, 1987; Arkes, Herren and Isen, 1988), it is not possible to rule out the possibility that they can influence the financial decisions of an investor, therefore weighing on the trend of the stock market. In fact many individual shareholders of a listed football club are supporters of that club (Morrow, 2003) and there is the possibility that their financial decisions are not driven by the rational logic of profit, but instead by short-lived emotions.

Another interesting reason for analyzing the football industry is that football clubs have a double nature: they are firms, and so they should maximize, or at least try to maximize, their profits and, at the same time, they are professional sport teams, with the clear objective of being as much competitive as possible and winning as many matches as they can.

At first glance, these two dimensions are in contrast with each other because being able to create a strong football team requires a large capital expenditure. On the other hand, a team which is not competitive will hardly be able to generate profits, because it will not obtain prizes from competitions and it will have less supporters willing to pay for watching the match or buying the club's merchandising.

Understanding the relationship of these two dimensions is particularly important, especially when a football club decides to enter the stock market, where it is legally obliged to maximize its profits and its principal objective becomes the making of money for its shareholders.

The football teams analyzed are 17 and they belong to several European countries. All of them were listed on the Dow Jones STOXX Football Index from 2005 to 2015. The sports Dataset includes all the 6892 matches played by these teams in the period analyzed and for every match it is specified when the match was played, the type of competition (national or European), the final result, the goal difference and, after having analyzed sports betting odds, if the team was favourite or the underdog, in order to understand how much the result was expected or not.

In an efficient market, stock prices of football clubs should include all available information, and so betting odds should be reflected properly in stock prices before matches. Instead, the results of the analysis of abnormal returns before matches show that investors have unrealistic expectations about the winning chances of clubs. This inefficiency can be exploited by professional investors, who can gain from these unrealistic expectations.

The abnormal results are analyzed both on the days before the match and on the days after the match in order to be able to understand the market behaviour before and after the match. In addition to the analysis of abnormal returns, an analysis of the volumes traded on the days before and after the match is also examined, so as to understand whether betting odds and match results offer enough information to an investor to trade on.

This empirical work contributes to the existing literatures in two ways: one by introducing the football betting odds in the regression models, so as to capture the level of surprise for the result, and the other by increasing the number of football teams and matches analyzed since the existing literature focuses on national matches in specific countries, while this dataset includes all national and European results of the football teams considered.

Gretl and R. statistical software are used for the statistical analysis while datastream is used to obtain all the financial data of the clubs in the sample.

The thesis consists of four chapters.

In the first chapter I explain in what and why sports clubs are different from traditional firms. Then I summarize the history, the motives and the evolution of football clubs' quotation on the stock market, also illustrating what are the benefits and risks in investing in such stocks.

In the second chapter I examine the time series of prices and returns of the Dow Jones STOXX Football Index and its components and in the last paragraph I briefly describe and analyze the football results of the clubs in the sample.

In the third chapter, I calculate football club beta using the theoretical "market model" and then I calculate abnormal returns of the football clubs in the sample and I analyze the relationship between them and the football results of the clubs. The analysis is done both using sports data as a whole and using only results of European competitions. The choice to focus on European competition matches is mainly due to the fact that European competitions are much more remunerative for a club and they have a greater media impact and for this reason I expect that the results of these competitions have stronger effects on abnormal returns.

In the regressions I use dummy variables, indicating whether the match played by a club of the sample is won, lost or tied, if the match is played at home or away from home and in which competition it is played. In addition to dummy variables, I use continuous variables such as the goal difference to catch the effect of the intensity of the result on abnormal returns. I also effect robustness checks including dummy variables indicating in which month and in which year the match is played, in order to understand whether a fix month or year effect is present.

The last variable I include in the models is a dummy variable indicating whether the club is favourite or the underdog in the match played, in order to capture the level of surprise of the result.

In the fourth chapter I focus on the analysis of abnormal returns and volumes. In the first part of the chapter I suggest a market inefficiency due to an irrational behaviour of investors. Then I verify if the hypothesis is reflected in the empirical results of the analysis of volume and abnormal returns, both evaluated before and after matches.

1. Football and Stock Market

Football is undoubtedly one of the most important sports in the world and it counts more than 250 million players all around the world. Football World Championships (the FIFA World Cup) is one of the most-watched events on TV and it is officially broadcasted in at least 200 countries ("2014 FIFA World Cup™, Television Audience Report").

Data concerning 2014 World Cup in Brazil say that a total of 1.013 billion viewers saw at least one minute of Germany's 1-0 win over Argentina in extra time at the Maracana Stadium in Rio de Janeiro. The 2014 final had an "*average in-home global audience*" of 570.1 million, an increase of 40 million compared to the 2010 World Cup final. FIFA claimed that 3.2 billion people watched at least one minute of a match ("2014 FIFA World Cup™ reached 3.2 billion viewers, one billion watched final - FIFA.com").

Comparing 2014 data not even an event such as the Super Bowl can relate to a World Cup final for numbers of viewers. Besides, people enthusiasm for a win, such as the conquest of the World Title, clearly shows the connection between football and people's behaviour. Think for example of the celebrations when Italy won the FIFA World Cup in 2006 or when Spain and Germany won the World Cup in 2010 and 2014, respectively.

But not only this, an analysis of Goldman Sachs suggests that since 1974 all the winners of the World Cup have outperformed the global market in the post-final month (averagely by 3.5%), with the only exception of Brazil in 2002, which, however, at that time was going through a financial crisis ("The World Cup and Economics 2014, Goldman Sachs").

On the other hand, still according to Goldman Sachs's analysis, the runners-up, after the final, seem to experience a negative period in the financial market. The average relative outperformance of the runner-up is 2.0% over the first month. Interestingly, the poor performance does not stop there, but it lasts for the next three months after the final, with an average relative fall by 5.6% over the first three months.

Literature concerning sports events and people's behaviour is very vast (Schwarz, Strack, Kommer & Wagner, 1987; Arkes, Herren & Isen, 1988; Hirt, Zillmann, Erickson & Kennedy, 1992; Schweitzer, Karla, Zillmann, Weaver & Luttrell, 1992; Wann & Dolan, 1994; Cirillo & Cantone, 2015) and numerous theoretical and empirical works examine the relation between sports results and stock quotes (Renneboog & Verbrandt, 2000; Ashton, 2003; Maniello, 2003; Ciarrapico, Cosci & Pinzuti, 2010; Castellani, Pattitoni & Patuelli, 2012; Sarac & Zeren, 2013).

Years after years, football is becoming a big world industry, catching the attentions of numerous firms. Sponsoring contracts by big sport multinationals (Nike, Adidas, Puma, Umbro) have brought a huge amount of money to clubs and television rights are sold to exorbitant prices. But more than one hundred years ago things were different.

Football was born in England in 1863 ("CALCIO - LA STORIA DEL CALCIO in 'Enciclopedia dello Sport' – Treccani") and at that time football clubs were football lovers' associations which gathered people willing to meet and play football. The main function of the club was to organize matches in order to properly allow people to have fun and play football.

The spreading of this sport and the amplification of this phenomenon, which was really liked by people attending matches, led owners of clubs to remunerate the best football talents, in order to guarantee their presence in the team. This was the beginning of football as an economic business ("History of Football - The Global Growth - FIFA.com").

The next step, just the same due to the growing popularity of football in the word and the increasing of national matches led to the change from amateur sport to professional sport with an evolution from "participating" to "winning".

Football clubs started looking for better players, more knowledgeable coaches and technical-tactical innovations to try to do the best possible result.

All this was possible just spending a great amount of money. Paying the best players gave the possibility to have a better competitive performance and this increased the lure of the team on the spectators.

The interest in the economy and management of the professional football clubs has increased in the last years and there has been a real in-depth analysis of the problems of this industry.

Football clubs have become real business and they belong to the entertainment and leisure sector, with similarities but also in competition with other free time activities like cinemas and theatres (Torkildsen, 2005).

They offer particular and in some cases unique goods: they offer emotions, passion and the sense of being part of a group sharing joy and suffering.

Each club must coexist with several stakeholders. In fact stakeholders participating in the football industry are very numerous and they are interested in the economic and financial growth of the club but without forgetting the results on the playing field. So, the goals of a football club are to offer entertainment with the game to its spectators, and to link the interests of the stakeholders participating in the business to the spectators' needs.

Therefore there are several dimensions a club has to confront itself with:

- Agonistic or sport dimension: coexistence with talents, coaches, other teams and government agencies or federal boards connected to the world of sport (FIFA, UEFA and of course football national federations);
- Economical and financial dimension: the relationship with investors, sponsors, television services, merchandising and club brand development;
- Individual and human dimension: the involvement of spectators and supporters;
- Communicative dimension: mass media interest which is linked to human aspect, in fact the diffusion of news is necessary to magnetize people's attention;
- Social dimension: the relationship with local authorities, public administration, municipalities, security forces, regional authorities and central government.

1.1 Objectives of football clubs

Professional team sports industries are very different from the traditional ones. Rottenberg and Neale, explained that there are two main differences between these industries. The first one is linked to the product supplied. Differently from traditional industries, where one firm produces one or more products, in sport industry every product (match) requires two firms (clubs) which must cooperate to create a unique joint product. In fact the game cannot be produced by a team alone (Rottenberg, 1956; Neale, 1964). Neale called this phenomenon "inverted joint product". Even or so if the product is not just a single game but it is a league championship and in this case more than two clubs are necessary.

Another key difference compared to traditional business is competition. Firms usually get benefits without competition because they can ensure a position of supremacy in the market. This is completely different in the sport sector: there is not one team that tries to bring into effect a monopolistic policy of the sector, buying all the best possible talents; if this happened, spectators probably would lose interest and sport clubs would be the greatest losers. A championship in which the title is decided on the last day is far more exciting than a championship in which the final winner is already known before playing a certain number of matches. The uncertainty of the result of the sport event between two clubs is something desirable for the sector as the involvement of the general public can only increase proportionally with the level of uncertainty: watching a match in which a team wins 10-0 can be enjoying but it is hard to think that a spectator wants a clear-cut difference such this week after week. If a lot of clubs are involved in producing only one product (a championship or an international tournament), a good degree of cooperation among clubs is necessary. Watching a well-organized tournament is certainly more exciting than watching a series of occasional matches. That is why club owners have come together and have created unions, federations and leagues in order to be able to decide together the most profitable conditions to sell the product, for example deciding how many clubs can join the product market, at what conditions, how many times the product (match) will be offered, the schedule and the places of the matches and to prevent illegal behaviours of clubs.

As I wrote before, in professional team sports, clubs face a lot of objectives and this fact brings inevitably to different choices regarding the distribution of talents among clubs, the salaries of managers and players, the ticket price policy, the target amount of revenues, etc.

Traditional firms have the main goal, and it is often the unique one, of maximizing their profits. In the United States a great number of economists have argued that also professional team sports clubs have the same objective: the maximization of profits.

The first economist to support this thesis was Rottenberg who wrote "*It should not be thought that wealthy teams will invariably want to assemble winning combinations of players ... A team will seek to maximise the difference between its revenues and its costs. If this quantity is maximized for any given club by assembling a team of players who are of lower quality than those of another club in its league, it will pay the former to run behind*". (Rottenberg, 1956, p. 255). So, according to Rottenberg, a sport club will always try to maximize profits and will not care of wins and competitiveness. He affirmed that, if the talent distribution is the only variable of a particular club, then that club will always try to buy and hire a number of talents in order to maximize the difference between seasonal revenues and seasonal costs. So the objective of a club will be $\max(\pi) = \max(R - C)$ where π are the seasonal profits, and R and C represent the revenues and the costs of the season, respectively. Therefore, according to Rottenberg, a club will hire a talent only when the marginal revenue produced by that talent will be greater than the marginal cost that the club must sustain to hire him.

The economic theory that considers the club as a profit maximizer is supported by a large number of American economists (Noll, 1974; Quirk and Fort, 1992; Vrooman, 1995) but it is not shared by everyone.

The first economist to show doubts on the idea of a club as profit maximizer was Sloane, that in 1971 analyzed English soccer. At that time, the majority of league clubs operated at a loss, quite the opposite of American sports leagues, in which almost all the clubs were profitable. Sloane wrote that "*It is quite apparent that directors and shareholders invest money in football* *clubs not because of expectations of pecuniary income but for psychological reasons as the urge for power, the desire for prestige, the propensity to group identification and the related feeling of group loyalty*" (Sloane, 1971, p. 134).

Sloane argued that the dynamics that moved European team sports are different from the ones of American team sports and affirmed that, for what regards European football, the true goal of a club's owner is not the profit maximization, but the utility maximization, which can be subjected or not to a financial solvency constraint. The objective of a club, according to Sloane, becomes: $\mathbf{max}(\boldsymbol{U})\,,\boldsymbol{subjected\ to\ R - C = \pi^0}$ where U is the utility of the owner of the club and π^0 is a fixed amount of positive or negative profits. According to Sloane the variables of the utility function are various:

- Playing success
- Attendance
- Revenue
- Profit
- Security
- Health of the league

Surely, the theory that sees a club not as a profit maximizer, but as an utility maximizer is not a common characteristic of European football only, but it was observed even in the American sporting leagues. In fact, Markham and Teplitz, after having interviewed ten owners of baseball clubs and various managers, reported that owners *"…were motivated to enter the baseball industry more out of reason of personal gratification, love of the game, devotion to professional sports generally, or out of civic pride than by the prospects of profits"*(Markham, & Teplitz, 1981, p. 26).

In 2003 Zimbalist introduced a new idea regarding the objectives of sport clubs owners, affirming that, since owners of sport clubs are often well-known businessmen, they take advantage of sport investment in order to develop or strengthen other business relations.

Zimbalist wrote that "*what might appear as utility-maximizing behaviour by an owner is really global (porfolio-wide) profit-maximizing behaviour. Put differently, owners find that the best way to profit maximize globally is to win maximize at the team level"*(Zimbalist, 2003, p. 16).

In fact, differently from other industries, entering the sport business, guarantees an incredible advantage in terms of public and media exposure to a businessman. Sport news are always reported on the first pages of newspapers, on the newscasts and they are discussed continuously by millions of supporters. In 1973, Koppet wrote that "*Club owners are not ordinary* *businessmen. To begin with, profit in itself is not the owner's primary motive. Any man with the resources to acquire a major league team can find ways to make better dollar-for-dollar investments. His payoff is in terms of social prestige…A man who runs a $100m-a-year business is usually anonymous to the general public; a man who owns even a piece of a ball club that grosses $5m a year is a celebrity. His picture and comments are repeatedly published in newspapers known in every corner of his community*" (Koppet, 1973, p. 11).

This vision may explain why in the latest years there is a so large number of rich and foreign investors that, even without any emotional connection toward a football club or sport club in general, are willing to buy it for a large amount of money.

Yueh, BBC chief business correspondent, analyzed the phenomenon of the recent acquisitions of football clubs from businessmen or societies belonging to the Middle-Eastern Asia, and she wrote that "*Measured by GDP per head, Qatar is the richest nation on earth, but is small, has substantial oil reserves and happens to be situated in a relatively unstable part of the world. By using football, they are putting themselves on the map and even adding a bit more security"* ("Why on earth buy a football club? - BBC News").

Joining the football industry is surely a really expensive investment, but at the same time, it is a really fast way to be known and so it can be extremely useful for businessmen or firms to make public their name or their brand.

Anyway this does not mean that all the acquisitions of sport clubs are moved by these reasons and that sport clubs are not able to be profitable and competitive at the same time.

Some owners of sporting clubs, when interviewed, had difficulty to explain what is their main objective, saying that winning and be profitable are two dimensions that are strictly connected. For example, Robert Kraft, owner of the New England Patriots, said that *"…if you're passionate about winning and you help put an organization in place that can win, the business part will follow"*(Zimbalist, 2003, p. 14). On the same line is also Robert Johnson, founder of the BET network and owner of the NBA Charlotte team who said "*I'm first and foremost a business guy and I don't see a distinction between a winning team and profitable team"*(Zimbalist, 2003, p. 14).

Even in the football industry, where clubs have often big economic losses, examples of clubs that are able to be at the same time competitive and profitable are present. FC Bayern Munich has been able to close the balance in active for 20 years and at the same time to win 9 championships, 9 national cups, 2 Germany super cups, 1 UEFA cup and above all 2 UEFA Champions Leagues, establishing itself as one of the most competitive football clubs of the latest years. In England, FC Arsenal, though competing with clubs that spend more than hundreds of million Euros every year, has been able to be profitable and competitive at the same time, ending almost all the seasons at the first ranks of Premier League. Among Italians football clubs, the most virtuous club is probably SSC Napoli that has been able to be profitable since 2007 and at the same time to affirm itself as one of the most competitive clubs of Serie A. Even ACF Fiorentina belongs to those clubs that are able to perform well in and out of the football field. Finally Juventus, after some years in which it ended the season with huge economic losses, seems determined to start a process of self-financing, reproducing FC Bayern Munich policy.

It is precisely in the football industry that regulations and laws are pushing towards the creation and the development of healthy and profitable clubs.

The financial Fair Play Regulation (FFP), a project introduced by the Executive UEFA Committee in September 2009, aims to make clubs be able to self-financing in the long run. The FFP aims to reach the following points:

1. No presence of past dues towards other firms, employees or other authorities.
2. Supply of financial information regarding the future.
3. Break-even budget requirement.

Clubs that do not reach these objectives would risk not to take part in UEFA competitions, which are the most remunerative for clubs. Michel Platini and other UEFA directors explained how it is important for the survival of leagues that clubs do not spend more money than what they can generate. According to Platini the effect of FFP on the football industry is tangible and he said that *"Aggregate net losses of Europe's clubs have fallen from 1.7bn euros in 2011 to 400m euros in 2014"* ("Michel Platini: Uefa to 'ease' financial fair play rules - BBC Sport").

Therefore, one could expect that clubs will start to behave like real traditional firms and that, although having the peculiar mission of being competitive and successful on the soccer field, they will also be able to make constantly positive profits and to self-financing.

So, even if football clubs may remain utility maximizers, the utility function will be subject to a positive financial solvency constraint. Coming back to Sloane utility function $\max(U)$, one could expect that in the followings years it will be subjected to the condition $R - C > 0$, so with a positive yearly flow of money, with companies that will try to conjugate the bond of being profitable and competitive, imitating American sport business.

1.2 Quotation of football clubs on the stock market: reasons, history and consequences

Football clubs are always looking for capital because they want to maintain high competitive standards.

It is obvious that, in order to catch the interest of the supporters, a club should always try to be successful on the football field. To reach this goal, the company must assemble a competitive team, engage a good manager and prepared directors and have a clear project of both the short term and long term objectives. These are the ingredients of success and they can be available only when the society is economically stable.

The average players' wage rises continuously year after year and buying talents has become incredibly expensive. In order to be competitive and be able to bear these costs, clubs have started to find alternative sources of financing. That is why some clubs have decided to enter the stock market. Stock markets allow investors to obtain shares of a firm and give the possibility to that firm to raise money at the lowest possible cost. Companies convert from being private to being public by the complicated process of quotation (IPO).

