Radboud Universiteit

Master Thesis

''Favorite-longshot bias in European Football betting market: Differences between popular and non-popular football competitions.''

Abstract

''The aim of this study is to investigate whether the favorite-longshot bias, an anomaly in sports betting, is present in ten different European football competitions across five years (2013-2018). The study also examines the difference in returns of betting on popular competitions versus betting on non-popular competitions. After performing Welch t-tests on the returns of 47.022 football matches, the results show that a favorite-longshot bias exists in almost all competitions and that there is no significant difference in returns between football competitions.''

Keywords: sports betting, behavioral finance, anomaly, market efficiency, gambling.

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Table of Contents

1. Introduction

In sports betting, people have a tendency to bet on the underdogs since you will generate higher returns when underdogs win. However, real life events have shown that betting on favorites will lead to higher returns in betting on football matches. This is also known as the favorite-longshot bias, an anomaly in behavioral finance, and more specifically in sports betting. This behavioral bias is the tendency of bettors to overvalue ''longshots'' or underdogs in sports (Ali, 1977; Ates, 2004; Buchdahl, 2016; Cain et al, 2000; Quandt, 1986; Williams & Paton, 1998), where actual results on returns show that betting on favorites have higher expected value compared to betting on longshots (Ates, 2004; Lahvička, 2014). Several studies found evidence of this bias in pari-mutuel betting markets (horse races) as well as in fixed-odds betting markets (football) (Williams & Paton, 1998).

Lahvička (2014) distinguished three explanations for the favorite-longshot bias. The first explanation assumes that bettors are risk-lovers, and bookmakers lower the odds on longshot to take advantage of this (Weitzman, 1965). The second explanation states that bettors overestimate the probability that a longshot will win, where the bookmaker will take advantage of by assigning lower odds to the longshot and higher odds to the favorite. The third explanation consists of the problem of information asymmetry, where bookmakers try to protect themselves against mispricing. If bookmakers underestimate longshots and thereby misprice them, informed insiders or the general public could react faster than the bookmakers to new information that is provided. This makes the bookmakers careful in setting the odds on longshots to protect themselves against asymmetric information.

According to Buchdahl (2016), one explanation of the existence of the favorite-longshot bias is the misjudgment of low and high probabilities, which are predicted by possibility and certainty effects. In betting, individuals are expressing risk-seeking utility towards the longshots or underdogs, while expressing risk aversion towards the proposed favorites. This is a well-known bias which was first stated by Kahnemann and Tversky (1979), who found that people tend to overweight small probabilities and underestimate large probabilities. This could contribute to a higher attractiveness of gambling (Kahnemann & Tversky, 1979). The probability weights that individuals assign to formulate the utility preference are a consequence of the misperception of the probabilities that are involved, or the odds proposed. As a result, the favorite-longshot bias is considered as a cognitive bias (Buchdahl, 2016).

Another explanation for the favorite-longshot bias is given by the rank-dependent utility model of Quiggin (1982) who states that the subjective probabilities, which are the estimated probabilities of individuals, will lead to people giving higher weights to small probabilities and lower weights to high probabilities. There is a difference between overestimating small probabilities and giving more weight to small probabilities. However, the betting behavior of both choices is similar. Individuals will place too much bets on longshots and too few bets on favorites, leading to lower odds for the longshots and vice versa higher odds for favorites. The explanation of Coleman (2004) on the longshot bias is that it is behavioral in the sense that bettors will know the returns that are on offer but decide whether to be risk averse or risk embracing when investing in either the favorite or the longshot. Only a minority of bettors is said to have inside information or high skill that will lead to a significant advantage in betting.

Thaler and Ziemba (1988) show that market efficiency and rational expectations can be tested better in wagering markets than in stock or other asset markets, because each bet has a termination point that is well defined. At this termination point the value becomes certain, hence there are no problems with respect to evaluating fundamentals. In addition to that, wagering markets have a higher chance of being efficient because repeated feedback is used to facilitate learning. Therefore, betting markets are considered efficient according to Thaler and Ziemba (1988).

Sufficient research has been conducted on the existence of the favorite-longshot bias in football betting markets, especially in European betting markets. This study also researches the European football betting market, since European football competitions are the most popular and well-known competitions in the world. The findings of these studies are stated in the next section of the study. However, because of the fact that bookmakers have to keep markets efficient (Thaler and Ziemba, 1988) and therefore have a high stake in the existence of the bias in European Football, it would be interesting to see whether the favorite-longshot bias is more present in certain markets than in other markets. For example, a popular football betting market such as the English Premier League or the Spanish Primera Division have significantly more people betting on games in these football competitions than for example the Dutch Eredivisie or the Danish Superligaen. Therefore, the aim of this study is to investigate whether (1) the favorite-longshot bias is present in both popular European Football competitions and less popular European Football competitions and (2) whether a significant difference can be seen in the returns of betting on popular football competitions versus betting on non-popular football competitions. To my understanding, comparing popular and non-popular competitions on a difference in returns has not been researched before.

There is a twofold contribution of this study. First, this study will either confirm or contradict the previously found evidence of the favorite-longshot bias in football betting markets. Second, the study will potentially lead to new insights into the market efficiency of football betting markets when a significant difference in returns between certain competitions is found. This could potentially trigger future research into market efficiency of betting markets. In order to find whether a favorite-longshot bias exists and whether there are differences between competitions, this study needs to test multiple hypothesis.

The first hypothesis that has to be tested will try to determine whether a favorite-longshot bias is present in all the football competitions that are incorporated in the research. Recall that the favorite-longshot bias is present when bettors overvalue longshots, but actual results show that betting on favorites yield higher returns compared to betting on longshots (Ates, 2004; Lahvička, 2014). In this research, the assumption is made that a team is a 'favorite' when the probability to win is higher than 65%. The other way around, a team is considered a 'longshot' when the probability to win is lower than 35%. In the method section it is further explained why these percentages are used and how they are calculated. My expectations are that only betting on favorites will yield higher returns than only betting on longshots, which is in line with the findings of Cain, Law and Peel (2000). Therefore, the first hypothesis that will be tested on all competitions tests whether returns of only betting on favorites will yield significantly higher returns than returns of only betting on longshots.

After testing whether the favorite-longshot bias exists in European Football betting markets, the study tries to investigate whether there are differences in returns between football competitions. The study also tests whether significant differences in returns can be observed between popular football competitions and less popular football competitions. To define a popular league, the revenue from broadcasting rights are used[1]. The following figure shows the revenue from broadcasting rights of the ten European football competitions used in this research in the 2016/17 season:

Revenue from broadcasting rights of European football leagues in 2016/2017 (in mln euros)	
England	€ 3.221.000.000
Spain	€ 1.484.000.000
Italy	€ 1.244.000.000
Germany	€ 960.000.000
France	€ 819.000.000
Russia	€ 84.000.000
Netherlands	€ 81.000.000
Denmark	€ 56.000.000
Poland	€ 43.000.000
Sweden	€ 37.000.000

Table 1: Revenue from broadcasting rights of European football leagues in 2016/2017 (in mln euros)

As can be seen from table 1, the top five broadcasting rights earners do earn significantly more than all other European competitions and hence are considered popular. Thus, the highest football competitions in England, Spain, Italy, Germany and France are considered as popular. On the other hand, the highest football competitions in Russia, the Netherlands, Denmark, Scotland and Poland are considered as non-popular, assuming the broadcasting rights did not change significantly in the last two years. This study tests whether the returns of betting on non-popular competitions are significantly higher than betting on popular competitions. The definition of a difference between football competitions can be stated as a significant difference in returns for only betting on favorites. After testing for difference in returns, it is

[1] Derived from https://www.statista.com

also interesting to see whether the favorite-longshot bias is still present when all five competitions are merged. This will be measured with the same method that is used for the individual competitions.

After the returns were analyzed, the conclusion is that for nine out of ten competitions the returns on favorites are higher than the returns on longshots. Four out of ten returns were significantly higher, thereby indicating a favorite-longshot bias. Since only one competition had higher returns from betting on longshots than betting on favorites, it can be concluded that a favorite-longshot bias is present in the dataset. A significant difference in returns between popular and non-popular football competitions could not be examined, where returns on popular competitions were even higher than returns on non-popular football competitions. Furthermore, a favorite-longshot bias was discovered after merging all popular competitions together, as well as merging all non-popular competitions together.

The study will continue with explaining previous findings on the topic. The methodology of the research is explained in the next section, as well as the data that is used in the study and how the data parameters are justified. The results will be explained in the section after the methodology, as well as performing robustness checks on the obtained results. After explaining the results, a discussion will emerge where the results are justified by previous findings or contradicted by previous findings and give new insights into the behavioral bias. Furthermore, potential future research is suggested in the discussion section. The study ends with a conclusion, where the results are briefly stated again.

2. Literature review

In order to understand the findings of the favorite-longshot bias in previous literature, it is helpful to understand what the characteristics of efficient betting markets are and how bookmakers make these markets efficient. The following section will first go into the theory of efficient markets to understand how efficient markets are explained in terms of betting markets. Second, the role of bookmakers is described in the determination of odds to understand the efficiency of betting markets with the help of bookmakers. After, the results of other studies on the favorite-longshot bias are discussed, as well as contradicting literature about the anomaly.

