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DRAW BIAS AMONG BETTORS IN FIFA WORLD CUP 2010: EVIDENCE FROM TURKISH FIXED-ODDS BETTING MARKET

Abstract

Sports betting literature investigates a variety of biases such as national sentiment, longshot-favorite bias, over bias in total markets, and popular team bias. The supply side of sports-betting has been extensively examined whereas relatively few studies have taken the consumer perspective and explicitly considered behavioral patterns of bettors. I explore the behavioral pattern of bettors on their betting choices for draws by using the FIFA 2010 World Cup – South Africa data collected from Turkish fixed odds betting market. My interest focuses on draw as it reflects a special feature of soccer competition and compared to many other sports competitions, draw is a likely outcome in a soccer game. The World Cup Data shows that there is a draw bias among bettors as they prefer to bet mostly on win of a side. In addition, the estimates based on the data indicate that even in a perfect uncertainty case with equal odds for each possible result, most of the bettors would prefer to bet on home-win or away-win. This bias can be explained by a particular probabilistic judgment on draws or the preferences (bettors don't like draws). To disentangle this joint effect, I designed two experiments by considering the games of leading 6 leagues in Europe at a weekend and the first games of the group stage in EURO 2012. The findings show that the bettors are overestimating the probability of the game result they bet on. There is nothing particular with draws as for the subjective probability. The results confirm the dislike of draws and the draw bias is not related to a particular probabilistic judgment.

Keywords: Betting, Soccer, Draw Bias, Bettors, Preferences, FIFA World Cup 2010

1. Introduction

Betting markets are experiencing an unprecedented growth over the past few years as a result of deregulations, abolition of national monopolies and the widespread use of internet which leads to advent of online gambling (Vlastakisa et al. 2009). And betting industry becomes one of the fastest growing industries and attracts the attention of casual bettors, pundits, and scientists alike (Strumbelj and Sikonja, 2010). The simplicity and uniformity of the rules of soccer and soccer betting procedures are factors in the popularity of that sport and soccer betting (Stefani, 1983). The rising popularity and importance of betting has been reflected in the literature and thus the literature on sports betting has gained momentum especially in the last two decades. Football, basketball, horseracing, and soccer have been the leading sports of the field. Economists have given great attention to the tests of market efficiency and rationality in stock markets (Thaler and Ziemba, 1988). Betting markets are of particular interest to researchers as there are many similarities between wagering in betting markets and trading in financial markets (Strumbelj and Sikonja, 2010). Besides, the sports betting market has several advantages over traditional asset markets in terms of efficiency tests. All bets reach a terminal value in a short period of time and so the success/failure of investment can be observed (Avery and Chevalier, 1999). Considerable research has been devoted to the efficiency tests of the sports betting markets (Thaler and Ziemba, 1988; Forrest and Simmons, 2008; Woodland and Woodland, 1994; Pope and Peel, 1989).[1] Another important issue which has been discussed in the literature is related to the existence of biases and their implications for market efficiency (Vlastakisa et al. 2009).

In sports betting, large individual differences are observed amongst people. Some will choose not to bet, some can see betting as a way of entertainment and probably a minority can regard betting as a source of income. Others may be attracted to betting on so-called “certainties” irrespective of the odds on offer and others may bet on the football team that they support to win out of loyalty, or bet against their team to have a financial return in case their team does not win (Milliner et al. 2008). The irrational behavior of bettors or more generally human-being leads to a variety of biases in sports betting market. Sports betting literature investigates biases such as national sentiment, longshot-favorite bias, over bias in total markets, and popular team bias. However, as

[1] As the efficiency discussion is beyond the scope of the paper, I prefer to skip it.

Nilsson and Andersson (2010) indicate, the supply side of sports-betting (i.e., bookmakers and gambling companies) has been extensively examined whereas relatively few studies (such as Paul and Weinbach, 2010; Pujol, 2008; Weinbach and Paul, 2009) have taken the consumer perspective and explicitly considered behavioral patterns of bettors.

I will explore the behavioral pattern of bettors on their betting choices for draws. My interest focuses on draw as it reflects a special feature of soccer competition. Compared to many other sports competitions, draw is a likely outcome in a soccer game because on average around 30% of games end with a tie. Draw outcome of a soccer competition is regarded as a disliked outcome for audience as especially most of the draws occur with a score of 0-0 or 1-1.[2] Thus, football authorities have taken various decisions to promote attacking style of play and decrease the number of draws. For example, in the middle of the 1990s, UEFA introduced the rule of 3 points for a win instead of 2 points. The main objectives were to achieve more goals per game, fewer draws and more exciting and attractive matches.[3] For 2006/07 season France Football Federation implemented a strategy to increase the number of goals by offering monetary award for wins with a winning margin of two goals or more. The Federation devised this plan to “combat the 0-0s” which were beginning to blight in French Ligue 1. More recently, after the FIFA World Cup 2010, FIFA considers some drastic changes for the next tournament. Due to the negative play in World Cups, it is planned to award four points for a victory in group games and implementing penalty shootouts (for group matches as well as knockout games) after 90 minutes of play. The planned change aims to offer greater incentive for victory and reduce the value of draw for teams. Regularity authorities in soccer have made attempts both domestically and internationally to foster attacking play and to decrease the draws.

Although draw reflects a unique feature of soccer and it is a likely outcome in a soccer game, there is no study which investigates how “draw” is considered by bettors. First, I focus on the choices of bettors in Turkish fixed-odds betting market and investigate the behavioral bias of bettors towards draw on the games of FIFA World Cup 2010. Later, I

[2] A draw with a score of 2-2, 3-3, and 4-4 can be entertaining, however those scores rarely occur.
[3] Since then, many theoretical and empirical studies have questioned the effects of this incentive change and some found significant changes in parallel to the planned outcomes whereas others did not find such effects (Guedes and Machado, 2002; Dilger and Geyer, 2009; Brocas and Carrillo, 2004; Aylott and Aylott 2007) .

will go deeper in analyzing the reasoning behind the observed draw bias by performing an experiment.

The World Cup Data show that there is a draw bias among bettors as they prefer to bet mostly on win of a side. However, the World Cup data cannot be sufficient enough to infer the reasoning(s) behind the draw bias. To disentangle this joint effect, I designed two experiments by considering the games of leading 6 leagues in Europe at a weekend and the first games of the group stage in EURO 2012. The experiment shows that the bettors are overestimating the probability of the game result they bet on. The results confirm the dislike of draws and the draw bias is not related to a particular probabilistic judgment. Draw bias can be explained by the preferences rather than the probabilistic judgment. Due to the disliked of draws (as they mostly end with a low-scoring and decrease the spectacle value of the game) and the nature of sports competition, bettors prefer not to bet on draws.

The paper is organized as follows: The next section gives the literature review for the studied biases. Section 3 describes the betting data on World Cup 2010. Section 4 includes the econometric tests of World Cup 2010 data and related findings. Section 5 includes the experiments and results. Section 6 concludes.

2. Literature Review

The literature deals with a variety of biases observed in sports betting market. The most prominent bias discussed in the literature is the favorite–longshot bias, first discovered in racetrack betting markets by Griffith (1949) (see Golec and Tamarkin, 1998; Woodland and Woodland, 1994; Vaughan Williams and Paton, 1997, 1998). The favorite-longshot bias is defined as “consistently observation of tendency of racetrack bettors to overbet underdogs and underbet favorites” (Woodland and Woodland, 1994). Favorites win more often than the subjective market probabilities imply; on the contrary longshots win less often (Cain et al. 2000). Bets placed on favorites yield a higher return than bets placed on longshots. The majority of studies have been conducted for pari-mutuel markets where the odds are determined by the bettors. A range of explanations for this bias has been proposed, attributing its cause either to bettors’ misperceptions, cognitive errors or preferences for risk, or to the rational decisions of bookmakers (Sung et al. 2009). Cain et al. (2000) investigate favorite-longshot bias for soccer games in UK in fixed-odd market where the bettors are only odd-takers. Evidence is found in favor of the traditional long-shot bias for soccer. However, this bias is found for bookmakers as they make the analysis through the odds offered by the bookmakers. Recently, Gil and Levitt (2007) verified the existence of the favourite–longshot bias by using the trading data from the gambling market for 2002 World Cup.

Page (2009) investigates whether optimistic bias, also known as wishful thinking that is as the overestimation of one's chances of success or ability, lead to a bias in the odds. Page analyzes a large dataset of international and European cup football matches from 1998 to 2007. As the share of UK bettors in Europe is relatively high, the author expects to find a bias in the odds given for British soccer teams in European cup games and British national team in international games. An optimistic bias would exist if the odds of British teams will be biased downward (lower odds and thus higher probability) and betting firms will offer downward biased odds for British teams. It is found that the odds of bookmakers are not affected by wishful thinking although wishful thinking exists at the level of bettor's decisions. This bias is eliminated by the market mechanism. The bias studied in the paper of Page (2009) can be also interpreted as a national sentiment.

Braun and Kvasnicka (2008) investigate how price setting behavior of bookmakers for international sport events is affected by national sentiment in the form of either a perception or a loyalty bias of bettors. Under perception bias, national sentiment may bias bettors' perceptions of the winning chances of their national team upwards. As the perception bias becomes stronger, the odds offered by the domestic bookmakers for such an outcome will be lower. Under loyalty bias, bettors may only consider whether to bet on their home team or not and so more favorable odds should be offered by bookmakers for the win of domestic teams. Based on a dataset of online betting quotas from twelve European countries for qualification games to the UEFA Euro 2008, the authors show that in Bulgaria, Denmark, and Italy, the bias is positive, in France, Slovenia, and Sweden, it is negative. Some bookmakers shade prices in favor of national team of the country they are operating in, and others shade prices against it. The negative bias is explained by committed bettors that only consider betting on the home team win (loyalty bias) and the positive bias is explained by both types of sentiment biases.

Avery and Chevalier (1999) consider two categories of anticipated sentiment variables which correspond to behavioral strategies of investors in stock markets. The first category is the hot-hand betting strategy in the football market which is similar to a momentum investment strategy in the stock market is tested. A hot hand bias can occur if fans choose to bet on teams that have been performing well recently. The second category deals with the prestige effects in football betting that is similar to the familiarity bias given by the individual investors preference for company shares which products are widely used or which prominently appear in the media.[4] The authors, using data of 2366 NFL games from 1982 to 1994, examine the relationship between the change in the betting line and the anticipated sentiment variables. The hot-hand variables are found to be statistically significant however their magnitudes are not strong in point-spread betting market for NFL. Bettors bet on teams that performed well in the past 2 weeks and bet against teams with longer winning streaks. It is shown that individuals bet on the popular teams (name recognition) or teams which are covered in the media.

An important bias is also observed on popular teams. The teams most known by the bettors may influence the bettors' behaviors. Bettors may feel anxiety while they're striking a bet on the teams they don't know much about (Sierra and Hyman, 2009). Kuypers (2000) offers a theoretical model and argues that bookmakers may set the odds by taking into account the presence of committed supporters in the betting market for a particular match. Franck et al. (2010) consider the popularity of a team as a source of sentimental betting and market inefficiency like Avery and Chevalier (1999), Forrest and Simmons (2008) and Braun and Kvasnicka (2008). It is argued that some fan bettors can be unwilling to bet against their favorite team due the loyalty towards their club moreover, these bettors can feel as showing their loyalty to a particular club by wagering their money on it. Thus, teams with comparatively larger fans attract more sentimental betting volume compared to less popular teams. However, bettors prefer to act against their financial interest by betting on their favorite team. They should prefer to diversify by betting on the non-preferred team such that, the utility gained from seeing their favorite team winning will offset the monetary losses of betting on the competing team might be offset. On the contrary, if the preferred team loses, they are monetarily compensated by their betting profits (Fellner and Maciejovsky, 2003). By

[4] In finance literature, this is defined as familiarity bias which argues the tendency of people investing in the familiar, highly recognized assets while often ignoring the principles of portfolio theory.

using data from eight well-known bookmakers for more than 16,000 English soccer matches played in the 2000/01 to 2007/08 seasons, Franck et al. (2010) find evidence that bookmakers offer more favorable odds for teams with a comparatively larger number of supporters. This implies that the odds of bets on popular teams are underestimated and no longer reflect the expected true winning probabilities. By this way, bookmakers attract larger share of the price-sensitive sentiment bettors. Market efficiency is clearly rejected. Forrest and Simmons (2008) find that in Spanish and Scottish soccer leagues more favorable odds are offered for bets on more popular teams. Bookmakers take into account the popularity of a club when pricing the bet and teams with relatively more supporters attracted a price advantage over 2001/02 to 2004/05. Similar results are also documented for Scotland. Those findings challenge the prediction of Kuypers (2000).

Paul and Weinbach, in a variety of studies, investigate the existence of a behavioral bias towards over in over/under betting market for different sports. There is a tendency of people especially to bet more on over compared to under in sports games. When total scoring is higher (lower) than a pre-specified value, an over (under) is achieved. For example, in a soccer game over means at least 3 goals in total. The over bias in total markets is studied for different sports (Paul and Weinbach, 2002 for football; Paul and Weinbach, 2005 for basketball and football; Paul et al. 2004 for basketball). The findings show that bettors systematically overestimate the chances of a game going over. More recently, Weinbach and Paul (2009) include the television broadcast factor in the over bias for American college football totals market. A slight non-significant bias toward the over is observed for the sample however this bias is only statistically significant for nationally televised games on major networks. This bias shows that bettors prefer to watch high scoring games on television. Golec and Tamarkin (2008) test the efficiency of the NFL (from 1993 through 2000) and NBA (from 1994 through 2002) betting markets with respect to over/under-bets. Regression tests of over/under-bets reject efficiency in both markets and they imply that there is a bias that makes the over a better bet than the under on average. However, on average over the full samples, betting the over is not significantly profitable. Considering the case of soccer, Paul and Weinbach (2009) test under/over market for 22 European Soccer Leagues with 15,570 games to determine whether the behavioral biases found in North American sports betting markets also exist in European soccer betting markets. Firstly, it is shown that only around 46% of games had more than 2 goals. In addition, betting on over for all games lose more than twice as much money as betting on under for all games. In 20 of 22 leagues, wagers on the over lost more than wagers on the under. It is found that the behavioral bias toward betting the over exists in Europe for soccer. In addition, they also analyze the possibility of multiple behavioral biases by incorporating the favorite-longshot bias. Those two biases are shown to co-exist.

Another line of literature deals with the learning process of bookmakers and bettors. Baryla Jr. et al. (2007) by using the opening and closing betting lines, examine NBA basketball games especially with a focus on early season. It is found that totals lines are upwardly biased early each season. As each season progresses, both the bookmakers' and betting public's forecast errors decrease with learning throughout each NBA season. The observation of early-season mispricing and late-season efficiency is interpreted in a similar way with the corporate IPOs. Early in the season, as there is less available information for bookmakers and/or bettors to predict team performance, the ability of the bookmaker and bettors to make accurate forecasts decrease. However, when the season progresses, additional data are revealed, team strength becomes more certain, and both opening and closing lines become more accurate indicators of observed outcomes. Pujol (2008) investigate the learning process of bettors in Quiniela[5] in which bettors try to forecast the results of a list of 15 given games in each week. Unlike betting markets that hinge on points spreads or odds, the participants in this market merely need to pick outright winners. The data set is formed by the 1063 Quinielas played between 1970 and 2000. From the total amount of money collected each week, a given percentage is distributed among the people who have predicted correctly at least 12 games. It is shown that the average percentage of winning bets increases as the competition advances. This is because soccer fans accumulate new information helping them to better identify which are the teams that will become the top ranked teams and which will become the bottom liners.

Borghesi (2008) investigate the weather bias in the National Football League (NFL) totals betting market. More specifically, the relationship between weather and bet outcome is considered as it may be systematically misvalued by gamblers. Evidence suggests that the market for NFL totals bets is both statistically and economically

[5] Quiniela is a popular Spanish lottery on soccer games: The name derives from the word *quince*, meaning fitfteen.

inefficient. A profitable opportunity exists because closing totals lines fail to fully reflect the effects of adverse weather on game outcomes.

The study of Nilsson and Andersson (2010), one of the few papers dealing with the behavioral patterns of bettors, shed light on the conjunction fallacy in sports betting by comparing the perceptions of bettors under single and combined-bets. They find that when a prediction with a low or intermediate likelihood of success is combined with one or two predictions with a high likelihood, participants were prone to perceive that it was more likely to come true. Although the betting on a single football game has a greater chance of success than that of betting on the outcome of a combination of events, the bettors tend to evaluate multiple-bets in a manner that runs counter to the laws of probability. This finding also helps to explain why multiple-bets are more popular than single bets.

Recently, Paul and Weinbach (2010) investigate which factors determine the betting volume for The National Basketball Association (NBA) and National Hockey League (NHL). This study is important in terms of understanding which factors play a role in their decision for betting. For this purpose, they collect actual betting volume across three on-line sportsbooks for the 2008-09 season and run a regression model with the independent variables such as the quality of teams, television coverage by network, day of the week, time of day, month of the season. For NBA, the estimates are all found to be statistically significant. This shows that betting on the NBA and NHL appears to be much more about consumption than investment. Also they consider over bias for NBA games and show that bettors appear to wager in greater numbers on games with higher totals (over/under bets). Bettors, like fans, appear to enjoy games where there is likely to be more scoring during the contest.

3. World Cup Study

3.1. Betting Market in Turkey

Spor Toto is the authorized public institution responsible for managing sports betting in Turkey. It has contracted this right to Inteltek Company under the name of “Iddaa” in 2004 for the first time and has renewed it for 10 years in 2008. Thus, currently the unique sports betting authority with the exclusion of horse betting is Iddaa which has begun operating in April 2004 and has shown a rising performance since then. There are two betting channels offered by Iddaa to bettors: Online and Bookies.

Bookies are privately owned shops and have the permission from Iddaa to offer this service. These bookies are widespread all over Turkey and their number almost reached to 5,500. On the other side, there are 5 companies in the online betting market namely bilyoner.com, nesine.com, misli.com, oley.com, and tuttur.com. Bilyoner.com, the first legal electronic betting platform of Turkey, was established in 26 March 2004. Bilyoner.com had over 700,000 and 950.000 members at end of 2007 and 2008, respectively. However, currently the number of members is expected to be around 1.5 million. The turnover of the company was 331 million TL in 2008 and rose to 425 million TL with an increase of 28% in 2009 (Sabah, 2010). The company has successfully used the first mover advantage and now dominates the electronic betting market in Turkey. Nesine.com, the second actor in the market, was established in 11 July 2006 and has been active since September 2006. Nesine.com has over 400.000 members. The other three companies are relatively new in the market and so they have low market shares compared to other two mature companies.

Since its establishment Iddaa (both online and bookies) has experienced an increasing performance and attracts the interest of wide range of people. The annual turnover of the whole market was 236 million TL in 2004 and rose dramatically to 2.3 billion TL in 2008. In 2010, the total turnover of Iddaa was 3.75 billion TL with a growth rate of 34%. Since the introduction of Iddaa in April, 2004 to December, 2010, the total turnover reached to 14.4 billion TL and 7 billion of it was distributed to the bettors. Iddaa also creates additional value for media, government, and Turkish soccer. The damage of illegal betting is assumed to be around 350-400 million dollar (Dogan News Agency, 2011). The turnover of the online betting market was 500 million TL in 2008 and 850 million TL in 2009. The online betting has reached a market share of around 30 percent in sports betting market (Aksar, 2009), however today it is assumed that the ratio of online sports betting reaches around 35-40%. Although the betting market is growing rapidly in Turkey, the services offered to bettors are relatively limited (although some improvements are observed recently) and there are some important differences compared to Europe and US betting market.