Football clubs that decide to enter the stock market believe in taking advantage of the feeling of belonging to the club of the supporters and to raise enough capital for their short-long term goals.

The capital raised by the market has made it possible for the club the construction or the renovation of its owned-stadium. It has become common for a club to build stadium as more innovative as possible, able to guarantee a very important economic source of income. The construction of a stadium requires a huge amount of capital. For example the Madison Square Garden and the new Yankee Stadium cost \$1.1 and \$1.3 billion respectively "World's Most Expensive Stadiums - Forbes,").

As regards recent European football examples, the Juventus stadium and the Allianz Arena cost about €100 million and €340 million, respectively ("Allianz Arena - Munich - The Stadium Guide", "BBC SPORT | Football | Europe | Juve set to make stadium history").

Such a high amount of money can hardly be raised from banks or other financial institution. Thus the offer of shares to the public may permit to bear the costs for the stadium and make its construction or renovation possible.

Besides, the quotation allows to raise the sufficient capital to buy players and manager (Smith, 2003) in fact top players can be very expensive and finding funds from the capital market permits clubs to purchase them.

Since IPO can help these purchases it can also allow to improve the quality of the team and its chance of winning. This is true specially for low-medium clubs. IPO was particularly useful for Division 1 clubs which thanks to the additional IPO resources were able to buy strong players and so to run for the promotion to Premier League, which can give them direct access to even larger amounts of money resulting from the sale of television rights to the different broadcasting networks. (Renneboog & Vanbrabant, 2000)

Another effect of being quoted on a stock market is an increase in the devotion of supporters and in the club image. The selling of shares to the general public is an opportunity to reinforce the loyalty and devotion of supporters (Schaffer, 2006). This growth of devotion can have positive effects like the increase in merchandise sales, visualizations on the club website, tickets sold and profits in general. Parents and grandparents can buy club shares as a gift for their kids and grandchildren who as a result could become supporters of the club for all their life (Schaffer, 2006).

The last big advantage is connected to liquidation. Football clubs are generally worth hundreds of million euros and it is difficult for the owners who want to sell their club to find buyers with enough financial means. The quotation on the stock market allows an owner to liquidate the club without renouncing, in the meanwhile, to the control of the club. In this case, the amount of money received from the sale of the shares is called "early money" (Schaffer, 2006). When owners sell part of the society to the general public, they immediately receive a huge amount of money, but they will receive less when the club is completely sold because the shareholders will have to be paid too. Thus entering the stock market can allow owners to collect their investment before selling the team to another private investors.

The first club that chose to enter the stock market was Tottenham Hotspurs, a leader club in the English League, in 1983. The club raised £3.3m in the IPO, a sum equivalent to around £100m today if inflated by football transfer fees (Dobson & Goddard, 2005).

In the following years, riding the wave of entering the stock market and following the example of Tottenham the number of English and Scottish clubs grew to 22 clubs in 1997. Not all these clubs were listed on the same market. For example in the 1996/1997 football season, 12 were quoted on LSE (London Stock Exchange), 8 on AIM (Alternative Investment Market) e 2 on OFEX (non-regulated and later called Plus Market).

Club	Stock Market
Aston Villa	LSE
Bolton Wanderers	LSE
Leeds United	LSE
Midlotian	LSE
Leicester City	LSE
Manchester United	LSE
Millwall	LSE
Newcastle United	LSE
Sheffield United	LSE
Southampton	LSE
Sunderland	LSE
Tottenham	LSE
Birmigham City	AIM
Celtic Glasgow	AIM
Charlton Atletic	AIM
Chelsea	AIM
Nottingham Forrest	AIM
Preston North End	AIM
QPR	AIM
West Browmich Albion	AIM
Arsenal	OFEX
Liverpool	OFEX

Table 1.1 English and Scottish football clubs listed on stock markets.

In the following decade, however, a lot of English clubs decided to end their adventure in the stock market, realizing an operation of delisting.

At the end of 2009 among the English teams only Preston North End (LSE), Millwall (AIM), Tottenham (AIM) and Arsenal (Plus Market) maintained their quotation. The main reason for the phenomenon of "delisting" is due to the fact that some clubs were bought by a single wealthy investor or by a rich family, who did not need external funds anymore. For example Manchester United was bought by the American magnate Malcolm Glazier, Chelsea by the Russian multibillionaire Roman Abramovic and Aston Villa by the American entrepreneur Randolph David Lerner.

The market quotation is not an exclusive phenomenon of English and Scottish clubs but it is also present in other European countries.

Denmark is one of the country in which the quotation of football clubs is not uncommon. It is the second European country for the number of listed clubs and it counts 5 listed clubs. The first one was Brøndby IF in 1991 and then Silkeborg, Aarhus, Copenaghen and Aalborg.

As for Turkey, another country where football is the national sport, the public offerings of soccer clubs began in 2002. Beşiktaş and Galatasaray sold their stocks in that year, Fenerbahçe in 2004 and Trabzonspor in 2005.

For what regards Italian football clubs, the first club to enter the stock market world was SS Lazio in 1998 that at that time was managed by Sergio Cragnotti. Few years later also AS Roma (2000) and FC Juventus (2001) entered the stock market.

In 2002 the Dow Jones STOXX Football Index was created. It is an index assembled by only European football clubs' stocks. The idea behind the creation of this index was to group together in a unique index all the football clubs listed for trading on European stock exchanges. In 2002, 33 clubs were part of the index. In 2008, 27 and now they are 22.

Obviously entering the stock market implies a change of the society' objectives. Conn, a football writer of the Guardian, wrote that *"…those clubs which have floated to become public companies now have as their principal objective the making of money for their shareholders."* (Conn, 1997, p. 154).

Entering the stock market forces, according to law regulation, the club to try to maximize profits. The managers of the club will be forced to achieve an adequate financial return for their own shareholders otherwise the quotes of the society would be of less value and managers would risk, for a hostile takeover, to lose their job. Thus, we can expect that listed clubs are on average more profit oriented than clubs that are not listed in the stock market.

In order to maximize the profits for their shareholders, clubs will have to find the right mix between competitiveness and managements of funds. If clubs did not spend anything for their own players, the success would certainly be compromised, and consequently profits would drop because less people would be interested in seeing matches of uncompetitive clubs. Instead, if more talents are acquired by the club, more supporters will be captivated and profits will increase too. Competitiveness will continue to grow until revenue derived from talents is greater than their cost (Szymanski & Hall, 2003). Beyond that point, a further growth of the expenses for players, even if success increases, would make profits decrease. This is due to the fact that, at a certain level, increasing competitiveness and the quality of the team becomes always more expensive while the earnings from an additional success decrease continuously (Szymanski & Hall, 2003). In the graph below we can see the relationship between profit (vertical axis) and competitiveness (horizontal axis) according to Szymanski and Hall.

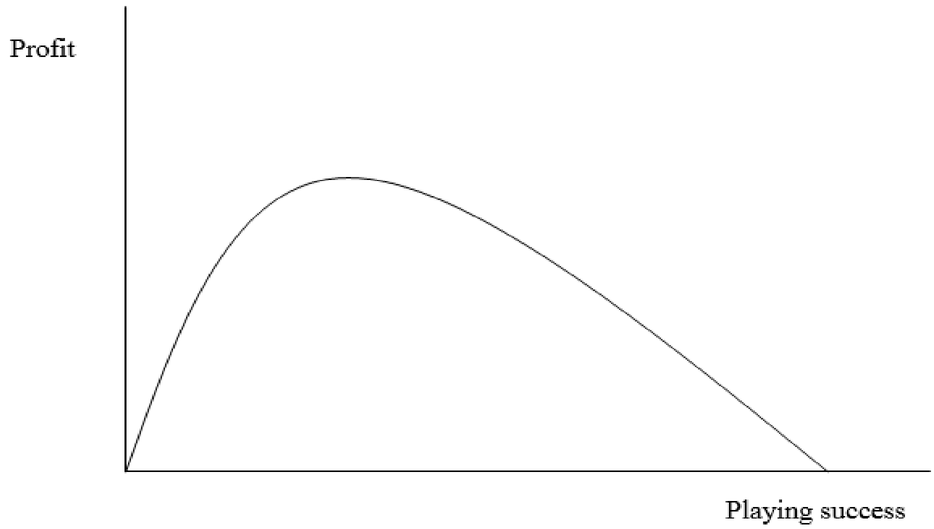

Figure 1.2 Relation between profit and competitiveness. Source: Szymanski and Hall, 2003.

1.3 Advantages and disadvantages of investing in football clubs listed on the stock market

Two parts are needed to have a successful IPO of Professional Sports Team; the presence of a club that offers the selling of shares and the presence of individuals or institutions that are willing to buy these shares. Without a proper demand for the shares supplied, the IPO would be a complete failure and no capital would be raised by the club.

As I wrote before, professional sports clubs have some peculiarities that make them differ from traditional business firms. So, some of the risks and advantages of clubs' stocks will be peculiar too, and it is important to know what they are in order to understand better stock movements and investors' behaviour.

The advantages of owning shares of sport clubs are more psychological than economical (Schaffer, 2006). The first advantage is the sense of membership that an investor gains when he owns shares of his favourite club. The sport club can be extremely important for the life of a supporter, and having the possibility to own a piece of the club is something that can be seen as a dream for him.

Schaffer affirms that another psychological advantage is given by the possibility to take part in shareholders' meetings. For an individual these events are an occasion to stay closer to the club and to develop a stronger feeling of belonging to it.

On the other hand owning a football club stock has also several disadvantages.

The first disadvantage is that a football club's stock price is very volatile. The volatility is due to the fact that, even if the sources of revenues for a club have increased compared to the past years, the economic performance of the club still depends mainly on the field results, which are of course often unpredictable.

The strong volatility of the stock price also depends on unpredictable events such as players' injuries, changes of coaches and transfers of players that can influence the competitiveness of the team.

Another disadvantage is that clubs rarely pay dividends. In fact when sport clubs offer an IPO, they often admit to the public that they will not pay any dividends (Lascari,1999).

In general the only opportunity for investors to have a good return on their purchase of stock can be achieved when the team is actually sold, giving investors the possibility to realize capital gains. Anyway these events are quite uncommon.

The high volatility and the dividend policy induce institutional investors to avoid owning sport clubs' stocks in their market portfolio. On the contrary shares are bought by supporters that, because of the psychological advantages described before, are more incentivize to own the share of the club. This can be due to the fact that, unlike stock prices of traditional business firms, individuals can obtain a great availability of information of the sport clubs and be always up to date with the club's events. Sport news are often on the first pages of newspapers and they are also reported on newscasts and websites. Supporters often tend to hypothesize a relation between football results of a club and its market performance and they think they are able to foresee easily the price trend.

However, football clubs often perform badly on the stock market because a club cannot base itself only on its match performances but it should be able to diversify its sources of revenue. If a club is not able to do that, losses will constantly occur and they will accumulate year after year (Ciarrapico, Cosci & Pinzuti, 2010).

With this work analysis, I will try to understand how strong is the relation between clubs' match results and their market performance, with the awareness that, as I explained before, to increase profits, winning is not enough but a careful management of the club is required.

2. Financial Data

In this chapter I will analyze the historical series of prices and returns of the DJ FOOTBALL index and of its components.

In the first part of the chapter I will present the DJ FOOTBALL index and I will define the variables and the statistical tests that I will use later. Then, I will analyze the previous index, focusing on its historical price series and on its daily log returns. I will use descriptive statistics and statistical tests to check the hypothesis of normality of the distribution, of the presence of autocorrelation and of the stationarity of the historical series.

In the last paragraphs I will analyze the daily log returns of the index' components.

The analyses that I will make in this chapter are important, because knowing the properties and the behaviour of prices and returns of the sample will allow to choose the rightest model for beta estimation in chapter three.

2.1 The financial dataset

Historical stock prices and returns of listed football clubs belonging to DJSTOXX FOOTBALL index are used in this paper. I used Datastream to find all the historical data and the statistical software R to compute all the statistical analyses. The time interval of the analysis goes from the beginning of August 2005 to the end of July 2015. 10-year data is a very long period and it allows to have a huge amount of data. I decided to start the analysis in August, when the football season starts.

Unfortunately I could not include all the actual 22 components of DJ STOXX FOOTBALL index in the sample of analysis because some clubs, now present in the index, joined the stock market after 2005.

2.2 Data sources and variable definitions

In order to analyse how sport results affect the financial status of clubs I started to analyse stock prices and returns of each club of the sample. I started from the stock prices of club i ($\mathbf{p_{it}}$) to compute its daily return. Using returns instead of prices has an important benefit: normalization.[1]

r_{it} is the logarithmic return[2] of a football club's stock price i and is defined as: $r_{it} = ln\,(p_{it}) - ln(p_{it-1})$.

Then I calculated mean, standard deviation, skewness[3] and kurtosis[4] of each club's daily log returns.

1) Mean: $\overline{r_i} = \frac{1}{T}\sum_{t=1}^{T} r_{it}$

2) Standard deviation: $S_{ir} = \frac{\sqrt[2]{\sum_{t=1}^{T}(r_{it}-\overline{r_i})^2}}{\sqrt[2]{T-1}}$

3) Skewness: $sk_i = \frac{\sum_{t=1}^{T}[(r_{it}-\overline{r_i})/S_{ir}]^3}{T}$

4) Kurtosis: $k_i = \frac{\sum_{t=1}^{T}[(r_{it}-\overline{r_i})/S_{ir}]^4}{T}$

2.3 Statistical hypotheses testing on football clubs shares

I used some statistical tests to analyse the behaviour of the variables, in order to understand better their distribution and their properties. I used the Jarque Bera test and the Shapiro-Wilk test to test the normality of variable distribution; the augmented Dickey–Fuller test (ADF) to test the presence of a unit root in the time series variables, the Ljung–Box test to test the

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[1] Measuring all variables in a comparable metric enables evaluation of analytic relationships amongst two or more variables despite originating from price series of unequal values.

[2] Logarithmic returns are useful for mathematical finance. One of the advantages is that the logarithmic returns are symmetric, while ordinary returns are not: positive and negative percent ordinary returns of equal magnitude do not cancel each other out and result in a net change, but logarithmic returns of equal magnitude but opposite signs will cancel each other out.

[3] Skewness measures the degree of asymmetry of a distribution around its mean. Positive skewness indicates a distribution with an asymmetric tail extending toward more positive values. Negative skewness indicates a distribution with an asymmetric tail extending toward more negative values. If the Skewness index is equal to 0, then the mass of distribution is symmetric.

[4] Kurtosis measures the degree to which a distribution is more or less peaked than a normal distribution. Positive kurtosis indicates a relatively peaked distribution. The kurtosis of any univariate normal distribution is 3. Distribution with kurtosis less than 3 are said to be platykurtic. Distributions with kurtosis greater than 3 are said to be leptokurtic.

presence of autocorrelation and the LM test to test the presence of eteroschedasticity. As these tests will be used from now on in the chapter, I am going to explain them in detail.

2.3.1 The Jarque Bera test

The Jarque–Bera test tests whether sample data have the skewness and kurtosis matching a normal distribution. The test statistic *JB* is defined as: $JB = \frac{n-k+1}{6}(S^2 + \frac{1}{4}(C-3)^2$, where n is the number of observations (or degrees of freedom in general); S skewness of the sample, C kurtosis of the sample, and k is the number of regressors (Jarque & Bera, 1987). Skewness and kurtosis are equal to: $S = \frac{\widehat{\mu_3}}{\widehat{\sigma^3}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2)^{3/2}}$, $C = \frac{\widehat{\mu_4}}{\widehat{\sigma^4}} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2)^2}$, where $\hat{u}_3$ and $\hat{u}_4$ are the estimates of third and fourth central moments, respectively, $\bar{x}$ is the sample mean, and $\hat{\sigma}^2$ is the estimate of the second central moment, the variance. The null hypothesis is of normality, and rejection of the hypothesis (because of a significant p-value) leads to the conclusion that the distribution from which the data came is non-normal.

2.3.2 The Shapiro-Wilk test

The Shapiro–Wilk test utilizes the null hypothesis principle to check whether a sample $X_1, ..., X_n$ came from a normally distributed population. The test statistic is: W= $\frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2}$ where $x_{(i)}$ is the i_{th} order statistic and $\bar{x} = (x_1 + \cdots + x_n)/n$ is the sample mean (Shapiro & Wilk, 1965). Like in the Jarque Bera test, the null hypothesis is of normality, and rejection of the hypothesis (because of a significant p-value) leads to the conclusion that the distribution from which the data came is non-normal.

2.3.3 The Augmented Dickey-Fuller test

The augmented Dickey–Fuller test (ADF) is a test for a unit root in a time series sample. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number: the more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. If the test statistic is less than the larger negative critical value, then the null hypothesis of $\gamma = 0$ is rejected and no unit root is present, meaning that the process is stationary[5].

The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$ where α is a constant, β the coefficient on a time trend and p the lag order of the autoregressive process. The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. The test statistic is: $DF_\tau = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$ (Fuller, 1976).

2.3.4 The Ljung–Box test

The Ljung–Box test is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags.

The test statistic is: $Q = n\,(n+2) \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k}$ where n is the sample size, $\hat{\rho}_k$ is the sample autocorrelation at lag *k*, and *h* is the number of lags being tested (Ljung & Box, 1978).

Under the null hypothesis the data are independently distributed[6] while under the alternative hypothesis the data are not independently distributed and they exhibit serial correlation.

Under H_0 the statistic Q follows a $\chi^2_{(h)}$. For significance level α, the critical region for rejection of the hypothesis of randomness is $Q > \chi^2_{1-\alpha,\mathrm{h}}$ where $\chi^2_{1-\alpha,\mathrm{h}}$ is the α-quantile of the chi-squared distribution with *h* degrees of freedom.

2.3.5 The Engle's Lagrange Multiplier Test for ARCH disturbances

Engle in 1982 proposed a methodology using the Lagrange multiplier test to test for the lag length of ARCH error. This methodology is a 2 step procedure, consisting firstly in the estimation of the best fitting autoregressive model AR (*q*): $y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{t-q} + \epsilon_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \epsilon_t$ and secondly in the regression of the error $\hat{\varepsilon}^2$, obtained from the

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[5] A stationary process is a stochastic process whose joint probability distribution does not change when shifted in time. Consequently, parameters such as the mean and variance, if they are present, also do not change over time and do not follow any trends.

[6] The correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process).

previous regression, on a constant and q lagged values: $\hat{\epsilon}^2{}_t = \hat{a}_0 + \sum_{i=1}^{q} \hat{a}_i \hat{\epsilon}^2{}_{t-1}$ where q is the length of ARCH lags (Engle, 1982).

The null hypothesis is that, in the absence of ARCH components, $\alpha_i = 0$ for all $i = 1, \dots, q$. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated α_i coefficients must be significant. In a sample of T residuals under the null hypothesis of no ARCH errors, the test statistic $T'R^2$ follows X^2 distribution with q degrees of freedom, where $T'$is the number of equations in the model which fits the residuals vs the lags (i.e. $T' = T - q$). If $T'R^2$ is greater than the Chi-square table value, the null hypothesis is rejected, concluding that there is an ARCH effect in the ARMA model. If $T'R^2$ is smaller than the Chi-square table value, the null hypothesis is not rejected.