2.1 Efficiency in betting markets

Thaler and Ziemba (1988) concluded that wagering markets have a higher chance of being efficient compared to financial markets because repeated feedback is used to facilitate learning. The efficient market hypothesis first quoted by Malkiel and Fama (1970) states that prices should reflect all available information and that there is no riskless profit to be gained when people have insider information. For sports betting markets to be efficient, a requirement is that there is no systematic deviation between expected game outcomes and a possibility of profitable arbitrage (Dana & Knetter, 1994). This implies that there should be no betting strategy that would win more than 52.4% of the time, also known as the 11-for-10 rule. The bettor needs to risk $11 for a chance to earn $10, which implies that the 'normal' bettor on average wagers at a loss (Vergin & Scriabin, 1978). Dana and Knetter (1994) found that individuals are incapable of forecasting the outcome of games. Furthermore, bettors overreact to noisy outcomes and thereby placing too much weight on the past performance while not considering recent performances in their expectations of the future. According to LeRoy (1989), betting markets are efficient when it creates fair bets (with an expected return of zero) on an information set. Even and Noble (1992) translate the three levels of the efficient market hypothesis of capital markets (weak, semi-strong and strong) into the betting markets. Betting markets are considered (1) weak when the terms of the bet and the prior betting outcomes are available, (2) semi-strong when all publicly available information is available, and (3) strong when both public and private information is available. The conclusion of Even and Noble (1992) is that it is not necessary for the market forecast to be an unbiased predictor of the actual outcome for gambling markets to be efficient. However, it is necessary that there is a 50% probability that the market forecast is higher than the actual outcome. When this condition is met, there is a weak form efficiency in betting markets. This study considers football betting markets to be at least weak form efficient.

2.2 Odd setting by bookmakers

According to the model of Levitt (2004), bookmakers have a three-way tradeoff for choosing profitable pricing strategies. Bookmakers can either balance the books, set the market-clearing price or be active in setting the odds. By balancing the books the bookmakers are passive in setting odds, meaning that they will lower odds of a team when large betting amounts are placed on this team until betting behavior balances. Avery and Chevalier (1999) conclude that bookmakers that balance their books are risk averse while bookmakers do not need any skill to forecast the outcomes of matches. An important note to this is that the odds set by bookmakers with balancing the books are not market efficient prices, as the true outcome probability of a match is biased by the adjustments made by the bookmaker. Because the bookmaker has a margin on the odds set, it should not be possible to follow an arbitrage betting strategy to lock in a risk-free profit. Furthermore, bookmakers are assumed to maximize profits and minimize risks in the process of determining the odds. Setting the odds in accordance to the bookmakers prediction of the match outcome is the second pricing strategy (Flepp, Nüesch & Franck, 2016). This strategy is proved feasible by Forrest, Goddard and Simmons (2005) as bookmakers turned out to be comparably good at predicting matches as the statistical models are nowadays. Therefore, this pricing strategy provides an efficient market while all available information about the match is incorporated in the price. The third pricing strategy is to actively set odds. This is done by deviating from the true outcome probability and thereby exploiting the preferences of bettors to achieve more profit. This requires bookmakers to be able to predict betting behavior. According to Makropoulou and Markellos (2011) active odds setting is an optimal response of bookmakers to the uncertainty of information. No matter which pricing strategy bookmakers use, the betting markets are inefficient when the bookmakers maximizes expected profit (Kuypers, 2000). In decreasing risks, bookmakers can differ bets to influence the demand for example by shortening odds for bets with high odds or by increasing odds for the low odds bets (Sestovic, 2017). This behavior of bookmakers could lead to the favorite-longshot bias according to Sestovic (2017). Ottaviani and Sorensen (2010) state that the favorite-longshot bias is more pronounced when bettors have more information and when the number of insiders increases. Realized market odds contain more information and less noise when amounts of bettors increase, making the posterior odds more extreme and thereby increasing the favorite-longshot bias (Ottaviani & Sorensen, 2010).

Given that gambling markets are at least weak form efficient, the existence of an anomaly in the form of the favorite-longshot bias is very surprising. The favorite wins more often than the market probabilities subjectively imply, and longshots win less often than the probabilities imply. This would violate the weak form market efficiency, since no bets should have positive expected value under this form of efficiency. One explanation for this anomaly is that gamblers are risk-loving, indicating that they do know what the correct probabilities are, but still prefer the bet that has a higher return and a lower probability (Cain, Law & Peel, 2000). This study investigates whether the bias described above is present in European Football betting markets.

2.3 Evidence of the favorite-longshot bias

As explained above, a bookmaker sets the odds in sports betting. The bookmaker also applies a margin to the odds, which ensures the profit of the bookmaker. This margin is set by shortening the odds relative to the fair expectation of each outcome happening (Buchdahl, 2016). For example, when two teams have the same fair odds of 2.00 and the bookmaker demands a margin of 2.5% equally across both teams, the bookmaker will shorten the odds of both teams to 1.95. The fair expectation of the outcome is then 2.00, but the odd that the bookmaker presents is 1.95. Buchdahl (2016) also states that odds of longshots are shortened more than odds on favorites. The reason for this is the favorite-longshot bias. The favorite-longshot bias could also be explained by insiders and outsiders according to Shin (1991). The model of Shin (1991) on horse racing shows that bookmakers are faced by some insiders and some outsiders. The insiders know which horse will win and the outsiders have preferences which are divided over all horses in the competition. Therefore, Shin (1991) demonstrates that odds have to be set in such a way that enough revenue can be used from outsiders to pay the winnings of the insiders, indicating that a favorite-longshot bias should exist under the outsiders.

Most studies found that the favorite-longshot bias exists in pari-mutuel betting markets, also known as horse racing (Ali, 1977; Quandt, 1986; Thaler & Ziemba, 1988). Pari-mutuel betting markets are markets were odds are given based on the total amount of bets that are placed on the winner and then divided by the sum of all the bets placed minus the track take. The track take is the percentage of all bets placed that the bookmaker gains from the bet. Thus, the odds in pari-mutuel betting are not known beforehand, whereas in fixed odds betting markets the odds are known before the match. For the past two decades, the football betting market is being investigated on the favorite-longshot bias and market efficiency. The results of the studies are stated in the next section.

2.4 Favorite-longshot bias in football

Vlastakis, Dotsis and Markellos (2009) examined the efficiency of the European Football betting market in the years 2002-2004 and found that the favorite-longshot bias is persistent in the dataset. The research also found that formal econometric models could lead to more accurate forecasts that can be used to form profitable betting strategies. Cain, Law and Peel (2000) examined the efficiency in football betting in the United Kingdom during the 1991/92 season, as well as the favorite-longshot bias in this betting market. Their results show that the favorite-longshot bias is persistent in this market both in results (home win, away win or draw) and in specific scores. Furthermore they found that certain trading rules could be profitable. Although some fixed odds for particular score outcomes offer profitable betting opportunities, this is rarely the case. Another study by Cain, Law and Peel (2003) examined the existence of the favorite-longshot bias in multiple sports for multiple years that differ for every sport. They found that the favorite-longshot bias is not only persistent in horse-race betting, but also in other sports such as boxing, cricket, snooker and tennis. However, they conclude that it is not clear whether the bias is persistent only in the very high and low ends of the possibilities, or if the returns as a result of betting increase as a function of a winning probability that is continuously monotonic. The authors also conclude that it remains unclear whether the evidence of a reverse bias holds or under which circumstances it might occur. More empirical evidence on this matter is needed before theories can properly explain this phenomenon. Results of Andrikogiannopoulou & Papakonstantinou (2011) show that prices that are set by bookmakers on football matches are inefficient, since a favorite-longshot bias can be seen in their dataset containing 10.000 football matches over the years 2005-2009. They conclude that the weak form of the efficient market hypothesis is violated due to the existence of the favorite-longshot bias in the football betting markets.

2.5 Favorite-longshot bias in other sports

Another finding of Cain, Law and Peel (2003) is that the favorite-longshot bias is not present in the betting market for baseball in the United States. Bookmaker margins and the degree of insider trading are said to be low in this sport, which could potentially explain the absence of the favorite-longshot bias. Namely, Woodland and Woodland (1994) claimed that bettors on baseball are the most knowledgeable sport gamblers. Furthermore, Shin's model showed that the favorite-longshot bias is persistent when there are enough insiders in the gambling circuit.

Lahvička (2014) concluded in his research on the absence of the favorite-longshot bias in tennis that it is much stronger in later-round matches, in high-profile tournaments and in matches between players that were lower ranked. He argues that these results cannot simply be explained by the overestimation of the chances of longshots or the risk-loving attitudes of bettors. The proposed results are consistent with the protective nature of bookmakers who are protecting themselves against better informed insiders as well as the general public who tent to exploit new information when it comes available.