Football betting has been available in Turkey since 2004. So the market is relatively young. The other sports such as basketball, formula, tennis, and volleyball were made available for betting in 2008. As a result of the popularity of football in Turkey and the delay of introduction of other sports betting, football betting still dominates the market. The online betting companies and the bookies are odd-takers thus they don't have the right to modify those odds. Thus, the bettors are faced by the same odds whether they play online or through bookies. There is a fixed-odds betting market in which the odds are determined by Iddaa in Turkey. The newsletter showing the games and their odds are published twice in a week, on Tuesdays and Fridays. The newsletter of Tuesday contains the odds for the games of Tuesday, Wednesday and Thursday and the newsletter of Friday includes the remaining. So at maximum, you can bet on a Monday's game on Friday. Certainly, the most important limitation on bettors in Turkey is the minimum number of games that a bettor must bet on. In Europe and US, it is mostly possible to bet on single games and also live betting is available. But in Turkey, bettors must choose at least 2 or 3 games from major leagues or 4 games from non-major leagues to create a coupon. However recently more games are made available to make single bets and also live betting opportunity is tested on some games. In 2007, online betting from other foreign companies was strictly forbidden by the law.

3.2. FIFA World Cup - South Africa 2010

The 2010 FIFA World Cup South Africa hosted 32 participating national soccer teams from June 11th to July 11th 2010. The final game ended with the victory of Spain against Netherlands after extra-time. FIFA World Cup 2010 attracted the interest of sports lovers and especially bettors in Turkey. The highest turnover on the basis of league/competition for the betting market of Turkey was achieved during FIFA World Cup South Africa in 2010 (Dogan News Agency, 2011).

In the group stage, there are eight groups with four teams in each. Each team plays 3 games in this stage. The top two teams in each group advance to the final rounds starting with the round of 16. In total, 64 matches are played during the tournament. 48 of those 64 matches are played in the group stage and another 16 in the final rounds. In the final rounds, matches that are tied after the official 90 minute match time are followed by an extra-time period and, if necessary, by a penalty shootout to determine the team qualifying for the next round. As the betting market considers the result after

90 minute as the outcome of a game, if a game goes to extra-time, it is regarded as a draw. There is no home team advantage in World Cup games except the organizing country which is South Africa in the last World Cup.

The data about draws occurring in the latest and some previous World Cups are presented in table 1. In FIFA World Cup South Africa, in the group stages 14 of 48 games (29%) ended as a draw and in the elimination stages 4 of 16 (25%). In total, the teams couldn't manage to beat each other in 18 games during the tournament. When I consider the mean of draws in the previous 7 World Cups, it is observed that the minimum number of draws was experienced in 1994 by 23% whereas in France 98, 17 of 52 games ended as draw.

Table 1. Percentage of Draws occurred in Each Group and Final Stages per World Cup

	Mexico 1986	**Italy 1990**	**USA 1994**	**France 1998**	**Korea-Japan 2002**	**Germany 2006**	**South Africa 2010**
Group games							
A	3/6	0/6	1/6	2/6	3/6	0/6	2/6
B	2/6	1/6	2/6	4/6	1/6	2/6	1/6
C	1/6	0/6	3/6	2/6	1/6	1/6	3/6
D	1/6	1/6	0/6	2/6	1/6	2/6	1/6
E	2/6	1/6	2/6	4/6	2/6	1/6	0/6
F	2/6	5/6	0/6	1/6	3/6	2/6	4/6
G	-	-	-	1/6	1/6	2/6	2/6
H	-	-	-	0/6	2/6	1/6	1/6
Total groups	11/36 (30%)	8/36 (22%)	8/36 (22%)	16/48 (33%)	14/48 (29%)	11/48 (22%)	14/48 (29%)
Final rounds							
Round 16	1/8	4/8	2/8	2/8	3/8	2/8	2/8
Quarter finals	3/4	2/4	1/4	1/4	2/4	2/4	1/4
Semi finals, finals (third place game)	1/4	2/4	1/4	1/4	0/4	2/4	1/4
Total final rounds	5/16 (31%)	8/16 (50%)	4/16 (25%)	4/16 (25%)	5/16 (31%)	6/16 (38%)	4/16 (25%)
Total tournament	16/52 (30%)	17/52 (32%)	12/52 (23%)	20/64 (31%)	18/64 (28%)	17/64 (26%)	18/64 (28%)

Source: Archive of FIFA World Cup homepage (http://www.fifa.com/worldcup/)
* The statistics given in the table can be different from the actual statistics as betting markets consider only the result after 90 minutes.

3.3. Betting Data for FIFA World Cup - South Africa 2010

World Cup football matches are considered as the biggest TV show in the world and draw the interest of people from all over the world. Likewise, although Turkey couldn't manage to qualify for the tournament, the interest was on a large scale as a country addicted to soccer. Also bettors showed an enormous interest to games in World Cup and the highest turnover in 2010 for the bookmaker was achieved in this tournament.

In fixed-odds betting markets, the odds are posted several days prior to the game and are very rarely modified by bookmakers after the announcement. The fixed-odds betting has a different structure from the pari-mutuel system (as often used in betting on horse races) and from the point spread betting system (used for the most popular sports in the US). There also exists another system in which bettors trade the betting contracts. This is similar to the stock and future exchanges. Prices of traded contracts are determined by the demand for and supply of these contracts and the operator provides the trading platform and charges a commission over winnings. Within a fixed-odds betting system, the odds represent only the opinions of the experts of the bookmakers (Palomino et al. 2009).

I use a unique database showing the actual choices of bettors in a fixed-odd betting market. To my knowledge, there is no such study having a data on the choices of bettors in fixed-odds betting systems except a few experimental studies. The literature uses the odds, contracts exchanged or the change in point-spreads in their analysis. Three out of the five online betting companies of Turkey provide top 50 most preferred game list in their websites. The list is constructed ordering the games according to the actual choices of bettors. Any person can access this information from those websites and see the list of top 50 preferred games of the members at the current access time: however, no historical data is presented. The list is continuously updated and the games which have started are removed from the list.

I collect the data for the games in FIFA South Africa World Cup 2010 from those three online betting companies just before the kick-off of each game. As "Bilyoner" is the first betting platform of Turkey and with the highest market share by 1.5 million members, I prefer to use the data of Bilyoner. The data includes the percentage distribution of bettors' choices for each possible game outcome namely home win (1), draw (x), away win (2), home team not to lose (1x), home or away team win (12), away team not to lose (x2), under (less than 2.5 goals in total), and over (more than 2.5 goal in total). The percentage distribution of bettors' choices sums to 100% for each game. Home-away team separation in World Cup is used to name the first and second team, thus unlike compared to sports leagues, there is no home field advantage for the competing teams. All teams, except the team of the organizing country (namely South Africa for the last World Cup) play on foreign ground.

To have a clearer idea about what the data is and what it tells, let's consider the first game of World Cup 2010: South Africa vs. Mexico. The opening game of the tournament ended as a draw with a score of 1-1. 25.06% of bettors, who betted on this game included away-win namely the victory of Mexico in their betting coupons, whereas 19.08% of those bettors made their choice on the home-win namely the victory of South Africa. 14.31% of bettors bet on draw. For bets on the number of goals, around 29.49% (3.1%) of bettors who bet on the opening game include over (under) in their coupons.

In addition to betting choices, I also consider the result of online surveys which were conducted in www.mackolik.com[6] till the start of each game in World Cup 2010. People (whether they have membership or not) can vote for home-win, draw, or away-win for once. The survey data for all 64 games is collected. On average, 2,262 votes were used for each game.

3.4. Descriptive Statistics

For each game, the bettors' choices sum to 100%. However, bets on game results (1, x, or 2) and on total markets (under/over) are mutually exclusive. Thus, I also use the choices for only game results by normalizing the bets on 1, x, and 2. For example, in the first game of World Cup South Africa played against Mexico the bets on this game are distributed as 19.08%, 14.31%, and 25.06% on home-win, draw, and away-win, respectively. 58.45% of bets were done on game results, the majority of the remaining 41.55% were on total goal market namely under and over. When game results are

[6] www.mackolik.com provides detailed information about soccer from all over the world. In addition, live scores and betting information are also presented. The website has a global Alexa Traffic Rank of 7,714 and 74 ranking in Turkey.

normalized, 33%, 24%, and 43% of bets on game results were on home-win, draw, and away-win, respectively.

The descriptive statistics for bettors' choices are given in Table 2 and Table 3. In FIFA World Cup South Africa, on average draw was chosen by only 8%. When the bets only on game results are considered, it is seen that the bettors' choices on draws was around 11.7%. As the odds got lower which indicated a higher probability for draws according to the bookmaker, the choice of bettors on draws increased. However it stays far below the actual mean of draws in World Cup. Considering the home-win and away-win, the data shows that the bettors' choices on home-win and away-win were 33.8% and 26.4% (49.5% and 38.7% in the game result market), respectively.

Table 2. Descriptive Statistics of Bettors' Choices

	# of games	1	x	2	1x	12	2x	under	over
Group Games	48	0.325	0.078	0.264	0.019	0.004	0.026	0.095	0.190
		(0.273)	(0.084)	(0.265)	(0.019)	(0.006)	(0.025)	(0.053)	(0.143)
Elimination Games	16	0.377	0.087	0.265	0.022	0.003	0.014	0.044	0.186
		(0.243)	(0.056)	(0.271)	(0.018)	(0.002)	(0.012)	(0.029)	(0.082)
All Games	64	0.338	0.080	0.264	0.020	0.004	0.023	0.082	0.189
		(0.265)	(0.078)	(0.264)	(0.019)	(0.005)	(0.023)	(0.053)	(0.130)
All Games (choices on game results)	64	0.495	0.117	0.387					

* Values in parenthesis are the standard deviations.

Table 4 summarizes the actual game results, the prediction of the bookmaker according to the probabilities implied in odds, and the choices of bettors and survey participants in more detail. In FIFA World Cup 2010, 28% of games ended as a draw whereas win and loss have the mean value of 36%. When I consider the prediction of bookmaker, the bookmaker (Bilyoner) can be regarded as successful on average as the odds given for draw and away-win are in parallel to the actual results however the bookmaker overestimated the home-win. On average, the bettors chose the bet on home-win or away-win rather than draw. When the survey participants are considered, their choices are in parallel with the bettors.

Table 3. Summary Table of Bettors' Choices on Draw

Odds range for draw	Implied Probability	Prob.*	N (draws occurred)	% of choice for draws in betting market	% of choice for draws on game-result bets
odd<2	66-50%	55-42%	1(0)	53%	58%
2≤odd<2.5	50-40%	42-33%	0(0)	-	-
2.5≤odd<3	40-33%	33-28%	19(8)	13%	19%
3≤odd<3.5	33-28%	28-23%	20(4)	7%	10%
3.5≤odd≤4	28-25%	23-21%	15(4)	3%	4%
4<odd	25%	21%	9(2)	3%	6%
Average	26%	22%	64(18)	8%	12%

* Probabilities are achieved by normalizing the implied probabilities by using the mark-up of the bookmaker (which is around 20%).

When the choices of bettors on home-win, draw, and away-win are compared, it is seen that percentage of bettors choosing home-win and away-win are statistically higher than those choosing draw (25.8% at 1% level for home-win and 18.4% at 1% level) whereas the percentage of bettors choosing home-win and away-win are not statistically different from each other.

Table 4. Summary Statistics for Game Results, Odds, Choices of Bettors and Survey Participants in FIFA World Cup 2010

	1	X	2
PANEL A – Distribution of Game Results			
Group games	33.3%	29.2%	37.5%
Elimination games	43.8%	25.0%	31.3%
TOTAL	35.9%	28.1%	35.9%
PANEL B – Odds			
Group games	2.63	3.56	4.08
Elimination games	2.64	3.12	3.13
TOTAL	2.64	3.45	3.85
Probabilities	41.6%	25.4%	33.0%
PANEL C – Choices of Bettors			
Group games	32.5%	7.8%	26.4%
Elimination games	37.7%	8.7%	26.6%
Average	33.8%	8.0%	26.4%
Average (in game result market)	50.8%	11.6%	37.5%
PANEL D – Choices of Survey Participants			
Group games	45.8%	16.0%	38.2%
Elimination games	51.4%	13.6%	34.9%
Average	47.2%	15.4%	37.4%

1, x, and 2 represent home win, draw, and away win, respectively.

When the choices of bettors on game results are compared, it is seen that draw is less preferred. The difference between choices of bettors on home win and on draw is 25.8% (statistically significant at 1% level) and the difference between choices of bettors on away win and on draw is 18.4% (statistically significant at 1 level). Whereas there is no statistically significant difference between the choices of bettors on home win and on away win.

Table 5 gives the details of forecast accuracy of different parties and compares that with a random strategy by using a binomial test (Schmidt et al. 2008 and Borghesi, 2008). I predict a home-win, draw, or away-win according to the choices of bettors. The game result which was preferred by bettors at the most is considered as the prediction of bettors. In case of the FIFA rankings, I predict the win of a team if it has a better position in the ranking compared to its rival. However, if the ranking difference is less than 8, the game is predicted as a draw[7] (Stefani, 1983). In case of bookmaker prediction, I consider the outcome with the lowest odd as it reflects the most probable result by the bookmaker (Slamka et al. 2008). Both the predictions of bookmaker, FIFA Ranking differences, bettors, and online survey participants are significantly different from the predictions of a random strategy. Schmidt and Werwatz (2008) find that market predicts more accurately than the random predictor and the performance of market and bookmaker's odds are not different from each other in Euro 2000 tournament. Andersson et al. (2009) compare the prediction performance of bettors with laypeople for FIFA World Cup 2006 and they document that the performance of bettors and laypeople depends on the level of prediction tasks.

[7] 8 threshold level is chosen to have enough observations for draw prediction. When the ranking difference among two competing teams is less than 8, I assume that strength of two teams are close and draw is predicted.

Table 5. Comparison of forecast accuracy

	No. obs.	Hit rate	No. of successful home-win prediction	No. of successful draw prediction	No. of successful away-win prediction
Bookmaker	64	50.0%***	17(34)	0(1)	11(29)
	16	62.5%**	6(10)	0(0)	4(6)
FIFA Ranking	64	46.9%**	15(30)	4(15)	11(19)
	16	50.0%	4(7)	1(6)	3(3)
Bettors	64	48.4%***	17(35)	0(1)	14(28)
	16	56.3%*	6(11)	0(0)	3(5)
Online Survey	64	50.0%***	18(37)	0(1)	14(26)
	16	56.3%*	6(11)	0(0)	3(5)

64 observations are for the all games of World Cup whereas 16 observations include only the elimination games following the group games. In one case, the odds given for home-win and away-win are equal and the game ended with home-win, I count this as a successful prediction for the bookmaker. ***, **, and * significantly different from a random strategy at the 1%, 5% and 10% level, respectively: the p-values are calculated using a binomial test.

4. Econometric Methodology

4.1. Models

The descriptive statistics presents that the bettors often avoided including the draw in their betting coupons in the last World Cup. With the following regression estimates, I will explore the factors which can influence the choice of bettors for home-win, draw, and away-win. The dependent variable is the percentage of bettors' choices for each game result. As the dependent variables are percentages, OLS regression may not be ideal. The fitted values can lie outside the 0 to 100% range and it is not clear to interpret such a finding. In addition, the effect of a continuous independent variable tends to dissipate as it gets very large or very small because the effect must get smaller as the fitted value gets closer to the endpoints (Schanzenbach and Sitkoff, 2007). I also use a generalized linear model (GLM) with a logit link and the binomial family by the robust option to obtain robust standard errors. This will ensure that the predicted values fall within the interval of 0 and 1.

I rely on the literature for the choice of the independent variables. I include FIFA/Coca-Cola World Ranking (*Ranking Dif.*) as an independent variable to measure the relative strength difference between two national teams[8]. FIFA provides the historical data in its website and I use the most recent data (26 May 2010) published just before the start of World Cup 2010. FIFA Ranking was first introduced in August 1993 and has become a regular part of international sports reports and an important indicator for FIFA's member associations to find out where their respective teams stand in world football's pecking order. FIFA rankings are considered as tools in forecasting match outcomes. Suzuki and Ohmori (2008) show that FIFA rankings are an effective tool for forecasting the results of FIFA World Cup 1994, 1998, 2002, and 2006 and Leitner et al. (2010) also document that FIFA Rankings are good assessment of the teams' current abilities and has a good predictive power. Furthermore, Dyte and Clarke (2000) use the FIFA rankings to predict the distribution of scores in international soccer matches. Ridder et al. (1994) find that club teams of equal strength should have a 25% chance of ending the match with a draw. Thus, I consider the difference of two competing teams in a game as a variable affecting the choice of bettors. Considering the draw, as the ranking of two teams get closer, I expect to find an increase in the choice of bettors for draw. The ranking difference is used in absolute value for the case of draws as I deal with the difference with the relative strengths of teams. When the difference between the ranking of two teams gets larger, this signals the existence of a favorite in the game and bettors can choose the bet on the side with a higher position in FIFA Rankings. Stefani (1983) assumes that a tie is predicted in soccer for whenever the rating difference is between ±0.38 points in the analysis.

Second, I include team value difference (*Value Dif.*) as a predictor for choices of bettors. I collect the team value data from www.mackolik.com which publishes the team values of teams for each game. The value of the team is changing in line with the first eleven of national team. Thus, the impact of an important missing player due to injury or red card/yellow cards can be observed as a decrease in team value. I use the difference between teams as the independent variable. The interpretation of team

[8] A team's total number of points over a four-year period is determined by adding: The average number of points gained from matches during the past 12 months and the average number of points gained from matches older than 12 months (depreciates yearly). The number of points that can be won in a match depends on the following factors: Was the match won or drawn?; How important was the match (ranging from a friendly match to a FIFA World Cup™ match)?; How strong was the opposing team in terms of ranking position and the confederation to which they belong? These factors are brought together in the following formula to ascertain the total number of points: P = M x I x T x C.

value difference variable is likewise the FIFA rankings difference. A team with a higher value compared to the one of its rival can be preferred more by bettors whereas two teams having close values increases the tendency of bettors for choosing draw.

Third, I use the odds as the independent variable as they reflect the probability predictions of bookmaker on game results and meanwhile it determines the return of bettor from the bet. When the odd for a result is lower compared to three possible outcomes, this result is viewed as the most possible outcome by the bookmaker. However, including the odd only for a result and running separate regression for the choices on that result will not let us to see the impact of interaction among odds. Therefore, I introduce an *interaction among odds* variable as choices of bettors will not be only affected by the odd set by the bookmaker for one result; also the odds for the other 2 possible game results can be important on the choices of bettors. In addition, that will allow predicting the choices of bettors for a perfectly balanced game. I add the *draw odd* (Odd_x) variable and the *difference between home-win odd and away-win odd (Odd_1-Odd_2)* variable into Model 1 and 2. Odd_1-Odd_2 variable is expected to have a negative (positive) impact on the choices of bettors for home-win (away-win). A negative value for this variable means that home-team has a lower odd compared to the away-team and as this difference increase in magnitude (in favor of home-team), home-team win would be more preferred by bettors.