2.4 Descriptive statistics and statistical tests of the market index

2.4.1 The market DJ STOXXFOOTBALL index

The STOXX Europe Football Index covers all football clubs that are listed on a stock exchange in Europe or Eastern Europe, Turkey or the EU-Enlarged region. The index accurately represents the breadth and depth of the European football industry ("First European Football Index Launched By STOXX, Ltd"). The Dow Jones STOXX Football Index is free-float market capitalization weighted capped at 10% to prevent dominance by any individual club. Weightings will be recalculated every third Friday before end of a quarter.

The Dow Jones STOXX Football Index was launched on April 22, 2002 and at that time it included all 33 football clubs listed for trading on European stock exchanges.

Now the composition of the index is different: in fact some clubs that were listed in the stock market in 2002 are not listed anymore and some other clubs joined the index only after its creation. Now the club components are 22:

- Aalborg, Aarhus, Brondby, FC Copenhagen, Silkeborg (Denmark)
- Olympique Lione (France)
- Borussia Dortmund (Germany)
- AS Roma, FC Juventus, SS Lazio (Italy)
- Ajax (Holland)
- Ruch Chorzow (Poland)
- Benfica, FC Porto, Sporting Lisbona (Portugal)
- Teteks & Tetovo (Republic of Macedonia)

- Celtic Glasgow, (Scotland)
- Aik Fotboll (Sweden)
- Besiktas, Fenerbahce, Galatasaray, Trabzonspor (Turkey)

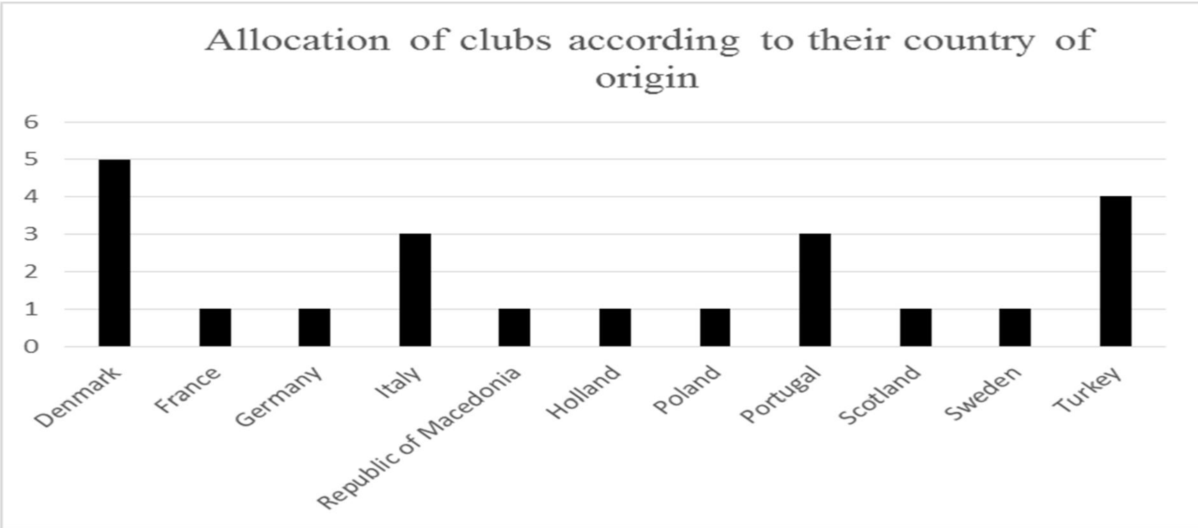

Figure 2.1: Allocation of clubs according to their country of origin.

All the teams that now belong to the index are in the top league of their national Championship. Almost all the teams have played at least some matches in the European competitions (the UEFA Champions League and the new "UEFA Cup", the UEFA Europa League). Some teams during the period of analysis were relegated in lower divisions, ether because of bad field results (Silkeborg and Ruch Chorzow), or because illegal sport behaviour (Juventus).

2.4.2 Statistical analysis of DJ STOXXFOOTBALL index

DJ STOXX FOOTBALL index from 2005 to 2015 lost around 25.88%. As we can see from the graph below, during the financial crisis the index price dropped and, after a fast recover in 2010, there was another long and slow downfall in 2011 that brought in 2013 the price of the index to its minimum level. Since 2013 the index has not shown signs of recovery.

Figure 2.2: Historical prices of DJ STOXX FOOTBALL index.

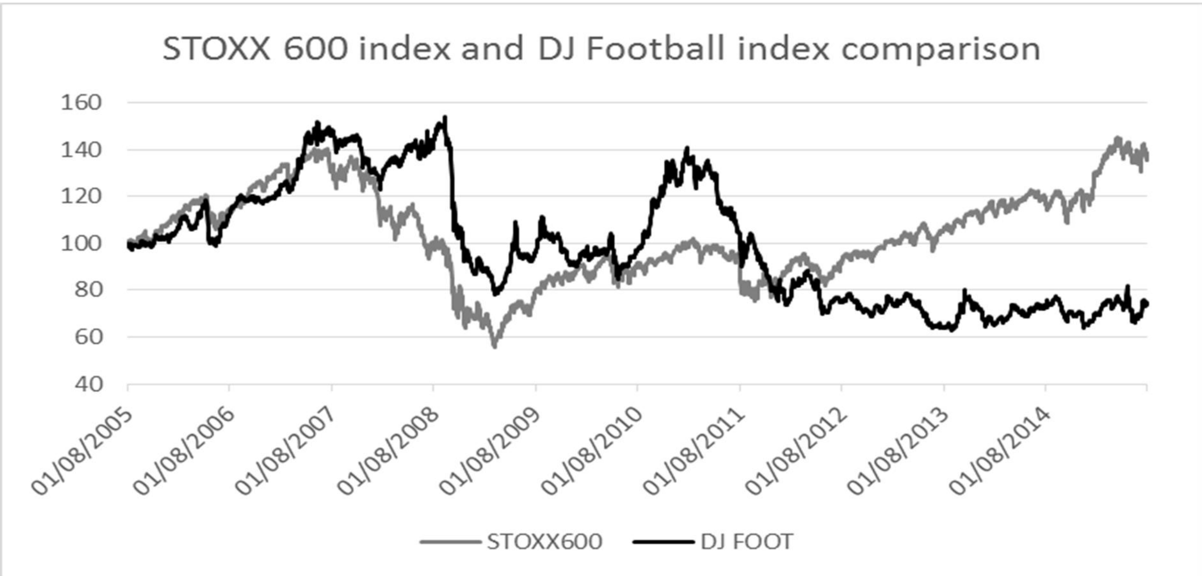

Figure 2.3: Comparison between STOXX Europe 600 and DJ FOOTBALL STOXX index.

If we compare the evolution of DJ FOOTBALL STOXX index with STOXX Europe 600 index[7] we can see that the trend of the indexes was similar until the financial crisis. After the crisis STOXX Europe 600 started a slow but incessant phase of growth and now its price is higher than its pre-crisis level. So we can say that since 2012 the STOXX Europe 600 has been over performing the DJ FOOTBALL STOXX index.

[7] STOXX Europe 600 index represents large, mid and small capitalization companies across 18 countries of the European region and so can be considered a good proxy for the entire European financial market.

I also grasped a difference in the volatility of the two indexes so I decided to compare even the daily log returns of the two indexes.

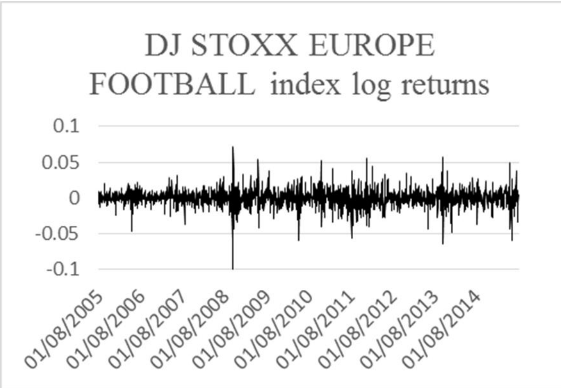

Figure 2.4: DJ FOOTBALL STOXX index log returns

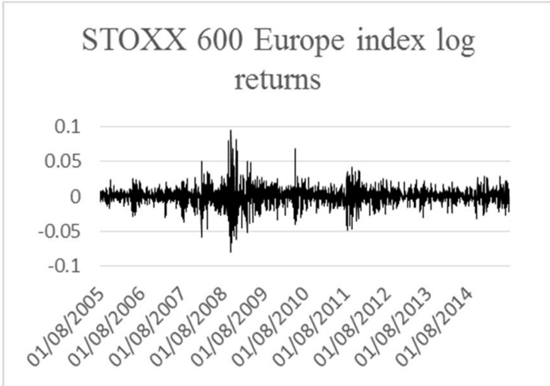

Figure 2.5: STOXX Europe 600 STOXX index log returns

Analysing daily log returns' graphs of the two indexes, one can see that, while after the financial crisis STOXX Europe 600 index volatility returned to pre-crisis level, the DJ FOOTBALL STOXX index's one did not and stayed constantly to a higher level than its pre-crisis level.
So, it seems that DJ FOOTBALL STOXX does not follow a stationary process neither in mean nor in volatility. The histogram of DJ STOXX FOOTBALL index prices show us how the prices' distribution is concentrated on the left of the figure. In fact the skewness coefficient is positive, meaning that the distribution is right-skewed. The distribution is also platykurtic, with a kurtosis coefficient statistically smaller than 3. This kind of behaviour is typical among stock prices, because it is very common that prices do not follow a normal distribution.

Histogram of DJ FOOTBALL STOXX index daily prices

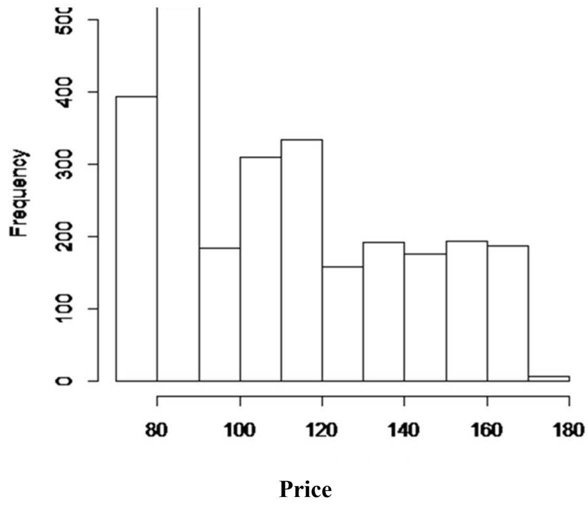

Figure 2.6: Histogram of DJ FOOTBALL STOXX index historical prices.

Min.	70.39
1st Qu.	84.045
Median	107.6
Mean	111.063
3rd Qu.	133.783
Max.	173.880
Variance	824.054
Skewness	0.439
Kurtosis	1.943

Table 2.1 Descriptive statistics of DJ FOOTBALL STOXX index prices.

To check the hypothesis of no stationarity of DJ STOXX FOOTBALL index price I used two statistical test: the Augmented Dickey-Fuller test (ADF) and the Phillips-Perron test[8] (PP)

- adf.test(logprez)
  Dickey-Fuller = -2.696, Lag order = 13, p-value = **0.284**
- pp.test(logprez)
  Dickey-Fuller Z(alpha) = -10.521, Truncation lag parameter =9, p-value = **0.523**

Both the “p-value” values are high and that means that the null hypothesis of the presence of unit root in the series can be accepted and the alternative hypothesis of stationarity in the series must be refused. These results are congruent with my previous considerations about the index trend.

[8] Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of Δy_t as regressors in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

I now focus the analysis on the DJ FOOTBALL STOXX index daily log returns. In the table below there are the descriptive statitics. The daily log returns do not seem to follow a normal distribution. In fact the Skewness coefficient is negative, and kurtosis coefficient is greater than 3 meaning that the distribution is leptokurtic. In fact the histogram below shows how the returns are clustered, creating an higher peak (higher kurtosis) than the curvature found in a normal distribution.

Min.	-0.100
1st Qu.	-0.006
Median	0
Mean	-0.000
3rd Qu.	0.005
Max.	0.072
Variance	0.000
Skewness	-0.478
Kurtosis	9.856

Table 2.2 Descriptive statistics of DJ FOOTBALL STOXX index daily log returns.

Histogram of DJ FOOTBALL STOXX index daily log returns

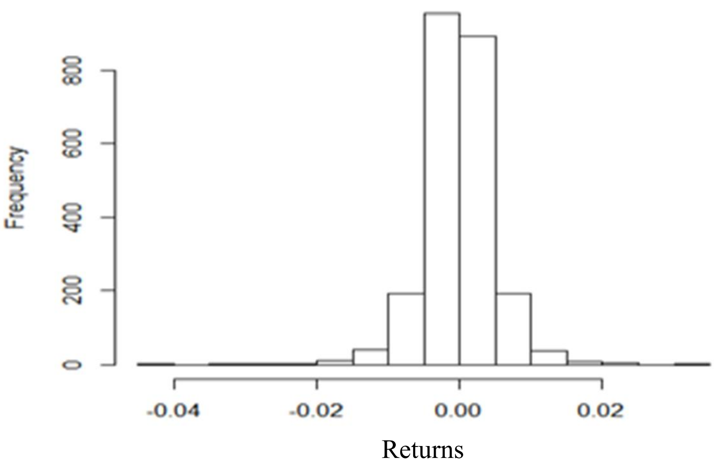

Figure 2.7: histogram of DJ FOOTBALL STOXX index daily log returns.

To check my considerations about the distribution of the returns I used some tests in order to test the normality of the distribution, the presence of autocorrelation among returns and the presence of eteroschedasticity effects. The null hypothesis of normality is rejected both by Jarque-Bera test and Shapiro-Wilk test.

Test	ST.TEST	p-value	Significance
Test ADF	-12,965	0,010	***
Test Jarque-Bera	5298,400	0,000	***
Test Shapiro-Wilk	0,932	0,000	***
Test Ljung–Box test	28,745	0,000	***
Test ARCH effects	462,010	0,000	***

Table 2.3. Test results on index' daily log returns. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

ADF test seems to confirm the stationary of the series. In fact the p-value is small and it brings to refuse the null hypothesis of presence of the unit root in the series and to accept the alternative hypothesis of stationary of the series. The Ljung-Box test verifies the presence of autocorrelation among returns. Lm test verifies the presence of eteroschedasticity in the series.

2.4.3 Statistical analysis of DJ STOXXFOOTBALL index components

The period of analysis of DJ FOOTBALL STOXX index components goes from August 2005 to July 2015.

As I wrote before, it was impossible to analyse all the 22 components of the index. Since 5 clubs joined the index only after 2005 (Olympique Lione, Teteks & Tetovo, Ruch Chorzow, Benfica, Rangers Glasgow, Aik Fotboll) I did not have so much data as the other clubs to do an appropriate statistical analysis. It is a pity that I did not have enough data to analyse Benfica and Olympique Lione because they are two top tier clubs in their league and they played successfully in European completions. Their inclusion will be possible only in future papers.

In this paragraph I analyse all the 17 components' daily log returns and I will do statistical tests, as I did in the previous paragraph, to test the normality of the distribution, the presence of autocorrelation among returns and the presence of eteroschedasticity effects. In the tables below there are the results of the tests and the sample estimation of the first four moments and the minimum and maximum of the clubs' daily log returns.

		Aalborg	**Aarhus**	**Brondby**	**Copenhaghen**	**Silkeborg**	**Borussia D.**
	ST.TEST						
Normality	JB	2042300	4464.5	2948700	24376	3742.3	18065
	Sign.	***	***	***	***	***	***
	W	0.697	0.913	0.632	0.851	0.794	0.894
	Sign.	***	***	***	***	***	***
Unit root	ADF	-12.945	-12.806	-15.845	-13.552	-16.206	-11.974
	Sign.	***	***	***	***	***	***
Autocorr.	BP	43.460	18.959	13.331	0.322	184.800	3.515
	Sign.	***	***	***		***	*
Eter.Cond.	LM	23.642	149.600	36.927	134.210	122.430	297.120
	Sign.	**	***	***	***	***	***

Table 2.4: Test results on daily log returns. . ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	ST.TEST	Roma	Juventus	Lazio	Ajax	Porto	Sporting
Normality	JB	30281	64233	25655	6679.8	65463	44925
	Sign.	***	***	***	***	***	***
	W	0.785	0.757	0.799	0.882	0.782	0.754
	Sign.	***	***	***	***	***	***
Unit root	ADF	-13.253	-13.839	-13.127	-14.481	-16.458	-16.445
	Sign.	***	***	***	***	***	***
Autocorr.	BP	3.249	25.111	6.185	216.790	228.930	95.560
	Sign.		***	***	***	***	***
Eter.Cond.	LM	439.290	672.760	531.800	114.890	501.810	135.650
	Sign.	***	***	***	***	***	***

Table 2.5: Test results on daily log returns. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	ST.TEST	Celtic	Besiktas	Fenerbahce	Galatasaray	Trabzonspor	Foot.index
Normality	JB	299090	19882	15947	14358	8130	5298.4
	Sign.	***	***	***	***	***	***
	W	0.402	0.830	0.823	0.824	0.847	0.932
	Sign.	***	***	***	***	***	***
Unit root	ADF	-12.554	-14.329	-13.496	-14.602	-14.658	-12.965
	Sign.	***	***	***	***	***	***
Autocorr.	BP	183.51	38.427	33.282	12.738	21.601	28.745
	Sign.	***	***	***	***	***	***
Eter.Cond.	LM	350.820	202.720	261.780	237.340	296.180	462.010
	Sign.	***	***	***	***	***	***

Table 2.6: Test results on daily log returns. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Club	Mean	Standard dev.	Skewness	Kurtosis	Min	Max.
Aalborg	-0.001	0.053	3.933	139.704	-0.764	1.249
Aarhus	-0.001	0.040	0.315	9.369	-0.280	0.264
Ajax	0.000	0.020	0.795	10.670	-0.102	0.171
Besiktas	0.000	0.035	0.191	16.503	-0.408	0.215
Borussia Dortmund	0.000	0.024	0.225	15.868	-0.216	0.240
Brondby	-0.001	0.043	-1.057	167.522	-0.992	0.817
Celtic	0.000	0.011	2.736	55.115	-0.109	0.159
Copenaghen	0.000	0.025	0.119	17.956	-0.249	0.266
Fenerbahce	0.000	0.028	0.100	15.096	-0.215	0.201
Galatasaray	0.000	0.029	0.170	14.474	-0.202	0.177
Juventus	0.000	0.026	0.359	27.272	-0.278	0.251
Lazio	0.000	0.035	0.486	18.315	-0.316	0.261
Porto	-0.001	0.040	0.141	27.512	-0.503	0.511
Roma	0.000	0.036	0.957	19.561	-0.382	0.266
Silkeborg	0.000	0.056	-0.017	8.859	-0.372	0.314
Sporting	0.000	0.054	0.710	23.257	-0.486	0.644
Trabzonspor	0.000	0.030	0.281	11.619	-0.217	0.198

Table 2.7: sample' estimation of the first four moments, of the minimum and maximum.