2.6 Contradicting evidence on the favorite-longshot bias

Interestingly, Deschamps and Gergaud (2007) found a positive favorite-longshot bias for home and away odds, and a negative favorite-longshot bias for draw odds in the English Football betting markets between 2002 and 2006. A draw bias is identified in where betting on draws yields a higher return than betting on either home or away wins. Other researchers find mixed evidence of the favorite-longshot bias in other sports than horse races. Forrest, Goddard and Simmons (2005) found scant evidence of a favorite-longshot bias, whereas Kuypers (2000) did not found such a bias. Dixon and Pope (2004) on the contrary found a negative favorite-longshot bias, which implies that betting on longshots will yield higher returns than betting on the favorites. Although Dixon and Pope (2004) found this inefficiency as a judgmental bias, they were not able to explain the reverse favorite-longshot bias in terms of known cognitive biases. Gil and Levitt (2007) found that shorting favorites earned higher returns than going long on favorites in the 2002 football World Cup betting market. Finally, Woodland and Woodland (2001) concluded that in hockey (NHL), there is a reverse favorite-longshot bias. According to Woodland and Woodland (2001), strategies have been identified where profitable wagering is achieved. Also, this profitable strategy is considered simple, namely betting on heavy underdogs was found to be profitable over some seasons. It would be interesting to see whether similar strategies could lead to positive returns in the dataset used in this paper.

3. Data & Methodology

3.1 Data

The data used in this study is derived from www.football-data.co.uk. This website provides data of past football match results, going back to the year 1993 for some football competitions. Data is available for all football competitions that are considered in this study. For this research, the data of the years 2013 to 2018 is used, meaning five seasons of data per competition. The years 2013 to 2018 are used since this provides a realistic overview of the current market efficiency of football betting markets. Furthermore, some of the non-popular competitions examined in this study did not have data available for years before 2013. The data includes a lot of parameters such as the total score, the half time score, and pre match bet quotations from multiple betting agencies. For simplicity, the betting agency that is used in this research is Bet365. This agency is used because Bet365 is said to update the match odds every fifteen minutes. For example, Bet365 will devaluate the odds of the underdog, when all of sudden large amounts of bets are placed on the underdog. Therefore, the odds that are used in this research will represent the odds that the respective match had just seconds before the game started. An important thing to note is that bettors who placed a bet on the underdog prior to a change in odds will still play for the odds they put their money on. This constant updating of the bookmaker could potentially lead to the odds representing betting behavior better, therefore making the odds move into a more objective probability and increasing market efficiency. Moreover, Bet365 is said to be the leading bookmaker in football betting, with an average daily visitor amount of 6.110.000 and an annual amount wagered on sports of £52.56 billion[2]. Therefore, bettors on Bet365 wager an amount of £144.000.000 on a daily basis.

3.2 Methodological approach

The main method used to investigate the favorite-longshot bias is to use the subjective and objective probabilities of outcomes. A subjective probability is defined as the probability that a certain outcome will happen ascribed by an individual. The odds prior to a match are the basis of these subjective probabilities. Also, these probabilities are categorized by a certain interval. For example, one interval would include all the bets that have winning probabilities from 90% to 95%. This includes all odds in the range of 1.05 (=1/0.95) to 1.11 (=1/0.9). The objective probability is the probability that is derived post match, where it is calculated by dividing the number of wins of a certain category by the total matches played (Griffith, 1949; Ali, 1977).

The method of Cain, Law & Peel (2003) will be used in this study, since there are a lot of different odd categories used in this study. The probability of winning could in this study easily be calculated by recalculating the odds, or dividing one by the odds. For example, when an odd prior to the match is 1.20

[2] Derived from www.top100bookmakers.com

for the favorite, the winning probability is 1/1.20 = 0.8333 or 83.3%. The team that is considered the 'favorite' is the team that has the highest probability to win the match.

Furthermore, the categories of the winning probabilities can now more easily be derived with a constant interval. The used intervals between categories are steps of 5%, since this could better reflect the return distribution of different probabilities. For example, the winning probabilities 80-85% might have a positive return, while the winning probabilities of 85-90% might have a negative return. When these winning probabilities are viewed together in the interval 80-90%, the return might give a biased view of the true returns for some winning probabilities. This will also correspond better to the subjective probabilities, since a team with an objective probability of 95% or higher for example will most likely also have a subjective probability of 95% or higher. In this study, 7 of the lowest probability categories are considered 'longshots', whereas 7 of the highest probability categories are considered 'favorites'. Therefore, longshots are teams that have winning probabilities of 35% or lower, whereas favorites are teams that have winning probabilities of 65% or higher. The reason for choosing a winning probability of 35% or lower as longshots is that there is no longshot that has a probability of 40%. When one team in a match has a winning probability of 40%, the other team also has a winning probability of more or less 40%, so there is neither a favorite nor a longshot in this match. The reason for choosing a winning probability of 65% or higher as favorites is that in these matches, the team is most likely both objectively and subjectively the favorite team. If the team has an objective winning probability of 50%, it might be that subjectively this team is not the favorite in the match and hence the team should not be called a favorite. Therefore, the 65% winning probability boundary is chosen to ensure the team is both objectively and subjectively the favorite.

The next step in the analysis is to calculate the mean return per category. In the end, these mean returns are necessary to investigate the favorite-longshot bias. For this research, an imaginary 1 euro bet is placed on every match that is played. After doing this, the returns of all matches are generated in percentages and the mean return is calculated as follows:

$$Mean\ return\ per\ category = \frac{\sum returns\ per\ category}{Total\ matches\ played\ per\ category}$$

After calculating the mean return per category, a one sample t-test is conducted to investigate whether the returns achieved in a category are significantly different from zero. The t-test has the following function:

$$t = \frac{\bar{X} - \mu}{S/\sqrt{N}}$$

Where $\bar{X}$ is the average return of the category, μ is zero, S is the standard deviation of the category and N is the number of observations in that category. These t-values give an overview of which probability categories have a return that is significantly higher or lower than zero, with the assumption of normally distributed returns that have a mean of zero.

After obtaining these results, the average return of favorites and longshots is calculated by multiplying the average return per probability category that is considered a favorite or a longshot by the amount of observations in that category. Eventually, two average return, two amounts of observations and two standard deviations are calculated, one for favorites and one for longshots.

A two sampled Welch t-test is conducted on the sample of returns on favorites and on the sample of returns on longshots to obtain a t-value. Declare et al (2017) and Moser and Stevens (1992) argue that a Welch's t-test should be used by default, where normally a Student t-test is used. Namely, a Welch's t-test has a better control of Type 1 error rates when the assumption of equal variances is not met. In this research, the variances of longshots are higher than the variances for favorites and therefore variances are unequal. Furthermore, it loses less robustness compared to a Student t-test when variances are equal. A two sampled Welch t-test has the following formula:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{(s_1)^2}{n_1} + \frac{(s_2)^2}{n_2}}}$$

Where $\overline{X_1}$and $\overline{X_2}$ are the average returns of favorites and longshots respectively, s_1 and s_2 are the standard deviations of favorites and longshots respectively, and n_1 and n_2 are the number of observations of favorites and longshots respectively. After performing this t-test, the t-value will represent the difference in returns between favorites and longshots. Since the hypothesis is stated in such a way that the returns on favorites should be higher than the returns on longshots, a one sided t-test is sufficient for this research. When the t-value is equal to or greater than 1,645, the returns on favorites are significantly higher than the returns on longshots with a 95% confidence interval.

Potential differences in returns between popular and non-popular competitions are investigated with a similar two sampled Welch t-test as described above, however in this case the mean return of the whole sample is used. As the hypothesis states that returns of non-popular competitions should be higher than popular competitions, the t-value should be equal to or greater than 1,645 in order to conclude a significant difference in returns of betting on popular competitions compared to betting on non-popular competitions.

The main aim of the results is to show whether higher returns can be obtained from betting only on favorites in comparison to the returns from only betting on longshots. In addition, the returns per category are compared between two competitions, where one competition is considered popular and the other competition is considered non-popular, to see whether significant differences in returns for every category can be examined.

4. Results

In the following part of the study, the results are discussed. First, the presence or absence of the favorite-longshot bias in all competitions will be discussed. As explained above, this will be done by performing a t-test that will compare the returns of only betting on favorites by the returns of only betting on longshots. Second, the five popular competitions as discussed in the introduction will be compared with the five non-popular competitions to conclude whether significantly different returns can be achieved when you only bet in the popular competitions or when you only bet in the non-popular competitions. After these results, robustness checks will be done to strengthen the previous findings.

To give an impression of the dataset that is used, summary statistics per country are presented below:

Country	Number of observations	Min winning probability	Max winning probability	Mean return of all observations
England	5700	2,94%	92,59%	-3,314%
Spain	5700	2,44%	96,15%	-7,265%
Italy	5700	2,94%	94,34%	-9,382%
Germany	4590	1,96%	94,34%	-5,702%
France	5700	2,94%	96,15%	-8,024%
Russia	3660	2,07%	99,01%	-8,052%
Netherlands	4590	3,45%	94,34%	-6,996%
Denmark	3312	6,34%	86,21%	-8,653%
Poland	4440	6,57%	84,75%	-6,326%
Sweden	3630	5,34%	89,29%	-9,248%
Total/average	**47022**	**3,70%**	**92,72%**	**-7,179%**

Table 2: Summary statistics of all football competitions.

The total amount of observations therefore is 47.022, and the mean return of all competitions together is -7,179%. This means that for this dataset, an individual would have lost 3375,71 euro's if he would have bet 1 euro on every outcome in every game. In the following section, more detailed results are shown on the achieved returns to give a better view on how the returns are distributed.