Finally, a dummy variable (*Game type*) is introduced in the model to capture effect of games played in different stages. In group games, each team play 3 games and top two teams in a group advance to the final rounds starting with the round of 16. I can assume that the bettors will prefer to bet more for draws in the elimination games as conceding a goal can result elimination and so the teams will play more conservatively. Even though the game ends as a draw, the teams have the opportunity to beat the rival in extra-time or in penalty shoot-out.

$$Choice_{1,x,2} = a + \beta_1.Game\,Type + \beta_2.Ranking\;\;Dif. + \beta_3.Odd_x + \beta_4.(Odd_1 - Odd_2) + \varepsilon \quad (1)$$

$$Choice_{1,x,2} = a + \beta_1.Game\;\;Type + \beta_2.Value\;\;Dif. + \beta_3.Odd_x + \beta_4.(Odd_1 - Odd_2) + \varepsilon \quad (2)$$

4.2. Findings

The findings of regression estimates are presented in Table 6. The explanatory power of models is quite high especially for home-win and away-win, whereas the case of draw, the explanatory power is at lowest compared to other two results. The OLS and GLM estimations are parallel to each other for both Model 1 and Model 2. *Game type* does not have a statistically significant impact on choices of bettors for home-win, draw, and away-win in both Model 1 and Model 2 for OLS and GLM estimations. Although I expect to see that bettors will prefer to bet more for draws in the elimination games, there is no impact of game type on bettors' choices. FIFA/Coca-Cola World Ranking difference (*Ranking Dif.*) which measures the relative strength difference between two national teams has a statistically significant and negative impact on choices for home-win. This is in line with expectations as a negative ranking difference (for home-win estimates) indicates the strength of home-team against away-win. When this difference increases, the bets on home-win should also increase. However, for choices on draws and away-win, no significant relation is found. Likewise, I found no statistically significant relation between team value difference (*Value Dif.*) and choices on game results. The coefficients estimates for *the difference between home-win odd and away-win odd* (Odd_1-Odd_2) are negative (positive) for the choices on home-win (away-win). This is in line with expectations as a negative value for this variable means that home-team has a lower odd compared to the away-team. As this difference increase in magnitude (in favor of home-team), home-team win is more preferred by bettors. On the other side, if this difference is positive, this implies that away-team is favored relative to home-team and therefore it will increase the choices on away-win. However, the difference between home-win odd and away-win odd variable doesn't have a statistically significant impact on the choices for draw. For choices on draws, only the odd for draw has a statistically significant impact. Therefore, the choices on draws are only triggered by the draw odd set by the bookmaker. The coefficient estimates for draw-odd are negative on choices for draw. No other variables affect the choices of bettors on draws. Draw-odd variable has a statistically significant and negative impact on choices for home-win. When draw is considered as a likely outcome by the bookmaker (by the other saying if the bookmaker sets lower odds for draw), the choices on home-win will increase. On the contrary, the draw-odd has a statistically significant and positive impact on choices for away-win.

Table 6. Regressions Estimates for Bettors' Choices

PANEL A - Draw

	OLS[1] (1)	OLS[1] (2)	GLM[2] (1)	GLM[2] (2)
Constant	0.31***	.0.3004***	2.039***	1.93***
	(0.09)	(0.104)	(0.692)	(0.746)
Game Type (elimination games=1, group games=0)	-0.0132	-0.0143	-0.066	-0.060
	(0.021)	(0.023)	(0.147)	(0.145)
Ranking Dif.	0.0002		0.0026	
	(0.000)		(0.0037)	
Odd_1-Odd_2	-0.0041	-0.004	-0.0111	-0.012
	(0.003)	(0.003)	(0.0271)	(0.028)
Draw-odd	-0.069***	-0.063***	-1.418***	-1.342***
	(0.025)	(0.031)	(0.223)	(0.246)
Team value Dif.		0.000		0.000
		(0.000)		(0.000)
N	64	64	64	64
Chi2	3.4	8.1	-	-
F	0.015	0.000	-	-
R-sq	0.36	0.35	-	-
Log Likelihood	-	-	-12.29	-12.29

PANEL B – Home-win

	OLS[1] (1)	OLS[1] (2)	GLM[2] (1)	GLM[2] (2)
Constant	0.7570***	0.732***	3.276***	1.929***
	(0.1609)	(0.161)	(1.230)	(0.746)
Game Type (elimination games=1, group games=0)	0.0401	0.054	0.17	-0.060
	(0.046)	(0.048)	(0.2414)	(0.1452)
Ranking Dif.	-0.0015*		-0.0096***	
	(0.001)		(0.003)	
Odd_1-Odd_2	-0.051***	-0.051***	-0.4262***	-0.0118**
	(0.008)	(0.013)	(0.083)	(0.028)
Draw-odd	-0.1449***	-0.138***	-1.432***	-1.3422***
	(0.046)	(0.046)	(0.383)	(0.246)
Team value Dif.		0.000		0.000
		(0.000)		(0.000)
N	64	64	64	64
F	16.85	18.48	-	-
Prob > F	0.000	0.000	-	-
R-sq	0.56	0.56	-	-
Log Likelihood	-	-	-23.89	-12.28

PANEL C – Away-win

	OLS[1] (1)	OLS[1] (2)	GLM[2] (1)	GLM[2] (2)
Constant	-0.079	-0.0643	1.1854	1.177
	(0.1329)	(0.1437)	(1.334)	(1.304)
Game Type (elimination games=1, group games=0)	-0.0076	-0.0116	-0.0723	-0.077
	(0.0412)	(0.041)	(0.2232)	(0.2215)
Ranking Dif.	-0.000		0.0004	
	(0.0008)		(0.0050)	
Odd_1-Odd_2	0.0660***	0.0615***	0.53***	0.5211***
	(0.0082)	(0.0158)	(0.055)	(0.086)
Draw-odd	0.1232***	0.1185**	-0.754*	-0.751*
	(0.0424)	(0.0466)	(0.437)	(0.427)
Team value Dif.		0.000		0.000
		(0.000)		(0.000)
N	64	64	64	64
F	39.45	35.38	-	-
Prob > F	0.0000	0.0000	-	-
R-sq	0.70	0.71	-	-
Log Likelihood	-	-	-19.43	-19.43

[1] The values are in parentheses are the robust standard errors, * p<.10, ** p<.05, *** p<.01

[2] Results were obtained using the GLM function in Stata with a logit link and the binomial family and robust standard errors. The values are in parentheses are the robust standard errors, * p<.10, ** p<.05, *** p<.01

Based on the estimates in Table 6, the choices of bettors on a perfectly balanced theoretical game (perfect uncertainty for a bettor) will be predicted. Before that, choices of bettors on 2 games of FIFA World Cup 2010 in which the bookmaker set almost equal odds for home-win and away-win are presented in Table 7. These two cases are close to a perfectly balanced game. It is seen that majority of bettors include the win of either side in their coupons.

Table 7. Choices of Turkish Bettors on 2 games of FIFA World Cup 2010

Teams	1	X	2	1X	12	2X	under	over
USA – GHANA	2.3	2.9	2.4	1.28	1.17	1.31	1.4	2.05
	29%	19%	20%	5%	1%	4%	12%	12%
NIGERIA - S. KOREA	2.4	2.9	2.3	1.31	1.17	1.28	1.45	1.95
	18%	8%	43%	2%	1%	9%	8%	13%

The perfectly balanced game is a game for which the bookmaker set equal odds for each game result. When the 20% mark-up in Turkish fixed-odds betting market is taken into the account, the odds for 1, x, and 2 are found to be 2.51 (33.3%). The choice on 1, x, and 2 are predicted as 39%, 14%, and 31% according to model 1 in OLS (and 46%, 17%, and 37% in game results). In terms of GLM estimates, I find similar results with OLS estimates. When I predict the choice of bettors on a game with 2.51 odd for each game result, it is found that the choice on home-win, draw, and away-win are 42%, 18%, and 35% (the remaining 5% is on the bets for under / over) and when they are normalized, the choices in game results should be 44%, 19% and %37 according to model 1. Both the predicted values of OLS and GLM models indicate that even though the game is considered as a balanced game by the experts of bookmakers, most of bettors tend to bet on the win of home-team or away-win. Bettors show a bias towards draw in that perfect uncertainty case with equal odds and in addition with no home-field advantage.[9]

[9] When I run the same regression without interaction of odds (by including only the related odd for each game result), similar results are found.

5. The experiments

5.1. The research question

FIFA 2010 World Cup Data analyzed above show that there is a draw bias among bettors as they prefer to bet mostly on win of a side. Even in the case of a perfect uncertainty, only 17% (in OLS) and 19% (in GLM) of choices would be made on draw. However, the World Cup data cannot be sufficient enough to infer the reasoning(s) behind the draw bias. This bias can be explained by a particular probabilistic judgment on draws or the preferences (bettors don't like draws). To disentangle this joint effect, I designed two experiments by considering the games of leading 6 leagues in Europe at a weekend and the first games of the group stage in EURO 2012.

5.2. The participants

I announced two invitations (at different dates) to the members in a famous forum of Turkey under betting section. I informed that I conducted a study on betting behavior and that I needed people with an interest in soccer betting. The first experiment was conducted on 4th of November, 2011 and the second on 6th of June, 2012 (before the start of the first games in group stage of EURO 2012). Different participants were chosen for those two experiments.

Basically, the participants were asked to make their choices on the given list of games. The participants of the first experiment chose 10 games from a list of 30 games from the leading 6 leagues of Europe namely Turkish Super League, England Premier League, Germany Bundesliga I, Spain La Liga, France Ligue 1, and Italy Serie A. However to avoid favorite team bias and also to leave participants with a reasonable number of games, I removed the games with the lowest odds (with another saying games with clear favorites) from each league and the number of selected games decreased to 30 (5 games x 6 leagues). This helped to present games with more balanced odds instead of games with clear favorites. The participants of the second experiment were asked to indicate their betting choices on the first 8 games in the group stage of EURO 2012. In EURO 2012, there is no strong home-field advantage and as Turkey doesn't take place in this tournament, the national bias is also eliminated.

Twenty-six males at an average age of 21.5 volunteered to participate in the first experiment. According to self reports, the participants made 7 coupons in a week and betted 51 TL (around 29 USD) per week. Based on their own choice, the participants received either a money transfer to their account in an online betting company, prepaid minutes for their cell-phone, or a bank transfer for their participation (worth about 6 USD). 17 (65%) participants made their choice on the money transfer to their account in an online betting company.

In the second experiment, twenty-four (24) males at an average age of 23 volunteered to participate in the study. According to self reports, the participants made 7 coupons in a week and betted 60 TL (around 32 USD) per week. Based on their own choice, the participants received a participation fee of 4 TL (around 2.2 USD) as either a money transfer to their account in an online betting company or prepaid minutes for their cell-phone. Differently from the first experiment, the participants could receive an additional fee of 6 TL (around 3.3 USD) depending on their success in predicting game results. After the collection of predictions of participants, a game (out of 8 games) is randomly chosen and it is notified to the participants. If the prediction of a participant is successful for that game, the participant will receive the additional award. With that incentive, I would like to make participants to pay attention on all games equally. All of the participants made their choice on the money transfer to their account in an online betting company.

5.3. The experiment design and procedure

The participants completed the study at home. Participants first received the questionnaires in which I provided the list of games. The games were presented with the odds set by the official legal betting authority of Turkey. The first experiment includes 30 games from the leading 6 leagues of Europe and the second experiment involves the first games of the group stage in EURO 2012. Participants were asked to make their bets and indicate their probability predictions on each game result. The participants were faced with a choice table as shown in Figure 1. After making bets and probability predictions, participants received another form in which they stated their age, gender, education, number of coupons, amount they betted, and a few other questions about their betting preferences. I prefer to distribute the second form after collecting the betting decisions not to affect their choices and predictions.

		1 (home-win odd)	X (draw odd)	2 (away-win odd)
Mainz	**Stuttgart**	2.3	3.2	2.2
If you decide to make bet on this game, please put a mark on your choice				
If you decide to make bet on this game, please indicate your probability predictions for each game result (your probability predictions should sum to 100%)		%	%	%
Explanation of your choice				

Figure 1. Example of Experiment Design

5.4. Descriptive Statistics

For the first experiment, I have 10 preferences of 26 bettors which sum to 260 observations from 6 different leagues. 43%, 33%, and 23% of 30 listed games ended as home-win, draw, and away-win, respectively. The average odds for home-win, draw, and away-win were 2.26 (37%), 3.05 (27%), and 2.53 (33%). 52% (30%) of bets were done on away-win (home-win) whereas only 18% of choices were done on draw.

In the second experiment, 3 of 8 games ended as draw. In 3 (2) games, the (away-team) home-team won. In total, I have 8 preferences of 24 bettors which sum to 192 observations. 64.06% (20.83%) of bets were done on home-win (away-win) whereas 15.1% of choices were done on draw. The average odds for home-win, draw, and away-win were 1.96 (45%), 3.1 (29%), and 3.3 (26%).

5.5. Findings

I compare the probability predictions of participants with those of the bookmaker on the game result they bet on (see Table 8). It is found that the bettors are overestimating the probability of the game result they bet on. And, accordingly they underestimate the probability of other two results. Those differences are statistically significant for games in both experiments. This is true for all 3 game results. We don't observe any differences for away-win, home-win, or draw. For any game result, their estimation errors are similar. This results show when people bet on draw, they behave in the same way when they bet on either home-win or way-win. In terms of probabilistic judgment, we don't observe any differences (or any particular behavior) for draw. Therefore, we conclude that bettors simply don't prefer to bet on draw.

Table 8. Prediction Comparison (difference between the predictions and probabilities) for bets on each game result

	Home-win	Draw	Away-win
First experiment (6 Leagues in Europe)			
For bets on home-win	0.1801***	-0.0583***	-0.1218***
For bets on draw	-0.1173***	0.2416***	-0.1244***
For bets on away-win	-0.1269***	-0.0626***	0.1891***
Second experiment (EURO 2012)			
For bets on home-win	0.0961***	-0.0283***	-0.0679***
For bets on draw	-0.0993***	0.1599***	-0.0605***
For bets on away-win	-0.1079***	-0.0245**	0.1325***

The experiment disentangles the joint effect of probabilistic judgment and preferences and supports the fact that the draw bias can be explained by the preferences. The nature of a sports competition and the special case of draws explain the draw bias. Compared to many other sports competitions, draw is a likely outcome in a soccer game because as on average around 30% of games end with a tie. Competition is defined as “a game or race or other contest in which people try to win.” The word comes from the Latin words *com* and *petere* which have the root meaning of striving together. Moreover, soccer game is defined as a competition in which the basic objective is to see which team of the two can score the most goals and thereby win the game (Brillinger, 2011). Skinner and Freeman (2009) defined the soccer game as an experiment to determine which of the two teams is in some sense superior given the date and circumstances of the match. The definitions of a soccer game indicate that the game is designed to achieve a winner and a loser.

Moreover, draw outcome of a soccer competition is regarded as a disliked outcome for audience as especially most of the draws occur with a score of 0-0 or 1-1. A draw, especially a scoreless draw decreases the spectacle value of the game (Calster et al. 2008). In the middle of the 1990s, UEFA recommended to the National Soccer Federations that the reward for a win would be 3 points instead of 2 points as under the old regulations. The main objectives of this change were to achieve more goals per game, fewer draws, and, more exciting and attractive matches. After the FIFA World Cup 2010, FIFA considers some drastic changes for the next tournament. Due to the negative play in World Cups, it is planned to award four points for a victory in group games and implementing penalty shootouts (for group matches as well as knockout games) after 90 minutes of play. The planned change aims to offer greater incentive for victory and reduce the upside for teams' content to play for a draw.[10] Due to the disliked of draws (as they end with a low-scoring and decrease the spectacle value of the game) and the nature of sports competition, bettors prefer not to bet on draws.

6. Conclusion

Sports betting literature investigates a variety of biases such as national sentiment, longshot-favourite bias, over bias in total markets, and popular team bias. However, as Nilsson and Andersson (2010) indicate, the supply side of sports-betting (i.e., bookmakers and gambling companies) has been extensively examined whereas relatively few studies (such as Paul and Weinbach, 2010; Pujol, 2008; Weinbach and Paul, 2009) have taken the consumer perspective and explicitly considered behavioral patterns of bettors. I explore the behavioral pattern of bettors on their betting choices for draws by using the FIFA 2010 World Cup – South Africa data collected from Turkish Fixed Odds betting market. The advantage of this data is that home-field advantage is not valid in World Cup games and as Turkey did not participate in FIFA 2010 World Cup, the national sentiment does not exist. My interest focuses on draw as it reflects a special feature of soccer competition. Compared to many other sports competitions, draw is a likely outcome in a soccer game because on average around 30% of games end with a tie.

In the most recent World Cup, on average draw was chosen by only 8% of bettors in Turkish fixed-odds betting market. When the bets only on game results are considered, it is seen that the bettors' choices on draws was around 12%. Considering the home-win and away-win, the data shows that the bettors' choices on home-win and away-win were 34% and 26% (50% and 38% in the game result market), respectively. Then, I explore the factors which can influence the choice of bettors for home-win, draw, and away-win by using OLS regression and a generalized linear model (GLM) with a logit

[10] http://sports.yahoo.com/soccer/news?slug=ro-fifaproposals090910

link and the binomial family. The coefficients estimates for the difference between home-win odd and away-win odd (Odd1-Odd2) are negative (positive) for the choices on home-win (away-win). However, the difference between home-win odd and away-win odd variable doesn't have a statistically significant impact on the choices for draw. For choices on draws, only the odd for draw has a statistically significant (and negative) impact. Draw-odd variable has a statistically significant and negative impact on choices for home-win. On the contrary, the draw-odd has a statistically significant and positive impact on choices for away-win. When I predict the choice of bettors on a game with 2.51 odd for each game result based on GLM estimates (model 1), it is found that the choice on home-win, draw, and away-win are 42%, 18%, and 35% (the remaining 5% is on the bets for under / over) and when they are normalized, the choices in game results should be 44%, 19% and %37.

The World Cup Data show that there is a draw bias among bettors as they prefer to bet mostly on win of a side. However, the World Cup data cannot be sufficient enough to infer the reasoning(s) behind the draw bias. This bias can be explained by a particular probabilistic judgment on draws or the preferences (bettors don't like draws). To disentangle this joint effect, I designed two experiments by considering the games of leading 6 leagues in Europe at a weekend and the first games of the group stage in EURO 2012. The experiment shows that the bettors are overestimating the probability of the game result they bet on. And, accordingly they underestimate the probability of other two results. This is true for all 3 game results. We don't observe any differences for away-win, home-win, or draw. For any game result, their estimation errors are similar. This results show when people bet on draw, they behave in the same way when they bet on either home-win or way-win. In terms of probabilistic judgment, we don't observe any differences (or any particular behavior) for draw. The results confirm the dislike of draws and the draw bias is not related to a particular probabilistic judgment. Due to the disliked of draws (as they mostly end with a low-scoring and decrease the spectacle value of the game) and the nature of sports competition, bettors prefer not to bet on draws.