Looking at the previous tables we can see that all clubs' returns are stationary in mean and that they do not follow a normal distribution. In fact both Jarque Bera test and Shapiro Wilk test refuse the null hypothesis of normal distribution. These test results were predictable looking at the descriptive statistics of table 2.4, in which the kurtosis and the skewness coefficients of all clubs' daily log returns are much different from the ones of a normal distribution. Kurtosis coefficients are in fact very high and far above 3 meaning that returns are concentrated around the mean creating an higher peak respect the one in a normal distribution. The Engle's Lagrange multiplier test for ARCH disturbances testing the presence of ARCH effects for all the clubs' log daily returns. Finally, the Ljung box test tests the presence of autocorrelation of log daily returns. Only the daily log returns of three clubs (A.S. Roma, Copenaghen and Borussia Dortmund) seems not to be correlated.

2.5 Football Performance Dataset

The football performance dataset includes the sports data regarding the clubs belonging to DJ STOXX index from 2005 and 2015. As I wrote in this chapter, the sample analysed consists of 17 clubs.

The football performance dataset includes data of 6892 football matches played by the sample clubs and it includes several variables:

1) **The match result**: three dummy variables (Win_{ij}, $Loss_{ij,}$ Tie_{ij}) indicating if team *i* won, tied or lost the *j* match. Among the 6892 matches, clubs won 3586 matches (52.03%), lost 1687 matches (24.48%) and tied 1619 (23.49%). The high number of wins can be explained by the fact that the clubs in the sample are top tier clubs in their national championship.
2) **The goal difference**: it measures the goal difference of the *j* match of team *i*. It can assume positive, negative and null values according to match results. The goal difference mean is 0.6263. A positive goal difference is something that one could expect because clubs in the sample have more wins than losses.
3) **The site of competition**: two dummy variables ($Home_{ij}$, $Away_{ij}$) indicating whether the match j was played at home of team *i* or not. 3441 (49.93%) matches were played at home and 3451 (50.07%) matches were played away from home.
4) **The type of competition**: three dummy variables ($Ncha_{ij}$,, $Clea_{ij}$, $Elea_{ij}$) indicating whether the match *j* was a national championship match, a UEFA Champions League match, or an UEFA Europa League match. 5838 (85.31%) matches were national championship matches, 524 (7.63%), were UEFA Champions League matches and 530 (7.68%) were UEFA Europa League matches.
5) **The year of competition**: a set of dummy variables ($Y05_{ij}$ $Y06_{ij}$ $Y07_{ij}$ $Y08_{ij}$ $Y09_{ij}$ $Y10_{ij}$ $Y11_{ij}$ $Y12_{ij}$ $Y13_{ij}$ $Y14_{ij}$ $Y15_{ij}$) indicating the year in which the match *j* was played. The number of matches analysed is almost uniformly distributed across years (about 9% per year)
6) **The month of competition**: a set of dummy variables (Jan_{ij}, Feb_{ij}, Mar_{ij}, Apr_{ij}, May_{ij}, Jun_{ij}, Jul_{ij}, Aug_{ij}, Sep_{ij}, Oct_{ij}, Nov_{ij}, Dec_{ij}) indicating the month in which the match *j* was played. The number of matches analysed is almost uniformly distributed across months (about 10% per month). The only exception are January (5.48%), June (0.30%) and July (2.32%) when less matches were played.

7) **The anticipated (expected) results**: two dummy variables (Fav_{ij}, Und_{ij}) indicating if the team *i* was favourite in the match *j* or not based on the information of pre-match betting odds. In 5195 (75.38%) matches team *i* was the favourite while only in 1697 (24.62%) matches team *i* was the underdog. This confirms the fact that the clubs in the sample are top tier clubs.

2.6 The inclusion of football betting odds in the model

Obviously not all the matches have the same degree of importance. Winning a national championship match against a top competitor of the league is not the same as winning against a bottom league club. This is due to the fact that winning against a bottom league club is an expected result. The inclusion of football betting odds in the model allows me to consider the expectation of the results by bettors. According to the efficient market hypothesis, the stock prices of soccer teams should reflect all the available information, including the one on expected results, which is implicit in the pre-match betting odds. Using this interpretation framework, only unexpected events may generate abnormal returns. In chapter three I will test the hypothesis that an unexpected result has a greater effect on abnormal returns than an expected one. To include betting odds I used historical data which includes betting odds from over 30 bookmakers ("Sport Stats: Sports Statistics, Standings, Fixtures & Results"). In the table below, one can see the absolute number of matches in which clubs were favourite and underdogs, according to each type of competition.

Expected results							
CLUB	**Fav Nat. Cham.**	**Fav Ch.L**	**Fav Eu.L**	**Und Nat Cham.**	**Und Ch.L**	**Und Eu.L**	**Total**
Aalborg	201	5	10	126	9	18	**369**
Aarhus	169	0	0	157	0	0	**326**
Ajax	240	1	23	87	2	11	**364**
Besiktas	321	16	23	7	33	25	**425**
Borussia D.	150	0	0	171	0	0	**321**
Brondby	254	26	8	87	11	2	**388**
Celtic	290	26	23	87	15	5	**446**
Copenaghen	347	39	18	37	16	4	**461**
Fenerbahce	220	4	30	160	4	11	**429**
Galatasaray	322	21	29	30	27	15	**444**
Juventus	288	40	19	20	32	6	**405**
Lazio	265	11	41	44	21	16	**398**
Porto	366	30	9	12	31	15	**463**
Roma	293	7	38	52	13	18	**421**
Silkeborg	309	20	23	35	22	13	**422**
Sporting	300	12	27	45	21	13	**418**
Trabzonspor	258	3	20	88	6	17	**392**
TOTAL	**4593**	**261**	**341**	**1245**	**263**	**189**	**6892**

Table 2.8 Absolute number of matches in which clubs were favourite and underdogs.

As I wrote before, almost all the clubs of the sample (with the only exceptions of the two Danish clubs, Aarhus and Silkeborg) are top tier clubs in their national league. So, the fact that 4593 out of 5838 (78.67%) clubs were expected winners is not surprising. In the European matches, where opponents quality is higher, things are different. In fact in the UEFA Champions League (the most important and prestigious European football competition), only half of the times the sample's clubs were favourite (261 out of 524 matches) while in the Europa League, where the opponents' level is weaker than in the UEFA Champions League, the percentage of times in which the clubs were favourite is higher and is equal to 64.38% but it is still smaller than the one in national championship competitions.

2.7 Tables regarding football clubs results

National and European matches				
Club	**Win**	**Tie**	**Loss**	**Total**
Aalborg	152	100	117	**369**
Aarhus	124	77	125	**326**
Ajax	262	96	86	**444**
Besiktas	215	98	108	**421**
Borussia Dortmund	189	96	103	**388**
Brondby	154	97	113	**364**
Celtic	303	77	83	**463**
Copenaghen	238	98	89	**425**
Fenerbahce	252	91	79	**422**
Galatasaray	231	95	92	**418**
Juventus	272	122	67	**461**
Lazio	183	109	137	**429**
Porto	278	73	54	**405**
Roma	233	107	106	**446**
Silkeborg	113	79	129	**321**
Sporting	211	100	87	**398**
Trabzonspor	176	104	112	**392**
Total Dataset	**3586**	**1619**	**1687**	**6892**

Table 2.9 European and national matches' results of each club of the sample.

Looking at the data, it is clear that almost all the clubs in the sample played more than 400 matches during the 10-year period of analysis. The only exceptions are the Danish clubs which played less matches, either because they played less matches in their national league compared to the other national leagues, and because they had less success in European competitions.

National matches				
Club	**Win**	**Tie**	**Loss**	**Total**
Aalborg	137	88	102	**327**
Aarhus	124	77	125	**326**
Ajax	224	75	53	**352**
Besiktas	178	87	80	**345**
Borussia Dortmund	166	87	88	**341**
Brondby	138	89	100	**327**
Celtic	273	59	46	**378**
Copenaghen	201	77	50	**328**
Fenerbahce	219	68	57	**344**
Galatasaray	203	76	66	**345**
Juventus	236	96	52	**384**
Lazio	163	94	123	**380**
Porto	230	51	27	**308**
Roma	200	84	93	**377**
Silkeborg	113	79	129	**321**
Sporting	175	76	58	**309**
Trabzonspor	159	88	99	**346**
Total Dataset	**3139**	**1351**	**1348**	**5838**

Table 2.10 National matches' results of each club of the sample.

Looking at the table above, one can see that national championship matches played by the clubs in the sample were 5838. Obviously the number of matches played by each team depended on the regulation of the league in which the club played in. Not all the national leagues have the same number of teams and that is the reason why the total amount of matches played by each club is different. We can see that some teams played an odd number of matches. This is not due to errors but it might depend on the fact that some leagues include playoffs which can create this kind of situation or on the fact that some matches in a particular year might have been cancelled.

European matches									
Club	**WCh.l**	**TCh.l**	**LCh.l**	**WEu.l**	**TEu.l**	**Leu.l**	**TotCh.**	**TotEu.**	**Total**
Aalborg	6	4	4	9	8	11	***14***	***28***	**42**
Ajax	14	15	19	24	6	14	***48***	***44***	**92**
Besiktas	8	3	9	29	8	19	***20***	***56***	**76**
Borussia	18	6	13	5	3	2	***37***	***10***	**47**
Brondby	1	1	1	15	7	12	***3***	***34***	**37**
Celtic	25	8	28	5	10	9	***61***	***24***	**85**
Copenaghen	20	9	20	17	12	19	***49***	***48***	**97**
Fenerbahce	15	11	16	18	12	6	***42***	***36***	**78**
Galatasaray	9	7	17	19	12	9	***33***	***40***	**73**
Juventus	25	17	13	11	9	2	***55***	***22***	**77**
Lazio	2	3	3	18	12	11	***8***	***41***	**49**
Porto	33	17	22	15	5	5	***72***	***25***	**97**
Roma	19	7	15	14	7	7	***41***	***28***	**69**
Sporting	9	8	15	27	16	14	***32***	***57***	**89**
Trabzonspor	2	5	2	15	11	11	***9***	***37***	**46**
Total dataset	**206**	**121**	**197**	**241**	**138**	**151**	**524**	**530**	**1054**

Table 2.11 European matches' results of each club of the sample.

The table above regards only European matches. The matches are split in UEFA Champions League matches and UEFA Europa League matches, Ch.l and Eu.l respectively.

Two clubs of the sample (Aarhus and Silkeborg) never took part in European competitions during the period of analysis and so they are not included in the previous table.

3. Statistical models after the inclusion of football performances data

In the last chapter I analyzed the historical series of prices and returns of Dow Jones STOXX Football index and of its components. Prices and returns do not follow a normal distribution. In fact, almost always, skewness and kurtosis coefficients differ from the ones of a normal distribution. The Engle's Lagrange multiplier test and the Ljung box test test the presence of autocorrelation of log daily returns and prices, respectively.
These information about football clubs' stock prices and returns are important because, when the properties and the behaviour of prices and returns of the team of the sample are known, they allow me to choose the rightest model for beta estimation.
In this chapter I will calculate football club beta using the theoretical "market model" and then I will calculate abnormal returns of the football clubs in the sample and I will analyse the relationship between them and the football results of the clubs obtained from the football dataset of chapter two. The analysis is done both using sports data as a whole and using only results of European competitions.

3.1 The "Market Model"

The "Market model" is a statistic linear model that links the returns of a firm with the returns of the market. In the model, the dependent variable is the return of the football club and the independent variable is the DJ STOXX FOOTBALL index's return. The Market Model is similar to CAPM but it differs from this because it does not include the risk free. The Market Model is $\boldsymbol{r_{it} = \alpha_i + \beta_i(r_{mt}) + \varepsilon_{it}}$ with $\boldsymbol{E(\varepsilon_{it} = 0)}$ and $\boldsymbol{var(\varepsilon_{it}) = \sigma^2_{\varepsilon i}}$

- Where r_{it} e r_{mt} are the logarithmic returns of the club *i* and of the index DJSTOXX FOOTBALL respectively, at time *t*;
- α_i, β_i, $\sigma^2_{\varepsilon i}$ are the model's parameters; Beta (β_i) represents the systemic risk of the club and it measures the sensitivity of a stock to stock market movements.

In literature the independent variable is often a market index (for example the Standard and Poor index or the Europe Stoxx 600 index). Instead, I decided to use the DJ Stoxx FOOTBALL index, described in chapter 2 because it represents the breadth and depth of the European football industry.[9]

3.2 Empirical analysis of the sample

The regression model used is a OLS (Ordinary Least Squares) model. The model is $\boldsymbol{y_i = x_i\beta + \varepsilon_i}$ where y_i is the dependent variable, x_i is the independent variable and ε is the error term of the regression. The Beta coefficients are calculated in order to minimize the square of the error terms: $\mathbf{Q(\beta) = ||y - \mu||\^{}2 = (y - X\beta)T\ (y - X\beta),}$ having then $\boldsymbol{\widehat{\beta} = (X^TX)^{-1}X^Ty}$ and $\mathbf{E\{\beta\}= \beta}$**.** The variance matrix is $\mathbf{V(\beta) =} \boldsymbol{S^2(X^TX)^{-1}}$ where $\mathbf{s^2}$ is the no distorted estimate for σ^2, calculated from $\boldsymbol{e = \hat{\varepsilon} = y - X\widehat{\beta}}$, with the use of the formula $\boldsymbol{s^2 = \frac{e^Te}{n-p}}$, and the standard errors are the square root of the matrix $\mathbf{V(\beta)}$ diagonal seen before.

The condition for OLS to be a good estimate are the following:

- **Strict exogeneity**: the errors in the regression should have conditional mean zero: $E[\varepsilon|X] = 0$.
- **Homoskedasticity**: the conditional variance of the error term should be a constant in all x and over time. Homoskedasticity implies that the model uncertainty is identical across observations. $E[\varepsilon_i^2 | X] = \sigma^2$
- **No autocorrelation:** error terms are independently distributed and not correlated: $E[\varepsilon_i\varepsilon_j | X] = 0$ for $i \neq j$

When eteroskedasticity and autocorrelation are present, the OLS estimator is not consistent anymore, and one should use the Newey West (1987) estimator, in which the error terms are calculated in order to be consistent both to eteroschedasticity and to autocorrelation (Heteroskedasticity and Autocorrelation Consistent, HAC). This method is perfect if correlation is restricted to the max number of lag. So the variance and covariance matrix become $\boldsymbol{V\{\widehat{\beta}\} = (X'X)^{-1}NW(X'X)^{-1}}$ with $\boldsymbol{NW = \sum_{t=1}^{T} e_t^2 x_t x_t' + \sum_{l=1}^{L}\sum_{t=l+1}^{T} w_l(e_t e_{t-l} x_t x_{t-l}' + e_{t-l} e_t x_{t-l} x_t')}$ and $\boldsymbol{w_l = 1 - \frac{l}{1+L}}$ where T is the number of observation and L is the number of lags.

The goodness of fit of the regression is measured by the R-squared (coefficient of determination). The R^2 is the ratio of the explained variation compared to the total variation: it

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[9] I also used as market index the Europe Stoxx 600 index obtaining similar results.

is interpreted as the fraction of the sample variation in y that is explained by x. $R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$ where $= \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$, $SST = \sum_{i=1}^{n}(y_i - \bar{y})^2$ and $SSR = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$. R^2 is always between 0 and 1. A value of R^2that is nearly equal to zero indicates a poor fit of the OLS line.

To verify if the estimated model is correct the first step is to analyze the behaviour of residuals. So I checked the presence of autocorrelation of residuals, eteroskedasticity and structural breaks using some statistical tests:

- **White Test**: it tests for the presence of eteroschedasticity in the model. The test statistics is $LM = nR^2$ where n is the sample size and R^2 is the coefficient of determination. Under the null hypothesis of omoschedasticity the test statistics follows a chi squared distribution with P-1 degrees of freedom. If nR^2 is greater than the Chi-square table value, the null hypothesis is rejected, concluding that there is eteroschedasticity in the model.
- **Breusch-Godfrey test**: it tests for autocorrelation in the errors in a regression model. It makes use of the residuals from the model being considered in a regression analysis, and a test statistic is derived from these. The null hypothesis is that there is no serial correlation of any order up to p.
- **Breusch–Pagan test**: it tests whether the estimated variance of the residuals from a regression are dependent on the values of the independent variables. In that case, heteroskedasticity is present. The test statistic is $\mathrm{LM} = \mathrm{nR}^2$ and under the null hypothesis of homoskedasticity it is asymptotically distributed as $\chi^2_{\mathrm{p}-1}$. If the Chi Squared value is significant with p-value below an appropriate threshold, the null hypothesis of homoskedasticity is rejected and heteroskedasticity assumed.
- **Cumulative sum test (CUSUM):** it is used for step detection of a time series. Under the null hypothesis the data are random while under the alternative hypothesis the data are not random. This test is based on the maximum distance from zero of a random walk defined by the cumulative sum of the sequence. A large enough distance is indicative of non-randomness of data.

3.2.1 Market Model's beta estimation and residual analysis

I analyzed with the "market model" all the 17 stock titles listed in the European market using, as I wrote before, the DJ STOXX FOOTBALL index as benchmark. The following tables show the coefficient estimates with their p-values.

Club	Alpha	P-value alpha	Beta	P-value beta
Ajax	0.000	0.979	0.231	0.000 (***)
Roma	0.000	0.618	0.970	0.000 (***)
Besiktas	0.000	0.781	1.366	0.000 (***)
Borussia D.	0.000	0.491	0.679	0.000 (***)
Celtic G.	0.000	0.385	0.092	0.001 (***)
Fenerbahce	0.000	0.318	1.211	0.000 (***)
Galatasaray	0.000	0.980	1.219	0.000 (***)
Juventus	0.000	0.793	0.982	0.000 (***)
Lazio	0.000	0.690	0.712	0.000 (***)
Aalborg	-0.001	0.398	0.409	0.000 (***)
Aarthus	-0.001	0.506	0.782	0.000 (***)
Brondby	-0.001	0.360	0.498	0.000 (***)
Porto	-0.001	0.474	0.095	0.171
Copenhagen	0.000	0.442	0.788	0.000 (***)
Silkeborg	0.000	0.837	0.256	0.019 (**)
Sporting L.	0.000	0.662	0.203	0.039 (**)
Trabzonspor	0.000	0.877	1.140	0.000 (***)

Table 3.1 Estimation of alpha and beta coefficients with their respective P-value. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The alpha coefficients are not statistically significant for all the 17 clubs in the sample. As can been seen in the table, almost all the estimates of Alpha are near to zero. The Beta coefficients are always significant except for the Portuguese team FC Porto, which has also the worst R-Squared of all the clubs analyzed and the highest beta are the ones of the Turkish clubs.

The highest Beta is the Besiktas one while the lowest is the one of Celtic. The Beta coefficient goes from a minimum of 0.091 to a maximum of 1.3667. We know that the higher the Beta, the higher the expected return to incentive the investors that cannot eliminate the systematic risk.