4.1 Evidence of the favorite-longshot bias

The favorite-longshot bias can be tested by comparing achieved returns of the 'favorites' to achieved returns of the 'longshots'. Recall that a team is called a favorite when the winning probability is 65% or higher, and a team is called a longshot when the winning probability is 35% or lower. Table 3 shows the data of the English competition, the Premier League, where the data is divided into twenty probability categories. For every probability category the number of observations, the mean return, the standard deviation and the corresponding t-value are calculated. When the t-value exceeds the value of 1,645 (for a 95% confidence level), the return of the category differs significantly from zero.

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	20	0,000	0,000
0,05-0,1	7,373%	217	3,646	0,298
0,1-0,15	17,919%	346	2,864	1,164
0,15-0,2	-10,950%	484	2,105	-1,144
0,2-0,25	-6,330%	594	1,847	-0,835
0,25-0,3	-7,994%	1355	1,651	-1,783**
0,3-0,35	-2,972%	710	1,482	-0,534
0,35-0,4	-6,302%	265	1,333	-0,770
0,4-0,45	-10,843%	350	1,156	-1,755**
0,45-0,5	10,972%	252	1,061	1,642*
0,5-0,55	-1,381%	257	0,955	-0,232
0,55-0,6	3,819%	215	0,850	0,659
0,6-0,65	1,267%	161	0,773	0,208
0,65-0,7	0,952%	126	0,692	0,155
0,7-0,75	-5,705%	95	0,644	-0,863
0,75-0,8	4,631%	111	0,523	0,933
0,8-0,85	-8,315%	108	0,532	-1,623*
0,85-0,9	7,333%	30	0,292	1,374*
0,9-0,95	-18,000%	4	0,474	-0,760
0,95-1	0,000%	0	0,000	0,000

*Table 3: English Premier League statistics per probability category. Total number of observations: 5700. Significance levels: *=90%, **=95%, ***=99%.*

The table shows that five probability categories are significant (indicated with a *-sign), which means that these categories either have a positive or negative return that differs significantly from zero. However, it is very difficult to draw conclusions from this table, since there are only two probability categories that are significant at a 95% level. Furthermore the mean returns in some categories are positive significant, whereas the mean returns in other categories are negative significant. Similar tables of all other competitions can be found in Appendix A.

It is not possible to make assumptions about the presence of a favorite-longshot bias in table 2 because of multiple reasons. First, the returns of the lower probability categories are biased because draws are also included in this table that influence the mean returns and t-values of these categories. Second, to test for a favorite-longshot bias, the sum of the returns of all probability categories should be compared instead of the individual probability categories for favorites and longshots. For example, the probability category 0,8-0,85 has a mean return of -8,315% that is significant at a 90% level. This would mean that you would have a return of -8,315% when you only bet on teams that have a winning probability between 80% and 85%. This would contradict the belief of a favorite-longshot bias, since you would expect less negative or even positive returns in the favorite categories.

In order to test for the presence of the favorite-longshot bias, draws need to be filtered out. Then, the average return of the probability categories that are considered 'favorites' and the categories that are considered 'longshots' are calculated. This will lead to the following results for the English Premier League.

Longshots				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-100,000%	20	0,000	0,000
0,05-0,1	4,265%	211	3,601	0,172
0,1-0,15	18,952%	248	2,918	1,023
0,15-0,2	-6,615%	291	2,139	-0,527
0,2-0,25	5,978%	312	1,926	0,548
0,25-0,3	-8,665%	385	1,590	-1,069
0,3-0,35	-15,844%	359	1,375	-2,183**
Total/weighted average	**-3,003%**	**1826**	**2,231**	**-0,575**
Favorites				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	0,952%	126	0,692	0,155
0,7-0,75	-5,705%	95	0,644	-0,863
0,75-0,8	4,631%	111	0,523	0,933
0,8-0,85	-8,315%	108	0,532	-1,623*
0,85-0,9	7,333%	30	0,292	1,374*
0,9-0,95	-18,000%	4	0,474	-0,760
0,95-1	0,000%	0	0,000	0,000
Total/weighted average	**-1,388%**	**474**	**0,589**	**-0,513**

Table 4: Returns of longshots and favorites in the English Premier League for every probability category and for all probability categories combined. Significance levels: 90%=, 95%=**, 99%=****

Table 4 shows that the mean return of longshots in the English Premier League is -3,003%, whereas the mean return of favorites in the English Premier League is -1,388%. This implies that less money is lost when betting only on favorites compared to only betting on longshots. To test whether this result is significant, a two sampled Welch t-test is conducted on both returns. The t-value from this test is 0,275 which corresponds to a p-value of 0,784. A significant difference is assumed when the p-value is equal to or lower than 0,05. As this is not the case, it can be concluded that there is no significant difference in returns of longshots and favorites and hence there is no favorite-longshot bias present in the English Premier League. Even though the return on favorites is higher (less negative) than the return on longshots, it cannot be concluded that a favorite-longshot bias exists in this dataset.

The same research is conducted on the other competitions in this study. The results of all competitions are stated in table 5. Extensive results of the studied competition can be found in Appendix B. As the t-values show, four out of ten competitions have significant t-values. In Italy, France, Denmark and Sweden, the average returns of betting on favorites are significantly higher than the average returns of betting on longshots. Since the returns of favorites are compared to the returns on longshots, a positive t-value indicates a higher return on favorites. In Germany the t-value is surprisingly negative, indicating that the return on longshots is higher than the return on favorites, which would imply a reverse favorite-longshot bias. However, this result is not significant and therefore it cannot be concluded that there is a reverse favorite-longshot bias.

Country	Number of observations		Average return		T-value
	Favorites	Longshots	Favorites	Longshots	
England	474	1826	-1,388%	-3,003%	0,275
Spain	597	1785	-3,318%	-6,881%	0,610
Italy	516	1794	-1,891%	-19,094%	3,377***
Germany	355	1351	-7,346%	-4,862%	-0,390
France	350	1810	1,691%	-12,685%	2,687***
Russia	290	1134	-7,203%	-13,729%	0,938
Netherlands	457	1376	-8,514%	-15,496%	1,166
Denmark	142	943	8,852%	-14,106%	3,124***
Poland	126	1278	-2,349%	-4,708%	0,308
Sweden	261	1064	3,234%	-18,289%	3,286***

*Table 5: Average return of betting on favorites and of betting on longshots. Significance levels: *=90%, **=95%, ***=99%*

As nine out of ten European football competitions show higher average returns on favorites than on longshots, four of which are significantly higher, it can be concluded that there is evidence of an overall favorite-longshot bias in European football competitions. The null hypothesis that betting on favorites does not earn significantly higher returns than betting on longshots can be rejected for four of the ten competitions, namely the Italian, French, Danish and Swedish football competitions.

Another remarkable result from table 5 is that in the French, Danish and Swedish football competitions, betting only on favorites earn positive returns (1,691%, 8,852% and 3,234% respectively). This result was based on 350 observations in the French competition, 142 observations in the Danish competition and 261 observations in the Swedish competition. Therefore, there is a viable risk free betting strategy that could have earned 26,93 euro’s in five years if a 1 euro bet was placed on every football match in France, Denmark and Sweden where one team had a win probability of 65% or higher. Although this betting strategy earned positive returns for the past five years, I expect this result to be random and based on luck, since seven out of ten competitions did not earn positive returns on the favorites.

4.2 Popular versus non-popular football competitions

The second aim of this study is to examine whether betting on non-popular football competitions will earn higher returns than betting on popular football competitions. This assumptions is based on the fact that bookmakers set the odds for every football match. Therefore, odds are determined based on market efficiency. When new information about match details prior to a match reaches bettors first, the bettors could take advantage of this information because match odds are not adapted fast enough by the bookmakers. Popular football competitions are assumed to have more bets placed on the matches in these competitions. This means that bookmakers need to be updating the odds faster than people can react to new information and therefore need to keep markets efficient. Otherwise, potential arbitrage opportunities can arise. As less popular football competitions have fewer people betting on these matches, bookmakers could potentially not react to new information fast enough and bettors can exploit these opportunities. Less popular competitions could also have more insider information that the bookmakers do not know of when calculating the odds. Considering all this, the hypothesis is that betting on non-popular football competitions will result in significantly higher returns than betting on popular football competitions.

In order to test the hypothesis, all popular football competitions as well as all non-popular football competitions are merged. Then the average returns per probability category are calculated. Finally, the returns per probability category are multiplied by the observations of that probability category to calculate the total return. Table 6 shows the returns per probability category and the total return for both non-popular and popular competitions.