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THE MARKET IMPACT OF RIVALRY BETWEEN SOCCER TEAMS: EVIDENCE FROM ROMAN RIVALRY

Abstract

This paper considers the game-related performance of two listed soccer clubs of Italy namely Roma and Lazio. It is found that stock prices of these two clubs are sensitive to game results. A win (loss) leads to a positive (negative) average abnormal return. I also introduce the performance of arch-rival in the analysis. The high level of rivalry in the sports should lead to pleasure at the suffering of another group (known in German language as schadenfreude) and I assume to see the pleasure of investor fans with the defeat of the arch-rival. Likewise, the win of the arch-rival can have a negative impact on the mood of investors. I find that a loss combined with a negative surprise coming from the arch-rival performance (a win or draw while a loss is expected) leads to a strong negative market reaction, on the contrary, when a loss is combined with a positive surprise (a loss or a draw when a win is expected) the reaction is not significant. This asymmetric effect is not found for the wins, where the positive effect holds regardless the performance of the arch-rival. This study shows that, when club supporters are experiencing the negative performance of their team, the news coming from the arch-rival results can change their investment decisions. It is therefore proved that, at least for this aspect, the investors (widely represented also by the club supporters) are driven by the emotions conveyed by rivalry which, considered as a source of emotions, may be market relevant.

Keywords: Abnormal return, Schadenfreude, rivalry, soccer, stock return, Roma, Lazio

1. Introduction

Soccer is considered as the most popular sport in Europe and plays an important role in the life of people following the games. Psychological research provides evidence on the role of the performance of sports clubs on the mood of fans (Sloan, 1979; Hirt et al. 1992; Kerr et al. 2005). The success of a team should lead a positive mood on its fans whereas team failure should lead to a negative mood[1]. And people in good moods are more optimistic in their choices and judgments than those in bad moods (Hirshleifer, 2001). Those emotions and feelings of investors influence their investment decisions (Lucey and Dowling, 2005). Motivated by this psychological evidence, a range of studies at both national and club level (Ashton et al. 2003; Boyle and Walter, 2003; Berument et al. 2006; Edmans et al. 2007; Berument et al. 2009) considering sports (especially soccer) performance as the mood variable, investigate the effect of sport results on the stock markets. While the studies on national soccer teams investigate the impact of sports performance of those teams on their national stock markets by a more psychological reasoning, the studies on club level explore the same research question motivated by both rational expectations and mood of investors. Club level studies consider the mood of fan investors following the games and investigate whether a positive (negative) market reaction after wins (defeats) occurs.

There is supportive evidence on the positive relation between the sport and economic performance of soccer clubs (Bernile and Lyandres, 2009; Panagiotis, 2009; Samagaio, 2009). Therefore the sport performance of teams on stock prices relies on a rational argument and, contrary to the listed companies generally issuing quarterly announcements, may feed weekly through the game results the investor opinions. Since soccer raises strong emotions among fans and the shareholder structure of the club is oriented towards supporters, I can claim that the game results affect the performance of stocks for two reasons mutually reinforcing: the emotions and the positive/negative impact of the game result on economic performance and they both move in the same direction. For example, Palomino et al. (2009) try to distinguish between these two possible explanations for the market reaction to game results by

[1]According to Bernhardt et al. (1998), game results also lead to physiological changes beyond changes in mood and self-esteem. They show that mean testosterone level increased (decreased) in the fans of winning (losing) teams for both in college basketball games and World Cup soccer games. Kloner et al. (2009) find that the emotional stress of loss and/or the intensity of a game played by a sports team in a highly publicized rivalry such as the Super Bowl can trigger total and cardiovascular deaths.

running a number of tests. There is evidence in favor of both rational expectations and investor sentiment in explaining the market reactions to game outcomes. In this study, I address a particular aspect of this issue isolating a stream of emotions that is not related to the economic result of the soccer club: it's the arch-rival's performance. The psychology literature has introduced the notion of Schadenfreude, demonstrating the supporter feelings are strongly influenced also by the rival's result (Combs et al. 2009). As at a weekend, fan investors can observe the performance of their favorite team and also the arch-rival, their mood and thus their investment decisions should be also affected by their arch-rival's performance at that weekend. In such a case I argue that the link between emotions and economic performance is weakened or not relevant at all: for instance the win of the rival negatively affects the emotions of the supporters without exerting any impact (after considering some control variables) on the economic performance of the club. The study therefore helps understanding the pure impact of emotions on stock performance of soccer club.

I find that fan investors react positively (negatively) to a win (a loss) of their favorite team. There is also supportive evidence for the rival effect on stock performance, at least when a loss occurs. A loss combined with a negative surprise coming from the arch-rival performance leads to a strong negative market reaction. On the contrary, a loss combined with a positive surprise of the rival do not create any investor reaction, therefore the negative effect the loss is counterbalanced by the positive surprise coming from the arch-rival performance. This asymmetric effect is not found for the wins, where the positive effect holds regardless the performance of the arch-rival. I can conclude that, at least for this aspect, the investors (widely represented also by the club supporters) are driven by the emotions conveyed by rivalry which, considered as a source of emotions, may be market relevant.

The rest of the paper proceeds as follows. The second section provides a review of the related literature. The third section gives information about the listed soccer clubs in Europe and describes the data and the hypotheses. The methodology is given in section 4. The fifth section presents and discusses the findings. Section 6 includes the robustness test and final section concludes.

2. Literature Review

To my knowledge, the first study exploring the effects of team sports results on the share price is conducted by Scherr et al. (1993) for the Boston Celtics, an American basketball team. They find a positive relation between the game results and stock prices especially during playoffs. A subsequent study about the Boston Celtics by Brown and Hartzell (2001) also show that investors consider the game result information. Losses of Boston Celtics significantly affect the stock price whereas wins do not. The effect of playoff games is higher compared to regular season games. When expectations about game results are controlled by using betting-market point spreads, mixed evidence is found as expected losses have a negative price impact and unexpected wins have no significant effect.

The first study investigating the effect of soccer results on the club's share price is conducted by Morrow (1999). For two British soccer clubs, namely Manchester United and Sunderland, Morrow finds a positive market reaction for wins and a negative market reaction for losses. The study of Morrow is followed by Renneboog and Vanbrabant (2000) who analyze 17 listed soccer clubs from 1995 to 1998. They find that a win leads to a positive abnormal return of 1% whereas defeats and draws result a negative abnormal return of 1.4% and 0.6%, respectively. Moreover, higher abnormal returns are found following the promotion and relegation games as those games are more important in terms of their impact on future cash-flows. However, contrary to what is expected, the impact of European cup games is not found to be significantly higher than other games. Later, Dobson and Goddard (2001), using the data for 13 listed soccer clubs in UK for the period from July 1997 to July 1999, test whether market reaction depends only on the match results or depends on the unanticipated component of the results. It is found that share prices react to the unanticipated component of the result. The effect of an unexpected win is higher compared to an expected win. The FA Cup and European elimination both results a significant negative share price reaction whereas the impact of European elimination is found to be higher. Zuber et al. (2005) by using the data of 10 professional soccer clubs namely Aston Villa, Chelsea, Charlton Athletic, Leicester United, Leeds United, Manchester United, Newcastle United, Southampton, Sunderland and Tottenham in the English Premier League analyze the effect of teams' performance on their stock prices in the period 1997-2000. The estimates of the regression models (for both raw returns and abnormal returns) indicate little or no significance in the relationship between returns and game-related information. Only the type of games variable is found to be significant in both models. The positive and significant coefficient is consistent with the expectation that teams benefit from cup games through more gate receipts, prize money, advertising, broadcasting and merchandising. The overall results document that there is little or no relationship between game-related information and returns, and that this behavior is not consistent with that observed in traditional markets around conventional corporate announcements expected to impact on cash flows and financial condition. Moreover, it is also shown that none of the teams exhibit a difference in returns between on-season and off-season at any reasonable level of significance. They conclude that soccer team investors do not respond to information that is expected to have a measurable impact on financial condition and shareholder wealth. A new investor type “soccer team investors” who are insensitive to traditional financial information is introduced. Ownership in their favorite team provides all of the value in the investment for them. So that, the ability of the firm to produce cash flows may be an irrelevant for these investors. Likewise most of the studies in the literature, Palomino et al. (2009) also use the data of 16 listed British soccer clubs. Different to the previous literature, they exclude those weekend games that are preceded by a Wednesday game to avoid contamination of event windows. They add three leads and three lags of market returns to the market model. Their initial tests show that the stock prices are sensitive to the game results. A positive average abnormal return of 53 basis points (statistically significant) is observed after a win and a loss is followed by a negative average return of 28 basis points (statistically significant). This finding is on the contrary of what is mostly found in the previous studies. However, a cumulative positive return of 88 basis points after a win and a cumulative negative return of 101 basis points after a loss are found over the first three days following a game. This is interpreted as the market being faster at processing good news than bad news. When expectations are controlled by using the odds, the market reaction is found to be higher after a win when the team is strongly expected to win compared to a win when the team is strongly expected to lose. This shows that investors overreact to a win, especially when the win was strongly expected which is on the contrary to the predictions. For the case of defeats, the finding is in parallel to what is predicted. Bell et al. (2009) also work on English soccer clubs. The dataset comprises of 5,187 games played in between the start of the 2000/01 season and the end of the 2007/08 season by 19 listed clubs. Their study includes surprise results as efficient market hypothesis assumes that a club’s share price should reflect all the information available to investors, including the expected results of forthcoming games. In addition, a variety of variables to measure the importance of games namely the degree of rivalry, closeness of the game to the end of the season, and goal difference. They find that points surprises and lagged points surprises have a positive effect on returns, however the magnitude of latter is much smaller. Home point surprise has a statistically significant positive impact. The effect of importance of the game variable whether measured by the degree of rivalry or the closeness of the match to the end of the season is very modest. When the goal difference variable is considered, it is achieved that goal surprises and lagged goal surprises have a negative effect on returns. As expected according to efficient market hypothesis, expected points have no effect whereas unexpected points have.

A limited number of studies are also performed for the listed clubs other than UK. Duque and Ferreira (2005) focus on two soccer clubs of Portugal namely Sporting SAD and F.C. Porto SAD, which are quoted in the Second Market of Euronext Lisbon Stock Exchange. They include only the games in national league and exclude European and Portuguese Football Cup games. For Sporting, a win results a positive return of 1.5% and a loss results a negative return of 1%. Draw is also found to have a negative effect on stock prices and its effect is surprisingly higher than a loss. For Porto, the win and loss have no effect on stock returns whereas only draw leads to a negative return of 1.2%. These findings are on the contrary of the existing literature. Finally, they introduce “relative points to victory” variable which measures the difference between the points of the firm and its follower (if the firm is the leader) or the leader (if the firm is the follower). Stock returns are found to be sensitive to changes in relative points to victory. With regard to the German team Borussia Dortmund, Stadtmann (2006) shows that there is a close relation between the club’s performance and stock price and the unexpected result influences stock price. However, contrary to the expectations but consistently with what found for UK, European games do not have a higher impact than games played in domestic league (Bundesliga). Stadtmann also includes the unexpected number of points gained by Bayern Munich as it is considered as the rival of Borussia Dortmund for championship. It is found that a success of Bayern Munich negatively influences the stock price of Borussia Dortmund. The only paper focusing on the impact of sports performance on stock prices for Italian soccer clubs belongs to Boido and Fasano (2007). They include the three Italian listed soccer clubs namely Lazio, Roma and Juventus for the period from January 2005 to June 2006. Their analysis considers the effect of trends in stock prices as a price increase (decrease) after a victory (loss) is more significant if it is able to counter a previously negative (positive) trend. The effect of a result is measured as the difference between the post game return and the average return observed in the trading days before. It is found that for all the clubs the average price/return ratio after wins is higher than average price/return ratio following losses.

On a multi-country based study, Scholtens and Peenstra (2009) find a positive (negative) effect of wins (defeats) on stock prices for 8 listed soccer teams in 5 European countries for the sample of 2000-2004. The response to a loss is found to be higher than to a win indicating an asymmetric market reaction. For national league games when expectations are controlled by using the quoted odds, on the contrary to what is predicted, the magnitude of expected results is higher than unexpected results. However, for European games, unexpected results lead to a stronger stock market reaction than expected results. This finding is associated with the larger importance of financial incentives in the European competition. Benkraiem et al. (2009) work with a more comprehensive data by including 18 European listed football clubs, however the time span of data covers only one year (July 13, 2006 to July 10, 2007). They find that the performance of listed football clubs affect both the abnormal returns and the trading volume around the dates of matches. The effect of a loss is higher than the effect of a win which indicates the allegiance bias in parallel with previous studies. Although the stock prices increase after a win, this effect is not significant according to the Wilcoxon test. This finding is interpreted as the anticipation of market for a positive result and so the information is already included in investors' anticipations. Conversely, in the case of a poor performance (defeat or draw), the share price undergoes a significant correction. However, the authors do not use the odds to control for expectations. When the match venue is considered, it is found that the stock market reaction is higher for home losses compared to away losses also an away win leads to a higher stock market return compared to a home win. Bernile and Lyandres (2009) focus only on Champions League and UEFA Cup games played during the period 1/2000 - 5/2006 by 20 listed soccer clubs. Their sample teams played in 595 unique matches, 31 of which featured two publicly traded clubs, corresponding to 626 observations. Before the analysis of the market's reaction to game results, they test the underlying assumption which argues that sport performance of clubs in European Cup games affect the value of clubs by influencing their operating performance. It is found that profitability is positively related to sports performance. The authors, by using the market model on an annual basis, show that the game results have an impact on stock prices of soccer clubs. More specifically, wins are followed by statistically insignificant average abnormal returns of 0.15%, while losses and draws result highly significant average returns of -2.2% and -0.9% respectively. This finding also supports the allegiance bias. The impact of an away win (home loss) is higher than a home win (away loss). Also, the market does not react to wins of favorites whereas wins by underdogs lead to market reaction. Likewise, losses by underdogs are greeted less unfavorably than losses by favorites.

To summarize, the findings in the literature provide supportive evidence for the relationship between sports performance and stock prices. A win leads to a positive stock market reaction whereas a loss is followed by a negative reaction. More specifically, the studies document a higher market reaction to losses compared to wins which is explained by the tendency of fans to be overly optimistic about their team's performance (Demir and Danis, 2011). Although the positive relation between market reaction and game results is widely supported in the literature, the underlying reason behind this relation is still at doubt. Because the positive relation can occur due to the rational reaction to news about the future cash flows of these listed clubs or/and alternatively investor sentiment triggered by the soccer results can influence stock returns. Psychological research provides evidence on the role of the performance of sports clubs on the mood of fans which can influence the investment decisions. Bernile and Lyandres (2009) for 20 European Clubs, Panagiotis (2009) for Greek Clubs, Samagaio (2009) for English Clubs and Barajas et al. (2005) for Spanish Clubs find supportive evidence on the positive relation between the sport and economic performance of soccer clubs. Palomino et al. (2009) try to distinguish between these two possible explanations for the market reaction to game results by running a number of tests, however evidence is found in favor of both rational expectations and investor sentiment or information salience in explaining the market reactions to game outcomes. Some studies control the expectations by using the odds quoted by the bookmakers and find that unexpected results matter more than the expected results. There exists no study considering the performance of arch-rival while investigating the impact of the sports performance of a team except Stadtmann (2006). Stadtmann explores the impact of the unexpected number of points gained by Bayern Munich as it is the main rival of Borussia Dortmund for championship. It is found that a success of Bayern Munich negatively influences the stock price of Borussia Dortmund.

3. Data and Hypotheses Development

3.1. Listed Soccer Clubs in Europe

Tottenham Hotspur was the first soccer club listed in the stock market in October 1983. For some years, Tottenham remained as the only listed club. Millwall in October 1989 and Manchester United in June 1991 followed Tottenham. These three clubs raised 3.3 million pounds, 4.8 million pounds, and 6.7 million pounds, respectively. In April 1997, Newcastle United managed to raise 50.4 million pound which is far higher than the amount of the previous clubs (Dobson and Goddard, 2001). Until today, 49 clubs were listed in Europe since 1983 (Appendix presents the list of these listed clubs). The peak number of listed clubs was reached in between 1999 and 2003 (Aglietta et al. 2010). However currently, there are only 23 listed clubs in Europe as many listed clubs, especially the ones in UK, were de-listed.

There are some indices covering the stocks of listed soccer clubs. One of the best known indices for the listed soccer clubs is the DJ StoXX Football Index whose composition is given in Appendix. This index includes all listed football clubs across Europe and Eastern Europe and covers 100% of the target market. As of January 31, 2011, the index includes 23 football clubs,4 from UK, 5 from Denmark, 4 from Turkey, 3 from Italy, 3 from Portugal, and 1 from Netherlands, France, Germany and Sweden respectively. By 11 March 2011, the market capitalization is 724.14 million euro and the index value is 149.13. Borussia Dortmund, Besiktas, Fenerbahce, Trabzonspor, and Parken Sport & Entertainment are the top 5 clubs of the index. The relatively low valued capitalization of soccer clubs may explain a low attractiveness of the football stock market for institutional investors (Aglietta et al. 2010). Bloomberg also has two football indices. The Bloomberg Football Club Index is a capitalization-weighted index of companies that own or operate an English or Scottish football club. The index was developed with a base value of 100 as of December 29, 1995. The Bloomberg European Football Club Index is a capitalization-weighted index of companies that own or operate a European football club. The index was developed with a base value of 100 as of December 29, 2000.

3.2. Data and Hypotheses

I first investigate whether the sports performance of two Italian clubs affect the stock prices in line with the previous literature. Soccer clubs which decide to go public will probably not attract many professional investors who generally take investment decisions on calculative, economic deliberations (De Ruyter and Wetzels, 2000). Likewise, according to Renneboog and Vanbrabant (2000) the shareholder structure of soccer clubs usually consists of one or a few stable controlling shareholders, some institutional investors and many individual investors who are also soccer fans. For example 35,113 people participated in the IPO of Fenerbahce, a famous soccer club of Turkey and 33,935 of those were small individual investors who demanded 1-1,000 lot. Thus, the impact of mood of fan investors can be observed on stock prices. In addition, investors should have reactions to sports performance as it directly has an impact on the future cash flows of the listed clubs (Bernile and Lyandres, 2009; Panagiotis, 2009; Samagaio, 2009). Therefore, decisions of investor fans are likely to be affected by sports performance. A win (loss) of a soccer club should influence the price of this club positively (negatively) and according to allegiance bias the effect of a loss should be higher than the effect of a win.