In the table below, I will analyze the behaviour of residuals, this is a necessary step to understand whether the model used is correct.

Club	White test p-value	Breusch-Pagan test p-value	Breusch-Goddfrey test p-value	CUSUM test p-value
Ajax	0.003 (***)	0.029 (**)	0.000 (***)	0.383
Roma	0.000 (***)	0.001 (***)	0.162	0.938
Besiktas	0.000 (***)	0.000 (***)	0.000 (***)	0.01 (**)
Borussia D.	0.000 (***)	0.088 (*)	0.000 (***)	0.171
Celtic G.	0.375	0.000 (***)	0.000 (***)	0.503
Fenerbahce	0.000 (***)	0.000 (***)	0.000 (***)	0.539
Galatasaray	0.000 (***)	0.000 (***)	0.033 (**)	0.997
Juventus	0.000 (***)	0.000 (***)	0.001 (***)	0.570
Lazio	0.000 (***)	0.053 (*)	0.000 (***)	0.537
Aalborg	0.984	0.315	0.000 (***)	0.928
Aarthus	0.000 (***)	0.000 (***)	0.000 (***)	0.254
Brondby	0.269	0.000 (***)	0.000 (***)	0.321
Porto	0.000 (***)	0.684	0.609	0.101
Copenhagen	0.004 (***)	0.000 (***)	0.000 (***)	0.822
Silkeborg	0.013 (**)	0.000 (***)	0.000 (***)	0.973
Sporting L.	0.452	0.033 (**)	0.000 (***)	0.907
Trabzonspor	0.000 (***)	0.125 (***)	0.000 (***)	0.514

Table 3.2 P-value of the test statistics used. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The White and Breusch-Pagan test shows the presence of eteroschedasticity for almost all the titles. The exception are Sporting, Brondby and Trabzonspor. The hypothesis of no autocorrelation is rejected for all the titles of the sample. The CUSUM test shows if there are structural breaks and only for the Turkish club Besiktas the hypothesis of no structural break is refused.

Due to the fact that eteroskedasticity and autocorrelation of residuals are present in almost all the clubs in the sample, I calculated the Market Model with HAC residuals. The results are showed in the table below.

Club	Alpha	P-value alpha	Beta	P-value beta	R^2	Adj. R^2
Ajax	0.000	0.962	0.231	0.000 (***)	0.016	0.016
Roma	0.000	0.628	0.970	0.000 (***)	0.096	0.096
Besiktas	0.000	0.808	1.366	0.000 (***)	0.193	0.192
Borussia D.	0.000	0.466	0.679	0.000 (***)	0.103	0.102
Celtic G.	0.000	0.494	0.092	0.001 (***)	0.008	0.008
Fenerbahce	0.000	0.357	1.211	0.000 (***)	0.240	0.239
Galatasaray	0.000	0.980	1.219	0.000 (***)	0.233	0.233
Juventus	0.000	0.809	0.982	0.000 (***)	0.189	0.188
Lazio	0.000	0.671	0.151	0.000 (***)	0.054	0.053
Aalborg	-0.001	0.343	0.000	0.000 (***)	0.008	0.007
Aarthus	-0.001	0.448	0.782	0.000 (***)	0.049	0.048
Brondby	-0.001	0.230	0.498	0.000 (***)	0.017	0.017
Porto	-0.001	0.173	0.095	0.228	0.001	0.000
Copenhagen	0.000	0.430	0.788	0.000 (***)	0.126	0.126
Silkeborg	0.000	0.709	0.256	0.019 (**)	0.003	0.002
Sporting L.	0.000	0.434	0.203	0.039 (**)	0.002	0.001
Trabzonspor	0.000	0.878	1.140	0.000 (***)	0.187	0.187

Table 3.3 Table 4.1 Estimation of alpha and beta coefficients with their respective P-value and estimation of the R^2 and of the adjusted R^2. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

P-value of coefficients are risen but there are no changes for what regards the significance of coefficients. The alpha intercept is still now not statistically significant.

3.3 Inclusion of football performances data

A big amount of papers studies the relationship between football results and market movements. There are evidence that sport results have a great impact on the mood of an individual, who changes his degree of optimism and pessimism according to the result. Some authors have verified these hypotheses empirically and have found a significant reaction between football results and stock market performance. This reaction is particularly strong in countries where football is deeply rooted (Italy, Germany, Turkey, England). This relationship is statistically significant at club levels, and even at national levels. For example, Ashton (2003) found a strong relationship between England team and the English index. At club level instead, Renneboog & Verbrandt (2000) analyzed whether the stock price of English clubs, listed in the London Stock Market and in the AIM, were influenced by the football performances of the previous week and they discovered that wins were followed by positive abnormal returns while losses and ties were followed by negative abnormal results. They also saw a different impact in abnormal returns between European matches and national championship matches. Maniello (2003) studied the relationship between the field's results and the stock market trend of the three listed Italian Football clubs (Juventus, Lazio and Roma) and he discovered that a win rises the stock market price in half of the times while a loss and a tie generate a negative market reactions. Ciarrapico, Cosci & Pinzuti (2010) showed that there is a significant relationship between the ranking of a club and its stock market price trend. Castellani, Pattitoni & Patuelli (2012) found that between 2007 and 2009 there was a positive relationship between football performance and financial performance of the clubs belonging to the Dow Jones STOXX Football index. Sarac & Zeren (2013) studied how the football performance of three Turkish clubs (Besiktas, Galatasaray and Fenerbahce), misured in goal difference, is positive correlated with their trend in the Stock Market.

3.3.1 Variable definitions and hypothesis description

To understand whether football results of a club have an impact on its stock price I analyzed the relationship between the abnormal results and the match results of a club. In finance, an abnormal return is the difference between the actual return of a security and the expected return. In this case the abnormal return of a club is equal to the actual return of its stock minus the theoretical one calculated using the Market model formula $AR_{i,t} = R_{i,t} - E\left(R_{i,t}\right) = R_{i,t} - \widehat{\alpha_i} - \widehat{\beta_i} R_{m,t}$, with alpha and beta calculated using the OLS method explained before;
I focused on the relationship between football results and abnormal returns, but of course there are also other many drivers that can influence the stock price of a club and affect the daily return: market share of the clubs, income from broadcasts, popularity in the media, the player salaries and the player transfers. Other variables which can influence are also the country index, contract durations of players, contract duration of coaches and results of international game. Therefore, I do not expect that all the amount of the abnormal return is explained by match results.
Almost all the matches analyzed in the sample are played when the stock market is closed. In fact National championship matches are usually played on Saturday or Sunday and European matches are played at evening time. In the regressions made I will associate the match results of a team with the corresponding the abnormal return measured on the first opening day of the market after the match.

As I wrote at the end of chapter two, I used several variables to measure properly the football performance of a team. Just for clarity, these variables are:

- **The match result**: three dummy variables (Win_{ij}, $Loss_{ij}$, Tie_{ij}) indicating if team *i* won, tied or lost the *j* match.
- **The goal difference**: it measures the goal difference of the *j* match of team *i*. It can assume positive, negative and null values according to the match results.
- **The site of the competition**: two dummy variables ($Home_{ij}$, $Away_{ij}$) indicating whether the match j was played at home of team *i* or not.
- **The type of the competition**: three dummy variables ($Ncha_{ij}$,, $Clea_{ij}$, $Elea_{ij}$) indicating whether the match *j* was a national Championship match, a UEFA Champions League match, or a UEFA Europa League match.
- **The year of the competition**: a set of dummy variables ($Y05_{ij}$ $Y06_{ij}$ $Y07_{ij}$ $Y08_{ij}$ $Y09_{ij}$ $Y10_{ij}$ $Y11_{ij}$ $Y12_{ij}$ $Y13_{ij}$ $Y14_{ij}$ $Y15_{ij}$) indicating the year in which the match *j* was played.
- **The month of the competition**: a set of dummy (Jan_{ij}, Feb_{ij}, Mar_{ij}, Apr_{ij}, May_{ij}, Jun_{ij}, Jul_{ij}, Aug_{ij}, Sep_{ij}, Oct_{ij}, Nov_{ij}, Dec_{ij}) variables indicating the month in which the match *j* was played.
- **The anticipated (expected) results**: two dummy variables (Fav_{ij}, Und_{ij}) indicating if the team *i* was favourite in match *j* or not based on the information of pre-match betting odds.

3.3.2 Statistical models used

Model 1: $\boldsymbol{AR_{i,t} = \alpha_1 W_{i,t} + \alpha_2 L_{i,t} + \alpha_3 D_{i,t} + \varepsilon_i}$

As I wrote before $\boldsymbol{W_i, L_i, D_i}$ are three dummy variables indicating whether the club *i* won, lost or tied the match, respectively**.** This is the starting model: it is very simple and the aim of the model is to test whether football results of a team affects its abnormal returns. I expect that a win has a positive effect on the abnormal return while a defeat has a negative effect. I also expect that a tie is considered a neutral result and so that it has a null effect on the abnormal return. So my hypotheses for the model 1 are the following $\boldsymbol{\alpha_1 > \alpha_3 > \alpha_2}$ **and** $\boldsymbol{\alpha_1 > 0,\ \alpha_3 = 0\ and\ \alpha_2 < 0}$.

Model 2: $\boldsymbol{AR_{i,t} = \gamma_0 + \gamma_1 Goaldifference_{i,t} + \gamma_2 Goaldifference_{i,t}{}^2 + \varepsilon_{i,t}}$

In this regression I measured the football performance in terms of the goal difference. A positive goal difference in a match is associated with a win, a null goal difference with a tie and a negative one with a loss. The aim of this model is to check whether the intensity of the result also affects the abnormal return. In line with what I wrote about model 1, I suppose that a positive goal difference (that means a win) has a positive effect on sport returns. I also suppose a negative quadratic relation between the coefficient of the Goal difference and abnormal returns because I expect that abnormal returns will increase less than proportionally with the goal difference. So I will expect $\boldsymbol{\gamma_1 > 0 > \gamma_2}$

Model 3: $\boldsymbol{AR_{i,t} = \alpha_1 W_{i,t} Home_{i,t} + \alpha_2 W_{i,t} Away_{i,t} + \alpha_3 L_{i,t} Home_{i,t} +}$
$\boldsymbol{\alpha_4 L_{i,t} Away_{i,t} + \alpha_5 D_{i,t} Home_{i,t} + \alpha_6 D_{i,t} Away_{i,t} + \varepsilon_{i,t}}$

In the third model I specified whether the match was played at home or away from home in order to check whether the site of competition affects the abnormal returns. In 2012, Reade studied the importance of playing a match at home. He wrote that "*…one of the most sustained patterns in sport, likely throughout its organized existence, is the home advantage. Pair two completely evenly matched teams together and the team playing in their own surroundings will win more than 50% of the time*" ("Home advantage in football – what can the data tell us? | Football Perspectives," n.d.).

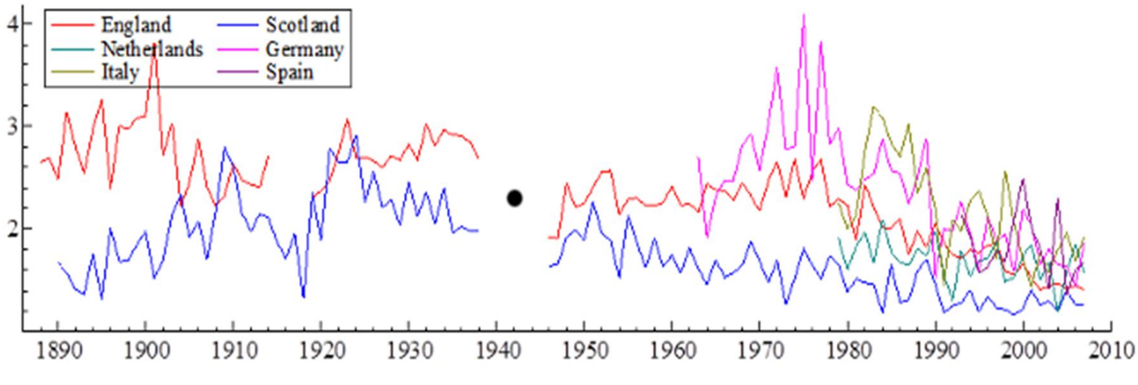

Figure 3.1 Ratio of home to away wins of European clubs. Source: www.Soccerbase.com

The figure above plots the extent of home advantage over more than one century in European football; since the late 1800s the ratio of home to away wins had been comfortably above unity throughout the sample. Even if it appears that home advantage has decreased since the early 1990s, the ratio remains nearer two than one.

The starting hypotheses are similar to the ones of model 1 but with the additional expectation that winning far from home will have a greater effect on abnormal returns than winning at home. The opposite consideration regards losses: losing at home will have a more negative effect than losing away from home. Therefore, I will expect that $\boldsymbol{\alpha_2 > \alpha_1 > 0}$ and that $\boldsymbol{\alpha_3 < \alpha_4 < 0}$.

Model 4: $\boldsymbol{AR_{i,t} = \gamma_1 WinNat + \gamma_2 LossNat + TieNat + \gamma_4 WinEur + \gamma_5 LossEur + \gamma_6 TieEur + \varepsilon_{i,t}}$

In model 4, I specified whether the match was played in a national championship or in a European competition, in order to verify whether the type of competition has different impact on the abnormal returns. European competitions, especially Champions League, are extremely remunerative for a club: the income generated by the market pool and by the performance's prizes can sometimes exceed €30m. For this reason, I expect than European matches have a stronger effect on abnormal returns supposing that γ_4 , γ_5, γ_6 will be greater, in absolute terms, than $\gamma_1, \gamma_2, \gamma_3$ respectively. In the last part of the chapter, I will focus on the Champions League games, analyzing the impact of these matches on the abnormal returns.

Robustness check

The football season is very long (10 months) and so it may be the case that abnormal returns are influenced by the period of time in which the game is played. In particular, I expect that the matches played at the end of the season generate a higher impact in the financial market because these matches are crucial for winning a trophy. So I included in the regression the month in which a match is played in order to check whether it is true that a month effect exists.
The time frame of the analysis is quiet long (10 years) and so it is possible that the year in which matches are played affects the abnormal returns. For this reason, I did a robustness check even for years in order to understand if there is a significant year effect in the analysis.

Model 5:

$$\boldsymbol{AR_{i,t} = \gamma_0 + \gamma_1 WinFav + \gamma_2 LossFav + \gamma_3 TieFav + \gamma_4 WinNfav + \gamma_5 LossNfav + \gamma_6 TiesNfav_1 + \varepsilon_{i,t}}$$

In Model 5, I specified whether the results of a match is expected or unexpected match results. During a season, a club plays against lots of teams and, of course, not all these teams are competitive in the same way. Not all the matches have the same value and investors know it. To say whether a result was expected or not I used the bet quotes of football matches. I expect larger abnormal returns, in absolute terms, after unexpected events and so $|\boldsymbol{\gamma_1}| < |\boldsymbol{\gamma_4}|$ and $|\boldsymbol{\gamma_2}| > |\boldsymbol{\gamma_5}|$

Another consideration is that if the market is efficient, then the price of a soccer team should incorporate all the information available and react to match results only when they are unexpected. So, if the pre-match betting odds fully reflect all available information on the most likely match score, $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$ should both be equal to 0. If, on the other hand, pre-match betting odds only partially reflect available information on the most likely match score or the mood effect is particularly strong, $\boldsymbol{\gamma_1}$ and $\boldsymbol{\gamma_2}$ will differ from 0.

3.3.3 Commentary on the results

In the following table, I will show the empirical results of the models discussed previously.

Variable	Coefficient	Standard error	P-value	Significance
Win	0.006	0.001	0.000	***
Loss	-0.013	0.001	0.000	***
Tie	-0.008	0.001	0.000	***

Table 3.4 Results of the model 1 ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of the first model are present in the table above. Data show that a win generates a significant positive market reaction (0.6%) while a loss has a negative market reaction (-1,28%). Also, a tie generates a negative significant market reaction (-0.8%). This means that investors consider a tie not a neutral event but a negative one. This is probably due to the fact that almost all the clubs in the sample are first tier clubs and so a tie is seen in negative terms. Another explanation is that ties guarantee 1 point against 3 points of the win, reducing the probability of winning a championship or a cup.

Variable	Coefficient	Standard error	P-value	Significance
Constant	-0.00402	0.00052	0.00000	***
Goal difference	0.00463	0.00028	0.00000	***
Goal difference^2	-0.00029	0.00008	0.00070	***

Table 3.5 Results of the model 2 ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Model two analyzes whether the intensity of the results affects the abnormal returns. As I expected the goal difference has a positive effect on abnormal returns. Even the hypothesis about the goal difference square is confirmed. The negative coefficient of the quadratic term (–0.029 per cent) is probably due to the fact that a greater overall goal difference at the end of a league rarely gives a significant advantage.

Variable	Coefficient	Standard error	P-value	Significance
Win home	0.004	0.001	0.000	***
Win away	0.007	0.001	0.000	***
Loss home	-0.016	0.002	0.000	***
Loss away	-0.011	0.001	0.000	***
Tie home	-0.011	0.001	0.000	***
Tie away	-0.007	0.001	0.000	***

Table 3.6 Results of the model 3 ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The table above shows the results of the third model. The signs of the coefficients are in line with model one and two. The results of the model confirm the hypotheses I made before: winning away and losing at home have a greater impact, in absolute terms, on the abnormal returns than winning at home and losing away respectively. Even in this model every estimate is statistically significant.

Variable	Coefficient	Standard error	P-value	Significance
Win national championship	0.006	0.001	0.000	***
Loss national championship	-0.013	0.001	0.000	***
Tie national championship	-0.009	0.001	0.000	***
Win European match	0.002	0.002	0.250	
Loss European match	-0.014	0.002	0.000	***
Tie European match	-0.008	0.002	0.000	***

Table 3.7 Results of the model 4 ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of model four are not in line with my previous expectation. European matches do not have a stronger effect on abnormal returns than national championships' matches. Losing and tying in the two competitions generate quite the same reaction on abnormal returns. One can also see that winning a European match does not create a statistically significant market effect (even if the sign of the coefficient is positive, the P-value is over 0.05). In the last paragraph of the chapter I will split European matches into UEFA Champions League' matches and UEFA Europa League' matches in order to analyze if also the type of European competition affects abnormal returns with a different intensity.