Probability Category	**Mean return**		**Number of observations**		**Standard deviation**		**T-value**	
	Non-popular	Popular	Non-popular	Popular	Non-popular	Popular	Non-popular	Popular
0-0,05	-100%	-59,686%	18	191	0,000	3,279	0,000	-2,515***
0,05-0,1	-42,322%	-31,976%	314	835	2,595	3,015	-2,890***	-3,065***
0,1-0,15	-17,565%	-5,817%	771	1603	2,426	2,592	-2,011**	-0,899
0,15-0,2	-11,899%	-10,819%	1229	1747	2,068	2,107	-2,017**	-2,146**
0,2-0,25	-9,788%	-8,957%	1918	2657	1,813	1,820	-2,365***	-2,536***
0,25-0,3	-5,212%	-7,157%	4381	5941	1,623	1,603	-2,126**	-3,442***
0,3-0,35	-8,889%	-5,226%	3666	4721	1,466	1,482	-3,672***	-2,422***
0,35-0,4	-4,088%	-6,911%	1281	1262	1,261	1,267	-1,160	-1,938**
0,4-0,45	-5,706%	-6,641%	1356	1815	1,157	1,161	-1,816**	-2,438***
0,45-0,5	-3,844%	-0,177%	1143	1358	1,054	1,060	-1,233	-0,061
0,5-0,55	-8,515%	0,186%	939	1346	0,959	0,960	-2,721***	0,071
0,55-0,6	-2,779%	1,445%	733	981	0,862	0,854	-0,873	0,530
0,6-0,65	-4,731%	-5,562%	607	641	0,788	0,786	-1,480*	-1,791**
0,65-0,7	-5,261%	-5,178%	475	725	0,712	0,710	-1,611*	-1,963**
0,7-0,75	3,724%	-6,199%	301	377	0,599	0,646	1,079	-1,863**
0,75-0,8	-3,485%	1,163%	233	392	0,570	0,549	-0,933	0,419
0,8-0,85	-11,081%	0,732%	185	447	0,543	0,461	-2,776***	0,336
0,85-0,9	0,413%	-2,255%	63	208	0,386	0,410	0,085	-0,792
0,9-0,95	1,875%	1,078%	16	116	0,264	0,276	0,285	0,421
0,95-1	3,000%	0,778%	3	27	0,016	0,202	3,182**	0,201
Total/average	**-7,737%**	**-6,786%**	**19632**	**27390**	**1,520**	**1,638**	**-7,134*****	**-6,857*****

Table 6: Non-popular and Popular competitions returns per probability category.
*Significance levels: *=90%, **=95%, ***=99%.*

Table 6 shows that especially the lower probability categories have returns that are significantly different from zero for all competitions. This can be seen in the returns as well, since the returns for the probability categories in the range of 0-0,45 are all below -5%, except for the category 0,35-0,4 for non-popular competitions (which is -4,088%). For several higher probability categories the returns are positive, however not significant. The mean return for all non-popular football competitions combined is -7,737%

and the mean return for all popular football competitions combined is -6,786%. There is one probability category in the table that shows a positive significant t-value. However this is the category 0,95-1 for non-popular competitions, which only has 3 observations with a mean return of 3%.

After performing a two sampled Welch t-test on the mean returns of both the popular and non-popular football competitions, a t-value of -0,648 is found. Since the t-value is not higher than 1,645 which is the critical value for a significance level of 95%, it can be concluded that there is no significant difference on betting returns between popular and non-popular football competitions. The hypothesis is therefore rejected. Actually, the return on popular competitions is even higher than the return on non-popular competitions.

After testing the presence of the favorite-longshot bias in every football competition, the same test is done for both the popular football competitions and the non-popular football competitions. The results that can be found in table 6 are used to calculate the mean returns on favorites and on longshots. Therefore, each competition is weighted equally in the analysis of returns, while the aim of the analysis is to separate popular competitions from non-popular competitions and not compare within the five popular competitions for example. The results can be found in table 7.

	Number of observations		**Average return**		**T-value**
	Favorites	Longshots	Favorites	Longshots	
Popular competitions	2292	6550	-2,457%	-12,450%	-3,550***
Non-popular competitions	1276	5807	-3,272%	-13,237%	-3,357***

Table 7: Favorite-longshot bias of popular and non-popular competitions. Significance levels: 90%=, 95%=**, 99%=****

The popular competitions show a return on favorites of -2,457% and a return on longshots of -12,450%. Calculating the two sampled t-test value results in a t-value of -3,550 meaning that the returns on favorites are significantly higher than the returns on longshots at a 99% confidence interval. As for the non-popular competitions, the results are very similar. Returns on favorites are significantly higher than returns on longshots at a 99% confidence interval (t-value of -3,357), indicating that a favorite-longshot bias exists in non-popular football competitions. In this data, the favorite longshot bias is slightly stronger for popular competitions than for non-popular competitions, because the differences in returns are higher for popular competitions (9,993%) than for non-popular competitions (9,965%) which can also be seen in a higher t-value (-3,550 compared to -3,357).

4.3 Robustness checks

The results in section 4.1 and 4.2 have shown that a favorite-longshot bias exists in several countries and that the bias exists for the whole sample. To check for veracity of the results, the following section consists of robustness checks. Robustness checks are conducted to strengthen the findings of both the existence of the favorite-longshot bias in the competitions and the difference in returns between popular and non-popular competitions.

4.3.1 Favorite-longshot bias

The first robustness check focuses around the definition of a favorite and a longshot in the dataset. Previously, a team was considered a 'favorite' when the probability of winning was equal to or higher than 65%. On the other hand, a team was considered a 'longshot' when the probability of winning was equal to or lower than 35%. By using these assumptions, the probability categories in the range of 0,35-0,65 were left out of the analysis. Arguably, a favorite is the team with the highest win probability. Therefore, when a team has a win probability of 50%, it is impossible that the other team also has a win probability of 50% due to the possibility of a draw in football matches. The analysis of the existence of the favorite-longshot bias is performed again, however this time a team is considered to be a favorite when the probability of winning is equal to or higher than 50%. On the other hand, a team is considered to be a longshot when the probability of winning is equal to or lower than 35%. The reason that the longshot probability is similar to the previous analysis is that when the probability of a team is around 40%, the other team also has a winning probability of around 40%, hence there is no favorite or longshot to be assigned. Only when the probability is equal to or below 35% a favorite and a longshot can be separated.

Country	Number of observations		Average return		T-value
	Favorites	Longshots	Favorites	Longshots	
England	1107	1826	0,011%	-3,003%	0,528
Spain	1170	1785	-3,048%	-6,881%	0,662
Italy	1164	1794	0,541%	-19,094%	3,992***
Germany	846	1351	-3,311%	-4,862%	0,252
France	973	1810	-1,857%	-12,685%	2,140**
Russia	682	1134	-3,372%	-13,729%	1,575*
Holland	1012	1376	-6,517%	-15,496%	1,551*
Denmark	535	943	-1,288%	-14,106%	1,962**
Poland	609	1278	-9,448%	-4,708%	-0,790
Sweden	717	1064	-2,430%	-18,289%	2,575**

Table 8: Returns on favorites and longshots per country with favorites including all bets with winning probability of 50% and higher. Significance levels: 90%=, 95%=**, 99%=****

Comparing table 8 to table 5 in section 4.1 it can be seen that in table 8, six out of ten competitions have significant differences between favorites and longshots, thereby exhibiting a favorite-longshot bias. In table 5 only four out of ten competitions had significant differences between favorites and longshots. Hence, by including more probability categories to favorites, the evidence of a favorite-longshot bias in European football competitions becomes stronger. In table 5, the German football competition showed less negative returns for longshots than for favorites. After including more probability categories for the favorites, this result reversed. However for the Polish football competition the effect reversed as well, where in table 8 the favorites have more negative returns than the longshots. A final notable different result compared to table 5 is that in table 5 three competitions (France, Denmark and Sweden) showed positive returns for favorites where after including the probability categories 0,5-0,65 as favorites these competitions showed negative returns. For two other competitions however, this effect reversed. In England and Italy, the returns on favorites were negative in table 5 (-1,388% and -1,891% respectively) and became positive in table 8 (0,011% and 0,541% respectively) after including more probability categories as favorites.

4.3.2 Popular versus non-popular competitions

The second robustness check concerns the difference in returns between popular and non-popular football competitions. Recall that in table 1, the broadcasting revenues of all football competitions in this research are stated. For this research, the top five competitions in this table were considered popular, whereas the bottom five competitions were considered non-popular. Because the broadcasting revenues are different, the amounts of bets placed on these competitions will differ as well. Therefore, it would be interesting to see how the mean return of both popular and non-popular competitions will differ when the returns are weighted according to the broadcasting revenue. For example, the total amount of broadcasting revenue for the popular competitions is 7.728.000.000 euro, and the broadcasting revenue of the English football competition is 3.221.000.000 euro, which is 41,68% of the total. In calculating the average return of popular football competitions, the return of the English football competition (-3,314%) is then weighted as 41,68% of the total return. After calculating the weights for all competitions, the weighted average return of popular football competitions becomes -5,939% and -7,726% for non-popular football competitions. After performing a two sampled Welch t-test similar to what has been done in section 4.2, a t-value of -1,218 is derived with a corresponding p-value of 0,112. Therefore, the returns on popular competitions still do not differ significantly to returns on non-popular competitions. Surprisingly, the returns are contradicting the hypothesis that returns on non-popular football competitions are higher than returns on popular football competitions.

5. Discussion

The results of this study show that there is evidence of a favorite-longshot bias in European football betting markets. This result confirms the findings of earlier studies, where the same bias was found in football betting markets. However, the results also contradict other studies. For example, the studies of Forrest, Goddard and Simmons (2005) and Kuypers (2000) found only scant or no evidence of a favorite-longshot bias. Deschamps and Gergaud (2007) found that markets were inefficient, because several betting strategies generated abnormal returns in the years 2002-2006. The authors indicate that the best possible strategy is to bet on the best available long draw odds, however this return is not significant.