The relation between the sports performance of soccer clubs and their stock returns are studied in the literature. What I introduce is the inclusion of arch-rival's performance into the analysis with reference to the human psychology. Although people are expected to feel sorry and sympathy when others suffer this is not always true and sometimes people can have pleasure at the other's pain (Leach et al. 2003; Combs et al. 2009). Psychology literature name this as "*schadenfreude*" which derives from the combined terms *schaden*, meaning ''harm,'' and *freude*, meaning ''joy'' and which is borrowed from German as English language has no word for it (Combs et al. 2009). According to Koyama and Reade (2009), supporters do not get utility only when their team performs well but also when a rival team has been defeated. Considering the high level of rivalry in the sports, it is surprising the limited number of studies analyzing the feeling of the fans after the defeat of their arch-rival. Leach et al. (2003) initially show that Dutch soccer fans regard Germany as a rival in soccer. Their main interest is Dutch reactions to elimination of Germany in FIFA World Cup 1998. The finding documents that soccer fans in the Netherlands gain pleasure with the unexpected loss of Germany to Croatia even if Germany was placed in a different grouping of teams and exited the tournament earlier than the Netherlands. Moreover, as the participants' domain interest in soccer increase (which is assessed by three items: "I enjoy watching soccer on television", ''I am interested in soccer", ''I have regularly watched/listened to the World Cup"), the pleasure of participants with Germany's loss increase. The defeat of rival may be more beneficial psychologically when there is greater interest in soccer. Cikara et al. (2011) also argue that Red Sox and Yankees fans report feeling pleasure when they watch their rival fail to score against their favored baseball team, and also against a less competitive team in the same league (i.e., the Orioles). According to Havard (2010), an alumnus of The University of Texas at Austin will experience joy when the rivals face a dealt at the hands of someone other than Texas, such as was the case with the 2009 BCS National Championship game where Florida defeated Oklahoma.

In soccer, club affiliation is assumed to be generally more important than national identity (Boyle and Walter, 2003)[2]. Thus, I should expect to see the pleasure of investor fans with the defeat of the arch-rival. Likewise, the win of the arch-rival can have a negative impact on the mood of investors. In sum, I hypothesize that the fan investors' mood is not only related with their favorite team's performance but also related to the performance of the arch-rival. Thus, the positive mood impact of a win should rise when combined with the loss of arch-rival; on the contrary the negative mood effect of loss should increase with the win of arch-rival.

> **H_1:** The stock price impact of a win combined with the loss of the arch-rival should be higher than the one of a win combined with the win of arch-rival.
> **H_2:** The stock price impact of a loss (in absolute value) combined with the loss of the arch-rival should be lower than the one of a loss combined with the win of arch-rival.

I tested a further development of the above hypotheses by considering the unexpected performance of the arch-rival according to the odds offered by the bookmakers. As I'll explain in the next section, the unexpected performance is measured using the odds

[2] The effect of rivalry is also observed on the attitude of fans towards sponsors. Sponsorship with a particular team can alienate the fans of rival teams from the sponsor. The products of sponsors are even treated negatively from the fans of the rival teams (Theofilou et al. 2008). For example, the communications company NTL had a joint sponsorship with Glasgow Rangers and Celtic (Davies et al. 2006) as the rivalry among those clubs is very intense.

given by the bookmakers. The fans should be more interested in the unexpected performance of their arch-rival.

> **H_3:** The stock price impact of a win combined with an unexpected negative performance of arch-rival should be higher than the one of a win combined with unexpected positive performance of arch-rival.
>
> **H_4:** The stock price impact of a loss (in absolute value) combined with the unexpected negative performance of the arch-rival should be lower than the one of a loss combined with the unexpected positive performance of the arch-rival.

The rivalry among clubs in any sports has always been in the interest of both domestic and international fans and media. The rivalry between clubs is considered as the main source for the attractiveness of a league (Mason, 1999). According to Madeiro (2007), the rivalry among competing teams motivates the consumption of fans, the media attention and so the investment of corporate sponsors. The important problem about the test of above hypotheses lies with the definition of arch-rival. The teams compete with many teams in a season over years, however not all these teams are considered as the rival. Politics, history, religion, the fan's socio-economic backgrounds can be the source of the rivalry. Even though there are rivalries between teams further apart, especially the local derbies are the main rivalries. I focus on the rivalry between Lazio and Roma which is regarded as one of the most important rivalries of the world soccer according to the greatest rivalries list published by Duke (2008) from CNN, Fortune (2009) from Dailymail, and Rice (2010) from The Independent. Moreover, both the list of Skysports[3] and the http://www.footballderbies.com/ website which present the list of city derbies and rivalries consider this rivalry in the top 10 derbies. Furthermore, soccer is one of the major expressions of Italian social life and it is a fundamental component of Italian culture. The rivalry among Roma and Lazio soccer clubs which share the same stadium lies in the centre of Italian soccer culture: whereas Roma supporters are famous for being mostly left wing whereas Lazio fans are known as right-wingers (Scalia, 2009). The derby games are more than a game and it is a battle for city pride and bragging rights (Guschwan, 2007).

[3]http://www.skysports.com/interactive/top_tens_story/0,25722,15881_4561403,00.html

Both Lazio and Roma are listed in BorsaItaliana. As the FTSE Italia All Share index is available from 31.12.2002, the data might cover the period from 31.12.2002 to end of 2009/10 season. However, Lazio from 1999 to 2004 experienced 6 stock splits and reverse stock splits (on 07.08.2000, 23.10.2000, 24.06.2002, 01.07.2003, 09.02.2004, 24.05.2004). The finance literature documents the existence of abnormal returns after the announcement of stock-splits and post-split abnormal returns (Chen et al. 2011; Desai and Jain, 1997; Ikenberry et al. 1996; Ikenberry and Ramnath, 2002). Thus, I prefer to the start the dataset for Lazio by the first game of 2004/2005 season.[4] The stock prices and market index data were collected from Thomson Financial Datastream. The results of soccer games, including league games, national cup games, and European Cup games (Intertoto, Champions League, and UEFA Cup) and the related odds were collected from www.betexplorer.

4. Methodology

I use the event study methodology to analyze the impact of sports performance of soccer clubs on their stock prices. Event studies are widely used in finance to analyze the effect of specific events on stock market. In this case, the event is the game result, namely win, draw, and loss.

Daily stock returns for the teams are calculated as $R_t = \ln(P_t) - \ln(P_{t-1})$, where R_t is the return for day t, P_t and $P_{t-1}$are the closing prices on day t and day t-1, respectively. *FTSE Italia All Share index* is used in the study since these two Italian soccer clubs are both included in this index. I use market model to calculate normal returns for each club. The model is defined as

$$R_{it} = a_i + \beta_i R_{mt} + \varepsilon_i \qquad (1)$$

where R_{mt} is the return of market index at day t, a_i and β_i are the estimated values for the given period. β_i is the sensitivity of stock prices to market return. Abnormal returns are calculated for each team separately as

[4] The data period of 16.03.2004 to 20.05.2004 for Lazio was not available due to the trading suspension.

$$AR_{it} = R_{it} - (\hat{a}_i + \hat{\beta}_i R_{mt}) \tag{2}$$

Abnormal return is the difference between the actual return and the normal (expected) return. The estimation period is used to estimate the parameters in model 1 and it shouldn't overlap with the event period. Since, the soccer games are played more frequently (at least on weekly basis on on-season period) compared to the other events considered in finance, I cannot use pre-event data as estimation window. Thus, I follow the approach of Brown and Hartzell (2001), Scholtens and Peenstra (2009)[5], and Palomino et al. (2009) and include whole sample period available as the estimation period.

Abnormal returns are calculated for the first trading day following a game day and I use 1-day window as event period to prevent the effect of an overlapping game. By removing the overlapping cases, I also compute cumulative abnormal return *(CAR(1,2))* for the two trading days following a game thus I check whether the impact of game results last over two days following game day. First, I test the significance of the abnormal returns in the first (and in the first two) trading day(s) following the game days by using the Wilcoxon signed-rank test, which is distribution-free and robust to event clustering (Palomino et al. 2009). Later, the effect of game results on abnormal returns are analyzed through the regression models by including additional variables. I run the following regressions:

$$AR(1) = a + \beta_1.Win + \beta_2.Loss + \beta_3.Control\ \ Variables + \varepsilon \tag{3}$$

$$AR(1) = a + \beta_1.Goal\,difference + \beta_2.Control\ \ Variables + \varepsilon \tag{4}$$

where *AR(1)* is the abnormal return the first day following a game, *Win* and *Loss* are dummy variables measuring the outcome of a soccer game: *Win* (*Loss*) variable takes the value of one if the team wins (losses) and zero otherwise. The G*oal-difference* variable is the difference between the number of goals scored and number of goals conceded.[6] A positive (negative) value reflects a win (loss) whereas a value of zero

[5]Scholtens and Peenstra (2009) use this approach for the robustness of their findings and this method gives results that are in line with the method which use an estimation period of 250 trading days to calculate the normal returns.
[6] The case for determining the result of two-legged games is rather complicated. For example, although the game ended with the victory of Roma to Middlesbrough by 2-1 on 16.03.2006, due to the loss in the first game by 1-0; by away goals rule Roma was eliminated from UEFA Cup. I prefer not to count this

means a draw. Compared to win/loss dummy variable, goal difference variable also considers the magnitude of a win or a defeat as investors can react strongly to a win (loss) with a higher positive (negative) goal margin. *Control Variables* is a vector of the following variables included consistently with previous studies:

- *Post-March* is a dummy equals to one when games are played after March. It's used because the games through the end of season are more important in terms of determining the final position in competition that the club participates (Palomino et al. 2009);
- *Away-Game* is a dummy equals to one if the game is an away game and zero for a home game;
- Two more dummy variables are introduced because the teams compete in different competitions such as domestic league, domestic cup games, and European games. *Serie A* equals to one if the game is a domestic league game and zero otherwise; *European Cup* dummy is equal to one if the game is played in UEFA League or Champions League;
- Finally, *Lazio* is dummy variable equal to one if Lazio is playing and used to separate the impact of two clubs.

The models (3) and (4) are in line with the previous literature because they only analyze the impact of a team performance on its stock price and I used them as a preliminary check to show the consistency of the data with the literature results.

To consider the interaction among the performance of a team and its arch-rival, I initially create dummy interaction variables for *win-win, win-loss, loss-win, and loss-loss.* More specifically, for example a *win-win* (*loss-loss*) dummy variable takes the value of one if the considered team and its arch-rival both win (loss) at the weekend in a Serie A game and zero otherwise. The reaction of fan investors to the combined effect of their favorite team's performance and of the arch-rival's performance can also occur due to fundamentals of the team economics. As these two teams get close to each other in terms of rankings in Serie A, the fan investors should consider more about the performance of their arch-rival because the final position of their team will be directly related to their arch-rival's performance. To control for this aspect, I introduce

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game as a win in spite of the fact that the official result is a win as it leaded to elimination. Thus, I count this game as a loss. There are a few cases for each club and these two-legged games situations are controlled by one by one.

the ranking difference between two teams in terms of their league positions in the model. Model 5 allows us to test the hypothesis 1 and 2.

$$AR(1) = a + \beta_1.WW + \beta_2.WL + \beta_3.LW + \beta_4.LL + \beta_5.PostMarch + \beta_6 Lazio + \beta_7.Ranking\ Dif. + \beta_8.Away\ game + \varepsilon \qquad (5)$$

To further investigate the interaction among the performance of a team and its arch-rival, I also include dummy interaction variables by considering the unexpected performance of arch-rival. The fans should be more interested in the unexpected performance of their arch-rival as the mood of fan investors should be more positively (negatively) affected after an unexpected loss (win) of the arch-rival. I follow the approach of Zuber et al. (2005) to determine the unexpected performance of the arch-rival by using the final odds. In soccer betting, the abbreviation for a home win, a draw, and an away win is 1, x, and 2, respectively and they reflect the subjective expectations of the bookmaker. I obtain the subjective winning probabilities (SWP) by taking the inverse of final odds (1/odd) set for Roma and Lazio in each game. If SWP>0.6 (<0.4), a team is expected to win (lose) the game, whereas if0.6≥SWP≥0.4, a team is expected to draw[7]. Positive surprise occurs (PS) when the arch-rival is expected to win but achieves a draw or a loss; negative surprise dummy (NS) occurs when the arch-rival is expected to lose but achieves a draw or a win[8].Table 1 presents examples of achieving surprise variables by using the odds. On 25.04.2010, Roma had a home game against Sampdoria. The odds were set as 1.45 for home win of Roma, 4.07 for draw, and 7.27 for an away win of Sampdoria. A bettor who put 1 euro on Roma (Sampdoria) received 1.45 euro (7.27 euro) which means 45% (627%) of profit. Subjective winning probability (SWP) is found to be 0.6897 by taking the inverse of odd set for Roma. As SWP is above 0.6, Roma was expected to win the game however the game ended with the defeat of Roma. Considering the Lazio supporters, this result was defined as a positive surprise as the game ended negatively from what was expected.

[7] When I use 0.35-0.65 threshold levels instead of 0.4-0.6, the results do not change. In accordance with the literature, I prefer to include the latter for determining the expectations.
[8] Negative-positive surprise is used from the view point of a team considering its arch-rival. For example, the positive surprise (which occurs when the arch-rival is expected to win but achieves a draw or a loss) is actually a negative surprise for the supporters of the arch-rival.

Table 1. Positive/Negative Surprise Performance based on Odds

Game	Game Date	1	x	2	SWP	Expected result	Actual Result	Variable
Roma -Sampdoria	25.04.2010	**1.45**	4.07	7.27	0.6897	W	L	PS
AC Milan - Roma	24.05.2009	1.74	3.39	**4.69**	0.2132	L	W	NS
Lazio - Cagliari	25.01.2009	**1.63**	3.39	5.73	0.6135	W	L	PS
Chievo- Lazio	20.02.2005	2.26	2.85	**3.2**	0.3125	L	W	NS

1,x, and 2 represent the odds for home win, draw, and away win, respectively. SWP, PS, and NS reflect subjective winning probability, the positive surprise, and negative surprise, respectively.

To have the interaction among the performance of a team and surprise performance of its arch-rival, I create 4 dummy interaction variables for *win-positive surprise of arch-rival (WPS), win-negative surprise of arch-rival (WNS), loss-positive surprise of arch-rival (LPS), and loss-negative surprise of arch-rival (LNS).* More specifically, for example WPS dummy variable takes the value of one if the considered team wins and its arch-rival has a negative surprise performance for that team at the weekend in a Serie A game and zero otherwise. Model 6 allows us to test the hypothesis 3 and 4.

$$\begin{aligned} AR(1) = a + \beta_1.WPS + \beta_2.WNS + \beta_3.LPS + \beta_4.LNS + \beta_5.PostMarch + \beta_6 Lazio + \\ \beta_7.Ranking\ \ Dif. + \beta_8.Away\ game + \varepsilon \end{aligned} \tag{6}$$

5. Results

5.1. The stock market reaction to game results

Table 2 presents the average abnormal returns following the game day (AAR(1)) and cumulative abnormal returns over two days following the soccer matches (ACAR(1, 2)). The abnormal returns are also categorized according to game results and also by game venue for Roma and Lazio separately. It is found that the stocks prices of those two clubs are sensitive to sports performance.

A win leads to a positive AAR(1) of 0.0065 (statistically significant at the 10% level), and 0.0115 (statistically significant at the 1% level) for Roma and Lazio, respectively. The impact of a win diminishes over the first two days following a game for both clubs and the ACAR(1, 2) is significant only for Lazio. A loss is followed by a negative AAR(1) of 0.0189 (statistically significant at the 1% level) and a negative ACAR(1, 2) of 0.0164 (statistically significant at the 1% level) for Roma. For Lazio, a loss triggers a negative AAR(1) of 0.0097 (statistically significant at the 1% level) and a negative ACAR (1, 2) of 0.0127 (statistically significant at the 1% level). The magnitude of the reaction after a win is less (higher) than a loss for Roma (Lazio) which supports (contradicts) the allegiance bias. When I compare the average abnormal return after a win and a loss, I find that the difference is statistically significant at the 1% for both clubs.

Table 2. Abnormal Returns after game results

	Roma				Lazio			
	N	AAR(1)	N	ACAR(1,2)	N	AAR(1)	N	ACAR(1,2)
Win	204	0.0065* (0.084)	184	0.0049 (0.587)	102	0.0115*** (0.000)	92	0.0080** (0.038)
Draw	90	-0.0101*** (0.000)	83	-0.0067*** (0.001)	76	-0.0020 (0.402)	71	-0.0009 (0.231)
Loss	99	-0.0189*** (0.000)	88	-0.0164*** (0.000)	94	-0.0097*** (0.003)	87	-0.0127*** (0.002)
Home-win	129	0.0057 (0.673)	118	0.0036 (0.906)	62	0.0055** (0.049)	54	0.0006 (0.651)
Home-draw	35	-0.0143*** (0.001)	34	-0.0139*** (0.002)	37	-0.0010 (0.862)	35	0.0024 (0.623)
Home-loss	35	-0.0268*** (0.000)	33	-0.0290*** (0.000)	37	-0.0132** (0.012)	34	-0.0182*** (0.000)
Away-win	75	0.0078** (0.025)	66	0.0070 (0.314)	40	0.0207*** (0.000)	38	0.0185*** (0.008)
Away-draw	55	-0.0075*** (0.002)	49	-0.0017** (0.044)	39	-0.0029 (0.308)	36	-0.0041 (0.215)
Away-loss	64	-0.0146*** (0.000)	55	-0.0088*** (0.008)	57	-0.0075* (0.08)	53	-0.0091 (0.141)

-AAR and ACAR stands for the average abnormal return and average cumulative abnormal return.
-This table presents the average abnormal returns following the soccer games. The p-values of the Wilcoxon signed-rank test are given in parentheses. Number of observations for AR(1) and CAR(1,2) is different as sometimes teams play both on Thursday and at the weekend. Thus to avoid this overlap, these observations are removed while competing CAR(1,2).
- ***, **, * represent statistical significance at the 1%, 5%, and 10% level, respectively.

When the game venues are considered, I observe that the impact of a loss at home venue is strictly higher than an away loss for both clubs. A loss at home venue in front of supporters leads both to a higher negative AAR (1) and ACAR (1, 2). The difference between the AAR(1) after a home-loss and an away-loss is statistically significant at the 10% level for both clubs. As a home-win is highly expected, for both clubs, the impact of an away-win is higher than a home-win. However, the difference is statistically significant only for Lazio. The AAR(1) subsequent to a draw is negative for both clubs but it is only statistically different from zero for Roma.

Table 3 presents the regression results for Roma and Lazio (models 3 and 4). The first model confirms that there is a statistically significant positive (negative) reaction to a win (a loss). When goal difference is used instead of win/loss, it is found that coefficient for goal difference is 0.0062 (statistically significant at 1% level). This confirms the importance of high scoring wins/losses for these two clubs. The coefficient for away games is 0.0062 (statistically significant at 5% level) in both models. The performance of a team at away venue matters for the investors. Although the games after March are important in terms of determining the final position of teams in competitions, the PostMarch dummy does not have a significant impact on the market reaction. The investors do not distinguish the importance of games whether they are before or after March. The teams benefit more from European games through more gate receipts, monetary awards, reputation and broadcasting revenues, however no statistically significant relation is found between European Cup dummy and market reaction. The findings support the existence of relationship between abnormal returns and game-related information, therefore confirming the literature results that investors are sensitive to sports performance of the soccer clubs.