Variable	Coefficient	Standard error	P-value	Significance
Win in January	0.005	0.002	0.035	**
Lose in January	-0.014	0.004	0.001	***
Tie in January	-0.005	0.004	0.197	
Win in February	0.005	0.002	0.018	**
Lose in February	-0.015	0.003	0.000	***
Tie in February	-0.005	0.003	0.105	
Win in March	0.006	0.002	0.003	***
Lose in March	-0.014	0.003	0.000	***
Tie in March	-0.007	0.003	0.018	**
Win in April	0.006	0.002	0.001	***
Lose in April	-0.017	0.003	0.000	***
Tie in April	-0.006	0.003	0.026	**
Win in May	0.003	0.002	0.134	
Lose in May	-0.008	0.003	0.006	***
Tie in May	-0.010	0.003	0.004	***
Win in June	0.015	0.020	0.012	**
Lose in June	0.014	0.017	0.424	
Win in July	0.004	0.004	0.364	
Lose in July	-0.016	0.007	0.014	**
Tie in July	-0.005	0.006	0.424	
Win in August	0.006	0.002	0.002	***
Lose in August	-0.018	0.003	0.000	***
Tie in August	-0.012	0.003	0.000	***
Win in September	0.007	0.002	0.000	***
Lose in September	-0.015	0.003	0.000	***
Tie in September	-0.011	0.003	0.000	***
Win in October	0.008	0.002	0.000	***
Lose in October	-0.008	0.003	0.002	***
Tie in October	-0.011	0.003	0.000	***
Win in November	0.005	0.002	0.003	***
Lose in November	-0.011	0.003	0.000	***
Tie in November	-0.008	0.003	0.003	***
Win in December	0.005	0.002	0.012	**
Lose in December	-0.009	0.003	0.004	***
Tie in December	-0.009	0.003	0.004	***

Table 3.8 Results of the robustness check of months. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

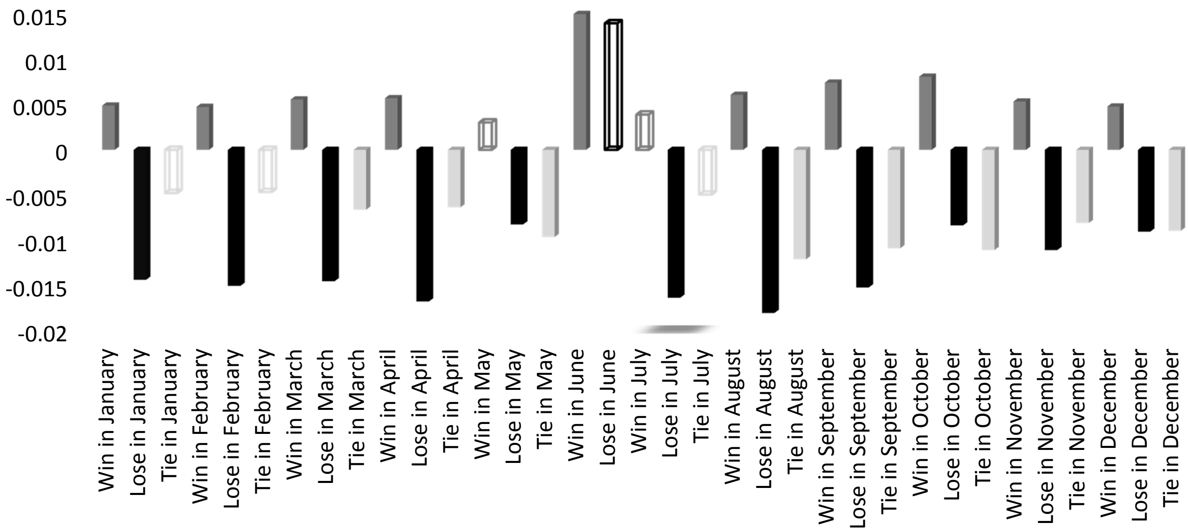

Figure 3.2 Results of the robustness check of months. Dark gray bar, black bar and light gray bar represent wins, losses and ties respectively. When the bar is empty, it means that the estimate is not statistically significant different from zero.

The table and the figure above show the presence of a month effect. The figure seems to confirm the hypothesis that the month in which the match takes place influences the magnitude of abnormal returns. Months in which abnormal returns are higher are the ones at the beginning of the season (July, August and September). This is probably due to the fact that in these months clubs play the play-offs to enter European competitions, and so these matches are incredibly important for the balance sheet of the club. Winning in June seems to have a huge positive effect on abnormal returns, probably because in June the finals of the European trophies and the playouts of some National championship leagues take place. In January and February coefficients of ties are not statistically significant and this is probably due to the low number of matches that take place in these months.

Variable	Coefficient	Standard error	P-value	Significance
Win in 2005	0.001	0.003	0.608	
Lose in 2005	-0.012	0.004	0.003	***
Tie in 2005	-0.005	0.004	0.204	
Win in 2006	0.002	0.002	0.213	
Lose in 2006	-0.012	0.003	0.000	***
Tie in 2006	-0.003	0.003	0.325	
Win in 2007	0.004	0.002	0.061	*
Lose in 2007	-0.010	0.003	0.000	***
Tie in 2007	-0.005	0.003	0.050	*
Win in 2008	0.008	0.002	0.000	***
Lose in 2008	-0.010	0.003	0.001	***
Tie in 2008	-0.002	0.003	0.607	
Win in 2009	0.007	0.002	0.000	***
Lose in 2009	-0.012	0.003	0.000	***
Tie in 2009	-0.006	0.003	0.022	**
Win in 2010	0.009	0.002	0.000	***
Lose in 2010	-0.012	0.003	0.000	***
Tie in 2010	-0.017	0.003	0.000	***
Win in 2011	0.005	0.002	0.015	**
Lose in 2011	-0.017	0.003	0.000	***
Tie in 2011	-0.015	0.003	0.000	***
Win in 2012	0.003	0.002	0.067	*
Lose in 2012	-0.009	0.003	0.003	***
Tie in 2012	-0.006	0.003	0.038	**
Win in 2013	0.008	0.002	0.000	***
Lose in 2013	-0.015	0.003	0.000	***
Tie in 2013	-0.011	0.003	0.000	***
Win in 2014	0.007	0.002	0.000	***
Lose in 2014	-0.019	0.003	0.000	***
Tie in 2014	-0.012	0.003	0.000	***
Win in 2015	0.003	0.002	0.206	
Lose in 2015	-0.016	0.004	0.000	***
Tie in 2015	-0.008	0.004	0.047	**

Table 3.9 Results of the robustness check of years. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

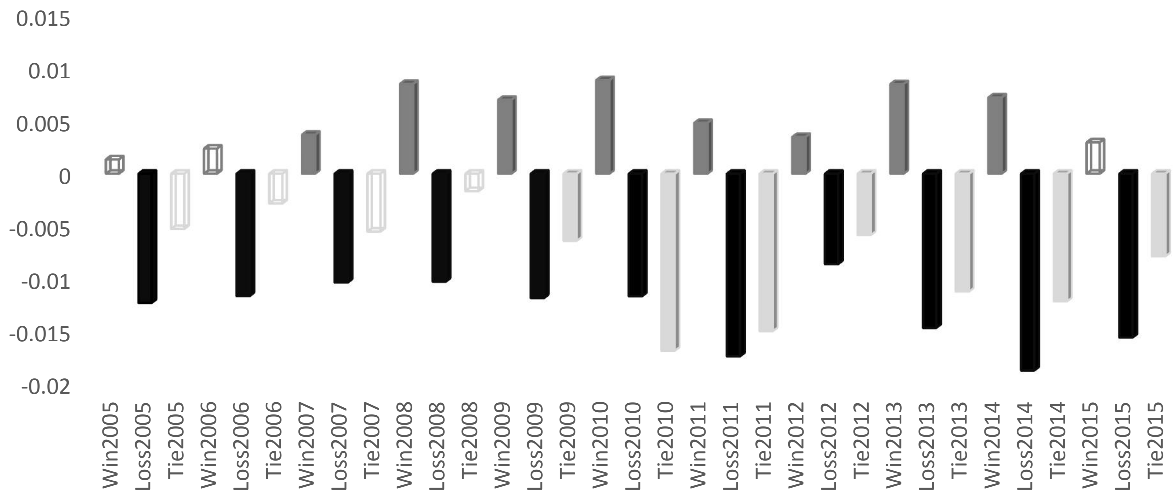

Figure 3.3 Results of the robustness check of years. Dark gray bar, black bar and light gray bar represent wins, losses and ties respectively. When the bar is empty, it means that the estimate is not statistically significant different from zero.

The table and the figure above show that abnormal returns following wins, losses and ties are different accordingly to the year in which matches were played. As I wrote before there are many variables that can influence the stock price of a club and affect its daily return. So, the year effect is probably due to a change in those variables (for example a change in the market share of clubs, a change in the income derived from broadcasts, a change in the tax legislation, or a change in the normative regarding the player salaries and the player transfers).

Variable	Coefficient	Standard error	P-value	Significance
Favourite and win	0.004	0.001	0.000	***
Favourite and loss	-0.016	0.001	0.000	***
Favourite and tie	-0.010	0.001	0.000	***
Not favourite and win	0.016	0.002	0.000	***
Not favourite and loss	-0.009	0.001	0.000	***
Not favourite and tie	-0.003	0.002	0.063	*

Table 3.10 Results of the model 5. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of model 5 confirm the hypotheses I made before. Unexpected results have a greater impact than the expected ones on the abnormal returns. The effect on the abnormal returns of an unexpected win is 1.2% higher than the effect of an expected win. On the other hand, an unexpected loss brings the abnormal returns down of 1.6% against the 0.9% of an expected one. One can see that the "expected effect" affects also ties (-1% when a favourite club ties, -0.3%

when a not favourite club ties). This fact helps to explain why ties in the previous models have a so large negative effect and not a neutral one: the clubs in the sample are first tier clubs and they are supposed to win almost every match. Another interesting consideration regards expected results. Expected results move in line with model 1 and affect abnormal returns, although in a minor way than unexpected results. This means that the price of a soccer teams does not incorporate all the information available and reacts to match results even when they are expected.

I will compare now the R^2 of the models that I used.

Model used	**Adjust R^2 (in percentage)**
Model 1	5.529%
Model 2	4.434%
Model 3	5.804%
Model 4	5.573%
Model 5	6.387%

Table 3.11 Models' adjusted R^2 calculation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The R^2 of the models is not very high. There are two main reasons that may explain this fact. Firstly, as I wrote before, there are many variables that affect the abnormal returns and all the abnormal returns' behaviour cannot only be explained by the match results. Secondly, the sample size is very high (6892 observations) and this makes difficult to have a high R^2.

Even if the R-squared value is low, almost all the predictors of the regression analyzed are statistically significant and so, regardless of the R-squared, the significant coefficients still represent the mean change in the response for one unit of change in the predictor, holding other predictors in the model constant.

Focusing on the R-squared of the models, one can see that the last model has the higher R^2, meaning that the inclusion of bet quotes makes the model more fitting to reality.

3.4 European football competitions

The European football competitions which the clubs analyzed took part in are two: UEFA Champions League and UEFA Europa League[10]. They are annual continental club football competitions organized by the Union of European Football Associations (UEFA) and contested by top-division European clubs. The UEFA regulation states that "*the number of teams of a specific country into the UEFA Champions League and in the UEFA Europa League is based upon the UEFA coefficients of the member associations*" ("UEFA. (2012). Regulations of the UEFA Champions League 2012-15 Cycle, 2012-13"). These coefficients are generated by the results of clubs representing each association during the previous five UEFA Champions League and UEFA Europa League/UEFA Cup seasons. The higher an association coefficient, the more teams represent the association in the UEFA Champions League and the UEFA Europa League, and the fewer qualification rounds the association's teams must compete in.

3.4.1 The economic importance of European competitions

In the table below, one can see how much the clubs of the sample have gained in the UEFA Champions league and in the UEFA Europa league during the period of analysis. I did not include in the analysis the two Danish clubs, Silkeborg and Aarhus, because they did not play any European match during the period of analysis.

[10] The UEFA Europa League was previously called the UEFA Cup. The competition has been known as the UEFA Europa League since the 2009–10 season following a change in format. For UEFA footballing records purposes, the UEFA Cup and the UEFA Europa League are considered the same competition, with the change of name being simply a rebranding.

Club	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
Aalborg	0.0	0.0	0.3	12.2	0.0	0.0	0.0	0.0	0.0	3.7	**16.2**
Ajax	10.5	0.3	0.00	0.5	1.9	13.4	18.3	21.1	21.6	23.4	**110.9**
Besiktas	0.0	0.2	10.0	0.00	21.5	8.9	9.7	0.0	0.0	7.9	**58.1**
Borussia	0.0	0.0	0.0	0.0	0.0	4.7	26.6	55.7	34.7	33.5	**155.2**
Brondby	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.3**
Celtic	0.0	15.7	13.0	12.8	2.1	0.0	2.2	24.3	17.6	3.4	**91.1**
Copenaghen	0.0	12.2	0.2	0.4	2.0	22.2	1.7	3.5	21.5	2.5	**66.3**
Fenerbahce	8.0	0.3	17.3	14.2	5.5	0.0	0.0	11.9	0.0	0.0	**57.2**
Galatasaray	0.0	14.0	0.3	0.5	5.3	0.0	0.0	25.5	21.1	18.6	**85.3**
Juventus	18.1	0.0	0.0	22.1	22.7	1.9	0.0	67.1	50.1	89.1	**271.2**
Lazio	0.0	0.0	16.4	0.0	2.1	0.0	2.9	10.3	9.5	0.0	**41.2**
Porto	0.00	11.5	11.6	14.5	19.0	8.0	13.3	20.3	15.5	27.4	**141.0**
Roma	0.0	31.1	28.9	26.1	2.4	31.4	0.0	0.0	0.0	47.2	**167.1**
Sporting	0.0	7.8	9.1	11.6	2.5	2.2	4.6	2.3	0.0	14.9	**55.0**
Trabzonspor	0.0	0.0	0.0	0.0	0.0	0.0	24.2	0.0	7.9	5.1	**37.2**

Table 3.12 Total amount per year of the money gained by each team in the period of analysis. Data are expressed in millions of Euros.

The amount of money gained by a team in each year depends on its performance in the competition and its national television market allocation. The total amount of money gained in these years by the clubs of the sample is over €1200m. In the table below the amount of money received are split according to the competition.

Club	Champions League	Europa League	Total revenue
Aalborg	3.74	12.21	**15.95**
Ajax	105.33	5.60	**110.94**
Besiktas	26.39	21.70	**48.09**
Borussia	155.22	0.00	**155.22**
Brondby	0.30	0.00	**0.30**
Celtic	47.55	30.54	**78.09**
Copenaghen	51.43	14.60	**66.03**
Fenerbahce	19.97	19.94	**39.90**
Galatasaray	65.14	19.80	**84.93**
Juventus	218.61	52.60	**271.21**
Lazio	22.61	2.09	**24.69**
Porto	82.91	46.55	**129.46**
Roma	77.29	60.81	**138.10**
Sporting	23.63	22.21	**45.85**
Trabzonspor	36.34	0.88	**37.21**
Total	**936.44**	**309.52**	**1245.97**

Table 3.13 Total amount of the money gained by each team in the period of analysis, split according to competition. Data are expressed in millions of Euros.

The UEFA Champions League is much more remunerative for a club than the UEFA Europa league. In fact during the 2012-15 cycle, clubs in the UEFA Europa League received about €1 every €4.3 received by clubs in the UEFA Champions League. In 2015 the total participation payments reached for the UEFA Champions league was €1.030bn. Each club was entitled to a minimum payment of €8.6 for participating in the competition. Additionally, performance bonuses were paid for every win (€1m) or draw (€0.5m) in the group stage, as well as for each knockout round. The performance bonuses for reaching each knockout round were €3.5m for the last 16, an additional €3.9m for the quarter-finals, €4.9m more for the semi-finals, €6.5m for the final and €4m for winning the final. Moreover, €492,900,000m derived from the market pool were divided according to the proportional value of the national television market allocated to each individual club. This incredible amount of money makes crucial for a club to do well in this competition. I will now focus the analysis on European matches, to understand whether this huge amount of money guaranteed by European competitions affects abnormal returns and investors' behaviour.

3.4.2 Application of the models just to the European matches

I included in the model both the results in the UEFA Europa League and the results in the UEFA Champions League in order to understand whether abnormal returns are different according to the competition in which the match is played.

$$\begin{aligned} AR_{i,t} = {} & \gamma_1 WinChal + \gamma_2 LossChal + TieChal + \gamma_4 WinEurl + \gamma_5 LossEurl \\ & + \gamma_6 TieEurl + \varepsilon_{i,t} \end{aligned}$$

Considered that prizes of the UEFA Champions League are considerably higher than the ones of the UEFA Europa League, I expect that abnormal returns following a UEFA Champions League match are higher than the ones of a UEFA Europa League match. I therefore hypothesize that γ_1, γ_2 and γ_3 will be higher, in absolute terms, than γ_1, $\gamma_2$and γ_3.
I then focused only on the UEFA Champions League matches and I applied the regression models discussed in the previous paragraphs.

- $AR_{i,t} = \alpha_1 W_{i,t} + \alpha_2 L_{i,t} + \alpha_3 D_{i,t} + \varepsilon_i$
- $AR_{i,t} = \alpha_1 \, W_{i,t} \, Home_{i,t} + \alpha_2 \, W_{i,t} \, Away_{i,t} + \alpha_3 \, L_{i,t} \, Home_{i,t} + \alpha_4 \, L_{i,t} \, Away_{i,t} + \alpha_5 \, D_{i,t} \, Home_{i,t} + \alpha_6 \, D_{i,t} \, Away_{i,t} + \varepsilon_{i,t}$
- $AR_{i,t} = \gamma_0 + \gamma_1 WinFav + \gamma_2 LossFav + \gamma_3 TieFav + \gamma_4 WinSfav + \gamma_5 LossSfav + \gamma_6 Tiesfav_1 + \varepsilon_{i,t}$

The economic consequences of every single UEFA Champions League match is enormous and so I expect that coefficients of the regression will be higher than the ones obtained analysing the entire sample of matches.

3.4.3 Commentary on the results

Variable	Coefficient	Standard error	P-value	Significance
WinChamp	0.007	0.002	0.009	***
LossChamp	-0.017	0.003	0.000	***
TieChamp	-0.012	0.003	0.000	***
WinUefa	-0.002	0.002	0.369	
LossUefa	-0.010	0.003	0.000	***
TieUefa	-0.005	0.003	0.126	

Table 3.14 Results of the model. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

As can be seen, the coefficients of the UEFA Champions League matches are considerably higher, in absolute terms, than the UEFA Europa League ones. Moreover, they are even higher than the national Championship coefficients calculated in the model 4 of the previous paragraph. This is in line with the hypotheses I made before. Among all the Europa league matches, only losing affects in a statistically significant way the market. There are two possible reasons to explain this fact. Firstly, the UEFA Europa League is not so much remunerative for a club; secondly, the teams of the sample are usually very competitive in Europa League and so investors do not reward the positive results of this competition.
Now I will consider the analysis's results only of the UEFA Champions League.

Variable	Coefficient	Standard error	P-value	Significance
WinChamp	0.007	0.003	0.025	**
LossChamp	-0.017	0.003	0.000	***
TieChamp	-0.012	0.004	0.001	***

Table 3.15 Results of the model 1 applied to Champions League matches only. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

All the results of the UEFA Champions League matches affect the abnormal returns in a statistically significant way. All the signs of the coefficient are in line with the ones calculated in the previous models and the average impact of a result is high compared to the UEFA Europa League matches and national Championship matches. A win guarantees an average positive abnormal return of 0.7% while a loss and a tie generate a negative market reaction on abnormal returns of -1.7% and -1.2% respectively.