Woodland and Woodland (2001) found that in the National Hockey League in the United States, strategies have been identified where profitable wagering is achieved. This strategy involved betting on heavy underdogs. After examining the football dataset used in this study there is also a profitable betting strategy that would generate a positive return over the last five years. However, betting on heavy underdogs in football is in most cases not profitable. The strategy that was showed to be profitable in this dataset was betting only on favorites in France, Denmark and Sweden when favorites are considered to have a winning probability of 65% or higher. The profit that would have been realized when this strategy was followed is 26,93 euros when 1 euro was bet on every outcome in the French, Danish and Swedish competition that had a favorite with a winning probability of 65% or higher. This example shows that market efficiency differs between sports, but in all sports betting markets the efficiency of the market is considered weak (Deschamps & Gergaud, 2007; Woodland & Woodland, 2001). The weakness of market efficiency in betting markets contributes to the existence of the favorite-longshot bias. Therefore, the football betting markets examined in this study are weak form efficient.

Furthermore, Dixon and Pope (2004) also found that betting markets are inefficient and that model probabilities constructed by the authors can be exploited in order to earn positive abnormal returns. Part of this market inefficiency can be explained in terms of judgmental bias, or in this study a reverse long-shot bias. An example of this judgmental bias is the under- or over-reaction to recent news. However Dixon and Pope (2004) had difficulties explaining the inefficiency in terms of cognitive biases. They conclude that the market of betting could be understand better when the other side of the market, or the volume of bets, will be studied. Studying this could be informative for the consensus expectations of bettors. For this research, studying the volume of bets could also be a possible measurement to either confirm or contradict the favorite-longshot bias that is found in the data.

To my understanding, comparing popular and non-popular football competitions on betting returns is something that has not been studied before. The similarity of the returns of popular and non-popular competitions could imply that the market efficiency is equal between these competitions, or that new information is processed fast enough in non-popular competitions so that no arbitrage opportunities will emerge. Although this research tries to make a difference between popular and non-popular football competitions, the difference might not be large enough to see a difference in returns. Namely, this study considers the Russian football competition to be non-popular, while the broadcasting revenue is €84 million annually. Therefore, it would be interesting to see when very non-popular football competitions are compared to the most popular football competitions. For example taking the Albanian, Lithuanian, Luxembourgian, Icelandic and Andorran football competitions will potentially lead to different results in returns. However, the data from these countries are not publicly available and therefore could not be compared to the data in this research. Possible future research could gather this data and perform similar analysis to this study to see whether the results will differ.

Future research on this topic could include a larger time period to investigate whether the results remain robust. In this study, the years 2013-2018 are examined. However, betting on football matches increased in popularity over the past years. When less bettors are betting on football matches, setting market efficient odds becomes less important for bookmakers. Therefore, it could be that betting on favorites or on longshots implied different returns then compared to nowadays. It will be interesting to see whether the evolution of gambling on sports led to differences in returns. Another way for future research to improve this study is to measure the amount of insider trading in betting markets. While insider trading affects the ability of bookmakers to forecast outcomes (Schnytzer, Lamers and Makropoulou, 2009), it will be interesting to see what the amount of insider trading per competition is and how this affects returns of betting on football matches. As football is heavily prone to matchfixing nowadays, this is a feasible matter to concern in future research. Another limitation of this research which can be corrected for in future research is that this research does not take into account multiple bookmakers and therefore multiple odds. In this research, Bet365 is chosen as the odd setter, while there are numerous bookmakers all over the internet. It will be interesting to see if large differences between odds of bookmakers can be seen and therewith if profitable betting strategies could be achieved.

6. Conclusion

In this study 47.022 football matches are analyzed from ten different football competitions over the years 2013-2018. Returns of betting on football matches were derived, where 1 imaginary euro was bet on every single match outcome. Then matches were divided into winning probability categories based on the odds given by the bookmaker Bet365. Average returns per probability category are calculated to give an overview of the distribution of returns for every competition. To be able to test the presence of the favorite-longshot bias, the data is split into odds that are considered favorites and odds that are considered longshots. Draws were left out of the analysis, since the possibility of a draw is not considered to be either a favorite nor a longshot. After calculating the average returns of all favorites and all longshots per competition, a two sampled Welch t-test was conducted to test for significant differences in returns. The hypothesis that was tested to find evidence for a favorite-longshot bias is that returns on favorites are significantly higher than returns on longshots. The results of this test showed that in four out of ten competitions, favorites earned significantly higher returns than longshots. One competition showed a reversed effect, however insignificant. After changing the benchmark of winning probabilities that were assigned to favorites, the results remained robust. Therefore, it can be concluded that in European football competition there is evidence of a favorite-longshot bias in the years 2013-2018. This evidence of the existence of the favorite-longshot bias in football is in line with the findings of for example Vlastakis, Dotsis and Markellos (2009), Cain, Law and Peel (2000), Cain, Law and Peel (2003) and Andrikogiannopoulou & Papakonstantinou (2011), who all found evidence of a favorite-longshot bias in football.

After examining the presence of the favorite-longshot bias in the data, this study tries to investigate whether particular football competitions could outperform other football competitions. The assumption was made that popular football competitions experienced lower returns than less popular football competitions because popular football competition betting markets are assumed to be more efficient. After merging the data of five popular competitions and five non-popular competitions, a two sampled Welch t-test was performed to determine whether average returns of the combined competitions differed significantly from each other. No significant difference between returns was examined, hence the conclusion is that there is no advantage to be gained when only betting on non-popular football competitions. Furthermore, the datasets described above were also tested on the existence of the favorite-longshot bias. When all popular competitions and all non-popular competitions were combined, the results remained robust, namely that the favorite-longshot bias was present in the data.

The conclusion of this study is that bookmakers underestimate the probability that favorites win football matches and therefore offer high prices for the underdogs. This causes bettors to bet more on underdogs, which is less profitable according to the analysis of returns in this study.

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Appendix

Appendix A: Returns per probability category

England:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	20	0,000	0,000
0,05-0,1	7,373%	217	3,646	0,298
0,1-0,15	17,919%	346	2,864	1,164
0,15-0,2	-10,950%	484	2,105	-1,144
0,2-0,25	-6,330%	594	1,847	-0,835
0,25-0,3	-7,994%	1355	1,651	-1,783**
0,3-0,35	-2,972%	710	1,482	-0,534
0,35-0,4	-6,302%	265	1,333	-0,770
0,4-0,45	-10,843%	350	1,156	-1,755**
0,45-0,5	10,972%	252	1,061	1,642*
0,5-0,55	-1,381%	257	0,955	-0,232
0,55-0,6	3,819%	215	0,850	0,659
0,6-0,65	1,267%	161	0,773	0,208
0,65-0,7	0,952%	126	0,692	0,155
0,7-0,75	-5,705%	95	0,644	-0,863
0,75-0,8	4,631%	111	0,523	0,933
0,8-0,85	-8,315%	108	0,532	-1,623*
0,85-0,9	7,333%	30	0,292	1,374*
0,9-0,95	-18,000%	4	0,474	-0,760
0,95-1	0,000%	0	0,000	0,000

Spain:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-43%	97	4,039	-1,056
0,05-0,1	-28,916%	249	3,224	-1,415*
0,1-0,15	-10,026%	389	2,581	-0,766
0,15-0,2	-6,892%	370	2,147	-0,617
0,2-0,25	-9,816%	499	1,819	-1,206
0,25-0,3	-6,202%	1138	1,641	-1,275
0,3-0,35	-1,160%	941	1,503	-0,237
0,35-0,4	-9,367%	237	1,278	-1,128
0,4-0,45	-6,286%	329	1,153	-0,989
0,45-0,5	-9,452%	281	1,051	-1,507*
0,5-0,55	-3,592%	255	0,963	-0,596
0,55-0,6	3,180%	194	0,849	0,522
0,6-0,65	-10,371%	124	0,791	-1,461*
0,65-0,7	-10,799%	169	0,726	-1,935**
0,7-0,75	-3,219%	73	0,640	-0,430
0,75-0,8	12,553%	85	0,459	2,519***
0,8-0,85	-4,508%	118	0,498	-0,984
0,85-0,9	-5,918%	61	0,445	-1,038
0,9-0,95	-1,723%	65	0,314	-0,443
0,95-1	0,654%	26	0,201	0,166

Italy:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	16	0,000	0,000
0,05-0,1	-66,452%	155	2,093	-3,953***
0,1-0,15	-31,997%	368	2,221	-2,764***
0,15-0,2	-10,664%	354	2,115	-0,949
0,2-0,25	-6,053%	608	1,850	-0,807
0,25-0,3	-10,442%	1200	1,601	-2,259**
0,3-0,35	-7,511%	993	1,496	-1,582*
0,35-0,4	0,477%	216	1,325	0,053
0,4-0,45	-5,989%	353	1,162	-0,968
0,45-0,5	-3,579%	273	1,060	-0,558
0,5-0,55	9,087%	300	0,950	1,656**
0,55-0,6	-1,927%	205	0,862	-0,320
0,6-0,65	-5,070%	143	0,787	-0,770
0,65-0,7	-8,200%	185	0,719	-1,552*
0,7-0,75	-0,783%	92	0,626	-0,120
0,75-0,8	-6,116%	95	0,595	-1,002
0,8-0,85	10,956%	90	0,349	2,976***
0,85-0,9	3,208%	48	0,356	0,624
0,9-0,95	9,000%	6	0,022	10,205***
0,95-1	0,000%	0	0,000	0,000