Table 3. Market reactions to game results: Regression results

	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)
Constant	-0.0064**	-0.0045***	-0.0096***	-0.0076***	-0.0157***	-0.013**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.006)	(0.005)
Win	0.0145***		0.0154***		0.0168***	
	(0.004)		(0.004)		(0.004)	
Loss	-0.0081*		-0.0083**		-0.0084**	
	(0.004)		(0.004)		(0.004)	
Goal Difference		0.0062***		0.0065***		0.007***
		(0.001)		(0.001)		(0.001)
Away					0.0062**	0.0062**
					(0.003)	(0.003)
Serie A					0.0027	0.0023
					(0.005)	(0.005)
European Cup					0.0008	-0.0002
					(0.006)	(0.006)
Post-March					0.0012	0.0027
					(0.004)	(0.003)
Lazio			0.0071**	0.0071**	0.0071**	0.0071**
			(0.003)	(0.003)	(0.003)	(0.003)
N	665	665	665	665	665	665
R^2	0.059	0.068	0.067	0.076	0.073	0.083
Adjusted R^2	0.056	0.067	0.062	0.073	0.063	0.074
F-Statistics	20.84	48.42	15.70	27.02	7.37	9.86
Prob>F	0.000	0.000	0.000	0.000	0.000	0000

***, **, * represent statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are given in parenthesis.

Post-March is a dummy equals to one when games are played after March; *Away-Game* is a dummy equals to one if the game is an away game and zero for a home game; *Serie A* equals to one if the game is a domestic league game and zero otherwise; *European Cup* dummy is equal to one if the game is played in UEFA League or Champions League; *Lazio* is dummy variable equal to one if Lazio is playing and used to separate the impact of two clubs.

5.2. The stock market reaction to the arch-rival performance

I hypothesize that the fan investors' mood is not only related with their favorite team's performance but also related to the arch-rival's performance as both teams play at the same weekend in domestic league. Table 4 summarizes the estimates of Model 5 and 6 considering the hypotheses 1-4 in section 3. The coefficient estimate for WW is 0.0122 (statistically significant at 5%) however WL is not statistically significant. Thus, hypothesis H_1 is not supported.

Table 4. Market reactions to the arch-rival's performance: Regression results (Serie A)

	AR(1)	AR(1)	AR(1)	AR(1)
Constant	-0.0025	-0.0044*	-0.0032	-0.0058
	(0.003)	(0.0026)	(0.004)	(0.0036)
WW	0.0124**		0.0122**	
	(0.0052)		(0.005)	
WL	0.0065		0.0067	
	(0.0052)		(0.005)	
LW	-0.0118**		-0.0119**	
	(0.0053)		(0.005)	
LL	-0.0167**		-0.0171**	
	(0.0066)		(0.007)	
WPS		0.0186*		0.018*
		(0.0100)		(0.0101)
WNS		0.0168***		0.0173***
		(0.0055)		(0.0057)
LPS		-0.0065		-0.0070
		(0.0092)		(0.0093)
LNS		-0.0201**		-0.02**
		(0.0086)		(0.0087)
Ranking Difference			0.00001	-0.0000
			(0.000)	(0.0003)
PostMarch			0.0028	0.0033
			(0.004)	(0.0043)
Lazio	0.0033	0.0035	0.0032	0.004
	(0.0035)	(0.0036)	(0.004)	(0.0041)
Away			0.0002	0.0010
			(0.004)	(0.0037)
N	485	485	485	485
R^2	0.046	0.041	0.047	0.042
Adjusted R^2	0.036	0.031	0.031	0.026
F-Statistics	4.65	4.08	2.94	2.63
Prob>F	0.000	0.001	0.003	0.008

For the interaction variables, the first letter indicates the result of the considered team and the latter indicates the result of its arch-rival after a weekend in a season of Serie A.
***, **, * represent statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are given in parenthesis

The coefficients estimates for LW and LL variables are -0.0119 and -0.0171, respectively (both statistically significant at 5% level). The relation between these two variables is against Hypothesis H_2, however a formal test of the equality of coefficients leads to the result that the coefficients for *LW* and *LL* are not statistically different from each other. Thus, hypotheses H_1 and H_2 are not supported according to the findings. This result indicates that although fan investors can observe the performance of both their favorite team and arch-rival performance, the performance of arch-rival does not affect the stock market reaction to the performance of the favorite team.

As for the case of unexpected performance of the rival, it is found that the coefficient estimates for the variable *WPS* and *WNS* variables are 0.018 and 0.0173, respectively (statistically significant at 1% and 10% level). The coefficient estimates support the Hypothesis 3 as the stock price impact of a win combined with a positive surprise (the unexpected negative performance of the arch-rival) is higher than the one of a win combined with a negative surprise (the unexpected positive performance of the arch-rival). However, the test of equality of coefficients indicates that those two coefficients are not statistically different from each other. Thus the positive market reaction following the win is not significantly affected by the unexpected (positive or negative) performance of arch-rival. The coefficients for *LPS* and *LNS* are respectively -0.0070 (not statistically significant) and -0.02 (statistically significant at 5%). This finding reflects that a loss combined with a positive surprise of the rival do not create any investor reaction, therefore the negative effect the loss is counterbalanced by the positive surprise coming from the arch-rival performance. On the contrary, when the loss is associated with a negative surprise it is found the strongest negative market reaction, the coefficient of LNS being -0.02. These findings provide evidence supporting Hypothesis 4 which claims the negative stock price impact of a loss combined with a negative surprise must be stronger than the one combined with a positive surprise.

6. Conclusion

The performance of a soccer team plays an important role both in its future cash flows and in the mood of its supporters. Therefore the stock performance may be influenced both by rational and emotional arguments, both exerting their impact in the same direction. Palomino et al. (2009) try to distinguish between these two possible explanations for the market reaction to game results by running a number of tests and they find evidence in favor of the importance of both rational expectations and investor sentiment.

In this study, I address a particular aspect of this issue isolating a stream of emotions that is not related to the economic result of the soccer club: it's the arch-rival's performance. I do it studying the cross performance of two well known rival teams, Roma and Lazio. Koyama and Reade (2009), Leach et al. (2003), and Cikara et al. (2011) argue that in the context of sports rivalry, fans feel pleasure when they their rival fails. Moreover, fans show their association with their favorite team after the defeat of rival (Dalakas et al. 2004). The psychology literature has introduced the notion of Schadenfreude, demonstrating the supporter feelings are strongly influenced also by the rival's result. And as at a weekend, fan investors can observe the performance of their favorite team and also of the arch-rival, their mood and thus their investment decisions should also be affected by their arch-rival's performance at that weekend. In such a case I argue that the link between emotions and economic performance is weakened or not relevant at all: for instance the win of the rival negatively affects the emotions of the supporters without exerting any impact (after considering some control variables) on the economic performance of the club. The study therefore helps understanding the pure impact of emotions on stock performance of soccer club.

The results show that fan investors react positively (negatively) to a win (a loss) of their favorite team. I show that although fan investors can observe the performance of both their favorite team and arch-rival performance, the performance of arch-rival does not affect the stock market reaction to the performance of the favorite team. However, when odds are taken into account to determine the unexpected performance of arch-rival, supportive evidence for the rival effect on stock performance is achieved, at least when a loss occurs. I find that a loss combined with a negative surprise coming from the arch-rival performance (a win or draw while a loss is expected) leads to a strong negative market reaction, on the contrary, when a loss is combined with a positive surprise (a loss or a draw when a win is expected) the reaction is not significant. This asymmetric effect is not found for the wins, where the positive effect holds regardless the performance of the arch-rival. This study shows that, when club supporters are experiencing the negative performance of their team, the news coming from the arch-rival results can change their investment decisions. It is therefore proved that, at least for this aspect, the investors (widely represented also by the club supporters) are driven by the emotions conveyed by rivalry which, considered as a source of emotions, may be market relevant.

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APPENDIX 1 List of Currently Listed Soccer Clubs/Composition of DJ StoXX Football (as of 31 January 2011)

Club	Weight (%)	Mcap (EUR Bil.)	Float Factor	Country
BORUSSIA DORTMUND	12.05	0.09	0.83	Germany
BESIKTAS	10.52	0.08	0.35	Turkey
FENERBAHCE SPORTIF HIZMET	10.22	0.07	0.15	Turkey
TRABZONSPOR SPORTIF YATIR	10.18	0.07	0.25	Turkey
PARKEN SPORT & ENTERTAINMENT	10.01	0.07	0.84	Denmark
JUVENTUS	7.83	0.06	0.32	Italy
GALATASARAY	7.8	0.06	0.23	Turkey
AS ROMA	7.2	0.05	0.33	Italy
OLYMPIQUE LYONNAIS	4.48	0.03	0.4	France
TOTTENHAM HOTSPUR	3.1	0.02	0.14	UK
CELTIC	3.05	0.02	0.46	UK
AFC AJAX	3.04	0.02	0.17	Netherlands
BRONDBY IF B	2.31	0.02	1	Denmark
LAZIO	2.03	0.01	0.33	Italy
ARHUS ELITE	1.72	0.01	0.64	Denmark
SPORT LISBOA E BENFICA	1.37	0.01	0.28	Portugal
MILLWALL HLDG	0.8	0.01	0.48	UK
SILKEBORG	0.68	0	0.56	Denmark
AALBORG BOLDSPILKLUB	0.39	0	0.75	Denmark
FUTEBOL CLUBE DO PORTO	0.38	0	0.21	Portugal
WATFORD	0.36	0	0.54	UK
AIK FOOTBALL	0.29	0	0.59	Sweden
SPORTING	0.18	0	0.08	Portugal

Source: STOXX® SPORTS INDICES, FACTSHEET of 31 January 2011.

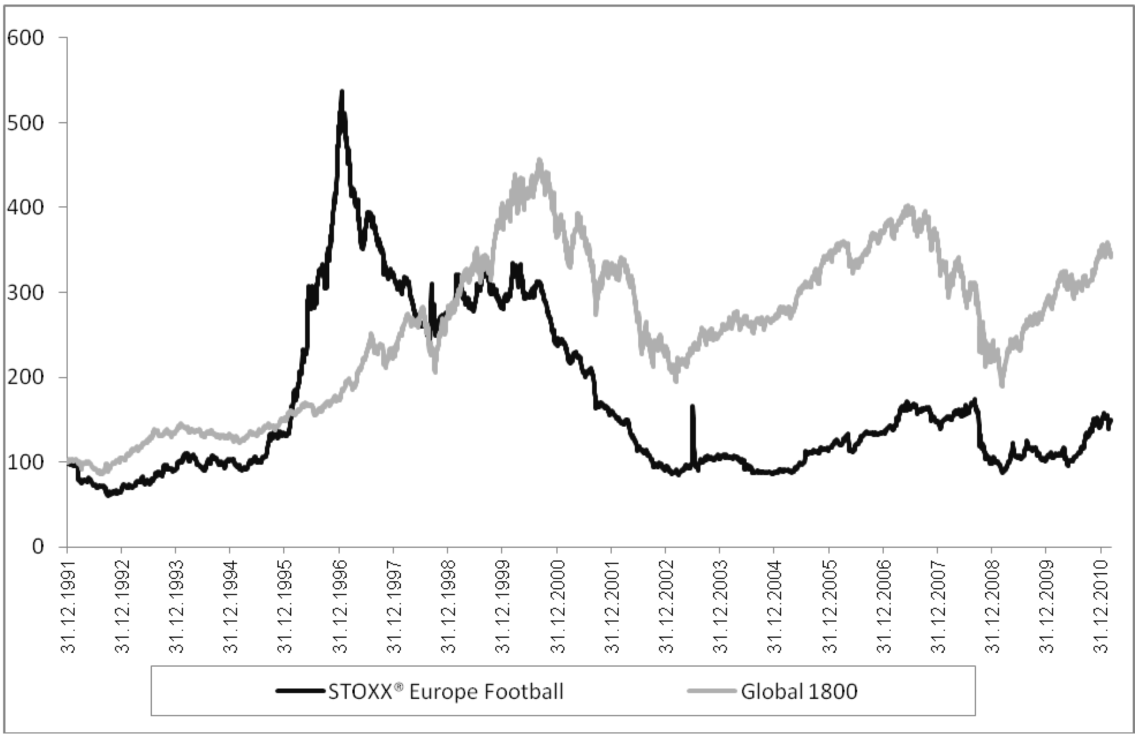
*DJ StoXX Football covers all football clubs that are listed on a stock exchange in Europe or Eastern Europe, Turkey or the EU-Enlarged region.

APPENDIX 2 List of All the European football clubs ever publicly traded

Club	Country
Aalborg Boldspilklub	Denmark
Aberdeen	Scotland
AGF Kontraktfodbold	Denmark
AIK Football	Sweden
Ajax	Netherlands
AkademiskBoldklub	Denmark
Arsenal	England
AS Roma	Italy
Aston Villa	England
Besiktas	Turkey
Birmingham City	England
Bolton Wanderers	England
Borussia Dortmund	Germany
Bradford City England	England
Brondby	Denmark
Charlton Athletic	England
Chelsea Village	England
FC Istres	France
FC Kopenhagen	Denmark
FC Porto	Portugal
Fenerbahce	Turkey
Galatasaray	Turkey
Glasgow Celtics	Scotland
Glasgow Rangers	Scotland
Grasshoppers Zurich	Switzerland
Hearts of Midlothian	Scotland
Juventus	Italy
Lazio Roma	Italy
Leeds United	England
Leicester City	England
Manchester City	England
Manchester United	England
Millwall	England
Newcastle United	England
Nottingham Forrest	England
Olympique Lyonnais	France
Preston North End	England
Queen Parks Rangers	England
Sheffield United	England
Silkeborg	Denmark
Southampton England	England
Sporting	Portugal
Sporting Lisboa	Portugal
Sunderland England	England
Swansea City England	England
Tottenham Hotspurs England	England
Trabzonspor	Turkey
Watford	England
West Bromwich	England

Source: Aglietta et al. (2010).

APPENDIX 3 Total Return Index (Euro Currency) of STOXX® Europe Football Index



IS THE SOCCER BETTING MARKET EFFICIENT? A CROSS-COUNTRY INVESTIGATION USING THE FIBONACCI STRATEGY

Abstract

The sports betting industry is one of the fastest growing industries in the world and therefore the literature on sports betting has gained momentum in the last two decades. The literature mainly focuses on testing the efficiency of the sports betting market. The prediction of game outcomes or comparing the odds of bookmakers by predicted odds and the search for betting strategies which yield significant positive returns have been the core of the market efficiency tests. This study, instead of making any predictions or generating odds to be compared by bookmakers' odds, implements the Fibonacci sequence on draws as a betting rule for 8 European soccer leagues for the seasons from 2005/2006 to 2008/2009. As the odds offered by bookmakers are narrowly distributed, implementing the Fibonacci strategy for 8 soccer leagues of Europe for 4 seasons yields positive return for all cases and also controlling with simulated data the strategy is found to be in most circumstances profitable. The results indicate that the bookmakers are inefficient in terms of predicting the draws and the soccer betting markets are inefficient. Therefore, the betters could exploit this inefficiency by following Fibonacci strategy assuming they have enough financial liquidity. Furthermore, I calculate the capital needed to pursue the strategy resorting to the Value at Risk (VaR) methodology and reveal that the VaR is only 143€ (assuming that the first bet is 1€) at 95% confidence level.

Keywords: Soccer betting, Market Efficiency, Fibonacci sequence, betting strategy

1. Introduction

Betting markets have experienced unprecedented growth over the past few years as a result of deregulations, abolition of national monopolies, and the widespread use of the internet which has led to the advent of online gambling (Vlastakisa et al. 2009). The gambling industry which includes betting markets is one of the fastest growing industries and the popularity of gambling is rapidly increasing. In the UK, for example, 68% of the population participated in some form of gambling in 2007 (Peel, 2008). Even in Turkey where the majority of its population is Muslim, 67.3% of population engaged in some form of gambling in 2008 (Sabah, 2009).[1] The rising popularity and importance of betting has been reflected in the literature and thus the literature on sports betting has gained momentum, especially in the last two decades. Football, basketball, horseracing, and soccer have been the leading sports in the field.

Economists have given great attention to the tests of market efficiency and rationality in stock markets (Thaler and Ziemba, 1988). In parallel, the efficiency of sports betting markets has been also tested. However, the sports betting market has several advantages over traditional asset markets in terms of efficiency tests. All bets reach a terminal value in a short period of time and therefore, the success/failure of any investment can be observed easily (Avery and Chevalier, 1999). So far there is evidence in favor of both the efficiency and inefficiency of the betting markets and this study contributes to the literature on the efficiency of the soccer betting markets, started by the pioneering research of Pope and Peel (1989). The market efficiency literature shows that there might be some profitable betting strategies which outperform bookmakers. However, their practicability is questionable due to the sophisticated statistical techniques used and the need for continuously updated multi dimensional information about the teams. This paper challenges the current literature by providing a simple and profitable betting strategy that rejects market efficiency in the soccer betting market.

There are two main categories of betting strategies: betting independently from the teams playing and betting according to the previous performance of the teams (Stefani, 1983). The latter includes predicting and betting by developing statistical models which cover a variety of relevant information such as past performances, number of goals

[1] Gambling is strictly prohibited by Islam as in many religions.

scored and conceded, injuries, home-field advantage, current league position, and the odds of the bookmakers. In this paper, contrary to most of the literature, I follow the first approach by implementing the Fibonacci sequence as a betting rule on draws. The Fibonacci betting rule is easy to implement and requires no knowledge about specific teams or soccer.

By a similar methodology to Archontakis and Osborne (2007), I try to exploit the inefficiencies of bookmakers in predicting the odds for draws. Although Graham and Stott (2008) argue that "none of the work published has been particularly successful at beating the bookmakers" and add "if it was successful, it would not have been published", I find a strategy that would have been profitable for eight leagues of the five European countries (England, France, Germany, Italy, Spain) in all four seasons that this study covers. This study extends the paper of Archontakis and Osborne (2007) in three different aspects: instead of using a fixed-odd for draws, I use real odds offered by the bookmakers; I deal with the issue of the games played at the same time; and I analyze a larger cross-country dataset including all the main European countries for the four annual seasons between 2005/2006 and 2008/2009. I also conduct a robustness test for the reliability of the Fibonacci strategy on draws and measure the risk embedded in the strategy.

The paper is organized as follows: The next section gives a literature review of market efficiency studies in the soccer betting market. Section 3 presents the dataset and also a brief summary of the odds for draws in major leagues of Europe. In Section 4, the betting rule is explained and implemented. Section 5 represents the results of the betting rule discussing drawbacks and offering alternatives, while Section 6 offers a conclusion.

2. Literature review

Research on the market efficiency in the betting markets has been widely conducted on horse racing and to a lesser extent on major sports in the U.S., such as baseball, football, and basketball. Thaler and Ziemba (1988) establish the definitions for weak and strong efficiency of betting markets. Under the condition of weak market efficiency, odds reflect the objective probabilities of results such that no strategy yields positive expected returns. Strong efficiency requires that all bets have the expected values equal to the total amount betted less transaction costs. Forrest and Simmons (2008) interpret the strong form of efficiency as no strategy exists that would improve on the (negative) expected return from betting randomly. Therefore, the prediction of match results or comparing the odds of bookmakers by predicted odds and the search for betting strategies which yield significant positive returns has been the core of market efficiency tests. If the market is efficient, there would not be any profitable strategies and all strategies would yield expected losses equal to the bookie's mark-up (Woodland and Woodland, 1994).