Variable	Coefficient	Standard error	P-value	Significance
winhome	0.003	0.004	0.392	
winaway	0.014	0.005	0.007	***
losshome	-0.025	0.005	0.000	***
lossaway	-0.013	0.004	0.000	***
tiehome	-0.016	0.005	0.003	***
tieaway	-0.009	0.005	0.107	

Table 3.16 Results of the model 3 applied to Champions League matches only. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Even for the UEFA Champions League matches, winning away and losing at home have a greater impact on abnormal returns than winning at home and losing away respectively. In particular, losing a match at home, decreases on average abnormal returns of -2.5% while winning away has a positive effect on abnormal returns of 1.4%. One can see that here the "home effect" is higher than the one calculated in the previous analyses.

Variable	Coefficient	Standard error	P-value	Significance
Favourite and win	0.001	0.003	0.855	
Favourite and loss	-0.030	0.006	0.000	***
Favourite and tie	-0.018	0.005	0.001	***
Not favourite and win	0.022	0.005	0.000	***
Not favourite and loss	-0.013	0.003	0.000	***
Not favourite and tie	-0.007	0.005	0.232	

Table 3.17 Results of the model 5 applied to Champions League matches only. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Unexpected results have a greater impact on abnormal returns than the expected ones. An unexpected loss generates a very negative effect on abnormal returns that go down of the 3% while an unexpected win affects positively on abnormal returns, causing a rise of 2.2%. An expected win does not generate, on average, a positive market return while an expected loss still generates a negative market reaction: investors' behaviour is strange because they do not reward an expected win but they penalize an expected loss. One possible reason of this is that investors of a particular team do not care, or care only in part of bet quotes, overestimating the winning chance of the club. The market efficiency analysis and the analysis of the abnormal returns before matches of chapter 4 will help to answer if these hypotheses are correct.

4. Market behaviour before and after matches: investors or supporters?

In the last chapter one can see that there are some ambiguous behaviours of abnormal returns and I supposed that a possible explanation for this fact is an inefficiency of the stock market of football clubs' stocks. I hypothesized that investors and supporters who buy or sell football clubs' stocks may overestimate or underestimate the winning chance of a club.

In an efficient market, all information available before the match is played should be incorporated immediately in the stock price. Given this, the results of a match should not affect the stock price unless the outcome of the game has been anticipated by the market. In particular, according to the efficient market hypothesis, only unexpected events, that is in our case unexpected wins and unexpected losses, may generate abnormal returns. In this chapter I will try to answer the question of whether the anomalies or the strange asymmetric trend of the abnormal returns are effectively due to a market inefficiency caused by an irrational behaviour of investors.

To answer this question I will analyse abnormal traded volumes and abnormal returns before and after matches.

4.1 Efficient or inefficient market?

The efficiency market hypothesis (EMH) states that the asset price always reflects all available information about the value of the firm. The EMH was developed by Fama in 1970 who said that, in an efficient market, "*…on the average, competition will cause the full effects of new information on intrinsic values to be reflected "instantaneously" in actual prices*" (Fama, 1970). The EHM affirms that economic agents behave in an absolute absence of human emotion in investment decision-making.

Since 1970 the EHM has not been universally accepted by all the economists. In fact, many investment professionals are still now very skeptical about it. For example, legendary portfolio manager Michael Price argued that "*...markets are not perfectly efficient. The academics are all wrong. 100% wrong. It's black and white*" (Tanous, 1999, p. 36). Criticism about the efficient market has brought to a new concept called behavioural finance. Behavioural finance argues that economic decisions of individuals and institutions are not only moved by rationality but also by emotional and psychological factors, which affect market prices, returns and the resource allocation. Behavioural finance theory's supporters think indeed that market participants make often irrational systematic errors, which are against the assumption of perfect rationality of market participants. These errors creates anomalies in the market because they affect prices and returns.

According to behavioural finance theory, investors are influenced in the estimate of the securities by their mood and by external causes which have nothing to do with the basics of security.

There are a lot of empirical and theoretical works explaining the relation between the mood of investors and their behaviour in the stock market. These works analyze how the actions of an investor are influenced by events happening outside the stock market. The events analyzed in literature are numerous and various: they can concern anything from weather conditions and level of temperature to the approaching of a holiday period.

Hirshleifer and Shumway (2003) observed a positive relation between nice weather conditions during the day and a positive trend of the stock market. In other studies, instead, a significant relation between lunar phases and investors' behaviour (Yuan, 2002) were analyzed. Other researchers proved how some tragic events, such as acts of terrorism (Drakos, 2010) and earthquakes (Shan, 2011) have negative effects in the stock market on the days after these disasters.

Also sports events can be considered events causing anomalies in the behaviour of investors because a sports performance, be it positive or negative, has an effect on the mood of a person. After a win we feel euphoric, while we can face a wave of pessimism because of a loss. In 1992 Hirt, Zillmann, Erickson and Kennedy discovered that the students of the University of Indiana credited in a better way their scholastic performance after having watched a win of their college basketball team than after having watched a loss. In 1992, a study by Schweitzer, Karla, Zillmann, Weaver, and Luttrell showed that the thought of a war probability in Iraq in 1990 was absolutely smaller among the student supporters of a winning team after an American football game.

Some psychological studies have asserted the relation between optimism/pessimism of people after a football match. For example, Wann and Dolan (1994) studied how the football results of one's own team condition the mood of supporters influencing their self-esteem and their feelings about life.

In 1987 Schwarz, Strack, Kommer and Wagner showed how the results of two matches of the German national football team played during the World Cup in 1982 had been able to influence people's point of view on their disposition and on their national values. Sports events not only influence the mood of people but also their economic behavior, leading a person to make irrational decisions. For example, Arkes, Herren and Isen (1988) discovered that the average selling of the lottery tickets in Ohio State increased after a win of Ohio State University football team.

Since sports results are able to influence people's mood and behaviour, it is not possible to rule out the possibility that they can influence the financial decisions of an investor, therefore weighing on the trend of the stock market.

Behavioural economists also argues that investors often have unrealistic expectations about the future cash flow of the company. The analysis of this inconsistency between expectations and reality has seen little attention in literature because it is difficult to measure investors' individual expectations. In sports industry this inability to price precisely a share is frequent and it mainly depends on investors' irrational evaluation. In fact a strong passion for a football team can affect the emotional state and the relevant behavioural factors of individuals (Cirillo & Cantone, 2015). Investors are overly optimistic about the possibility of win of their own team and so they, on average, end up disappointed after that the match is played with negative consequences for the abnormal returns. This can explain the reason why there is an asymmetric reaction of abnormal returns after matches. We saw in the previous chapter how losses have a greater effect in absolute value than wins. In particular, the analysis done on the sample evaluating all national football championship and European football championship matches has shown that a win leads on average to 0.6% increase in the abnormal yield and that a loss makes the yield decrease by 1.3%. Moreover, when we have analyzed just the sub-sample, including only the UEFA Champions League matches, we have seen that the asymmetric reaction is even greater because a win leads to 0.7% increase in AR and a loss leads to a 1.7% drop on average.

Obviously asymmetric reactions are not only a common event in the football sector but they are often common in the stock market sector. Skimmer and Sloane (2002) and Trueman, Wong and Zhang, (2003) discovered that the share of growth firms and in particular of internet firms also reacts in an asymmetric way to unexpected news relating to profits. The average negative effects originated by negative news about profits is greater in absolute value than a positive effect after the positive news on profits. This finding is in line with the idea that the apparent market inefficiency is due to the investors' inability to assign correct probabilities to event outcomes.

Now I consider the example where a team plays a football play-off match. Hypothesizing that after advancing to the next round the share has a fair value of V+ and that a loss and a resulting elimination makes the share value decrease to its fair value V-. Assuming also that the team concerned has an objective probability p to win this play-off match and advance to the next round and a probability (l-p) to be eliminated, it follows that the real share value should be equal to $V_0 = E(V_1) = \{p * V+\} + \{(1-p) * V-\}$, where $E(V_1)$ is the expected value of the share after the match**.** As one can see from the table below, if investors assign to events the correct probability p, V_0 will be equal to $E(V_1)$ because investors' ex-ante beliefs are unbiased.

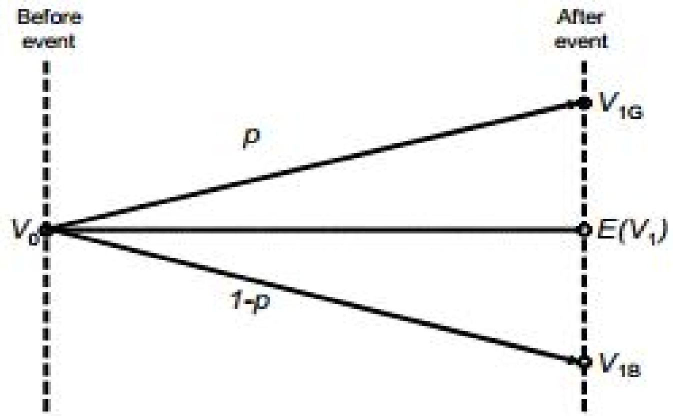

Figure 4.1 Investors' ex-ante beliefs are unbiased. Source: Késenne, 2007.

But if investors assign to the winning probability a different value than the objective one, then investors beliefs will be biased. Let us assume that an investor is over optimistic about the possibility of the team to advance to the next round and for this reason attributes the probability of advancing equal to q>p and the probability of an elimination equal to l-q<1-p.

Then, for this investor, the share value before the match will be considered the fair one when $V_0 = \{q * V+\} + \{(1-q) * V-\}$ but, in this case, it will not be equal anymore to the real expected value of the share $E(V_1)$. In fact $V_{0q} = E_q(V_1) > E(V_1)$, meaning that the pre-event value V_{0q} which equals the expectation of the post-event value under investors' subjective

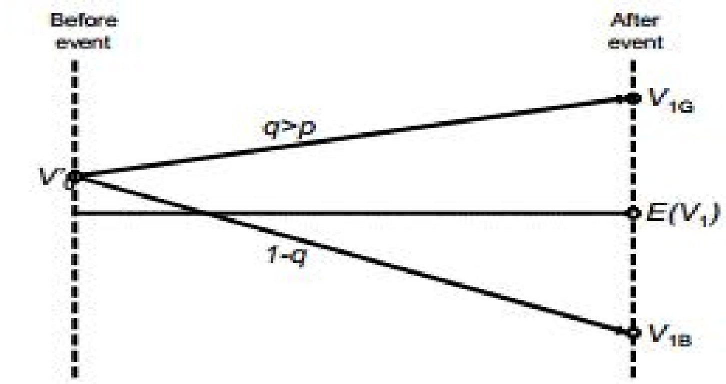

Figure 4.2 Investors' ex-ante beliefs are biased. Source: Késenne, 2007.

probability distribution, is higher than the expected post-event value under the true probability distribution $E(V_1)$. As a result, the expected change in value around the event is negative.
Thus, understanding the evolution of stock prices around resolutions of uncertainty is crucial for firm value maximization.
In this chapter I will try to verify if the hypothesis of inadequacy of football market shares, due to the irrational behaviour of investors, is reflected in empirical data. To be able to prove this hypothesis I will focus on volume analysis and abnormal returns both before and after matches. This analysis will be made only for the sample of the matches played in European competitions. This decision is due to the fact that European competitions matches produce a more incisive effect on stock market and on club evaluation. Moreover the asymmetric behaviour after a UEFA Champions League match is remarkable and greater than after a national championship match. In addition the UEFA European competitions matches are, in their last stages, knockout matches played over two legs with each team as the home team in one leg and the matches are played two weeks apart. As the advancement to the following phase only depends on the result of the team itself, the share value of the team does not rely on the result of other teams as in the national championships and so, there is not an interdependent risk which could contaminate the relation tests between the results and the share performances. Besides almost all European competition matches are played on Tuesday, Wednesday and Thursday and so there is not a potential weekend effect problem, which occurs in national championship matches.

4.2 Volume analysis before and after matches

To understand better investors' behaviour it is important to know if match results provide enough information to trade on. It is useful to analyse trading volumes after the match and compare them with a typical no game day in order to comprehend if investors use information derived by match results.

So, I will define the abnormal trading volume: $\boldsymbol{Volume} = \mathbf{ln}(\boldsymbol{volume}_{\boldsymbol{i,t}}) - \mathbf{ln}(\boldsymbol{volume}_{\boldsymbol{i,t-5}})$, where $volume_{i,t}$ represents the trading volume of the day after the match and $volume_{i,t-5}$ represents the trading volume of five market days before the match (that is a week before the match). As I wrote before, the decision to calculate the trading volumes variation in this way is due to the fact that t-5 is usually a no day game because European matches are usually played once every two weeks and almost all the national championship matches are played at the weekends.

First of all I will analyze whether abnormal volumes are statistically significant different from zero. In particular, I expect that on the day after a match abnormal volumes are positive, meaning that trading volumes after a match are on average greater than the ones on a no day match. In the table below it is possible to see the mean of the abnormal volumes of the European matches' sample.

Variable	**Coefficient**	**Standard error**	**P-value**	**Significance**
Constant	0.348	0.054	0.000	***

Table 4.1. Calculation of the average abnormal volumes after the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

As I expected, the results of the table shows that matches have a positive effect on the trading volumes. In particular, playing a football match raises trading volumes by 34,80% compared with the trading volumes of the week before.

Now I will analyze if abnormal volumes are influenced by a match result. To do this I will use the following regression $\boldsymbol{Avolume} = \boldsymbol{\alpha_1 W_{i,t}} + \boldsymbol{\alpha_2 L_{i,t}} + \boldsymbol{\alpha_3 D_{i,t}} + \boldsymbol{\varepsilon_i}$ where W, L and D are three dummy variable indicating whether the club i won, lost or tied the match. I expect that abnormal volumes are more influenced by a win and a loss than by a tie. The reason is that winning and losing a match are often decisive results, and so more informative for investors about the chances to access to the next round than a tie. The results of the regression are shown in the table below.

Variable	Estimate	Standard error	P-value	Significance
win	0.464	0.082	0.000	***
loss	0.425	0.093	0.000	***
tie	0.051	0.108	0.638	

Table 4.2 Calculation of the impact of wins, losses and ties of the UEFA European matches on abnormal trading volumes. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

As one can see, winning a match increases on average the abnormal volumes by 46.4% while losing a game increases them by 42.5%. From the regression results it seems that a tie does not have a statistically significant effect on abnormal volumes. This result is in line with the hypothesis I made before: a tie is a neutral results that guarantee less information than a win and a loss.

Now I will analyze whether the type of European competition also affects the abnormal volumes. In order to do so, I will introduce in the model two dummy variables, indicating whether the match is played in the UEFA Europa League and the UEFA Champions League. The regression then becomes: $\boldsymbol{Avolume = \alpha_1 Championsleague + \alpha_2 Europaleague + \varepsilon_i}$. I expect the UEFA Champions League matches have a higher impact on abnormal volumes than the UEFA Europa League's ones. The reason is that the UEFA Champions League is the most important European competition for clubs and, as I wrote in the previous chapter, it is extremely remunerative for a club. The results of the regression are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
Champions League	0.506	0.076	0.000	***
Europa League	0.191	0.075	0.011	**

Table 4.3. Calculation of the impact of the UEFA Champions League and the UEFA Europa League matches on abnormal volumes on the day after the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results point out that also the type of competition affects abnormal volumes. In fact when a club plays a UEFA Champions League match, its abnormal volumes rise on average by 50.6% and they rise by 19.1% when the club plays a UEFA Europa League. These results are in line with the hypotheses I made before.

Now I will add to the previous regression the results of the two competitions. In this way, I want to understand whether match results affect abnormal volumes differently according to the competition played. The results in the last table suggest, again, that wins and losses in the UEFA Champions League influence abnormal volumes strongly compared to the UEFA Europa League's ones. Even now, I hypothesize a neutral effect of ties on abnormal volumes. The regression used is the following: $\boldsymbol{AR_{i,t} = \gamma_1 WinChal + \gamma_2 LossChal + TieChal + \gamma_4 WinEurl + \gamma_5 LossEurl + \gamma_6 TieEurl + \varepsilon_{i,t}}$ and the results are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
WinChamp	0.710	0.130	0.000	***
LossChamp	0.483	0.131	0.000	***
TieChamp	0.144	0.165	0.384	
WinUefa	0.228	0.117	0.052	*
LossUefa	0.349	0.147	0.018	**
TieUefa	-0.018	0.155	0.905	

Table 4.4 Calculation of the impact of wins, losses and ties on the abnormal volumes of the day after the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

As expected, wins and losses in the UEFA Champions League move abnormal volumes in a stronger way than wins and losses in the UEFA Europa League. In particular, winning and losing a match of the UEFA Champions League raise the abnormal volumes by 71.0% and 48.3%, respectively, while abnormal volumes rise by 22.8% and 34.9% when a club wins or loses in the UEFA Europa League. Even now, ties do not affect in a statistically significant way abnormal volumes.

Now I will analyze how unexpected results in the two competitions affect abnormal volumes. Of course, I hypothesize that unexpected wins and unexpected losses have a greater impact on abnormal volumes. As I wrote in the previous paragraph, according to efficient market hypotheses, only unexpected results should have an impact on stock's returns and so one should also see an increase in the trading volumes when these unexpected events occur.

The regression used is:

$$\boldsymbol{AVolume_{i,t} = \gamma_1 WinFavChampL + \gamma_2 LossFavChampL + \gamma_3 TieFavChampL + \gamma_4 WinNfavChampL + \gamma_5 LossNfavChampL + \gamma_6 TiesNfav_1 ChampL + \alpha_1 WinFavEurl + \alpha_2 LossFavEurl + \alpha_3 TieFavEurl + \alpha_4 WinNfavEurl + \alpha_5 LossNfavEurl + \alpha_6 TiesNfav_1 Eurl + \varepsilon_{i,t}}$$

where ChampL and Eurl are two dummy variables indicating if the match was played in the UEFA Champions League or in the UEFA Europa League, respectively, and fav and Nfav are two dummy variables indicating if the club before the match was favourite or the underdog, respectively. Results are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
FavWinChamp	0.594	0.153	0.000	***
FavLossChamp	0.911	0.271	0.001	***
FavTieChamp	-0.036	0.231	0.876	
NfavWinChamp	1.005	0.244	0.000	***
NfavLossChamp	0.354	0.149	0.017	**
NfavTieChamp	0.330	0.235	0.160	
FavWinUefa	0.183	0.131	0.162	
FavLossUefa	0.727	0.241	0.003	***
FavTieUefa	-0.170	0.192	0.376	
NfavWinUefa	0.407	0.259	0.117	
NfavLossUefa	0.127	0.185	0.495	
NfavTieUefa	0.310	0.256	0.227	

Table 4.5 Calculation of the impact of wins, losses and ties on the abnormal volumes on the day after the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones and it considers whether the club was favourite or the underdog before the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of the regression restate that wins and losses in the UEFA Champions League always have a positive impact on abnormal volumes. This thing do not happen in the UEFA Europa League where only unexpected losses increase abnormal volumes in a statistically significant way (+72.7%).