Germany:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-32%	31	3,772	-0,476
0,05-0,1	-50,442%	113	2,647	-2,025**
0,1-0,15	5,761%	243	2,697	0,333
0,15-0,2	-8,061%	245	2,124	-0,594
0,2-0,25	2,035%	434	1,914	0,221
0,25-0,3	-6,096%	1214	1,630	-1,303*
0,3-0,35	-4,968%	601	1,507	-0,808
0,35-0,4	-3,014%	284	1,227	-0,414
0,4-0,45	-6,989%	349	1,167	-1,119
0,45-0,5	-14,330%	230	1,043	-2,084**
0,5-0,55	1,009%	229	0,966	0,158
0,55-0,6	1,391%	169	0,856	0,211
0,6-0,65	-7,086%	93	0,794	-0,860
0,65-0,7	-9,167%	114	0,724	-1,352*
0,7-0,75	-20,763%	59	0,685	-2,327**
0,75-0,8	-10,063%	48	0,613	-1,137
0,8-0,85	8,431%	65	0,380	1,787**
0,85-0,9	-14,698%	43	0,506	-1,904**
0,9-0,95	8,808%	26	0,013	34,508***
0,95-1	0,000%	0	0,000	0,000

France:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	24	0,000	0,000
0,05-0,1	-50,495%	101	2,472	-2,053**
0,1-0,15	-4,864%	257	2,597	-0,300
0,15-0,2	-18,027%	294	2,046	-1,511*
0,2-0,25	-12,730%	522	1,800	-1,615*
0,25-0,3	-10,055%	1034	1,592	-2,031**
0,3-0,35	-7,470%	1476	1,451	-1,978**
0,35-0,4	-15,688%	260	1,179	-2,146**
0,4-0,45	-3,774%	434	1,168	-0,673
0,45-0,5	12,186%	322	1,063	2,057**
0,5-0,55	-4,708%	305	0,965	-0,852
0,55-0,6	0,707%	198	0,858	0,116
0,6-0,65	-9,158%	120	0,798	-1,257
0,65-0,7	3,916%	131	0,680	0,659
0,7-0,75	-4,534%	58	0,646	-0,534
0,75-0,8	-1,151%	53	0,569	-0,147
0,8-0,85	3,379%	66	0,441	0,623
0,85-0,9	5,769%	26	0,312	0,943
0,9-0,95	1,733%	15	0,272	0,246
0,95-1	4,000%	1	0,000	0,000

Russia:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	6	0,447	-5,477***
0,05-0,1	-37,642%	81	2,773	-1,222
0,1-0,15	5,660%	191	2,687	0,291
0,15-0,2	-7,909%	254	2,112	-0,597
0,2-0,25	-18,201%	358	1,727	-1,994**
0,25-0,3	-4,503%	575	1,601	-0,675
0,3-0,35	-16,214%	835	1,412	-3,318***
0,35-0,4	-4,400%	265	1,222	-0,586
0,4-0,45	6,746%	232	1,178	0,872
0,45-0,5	-1,923%	181	1,058	-0,245
0,5-0,55	-3,088%	148	0,960	-0,391
0,55-0,6	2,893%	121	0,853	0,373
0,6-0,65	-0,846%	123	0,784	-0,120
0,65-0,7	-9,983%	115	0,725	-1,476*
0,7-0,75	-5,315%	73	0,647	-0,702
0,75-0,8	-2,479%	48	0,569	-0,302
0,8-0,85	-9,769%	39	0,537	-1,136
0,85-0,9	-10,667%	9	0,507	-0,632
0,9-0,95	9,750%	4	0,013	15,011***
0,95-1	2,000%	2	0,010	2,828

Netherlands:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	-100%	12	0,000	0,000
0,05-0,1	-29,197%	137	2,870	-1,191
0,1-0,15	-10,455%	275	2,537	-0,683
0,15-0,2	-4,621%	330	2,162	-0,388
0,2-0,25	-5,008%	519	1,875	-0,608
0,25-0,3	-5,295%	1262	1,644	-1,144
0,3-0,35	-12,274%	383	1,430	-1,679**
0,35-0,4	4,382%	173	1,348	0,427
0,4-0,45	-8,345%	252	1,153	-1,149
0,45-0,5	-2,511%	235	1,060	-0,363
0,5-0,55	-11,686%	236	0,964	-1,862**
0,55-0,6	-3,562%	185	0,863	-0,561
0,6-0,65	5,321%	134	0,765	0,805
0,65-0,7	-11,492%	132	0,728	-1,813**
0,7-0,75	-2,519%	79	0,629	-0,356
0,75-0,8	-6,488%	84	0,595	-0,999
0,8-0,85	-15,825%	103	0,568	-2,826***
0,85-0,9	0,087%	46	0,392	0,015
0,9-0,95	-0,750%	12	0,300	-0,087
0,95-1	5,000%	1	0,000	0,000

Denmark:

Probability Category	Mean Return	Number of observations	Standard deviation	T-Test
0,05-0,1	-100,000%	22	0,000	0,000
0,1-0,15	-41,544%	79	2,066	-1,787**
0,15-0,2	-31,935%	185	1,866	-2,328**
0,2-0,25	-9,047%	296	1,784	-0,873
0,25-0,3	-6,473%	822	1,642	-1,130
0,3-0,35	-7,026%	643	1,474	-1,209
0,35-0,4	-1,379%	261	1,220	-0,183
0,4-0,45	-8,799%	249	1,155	-1,202
0,45-0,5	-6,877%	220	1,052	-0,970
0,5-0,55	-6,960%	175	0,961	-0,958
0,55-0,6	2,017%	117	0,855	0,255
0,6-0,65	-9,545%	101	0,799	-1,200
0,65-0,7	4,297%	64	0,684	0,503
0,7-0,75	18,175%	40	0,503	2,284**
0,75-0,8	4,963%	27	0,510	0,505
0,8-0,85	10,500%	10	0,388	0,855
0,85-0,9	16,000%	1	0,000	0,000
0,9-0,95	0,000%	0	0,000	0,000

Poland:

Probability Category	Mean Return	Number of observations	Standard deviation	T-test
0-0,05	0%	0	0,000	0,000
0,05-0,1	51,067%	15	3,987	0,496
0,1-0,15	-50,738%	80	1,934	-2,347**
0,15-0,2	8,547%	179	2,219	0,515
0,2-0,25	-9,855%	310	1,792	-0,968
0,25-0,3	-1,752%	876	1,650	-0,314
0,3-0,35	-5,576%	1298	1,494	-1,345*
0,35-0,4	-10,822%	353	1,246	-1,632*
0,4-0,45	-8,908%	390	1,155	-1,523*
0,45-0,5	-4,388%	330	1,050	-0,759
0,5-0,55	-12,107%	214	0,959	-1,847**
0,55-0,6	-10,719%	160	0,874	-1,551*
0,6-0,65	-10,569%	109	0,797	-1,384*
0,65-0,7	-3,000%	67	0,707	-0,347
0,7-0,75	5,081%	37	0,604	0,511
0,75-0,8	-10,875%	16	0,621	-0,701
0,8-0,85	-18,167%	6	0,634	-0,702
0,85-0,9	0,000%	0	0,000	0,000
0,9-0,95	0,000%	0	0,000	0,000
0,95-1	0,000%	0	0,000	0,000

Sweden:

Probability Category	Mean return	Number of observations	Standard deviation	T-test
0,05-0,1	-81,458%	59	1,424	-4,393***
0,1-0,15	-30,192%	146	2,258	-1,615*
0,15-0,2	-23,886%	281	1,936	-2,068**
0,2-0,25	-6,726%	435	1,814	-0,773
0,25-0,3	-9,110%	846	1,608	-1,647**
0,3-0,35	-5,110%	507	1,505	-0,765
0,35-0,4	-2,834%	229	1,289	-0,333
0,4-0,45	-6,584%	233	1,150	-0,874
0,45-0,5	-2,797%	177	1,062	-0,350
0,5-0,55	-5,855%	166	0,957	-0,789
0,55-0,6	-1,660%	150	0,863	-0,235
0,6-0,65	-9,750%	140	0,796	-1,449*
0,65-0,7	0,948%	97	0,696	0,134
0,7-0,75	11,014%	72	0,550	1,700**
0,75-0,8	-1,862%	58	0,559	-0,254
0,8-0,85	-1,296%	27	0,480	-0,140
0,85-0,9	14,571%	7	0,020	19,392***
0,9-0,95	0	0	0,000	0,000

Appendix B: Favorite-longshot bias tests per country

England:

Longshots				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-100,000%	20	0,000	0,000
0,05-0,1	4,265%	211	3,601	0,172
0,1-0,15	18,952%	248	2,918	1,023
0,15-0,2	-6,615%	291	2,139	-0,527
0,2-0,25	5,978%	312	1,926	0,548
0,25-0,3	-8,665%	385	1,590	-1,069
0,3-0,35	-15,844%	359	1,375	-2,183**
Total/weighted average	**-3,003%**	**1826**	**2,231**	**-0,575**

Favorites				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	0,952%	126	0,692	0,155
0,7-0,75	-5,705%	95	0,644	-0,863
0,75-0,8	4,631%	111	0,523	0,933
0,8-0,85	-8,315%	108	0,532	-1,623*
0,85-0,9	7,333%	30	0,292	1,374*
0,9-0,95	-18,000%	4	0,474	-0,760
0,95-1	0,000%	0	0,000	0,000
Total/weighted average	**-1,388%**	**474**	**0,589**	**-0,513**