Studies on soccer betting markets are relatively scarce (Kossmeier and Weinberger, 2008). The study of Pope and Peel (1989) can be considered the first which covers a number of aspects of efficiency. They found that a fixed-odds betting market appeared to be efficient for the 1981/82 English soccer season since there was no profitable betting strategy. Again in the English soccer league, Dixon and Coles (1997) proposed a Poisson parametric model considering the possibility of potential inefficiencies in the soccer betting market. Their betting strategy requires betting at outcomes for which the ratio of model estimated probabilities to bookmakers' probabilities exceeds a specified level. They show that their strategy achieved positive returns for sufficiently high levels of that ratio. Kuypers (2000) tested the weak-form and strong form of efficiency in the English soccer league. He discovered a profitable betting rule which compares the predicted probability and implied probability from odds. Goddard and Asimakopoulos (2004) developed an ordered probit regression model to forecast the result of English league games. Their model includes a variety of variables such as past performances, team quality indicators, and geographical distance. By using the model as the basis of their betting strategy, a positive gross return of 8% was found for the games played in April and May in both seasons 1999 and 2000.Their model also creates a positive gross return at the beginning and at the end of the soccer season. Furthermore, Dixon and Pope (2004) used the model of Dixon and Coles (1997) and compared bookmakers' odds with the model probability estimates from a Poisson distribution. They found that placing bets on draws yielded less negative returns compared to placing bets on all home wins and away wins. The betting strategy, which requires betting when the ratio of the model probability to the bookmaker odds exceeds a critical value, generated a positive return. Moreover, Forrest et al. (2005) initially bet one unit for each of the three possible outcomes for every match in UK with 5 different bookmakers and their strategy lost between 10% and 12% due to bookmakers' markup. However, using the best available odds decreased the average loss to 6.6%. Alternatively, one unit bet on match outcome with the highest expected return according to the benchmark model strategy yielded a positive return in only 3 cases out of 30. Likewise, Graham and Stott (2008) tried to exploit the inconsistent pricing of a UK bookmaker by using a Probit model, but the strategy did not outperform the bookmaker. Forrest and Simmons (2008) by using a Probit model examined the efficiency of betting odds offered in the on-line betting market of Spain. It is found that the odds are influenced by the relative number of fans of clubs (named as the sentiment influence). They implemented a strategy of always placing a unit bet where mean home attendance difference exceeds some threshold levels. The strategy yielded losses, however they were much less severe than the return of -16% from a random betting strategy. They also implemented a second strategy which required placing a unit bet when forecast probability minus the bookmaker probability exceeds some threshold amount. For higher level of thresholds, although they find positive returns (7.7% for a gap>0.09 and 12.8% for a gap>0.10), the number of bets decreased rapidly due to the strong filter implemented and they concluded that betting rules do not reliably generate positive returns. Vlastakisa et al. (2008) by implementing Support Vector Machines technique in English Premier League found a positive out-of-sample profit, implied a deviation from the weak form of efficient market hypothesis. Recently, Milliner et al. (2009) found a profitable strategy based on betting on the away wins for a sample data of 194 league football games in 2007 played in the top four both English and Scottish soccer leagues. They also use a second data-set comprising all those matches held in the English and Scottish divisions (63 games) in 2008 for out of sample testing. The findings from comparing the estimated probability of an away win using discrete choice model and estimated probability of bookmakers indicate that the strategy can be profitable by avoiding the games where there is a clear favorite. This finding is consistent with previous research cautioning against a betting strategy based on a long-shot or on a clear favorite. The second approach is to use ordinary least squares regression with bookmakers' odds as the dependent variable to detect the mismatch between the bookmakers' odds for the away win and the predicted bookmakers' odds under the model. This strategy also gives positive profit both for in-sample and out-of-sample.

Overall, the literature shows that there are a few profitable betting strategies which outperform the bookmakers: however their practicability is questionable due to the sophisticated statistical techniques used and the need for continuously updated multi dimensional information about the teams.

3. Data Set and Betting Odds

The data comprise the results and final odds of the soccer matches played in 5 major primary European leagues, namely, Ligue 1 (France), Serie A (Italy), Bundesliga I (Germany), Premier League (England), and La Liga (Spain), and 3 major secondary leagues, namely, League Championship (England), Serie B (Italy) and Ligue 2 (France) for the 2005/06, 2006/07, 2007/08, and 2008/09 seasons. The results and the odds are collected from www.betexplorer.com, which provides the final offers from various online betting companies.

In soccer, betting on the result of a game is determined after 90 minutes of a full-regulation game, even if the actual result of the game is determined in extra-time or penalties. Because the present study deals only with national leagues there is no extra time or penalty kicks. Therefore, there are three outcomes of a game: home-side win, draw or away-side win. In general, the national leagues are made up of 20 teams and each team plays with all other teams both at home and away. For a 20 team league, there are 38 games to play for each team and 380 games in total in a full-season. However, some games are played contemporaneously and, therefore the number of non-simultaneously played games decreases to around 150 for a 20 team league. Table 1 exhibits the mean of draws and the weekly calculated coefficient of variation of draws in the 8 leagues of Europe. On average, Italy Serie B, France Ligue 2, and France Ligue 1 are the leading leagues in terms of draws. The probability of a draw in these 8 leagues ranges from 0.20 to 0.33 and the most homogenous distribution of draws occurs in Italy Serie B.

In betting, odds reflect the subjective expectations of bookmakers regarding the outcome of games. However, Milliner et al. (2009) argues that odds can be set with commercial and financial gains in mind and may not necessarily reflect the best assessment of match outcomes. In other words, they may be set with anticipated betting volumes in mind or set to influence betting volumes. In the soccer betting market, bookmakers offer betting odds for each of the three mutually exclusive outcomes which are for the home team win, away team win or draw. For example, Bwin, a world-wide famous betting company, on 01.04.2011 offered the following odds for UEFA European League game between Benfica and Liverpool: 2.35 for home win, 3.1 for draw, and 3.0 for away win. The odds represent the return from a 1 unit investment for each outcome. If 1 unit is bet on “Liverpool victory” and Liverpool wins the game, the return is 3 with a net profit will be 2. If the game ends as a home-win or draw, the 1 unit of money bet will be lost. The implied probability is calculated by taking the inverse of the odd. For the game above, the implied probabilities are 0.425, 0.322, and 0.333, respectively which sum to 1.08 indicating an 8% bookmaker markup on the odds. To convert the implied probabilities to probabilities, they must be normalized by dividing them with their sum. Thus the probabilities will be 0.393, 0.298, and 0.308 which sums to 1. In the case of equal probabilities for all outcomes (which implies maximum uncertainty) under the assumption of an 8% bookmaker markup, the odds for each outcome will be set to 2.77 which means equal probability of 33.33%.

Table 2 shows the summary of final offers of online betting companies for the 2005/06, 2006/07, 2007/08 and 2008/09 seasons. The lowest mean of odds for draws are offered for games in Serie B (Italy), Ligue 1 (France), and Ligue 2 (France) as the draws are more likely to occur in those leagues. It is observed that in Italy Serie A and B, the minimum of odds for a draw is 1.44 and 1.24, respectively which are far below the other leagues.[2]

[2] These extreme odds in the final weeks of the season imply that most of the teams in these leagues do not have any motivation as their league position has been already determined and match fixing might be probable. Therefore, many betting firms do not allow betting in these games.

Table 1. Mean and Coefficient of Variation of Draws in Major European Soccer Leagues

	2008/09	2007/08	2006/07	2005/06
France: Ligue 1	29.47%	30.53%	30.79%	31.05%
	(0.492)	(0.505)	(0.455)	(0.472)
France: Ligue 2	28.95%	31.32%	29.47%	33.16%
	(0.519)	(0.551)	(0.540)	(0.460)
Italy: Serie A	25.00%	29.47%	30.00%	28.42%
	(0.548)	(0.505)	(0.458)	(0.437)
Italy: Serie B	31.38%	30.50%	30.93%	32.45%
	(0.423)	(0.427)	(0.391)	(0.408)
Germany: Bundesliga I	23.97%	25.38%	25.62%	31.15%
	(0.585)	(0.723)	(0.609)	(0.492)
England: Premier League	25.53%	26.32%	25.79%	20.26%
	(0.513)	(0.471)	(0.629)	(0.644)
England: League Championship	29.17%	30.98%	22.28%	31.34%
	(0.485)	(0.427)	(0.453)	(0.409)
Spain: La Liga	21.84%	22.89%	25.79%	27.63%
	(0.582)	(0.583)	(0.575)	(0.522)

The values in parentheses show the coefficient of variation values. These are calculated by using the percentage of draws in each week in a season.

Table 2. Summary of the Final Offers for Draws of Online Betting Companies (2005/2006 to 2008/2009)

	N	Min.	Max.	Mean	St.Dev.
France: Ligue 1	1,520	2.33	7.69	3.097	0.376
France: Ligue 2	1,520	2.37	4.41	2.948	0.235
Italy: Serie A	1,520	1.44	7.16	3.310	0.731
Italy: Serie B	1,848	1.24	8.47	2.983	0.630
Germany: Bundesliga I	1,224	3.05	7.23	3.499	0.530
England: Premier League	1,520	2.96	9.93	3.603	0.741
England: League Championship	2,208	2.89	5.11	3.275	0.155
Spain: La Liga	1,520	2.93	7.71	3.451	0.595

Source: www.betexplorer.com

4. Methodology: The Fibonacci Betting Rule

Leonardo Pisano Fibonacci introduced the famous Fibonacci sequence in which the first two terms are 1 and after that each term is generated as the sum of its immediate two predecessors. The first 10 elements of the Fibonacci sequence are 1, 1, 2, 3, 5, 8, 13, 21, 34, and 55, respectively. The applications of the Fibonacci sequence are also increasing in various fields such as business, finance, economics, biology, archeology, and mathematics (Chen et al. 2007). The Fibonacci sequence can be observed in nature in the growth process of many forms such as cones, pineapples, petals of flowers; in the shapes of galaxies; and in the design of the chambers in the nautilus shell (Mitchell, 2001).

The growth rate of the Fibonacci numbers, a_{n+1}/a_n, converges towards a constant ratio 1.618 which is known as the golden ratio (ϕ, phi). Conversely, dividing any number in the Fibonacci sequence by the following number approaches a constant ratio of 0.618. In mathematical notations, the Fibonacci sequence is shown as $a_n = a_{n-1} + a_{n-2}$ where $n \geq 3$, $a_1 = 1$, and $a_2 = 1$. The partial sum of the Fibonacci numbers is calculated as:

$$\sum_{i=1}^{n} a_n = a_{n+2} - 1$$

I follow a betting rule similar to Archontakis and Osborne (2007) which requires betting on draws continuously until the last game of the season according to the amounts determined by the Fibonacci sequence. When a draw occurs at the n^{th} game, the revenue is the final amount betted (a_n) on that game times the given odd for the draw (x), whereas the total amount of money betted until the n^{th} game is equal to $a_{n+2}-1$. Then the profit (π) is calculated as the difference between revenue and total amount betted:

$$\pi = xa_n - (a_{n+2} - 1)$$

The required odd for draw to have one unit of profit is 2.618.[3] However, it's more interesting to derive the percent profitability than the profits in absolute terms. I define the profit margin (π_r) as the ratio of profit to the total amount betted:

$$\pi_r = \frac{xa_n - (a_{n+2} - 1)}{(a_{n+2} - 1)}$$

When I solve the equation for different levels of profit margins namely 1%, 5%, 10%, 15%, and 20% (for $n \to \infty$), the required fixed odds for draw (*x*) take the values of 2.644, 2.7558, 2.9089, 3.08, and 3.2725, respectively. Table 2 reports that the mean of

[3] For the proof, please see Archontakis and Osborne (2007).

odds for draws in all leagues are higher than the 2.618 which is enough for 1 unit of profit and higher than 2.9089, the threshold yielding a profit margin of 10% (in 5 of these 8 leagues, the means are above 3.2725 which gives a profit margin of 20%) with relatively small standard deviations, therefore there is room for a profitable strategy.

One could wonder why the Fibonacci strategy is implemented only on draws instead of on home and away wins. As Pope and Peel (1989) argue, the draw is the most difficult outcome to predict for bookmakers, whereas Dixon and Pope (2004) show that bookmaker predictions for draws are very narrowly distributed compared to the predictions of their model. This indicates that the bookmakers underestimate the variance in draw results and offer relatively stable odds, making the implementation of the strategy easier. In addition, this strategy cannot be implemented on home wins because the mean for each league is below the cutoff point of 2.618. On the other hand, the odds for away wins are very volatile which makes the implementation of the strategy very risky.

This study contributes to the literature extending Archontakis and Osborne (2007) in three aspects. First, instead of using 3 as a fixed odd for draws for all games, I use the average of final offers. When the fixed odd 3 is replaced by the real odds which were given by bookmakers for the games in World Cup 2002, the profit margin of the Fibonacci strategy, which was found as 25% in by Archontakis and Osborne, increases to 32.72%. As most of the online betting companies have dynamic odds which vary according to demand and the Fibonacci strategy must be implemented sequentially using final offers, this gives us more realistic results, especially in the final weeks of seasons when odds are lower. Second, the Archontakis and Osborne (2007) skip the games which were played at the same time in the 2002 FIFA World Cup, but in most of the major leagues, approximately 4 of the weekly games are played at different times (sometimes on different days and sometimes on the same day at different hours) and the remaining games are played at the same hour and day. To overcome the problem of simultaneously played games, the choice is made according to the highest odds on the draw. In that way, the returns will be maximized by benefiting from the difficulty in predicting draws. In case the highest odds are equal, the game which did not occur as a draw was chosen to find the worst-case results. This study also includes a larger data set for a longer time horizon by including eight European Leagues over four seasons.

Finally, I conduct robustness test for the reliability of the Fibonacci strategy on draws and measure the risk embedded in the strategy.

5. Results

5.1. Implementing the Fibonacci strategy in eight European Leagues

I apply the Fibonacci strategy to European soccer leagues and compare the returns from the Fibonacci strategy against the simplest strategy: betting continuously on the same outcomes (i.e. win, loss or draw) for every match. The results are reported in Appendix 1 and 3. Not surprisingly, since the odds incorporate the bookmaker markup, this strategy always yields a negative return except for five cases out of 96: the best result, a return of 5.46%, is achieved by betting on draws in Bundesliga I (Germany) in 2005-06. Compared to the Fibonacci strategy on draws, this strategy requires more frequent betting and the profit margins are strictly lower than the profit margins from the Fibonacci strategy. When the Fibonacci strategy is considered all the returns from 32 cases are positive. The highest average returns are achieved in the Premier League (England) with 45.16% and the Championship League (England) with 32.24% and Bundesliga I (Germany) with 42.53% whereas the lowest profits occur in Ligue 1 (France) with 22.45%, Ligue 2 (France) with 17.26% and Serie A (Italy) with 25.72%. The lowest average capital requirement is in Ligue 1 (France) and Serie B (Italy) with 394.75 and 711.5 monetary unit respectively.[4]

The findings of the betting strategy point to the inefficiency of bookmakers in predicting the odds for draws. The narrowly distributed odds offered by bookmakers give the chance to implement a profitable strategy. Archontakis and Osborne (2007) found a return of 25% by implementing the Fibonacci strategy on World Cup 2002. However, I find a return of 32.72% when the fixed odds of 3.0 are replaced by the real odds which are taken from www.betexplorer.com. Moreover, betting on all home wins, draws or away wins yield a return of 9.19%, 1.84% and -15.88% respectively in the World Cup 2002. However, Archontakis and Osborne (2007) indicate a return of -9.375% by betting solely on draws.

[4] It should be noted that these returns are pre-tax returns. Also the strategy can be implemented only in case the bookmaker allows betting on single outcomes instead of requiring a combination of some games.

Although the returns of the Fibonacci strategy are all positive for the leagues concerned, it is still risky in its nature. Archontakis and Osborne (2007) show that there is no finite amount of money to sustain the Fibonacci strategy. If the draw does not occur quickly, the betting strategy requires increasing the amount bet according to the Fibonacci sequence and further the bettor needs to continue betting while incurring a loss. The capital requirement to sustain the strategy will increase as the non-occurrence of a draw lasts. However, an occurrence of draw will recover all the bet money and yield a profit. A series of non-occurrence of draws during the final weeks can easily result in huge amount of losses. For example, if a draw doesn't appear in the last 10 games chosen, a bettor needs to bet a total amount of 55 units and, if this period extends to 15 games, the amount will reach 610 units. This situation can ruin the profits earned in the previous rounds, especially if this lack of draws is experienced through the end of the season. Then, the recovery of the amount betted is not possible if the season ends without a draw and the better has to wait for the following season.

To give a better sense of the risk embedded in the nature of the Fibonacci strategy and to determine the highest amount that a bettor must bet (or risk) to sustain the strategy, I implement a Value at Risk (VaR) approach. VaR is widely used in finance especially by financial institutions and regulatory bodies to measure risk. When I adapt the VaR to the Fibonacci strategy by considering all 8 leagues for 4 seasons, I find that the VaR is 143€ and 1596€ (assuming that the first bet is 1€) at 95% and 99.26% confidence levels, respectively. The results reveal that there is only 0.74% chance that the strategy would require more than 1596€.

While VaR shows the possible loss for a given confidence level, it does not consider the severity of an incurred damage. In finance literature expected shortfall (a.k.a. conditional VaR or expected tail loss) measures the size of the average loss when it exceeds the VaR level. When I adapt expected shortfall to the case of betting, it calculates the required amount to sustain the strategy beyond the VaR level. At 95% confidence level in case the VaR value of 143€ is exceeded, the bettor would need 1,194€ on average to sustain the Fibonacci strategy. However, at 99% confidence level, the bettor would need 5,747€ on average.

5.2. Robustness

A potential criticism could be made in the implementation of Fibonacci strategy only on draws, claiming there is anything special with draws. Thus, I simulated a random betting strategy in which the amounts are determined according to the Fibonacci sequence. A random betting strategy is repeated 1000 times for all 8 leagues over 4 seasons and then the returns of this strategy are compared with the return achieved from the Fibonacci strategy on draws. For that purpose, I perform a t-test and Wilcoxon signed-rank test which is distribution-free and robust to event clustering (Palomino et al. 2009). The results, which are presented in Table 3, show that the returns from the Fibonacci strategy on draws yield a higher return compared to random the Fibonacci strategy in all seasons for all leagues under consideration at a significance level of 1% except French Ligue 2 in 2008/09 and Spanish La Liga in 2007/08. The strategy also produces a higher return in Italian Serie B (for season 2008/09) at 10% significance level. Only for two cases, namely French Ligue 2 in 2008/09 and Spanish La Liga in 2007/08, the returns from the random Fibonacci strategy outperform the Fibonacci strategy on draws and the returns from the random strategy are higher than the Fibonacci strategy on draws at 1% level. In sum, in 30 out of 32 cases, I reject the null hypothesis of equal means and show that the returns from a Fibonacci strategy on draws are statistically significant and exceed the returns from a random Fibonacci strategy.[5]

[5] Appendix 3 summarizes the returns from various betting strategies.