The important results of the regression is that in the UEFA Champions League, unexpected results have a huge effect on trading volumes: in fact, an unexpected loss raises abnormal volumes by 91.1% and an unexpected win raises them by 100.5%. It is interesting that also expected wins and losses have a strong effect on trading volumes (+59.4% and +35.4%, respectively). This means that in the UEFA Champions League also expected results supply enough information for an investor to trade on and this is not in line with the efficient market theory.

Let us focus our attention on the analysis of trading volume variations on the day before the match of European competitions. The definition of abnormal volumes is more or less the same as before $\boldsymbol{Avolume = \ln(volume_{i,t}) - \ln(volume_{i,t-5})}$ with the only difference that t is now the day of the match[11] and not the day after the match. As I wrote in the first paragraph, investors should modify the stock price of a club according to the probability that they associate

[11] The trading market closes before the match is played.

with wins and losses, and so I expect that also trading volumes on the day of the match are higher than trading volumes on a typical no game day.
The table below shows the average abnormal volumes on the day of the match.

Variable	Coefficient	Standard error	P-value	Significance
Constant	0.166	0.057	0.004	***

Table 4.6. Calculation of the average abnormal volumes on the day of the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The result of the regression shows that the average abnormal volumes is positive (+16.6%), meaning that, on average, the trading volumes on the day of the match are greater than the ones of a no day game. Abnormal volumes are positive and statistically significant but they are smaller than the ones of the day after the match (+34.8%). This means that investors prefer waiting for the results of the match instead of trading with the uncertainty of the results.
Let us analyze if, even in this case, abnormal volumes are influenced by the type of competition that the club faces. I will use the following regression: $Avolume = \alpha_1 Champions + \alpha_2 Europaleague + \varepsilon_i$ and results are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
Champions	0.335	0.081	0.000	***
EuropaL	-0.003	0.081	0.971	

Table 4.7. Calculation of the impact of the UEFA Champions League and the UEFA Europa League matches on abnormal volumes on the day of the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

One can see that only abnormal volumes in the UEFA Champions League matches are statistically significant (+33.5%). So, investors on average, use pre-match information to trade only when the club is involved in a UEFA Champions League match. Even in this case abnormal volumes on the day of the match are smaller than the ones of the day after the match (33.5% and 50.6%, respectively).
Finally, I will analyze whether the betting odds affect the abnormal volumes. In particular, I will introduce to the previous regression two dummy variables indicating if the club is favourite or not (Fav and Nfav, respectively). The regression used is $\boldsymbol{AVolume_{i,t} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t}}$. The results of the regression are illustrated in the table below.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	0.397	0.115	0.001	***
NfavChamp	0.275	0.114	0.016	**
FavEurL	0.080	0.100	0.424	
NfavEurL	-0.158	0.135	0.243	

Table 4.8 Calculation of the impact of being favourite or the underdog before the match on the abnormal volumes on the day of the match. The calculation is made for both the UEFA Champions League matches and for UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

One can see that, again, only in the UEFA Champions League matches abnormal volumes are statistically positive. In particular, the fact of playing a match in this competition and of being favourite, has a positive effect on abnormal volumes (+39.7%). On the other hand, being an underdog raises abnormal volumes by 27.5%. So, investors prefer to use the pre-matches information to trade favourite teams than underdogs.

All these tables' results has helped us to understand better the behaviour of investors, in particular we have seen that investors prefer to know match results before trading and that abnormal volumes are statistically positive only for the UEFA Champions League matches. Another important result obtained is that investors do not trade only when the club faces an unexpected result, but also when it faces an expected one.

Obviously, abnormal volumes' analyses can make us understand only a little part of the investors' behaviour and for this reason, we need to complete the analysis with the study of the abnormal returns before and after matches.

4.3 Analysis of the abnormal returns before and after matches

In the first paragraph I wrote that investors probably overestimate, before a match, the winning chance of a club with the consequence that they, on average, end up disappointed after the match. This hypothesis is against the efficient market hypothesis that assumes that investor are rational and do not make systematic mistakes.

This hypothesis can be verified by an empirical analysis of the abnormal results before and after a match. In chapter three I estimated how match results are able to affect in a statistically significant way the abnormal returns on the day after the matches. In this paragraph, I will not focus again on this kind of relation but I will analyze the trend of the abnormal returns of favourite clubs and underdogs. This analysis will help us to understand whether investors behave in a different way according to the bet odds of a club. In particular, the analysis of the abnormal returns before the match takes place can explain if investors effectively overestimate the winning chances of a club. On the other hand, the analysis of the abnormal returns after the match can show how great the disappointment ex post is.

In an efficient market, an investor should be able to exploit all available pre-match information to move the stock's price in a proper way. From chapter three results, we know that, on average, a win is positive correlated with abnormal returns, while losses and ties are not. Knowing that, an investor should buy before the match stocks of clubs that are expected winners and should sell the stocks of clubs that are expected losers. For this reason, before a match the stock price of a favourite club should rise, while the stock price of an underdog should decrease.

I will now analyze the abnormal return of clubs before the match in order to verify if the reasoning I made before is confirmed by data.

The regression used is $\boldsymbol{AR_{i,t-1} = \gamma_1 Fav + \gamma_2 Nfav + +\varepsilon_{i,t-1}}$ where $AR_{i,t-1}$ is the abnormal return of the club i on the day of the match and Fav and Nfav are two dummy variables indicating if the club is favourite or not favourite according to bet odds. So, I expect that $\boldsymbol{\gamma_1}$ will be greater than zero and that $\boldsymbol{\gamma_2}$ will be negative. The results of the regression are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
Favorite	0.006	0.002	0.007	***
Not favorite	0.004	0.002	0.106	

Table 4.9 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns on the day of the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of the table show that being a favourite club before the match makes the abnormal returns rise (+0.6%) and this is in line with my expectations. Results of not favourite clubs are instead surprising because the $\boldsymbol{\gamma_2}$ coefficient is positive, even if not statistically significant different from zero. So, γ_2 result is not the one I expected, meaning that the stock price of underdogs does not fall before the match. This result may be due to the fact that investors do not behave in a rational way and they overestimate the winning chances of the underdog club.

Now I will introduce in the model two dummy variables indicating in which competition the match takes place (the UEFA Europa League and the UEFA Champions League). As we saw in the previous chapter, abnormal volumes of these two competitions are very different and so I expect that even abnormal returns can diverge. The regression used becomes: $\boldsymbol{AR_{i,t-1} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t-1}}$.

I expect that, if an irrational behaviour of investors occurs, it will occur more intensely in the UEFA Champions League matches, because this competition is the most important football club competition and so more able to make the investor irrational. The results are illustrated in the table below.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	0.007	0.003	0.0253	**
SfavChamp	0.007	0.003	0.0242	**
FavEurL	0.005	0.003	0.1037	
SfavEurL	-0.001	0.004	0.8855	

Table 4.10 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns on the day of the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of the table are very interesting. We see that the UEFA Europa League matches do not affect in a significant way the abnormal returns of clubs before the match. As it happened for abnormal volumes, it seems that investors are not particularly interested in the UEFA Europa League competition. This is probably due to the fact that the UEFA Europa League competition is considered a minor European competition, both because it guarantees lower prices and because the clubs that take part in it are weaker than the clubs playing in the UEFA Champions League.

On the other hand, as regards the UEFA Champions League results, we can see that being favourite or not affects abnormal returns in the same positive way (+0.7%). These results are astonishing because we were expecting negative abnormal returns for the not favourite clubs but they are statistically positive and equal to the ones of the favourite clubs. So, it really may be the case in which investors, probably moved by passion and hope of a victory, completely overestimate the winning chances of underdog clubs and they buy their stocks in the financial market.

These strange results made me investigate whether this behaviour of investors is only present on the day of the match or even on the days before the match. So I have analyzed the abnormal returns on the day before the match in order to understand better the behaviour of investors. The model used is almost the same that was used before: $\boldsymbol{AR_{i,t-2} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t-2}}$, with the only exception that now I analyze the abnormal returns on the day before the match ($AR_{i,t-2}$) instead of the ones on the day of the match. Results of the regression are shown below.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	0.0051	0.0027	0.0582	*
SfavChamp	-0.0058	0.0026	0.0282	**
FavEurL	0.0013	0.0023	0.5727	
SfavEurL	-0.0015	0.0031	0.6337	

Table 4.11 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns on the day before the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Even in this case, as before, being favourite or not for a UEFA Europa League match has not a statistically significant impact on abnormal returns. The results of the UEFA Champions League are now finally in line with the efficient market hypothesis, which see the abnormal returns before the match raise when a club is favourite and fall when it is underdog. In fact γ_1 is statistically positive (+0.51%) and γ_2 is statistically negative (-0.58%).

I will now analyze the cumulative behaviour of the abnormal returns in these two days before the match takes place. I define CUMAR as the sum of $\boldsymbol{AR_{i,t-1}}$ and $\boldsymbol{AR_{i,t-2}}$. **So,** $\boldsymbol{CUMAR_{i,t-1} = AR_{i,t-1} + AR_{i,t-2}}$. So the regression becomes: $\boldsymbol{CUMAR_{i,t-1} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t-1}}$.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	0.012	0.004	0.003	***
SfavChamp	0.001	0.004	0.755	
FavEurL	0.006	0.004	0.108	
SfavEurL	-0.002	0.005	0.677	

Table 4.12 Calculation of the impact of being favourite or the underdog on the cumulative abnormal returns before the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results in the table show that even in this case, the UEFA Europa League matches do not affect in a statistical significant way cumulative abnormal returns. This was expected because neither $\boldsymbol{AR_{i,t-1}}$ nor $\boldsymbol{AR_{i,t-2}}$ where affected by this type of European competition.

As regards the UEFA Champions League we can see now, that only for favourite clubs there is a positive significant relationship with cumulative abnormal returns (+1.2%). For underdogs the relationship is not statistically significant anymore. This is due to the fact that the positive abnormal returns on the day of the match are cancelled out by the negative ones on the day before the match.

These results are however still not in line with efficient market hypothesis because, as I wrote before, in an efficient market, the pre-match abnormal returns of underdog clubs should be negative, while here, they are just statistically equal to zero.

In particular, we have seen that there is an overconfidence effect about the winning chance of underdogs on the day of the match, and this drives up their cumulative abnormal returns. So, I will expect that the ex-post abnormal returns for underdogs will be negative because investors, on average, will be disappointed after the match and will regret their pre-match behaviour.

The cumulative abnormal returns of favourite clubs are very high (+1.2%) and so, it is possible that also the winning chances of favourite clubs are overestimated by investors before the match but we can only know it by looking at their abnormal returns after the match.

If investors overestimated the winning chances of favourite clubs, the abnormal returns of these clubs after the match would be negative, while if overestimation did not occur, the abnormal returns would be zero.

So, it is necessary to focus attention on the abnormal returns trend after the match, in order to verify whether overestimation occurs also for favourite clubs.

Therefore I will use the regression: $\boldsymbol{AR_{i,t} = \gamma_1 Fav + \gamma_2 Nfav + +\varepsilon_{i,t}}$ where $\boldsymbol{AR_{i,t}}$ is the abnormal return of a club i after the match is played. The results are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
Favourite	-0.008	0.002	0.000	***
Not favourite	-0.003	0.002	0.142	

Table 4.13 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns on the day after the match. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results in the table show that being favourite before a match lower the abnormal returns on the day after the match (-0.8%). This means that overestimation of the winning chances also occurs for favourite clubs, and that this overestimation is even stronger than the overestimation of the underdogs (having a negative but not statistically significant ex post abnormal return of 0.3%).

Now I will introduce in the regression the two dummy variables indicating the type of European competitions played and the regression becomes:

$$\boldsymbol{AR_{i,t} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t}}.$$

What I expect for underdogs playing in the UEFA Champions League is that their abnormal returns will be negative because, as we found out before, there had been an overestimation of underdogs' winning chances (in fact the cumulative abnormal returns are not negative in a statistically significant way).

Moreover I expect that the abnormal returns of favourite clubs will be negative, because the results in the last table suggest that overestimation of winning chances also occur for these clubs. The results of the regression are shown in the table below.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	-0.008	0.002	0.000	***
SfavChamp	-0.004	0.002	0.096	*
FavEurL	-0.006	0.004	0.113	
SfavEurL	0.000	0.003	0.856	

Table 4.14 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns on the day after the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results in the table confirm my previous hypotheses. In fact the abnormal return of the underdogs which played in the UEFA Europa League is, on average, negative in a statistically significant way and it is equal to -0.4%.

We can also see that both favourite and underdog clubs which played in the UEFA Champions League have a negative statistically significant market abnormal return the day after the match. So, as I wrote before an overestimation of the winning chances of a club occurs in the UEFA Champions League not only for underdogs but also for favourite clubs (which have an average cumulative abnormal return of +1.2% before a UEFA Champions League match is played).

I will now analyze whether this negative effect of overestimation occurs only the day after the match or it persists even two days after the match.

The regression becomes: $\boldsymbol{AR_{i,t+1} = \gamma_1 FavChampL + \gamma_2 NfavChampL + \alpha_1 FavEurl + \alpha_2 NfavEurl + \varepsilon_{i,t+1}}$ where $\boldsymbol{AR_{i,t+1}}$ is the abnormal return two days after the match. The results are illustrated in the table below.

Variable	Coefficient	Standard error	P-value	Significance
FavChamp	-0.005	0.002	0.017	**
SfavChamp	0.000	0.002	0.841	
FavEurL	0.000	0.002	0.979	
SfavEurL	-0.001	0.002	0.724	

Table 4.15 Calculation of the impact of being favourite or the underdog before the match on the abnormal returns two days after the match. The calculation is made for both the UEFA Champions League matches and for the UEFA Europa League ones. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of the table show that the disappointment effect for the favourite clubs lasts two days after the match. This is proved by the fact that $\boldsymbol{\gamma_1}$ coefficient is negative in a statistically significant way (-0.05%).

The other coefficients of the regression are statistically equal to zero, meaning that for the UEFA Europa League clubs and the underdog clubs playing in the UEFA Champions League, the ex-post regret is all absorbed the first day after the match.

To summarize, regression results show that Europe football market stock price is inefficient because investors, on average, overestimate on the two market days before the match the winning chances of clubs and this overestimation increases abnormal returns excessively. The effect of the overestimation is that, on the day after the match, the abnormal returns of football clubs are, on average, negative, reflecting the disappointment and the regret ex-post.

Overestimation of winning chances of clubs occur so frequently because, as I wrote in chapter 1, those who buy or sell football clubs' stocks are rarely professional investors, but instead they are often supporters of the club, and so more irrational and impulsive.

Conclusion

In this empirical work I have analysed the relationship between soccer match results and stock returns of listed European soccer teams and investigated if the stock market of football clubs is efficient.
Considering the sample of national and European matches the results obtained are in line with the assumptions made, in fact it is highlighted that a win averagely entails an increase of abnormal returns (+0.6%), while a loss and a tie have a negative impact on the market (-1.28% and -0.8% respectively).
This kind of relationship between match results and abnormal returns was, in fact, predictable because although match results are not actual cash flows, they have an effect on the stock prices of clubs since wins raise future cash flows and the value of the football club in several ways.
Analysing only Champions League matches it has become clear that European sport results have an increased effect on abnormal returns: winning guarantees an average positive abnormal return of 0.7% while losing and tying generate a negative market reaction on the abnormal returns of -1.7% and -1.2%, respectively. The stronger effect on abnormal returns of the results in the UEFA Champions League compared to the effect on abnormal returns of the results in national championships is due to the fact that the UEFA Champions League is a very profitable competition for a club, as both prizes and television rights arising from UEFA Champions League matches are certainly much higher than stemming arising from national championship matches.
The inclusion of football betting odds in the regression models has proved very useful because it has been possible to catch the expectations of supporters and investors, after splitting the results in expected and unexpected. As I hypothesized the results have highlighted that unexpected results have a greater effect on the abnormal returns than the expected ones. This is due to the fact that the unexpected results are against the prevision of the market and so it is quite reasonable a strong price correction after this kind of results. However, there is a clear asymmetric reaction of the abnormal returns after matches because losing a match has a stronger effect, in absolute terms, than winning a match. For example in the UEFA Champions League an unexpected loss generates a very negative effect on the abnormal returns that go down by 3% while an unexpected win affects positively abnormal returns, causing a rise of 2.2%. On the other hand, an expected win does not affect in a statistically significant way abnormal returns, while an expected loss generates a negative market reaction on abnormal returns of 1.3%. This

is clearly caused by a market inefficiency due to an irrational behaviour of investors that do not correctly process all the available information while forming their expectations of a company's future performance.

An important result of this empirical work has been to demonstrate that the European football market price is an inefficient market, because investors on average tend to overestimate the possibilities of win of a team, with an exaggerated increase of abnormal returns of the team on the days before the match.

In an efficient market a rational investor will buy, before the match, stocks of clubs that are expected winners and will sell the stocks of clubs that are expected losers since wins are positively correlated with abnormal returns, while losses and ties are not. For this reason, before a match the stock price of a favourite club should rise, while the stock price of an underdog club should decrease.

On the contrary the results of the analysis show that on the day of the match of the UEFA Champions League, abnormal returns of clubs rise in a significant way of +0.7% both for favourite clubs and underdog ones. The effect of this overestimation is that, because of an ex post disappointment effect, abnormal returns on the day after the match are, on average, negative in a statistically significant way for underdog clubs (-0.4%).

Interestingly enough also abnormal returns of favourite teams are on average negative (-0.7%). This is probably due to the fact that overestimation occurs also for favourite clubs. Cumulative abnormal returns of two days before the match are +1.2%, which is probably an excessive value. So, overestimation of win probability occurs both for favourite and underdog clubs and it may depend on the fact that those who buy or sell football club stocks are generally not professional investors but supporters, typically more irrational and impulsive.

I have focused on the relationship between football results and abnormal returns, but of course there are also other many drivers that can influence the stock price of a club and affect its daily returns such as its market share, the income from broadcasts, the popularity in the media, the players' salaries and the players' transfer prices. Other variables, which can influence the stock price, are the country index, contract duration of players, contract duration of coaches and results of international matches. Therefore, I do not expect that all the amount of abnormal returns is only explained by match results.

Even if the purpose of this work was not to create an investment portfolio or to identify a trading strategy, the results obtained may be very important because they can offer investors guidelines to be followed. For example professional investors should go short on football stocks before the match is played, in order to earn money exploiting the ex post disappointment effect. In this way, they can take advantage of the average excessive increase of football stock prices before the match, caused by the overestimation of the probability of win of clubs from no professional investors.

However, it should be noted that suggesting trading strategies at this point remains speculative, since in my analysis I have not considered transaction costs. A possible extension of this empirical work might be to try to analyze the profits an investor can obtain when transaction costs in the model are included in the analysis.

In this work I have verified that brand distortions also occur in financial markets, because the power of a brand can influence the mood and the behaviour of investors, who are guided in their choices more by their feelings and personal expectations than by rationality.

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