Table 3. Comparison of Fibonacci Strategy on Draws with Simulated Random Betting According to Fibonacci Sequence

Random Fibonacci vs Draw Fibonacci	**2005-2006**	**2006-2007**	**2007-2008**	**2008-2009**
France: Ligue 1	0.198	0.078	0.090	0.081
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
France: Ligue 2	0.049	0.044	0.283	-0.051
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Italy: Serie A	0.216	0.256	0.135	0.212
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Italy: Serie B	0.164	0.404	0.299	0.010
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.135)
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.122)
Germany: Bundesliga I	0.212	0.246	0.510	0.180
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
England: Premier League	0.443	0.203	0.535	0.340
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
England: League Championship	0.248	0.268	0.221	0.107
p-value of t-test	(0.000)***	(0.000)***	(0.000)***	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Spain: La Liga	0.244	0.331	-0.052	0.245
p-value of t-test	(0.000)***	(0.000)***	(0.064)**	(0.000)***
p-value of Wilcoxon	(0.000)***	(0.000)***	(0.000)***	(0.000)***

The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second rows following the difference between Fibonacci on draw and random betting according to Fibonacci. A positive difference indicates the outperform of Fibonacci on draws over random betting.
*, ** and *** indicate 10, 5 and 1% significance levels respectively.

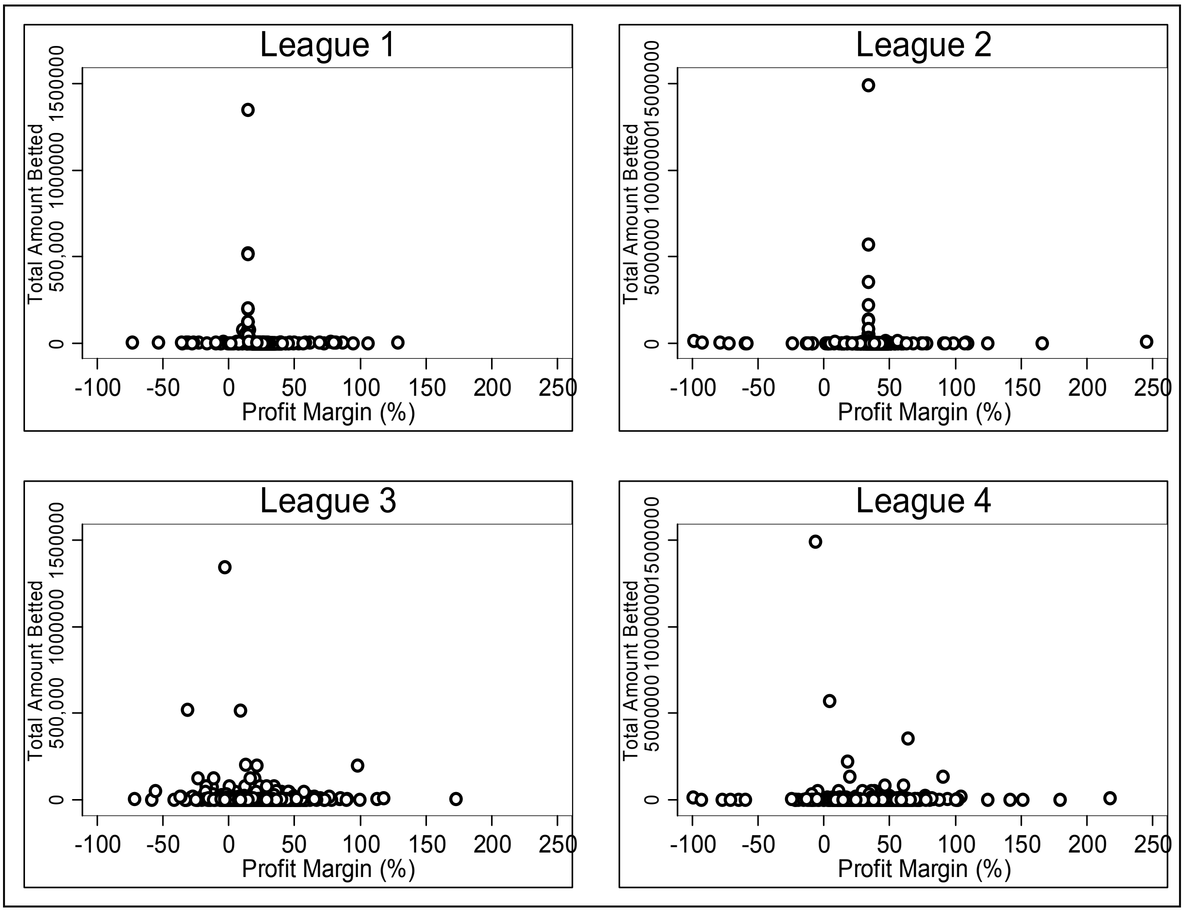
5.3. Betting on Simulated Data

The profitability of the Fibonacci strategy over so many Leagues and seasons is a noteworthy result, nevertheless it is does not guarantee the same will occur always in the future. In order to get a deeper understanding of the possible outcomes I implemented it in larger simulated dataset. The distribution of draws occurring in a league in a season is assumed to have a Bernoulli distribution with probability *p* for draws and with probability *1-p* for non-draws (home win or away win). As a first step, I simulate two leagues with the probabilities of 0.30 and 0.25, respectively, for draws. Both leagues are composed of 150 games, the approximate number of bets that can be placed according to the Fibonacci Strategy in a season for a League with twenty teams. The seasons are simulated 1000 times.

The fixed odd for all draws is assumed to be 3 for League 1 and 3.5 for League 2 as the odds for draw is lower in a league where the draws are more likely to occur. These two cases are used to compare the returns and amount wagered from a Fibonacci strategy under different league structures. The findings are reported in Figure 1 and the Appendix 2. The average total bet and profit margin are decidedly higher in League 2. As the draws are less frequent in League 2, the Fibonacci strategy requires more capital to sustain it, whereas the higher odd for a draw is increasing the profit margin. When negative profits are considered, the Fibonacci betting strategy yields negative profits 16 times in League 1 and 12 times in League 2 out of 1000 simulations, for a loss frequency of 1.6% in League 1 and 1.2% in League 2. So theoretically, the Fibonacci strategy is profitable with a probability of 98.4% and 98.8%.

The simulation went further by generating odds based on actual data instead of fixed odds to achieve more realistic findings. In simulated leagues with the draw probabilities of 0.30 and 0.25, respectively, I assume that in League 3 and 4 the odds are generated according to the historical mean and standard deviation values of Serie B (Italy) and Bundesliga I (Germany), respectively to tie the assumptions to real life experience. I use the generated odds based on historical values of Serie B (Italy) and Bundesliga I (Germany) as the mean of draws in these leagues are in parallel with the probability *p* used in the simulation. The findings are given in Figure 1 and Appendix 2. The use of the generated odds instead of fixed odds does not change the average profit margin values significantly. However, it causes the standard deviation of returns to increase, as seen in Figure 1 and Appendix 2. Similar to the findings of fixed odds, the Fibonacci strategy requires more capital where the draws are less likely to occur and the profit margin increases as bookmakers offer higher odds in these leagues. For the case of negative returns, League 3 yields a negative return for 108 cases, which indicates a positive return with the probability of 89.2%. This high number of negative returns is achieved due to the wide range of the odds for a draw in Serie B (Italy). As Table 2 reports, Serie B (Italy) has the highest value in terms of the difference between minimum and maximum values of odds with a relatively high standard deviation. This sometimes creates odds lower than 2.618 which are not sufficient for a profitable strategy. In league 4, the number of negative returns is 28 and strictly lower compared to league 3 due to higher odds offered for draw.

Figure 1. Betting on Draws Strategy Following a Fibonacci Sequence with Simulated Data



The distribution of draws occurring in simulated leagues is assumed to have a Bernoulli distribution with probability *p* for draws and with probability *1-p* for non-draws (home win or away win).
In league 1 and league 2 I use the fixed odds of 3 and 3.5, respectively. In League 3 and 4 the odds are generated according to the historical mean and standard deviation values of Serie B (Italy) and Bundesliga I (Germany), respectively as the mean of draws in those leagues are in parallel with the probability *p* used in the simulation.

6. Concluding Remarks

This study tests the efficiency of the soccer betting market by introducing a Fibonacci strategy similar to Archontakis and Osborne (2007) and extends it in many aspects. The proposed Fibonacci betting strategy assumes betting on draws in soccer leagues without any need for information on either teams or soccer. I find that Fibonacci strategy yields positive returns for all cases in which I implemented it in 8 European soccer leagues for 4 seasons. This occurs because the average mean of draws in major leagues of Europe is around 30% and the average odds for draws in the major leagues are narrowly distributed and over 2.6 which is the cut-off value for one unit of profit in Fibonacci betting rule. I report that the mean of odds for draws in all leagues are higher than 2.9 and could lead to a profit margin of 10%, therefore leaving sufficient room to exploit the market inefficiency, as long as the bettors have a sufficient capital to pursue the strategy. In simulation, I also find that in 30 out of 32 cases the returns from the Fibonacci strategy on draws are statistically significant and exceed the returns from a random Fibonacci strategy. In fact, the major drawback of this strategy is the need for capital to sustain the strategy when the draws do not appear for an extended period of time. To give a better sense of the risk in the nature of the Fibonacci strategy and determine the highest amount that a bettor must bet (or risk) to sustain the strategy, I measure its VaR. I find that the VaR of the Fibonacci strategy on draws is 143€ (assuming that the first bet is 1€) at 95% confidence level. In other words, there is only 5% chance that the strategy would require more than 143€. I run also a simulation procedure to assess the profitability of the strategy in a larger dataset, finding that under most circumstances it is profitable as well.

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APPENDIX 1 Results of Betting on Draws Strategy Following a Fibonacci Sequence in eight European Leagues

	Total Amount Betted	Total Return	Profit Margin	# of Single Bets	Highest Single Amount Betted
			France: Ligue 1		
2005-2006	568	727.2	28.03%	151	55
2006-2007	1096	1313.73	19.87%	150	144
2007-2008	1524	1847.5	21.23%	149	233
2008-2009	1147	1384.09	20.67%	142	233
			France: Ligue 2		
2005-2006	583	659.31	13.09%	98	144
2006-2007	397	439.92	10.81%	82	55
2007-2008	262	358.12	36.69%	89	34
2008-2009	337	365.58	8.48%	86	34
			Italy: Serie A		
2005-2006	325	404.6	24.49%	121	21
2006-2007	795	1,058.96	33.2%	118	89
2007-2008	4,883	5,733.33	17.41%	132	1,597
2008-2009	1,740	2,223.75	27.8%	139	377
			Italy: Serie B		
2005-2006	326	406.16	25.32%	111	21
2006-2007	449	652.2	45.26%	111	55
2007-2008	1,741	2,434.51	39.83%	50	610
2008-2009	330	378.95	14.83%	119	21
			England: Premier League		
2005-2006	10,443	15,674.78	50.1%	187	1,597
2006-2007	2,590	3,363.66	29.87%	178	610
2007-2008	1,485	2,363.48	59.16%	175	233
2008-2009	1,287	1821.19	41.51%	175	144
			England: Champions League		
2005-2006	601	819.09	36.28%	119	144
2006-2007	7,191	9,914.67	37.87%	125	2,584
2007-2008	546	746.62	36.74%	128	55
2008-2009	2,954	3,724.88	26.10%	129	610
			Germany: Bundesliga I		
2005-2006	533	695.01	30.4%	71	89
2006-2007	871	1,256.19	44.22%	94	144
2007-2008	1,345	2,204.38	63.89%	96	233
2008-2009	696	916.21	31.64%	95	89
			Spain: La Liga		
2005-2006	3,125	4,182.31	33.83%	188	610
2006-2007	2,138	3,002.56	40.44%	174	233
2007-2008	11,181	11,893.43	6.37%	168	2584
2008-2009	52,356	6,8638	31.1%	182	17,711

Profit Margin is calculated as the ratio of total return-total amounted betted to total amount betted. Highest Single Amount Betted is the maximum amount that a bettor have to bet (and have) to sustain the strategy.

APPENDIX 2 Summary Statistics for Betting on Draws Strategy Following a Fibonacci Sequence with Simulated Data

PANEL A

League 1; p=0.3; # of games per league=150; # of simulated leagues=1000; fixed odd=3.0

	Profit Margin	Total Bet	Total Net Payoff
Average	21.3	6 858.16	1 059.03
Min	-73.35	276	-3 964
Max	128.88	1 346 529	196 515
SD	11.29	50 708.83	7 399.03
Number of negative returns	16		

League 2; p=0.25; # of games per league=150; # of simulated leagues=1000; fixed odd=3.5

	Profit Margin	Total Bet	Total Net Payoff
Average	36.63	44 672.35	15 104.86
Min	-98.97	357	-121 008
Max	245.24	14 933 429	5 030 830
SD	15.02	527 808.8	177 951.9
Number of negative returns	12		

PANEL B

League 3; p=0.3; # of games per league=150; # of simulated leagues=1000; generated odds

	Profit Margin	Total Bet	Total Net Payoff
Average	21.28	6 858.16	696.25
Min	-71.63	276	-162 310
Max	172.6	1 346 529	192 755.2
SD	19.33	50 708.83	8 885.57
Number of negative returns	108		

League 4; p=0.25; # of games per league=150; # of simulated leagues=1000; generated odds

	Profit Margin	Total Bet	Total Net Payoff
Average	37.28	44 672.35	8 876.61
Min	-99.03	357	-980 759
Max	217.81	14 933 429	2 246 747
SD	20.59	527 808.8	91 970.26
Number of negative returns	28		

The distribution of draws occurring in simulated leagues is assumed to have a Bernoulli distribution with probability *p* for draws and with probability *1-p* for non-draws (home win or away win). The leagues are simulated with the given probabilities and leagues are composed of 150 games.
In league 1 and league 2 I use the fixed odds of 3 and 3.5, respectively. In League 3 and 4 the odds are generated according to the historical mean and standard deviation values of Serie B (Italy) and Bundesliga I (Germany), respectively as the mean of draws in those leagues are in parallel with the probability *p* used in the simulation.

APPENDIX 3 Returns from Different Betting Strategies in eight European Leagues

	DF	RF	H	D	A	R
			France: Ligue 1			
2005-2006	0.28	0.08	-0.12	-0.06	-0.14	-0.11
2006-2007	0.2	0.12	-0	-0.07	-0.2	-0.09
2007-2008	0.21	0.12	-0.1	-0.07	-0.14	-0.1
2008-2009	0.21	0.13	-0.11	-0.08	-0.12	-0.1
			France: Ligue 2			
2005-2006	0.13	0.08	-0.1	-0.06	-0.22	-0.13
2006-2007	0.11	0.06	-0.02	-0.15	-0.28	-0.15
2007-2008	0.37	0.08	-0.07	-0.06	-0.24	-0.12
2008-2009	0.09	0.14	-0.03	-0.15	-0.11	-0.1
			Italy: Serie A			
2005-2006	0.25	0.03	-0.11	-0.14	-0.25	-0.16
2006-2007	0.33	0.08	-0.13	-0.08	-0.24	-0.15
2007-2008	0.17	0.04	-0.06	-0.06	-0.22	-0.12
2008-2009	0.28	0.07	0.019	-0.17	-0.19	-0.12
			Italy: Serie B			
2005-2006	0.25	0.09	-0.08	-0.08	-0.27	-0.14
2006-2007	0.45	0.05	-0.13	-0.09	-0.21	-0.14
2007-2008	0.4	0.1	-0.13	-0.12	-0.2	-0.14
2008-2009	0.15	0.14	-0.08	-0.08	-0.15	-0.11
			Germany: Bundesliga I			
2005-2006	0.3	0.09	-0.2	0.055	-0.2	-0.11
2006-2007	0.44	0.2	-0.09	-0.13	-0	-0.07
2007-2008	0.64	0.13	-0.05	-0.13	-0.1	-0.09
2008-2009	0.32	0.14	-0	-0.16	-0.11	-0.09
			England: Premier League			
2005-2006	0.5	0.06	0.035	-0.29	-0.2	-0.15
2006-2007	0.3	0.1	0.006	-0.11	-0.26	-0.12
2007-2008	0.59	0.06	-0.1	-0.08	-0.28	-0.15
2008-2009	0.42	0.08	-0.06	-0.1	-0.18	-0.11
			England: Champions League			
2005-2006	0.36	0.11	-0.15	0.021	-0.18	-0.1
2006-2007	0.38	0.11	-0.01	-0.27	-0.05	-0.11
2007-2008	0.37	0.15	-0.12	0.012	-0.13	-0.08
2008-2009	0.26	0.15	-0.11	-0.04	-0.1	-0.08
			Spain: La Liga			
2005-2006	0.34	0.09	-0.16	-0.09	-0.03	-0.09
2006-2007	0.4	0.07	-0.07	-0.14	-0.07	-0.09
2007-2008	0.06	0.12	-0.02	-0.24	-0.02	-0.09
2008-2009	0.31	0.07	-0.04	-0.26	-0.04	-0.12

The numbers refer to the rate of return, which could have been achieved by betting on only home wins (**H**), only on draws (**D**), only on away wins (**A**), and on any possible result for each game randomly (**R**). Moreover, **RF** and **DF** represent random Fibonacci strategy and Fibonacci strategy on draws, respectively. The returns from random strategies are the averages of 1000 trials.

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Titolo della tesi : Three Essays on Sports Economics

Abstract of the PhD dissertation

In the first paper, I explore the behavioral pattern of bettors on their betting choices for draws by using the FIFA 2010 World Cup data collected from Turkish fixed odds betting market. Data shows that there is a draw bias among bettors as they prefer to bet mostly on win of a side. Experiments indicate that the draw bias can be explained by the preferences rather than the probabilistic judgment. The second paper considers the game-related performance of two listed soccer clubs of Italy namely Roma and Lazio. I introduce the performance of arch-rival in the analysis. When club supporters are experiencing the negative performance of their team, the news coming from the arch-rival results can change their investment decisions. The third paper implements the Fibonacci sequence on draws as a betting rule. As the odds offered by bookmakers are narrowly distributed, implementing the Fibonacci strategy for 8 soccer leagues of Europe for 4 seasons yields positive return for all cases.

Abstract della tesi di dottorato

Nel primo saggio, analizzo il comportamento e le scelte degli scommettitori Turchi riguardo le partite della Coppa del Mondo di Calcio 2010. L'analisi dimostra che vi è una distorsione nei riguardi dei pareggi, dato che gli scommettitori preferiscono scommettere sulla vittoria di una delle due squadre. E' stato condotto anche un esperimento che mostra che questo comportamento può essere spiegato dalle preferenze degli scommettitori piuttosto che dai loro giudizi di probabilità. Il secondo saggio analizza l'impatto die risultati delle partite sulle performance dei titoli azionari di due club quotati, Roma e Lazio. Nell'analisi introduco l'impatto che la performance del club rivale ha sui titoli della società. Quando una squadra perde la performance della rivale influenza la reazione del mercato azionario alla sconfitta. Il terzo saggio applica la successione di Fibonacci alle scommesse sui pareggi. Poiché le quote sui pareggi sono piuttosto stabili, in tutti i casi esaminati l'applicazione della strategia avrebbe portato a un rendimento positivo.

Firma dello studente

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