Spain:

Longshots				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-43,299%	97	4,039	-1,056
0,05-0,1	-28,249%	177	3,340	-1,125
0,1-0,15	-14,829%	263	2,546	-0,945
0,15-0,2	2,253%	233	2,224	0,155
0,2-0,25	-7,486%	251	1,863	-0,636
0,25-0,3	0,340%	412	1,658	0,042
0,3-0,35	5,773%	352	1,475	0,734
Total/weighted average	**-6,881%**	**1785**	**2,267**	**-1,282**

Favorites				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	-10,799%	169	0,726	-1,935**
0,7-0,75	-3,219%	73	0,640	-0,430
0,75-0,8	12,553%	85	0,459	2,519***
0,8-0,85	-4,508%	118	0,498	-0,984
0,85-0,9	-5,918%	61	0,445	-1,038
0,9-0,95	-1,723%	65	0,314	-0,443
0,95-1	0,654%	26	0,201	0,166
Total/weighted average	**-3,318%**	**597**	**0,589**	**-0,513**

Italy:

Longshots				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-100,000%	16	0,000	0,000
0,05-0,1	-65,789%	152	2,113	-3,839***
0,1-0,15	-28,115%	305	2,280	-2,154**
0,15-0,2	-7,412%	226	2,172	-0,513
0,2-0,25	-10,276%	315	1,819	-1,003
0,25-0,3	-15,360%	406	1,547	-2,001**
0,3-0,35	-7,837%	374	1,414	-1,072
Total/weighted average	**-19,094%**	**1794**	**1,848**	**-4,375*** **
Favorites				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**t-value**
0,65-0,7	-8,200%	185	0,719	-1,552*
0,7-0,75	-0,783%	92	0,626	-0,120
0,75-0,8	-6,116%	95	0,595	-1,002
0,8-0,85	10,956%	90	0,349	2,976***
0,85-0,9	3,208%	48	0,356	0,624
0,9-0,95	9,000%	6	0,022	10,205***
0,95-1	0,000%	0	0,000	0,000
Total/weighted average	**-1,891%**	**516**	**0,597**	**-0,720**

Germany:

Longshots				
Probability Category	Mean returns	Number of observations	Standard deviation	T-value
0-0,05	-32,258%	31	3,772	-0,476
0,05-0,1	-42,857%	98	2,821	-1,504*
0,1-0,15	8,537%	164	2,715	0,403
0,15-0,2	-5,128%	156	2,185	-0,293
0,2-0,25	-1,846%	221	1,898	-0,145
0,25-0,3	1,209%	340	1,644	0,136
0,3-0,35	-5,780%	341	1,427	-0,748
Total/weighted average	**-4,862%**	**1351**	**2,030**	**-0,880**
Favorites				
Probability Category	Mean returns	Number of observations	Standard deviation	T-value
0,65-0,7	-9,167%	114	0,724	-1,352*
0,7-0,75	-20,763%	59	0,685	-2,327***
0,75-0,8	-10,063%	48	0,613	-1,137
0,8-0,85	8,431%	65	0,380	1,787**
0,85-0,9	-14,698%	43	0,506	-1,904**
0,9-0,95	8,808%	26	0,013	34,508***
0,95-1	0,000%	0	0,000	0,000
Total/weighted average	**-7,346%**	**355**	**0,601**	**-2,304*** *

France:

Longshots				
Probability Category	**Mean Return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-100,000%	24	0,000	0,000
0,05-0,1	-57,609%	92	2,340	-2,361**
0,1-0,15	5,952%	210	2,733	0,316
0,15-0,2	-14,720%	214	2,084	-1,033
0,2-0,25	-12,252%	353	1,804	-1,276
0,25-0,3	-13,801%	478	1,563	-1,930**
0,3-0,35	-5,551%	439	1,421	-0,818
Total/weighted average	**-12,685%**	**1810**	**1,855**	**-2,909*** **
Favorites				
Probability Category	**Mean Return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	3,916%	131	0,680	0,659
0,7-0,75	-4,534%	58	0,646	-0,534
0,75-0,8	-1,151%	53	0,569	-0,147
0,8-0,85	3,379%	66	0,441	0,623
0,85-0,9	5,769%	26	0,312	0,943
0,9-0,95	1,733%	15	0,272	0,246
0,95-1	4,000%	1	0,000	0,000
Total/weighted average	**1,691%**	**350**	**0,580**	**0,546**

Russia:

Longshots				
Probability Category	**Mean Return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	-100,000%	5	0,000	0,000
0,05-0,1	-36,863%	80	2,790	-1,182
0,1-0,15	8,322%	180	2,723	0,410
0,15-0,2	-10,788%	193	2,094	-0,716
0,2-0,25	-22,604%	197	1,704	-1,862**
0,25-0,3	-1,883%	231	1,609	-0,178
0,3-0,35	-26,806%	248	1,315	-3,211***
Total/weighted average	**-13,729%**	**1134**	**1,971**	**-2,346*** **
Favorites				
Probability Category	**Mean Return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	-9,983%	115	0,725	-1,476*
0,7-0,75	-5,315%	73	0,647	-0,702
0,75-0,8	-2,479%	48	0,569	-0,302
0,8-0,85	-9,769%	39	0,537	-1,136
0,85-0,9	-10,667%	9	0,507	-0,632
0,9-0,95	9,750%	4	0,013	15,011****
0,95-1	2,000%	2	0,010	2,828
Total/weighted average	**-7,203%**	**290**	**0,641**	**-1,914** **

Netherlands:

Longshots				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,05-0,1	-26,515%	132	2,921	-1,043
0,1-0,15	-18,510%	208	2,464	-1,083
0,15-0,2	-25,532%	188	1,956	-1,790**
0,2-0,25	-13,839%	242	1,787	-1,205
0,25-0,3	-8,919%	297	1,587	-0,969
0,3-0,35	-10,272%	309	1,404	-1,286*
Total/weighted average	**-15,496%**	**1376**	**1,948**	**-2,951*** **

Favorites				
Probability category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	-11,492%	132	0,728	-1,813**
0,7-0,75	-2,519%	79	0,629	-0,356
0,75-0,8	-6,488%	84	0,595	-0,999
0,8-0,85	-15,825%	103	0,568	-2,826***
0,85-0,9	0,087%	46	0,392	0,015
0,9-0,95	-0,750%	12	0,300	-0,087
0,95-1	5,000%	1	0,000	0,000
Total/weighted average	**-8,514%**	**457**	**0,614**	**-2,963*** **

Denmark:

Longshots				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,05-0,1	-100,000%	22	0,000	0,000
0,1-0,15	-40,795%	78	2,078	-1,733**
0,15-0,2	-32,938%	146	1,861	-2,138**
0,2-0,25	7,937%	175	1,901	0,552
0,25-0,3	-5,434%	249	1,598	-0,537
0,3-0,35	-11,527%	273	1,403	-1,357*
Total/weighted average	**-14,106%**	**943**	**1,684**	**-2,573*** **

Favorites				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	4,297%	64	0,684	0,503
0,7-0,75	18,175%	40	0,503	2,284**
0,75-0,8	4,963%	27	0,510	0,505
0,8-0,85	10,500%	10	0,388	0,855
0,85-0,9	16,000%	1	0,000	0,000
0,9-0,95	0,000%	0	0,000	0,000
Total/weighted average	**8,852%**	**142**	**0,583**	**1,808** **

Poland:

Longshots				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	0,000%	0	0,000	0,000
0,05-0,1	51,067%	15	3,987	0,496
0,1-0,15	-50,738%	80	1,934	-2,347**
0,15-0,2	7,485%	165	2,208	0,435
0,2-0,25	1,887%	222	1,875	0,150
0,25-0,3	-3,304%	381	1,604	-0,402
0,3-0,35	-7,516%	415	1,413	-1,084
Total/weighted average	**-4,708%**	**1278**	**1,753**	**-0,960**
Favorites				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	-3,000%	67	0,707	-0,347
0,7-0,75	5,081%	37	0,604	0,511
0,75-0,8	-10,875%	16	0,621	-0,701
0,8-0,85	-18,167%	6	0,634	-0,702
0,85-0,9	0,000%	0	0,000	0,000
0,9-0,95	0,000%	0	0,000	0,000
0,95-1	0,000%	0	0,000	0,000
Total/weighted average	**-2,349%**	**126**	**0,660**	**-0,400**

Sweden:

Longshots				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0-0,05	0,000%	0	0,000	0,000
0,05-0,1	-81,458%	59	1,424	-4,393***
0,1-0,15	-29,045%	134	2,288	-1,469*
0,15-0,2	-27,566%	196	1,908	-2,023**
0,2-0,25	3,522%	224	1,892	0,279
0,25-0,3	-15,144%	195	1,534	-1,379*
0,3-0,35	-12,480%	256	1,391	-1,436*
Total/weighted average	**-18,289%**	**1064**	**1,765**	**-3,381*** **
Favorites				
Probability Category	**Mean return**	**Number of observations**	**Standard deviation**	**T-value**
0,65-0,7	0,948%	97	0,696	0,134
0,7-0,75	11,014%	72	0,550	1,700**
0,75-0,8	-1,862%	58	0,559	-0,254
0,8-0,85	-1,296%	27	0,480	-0,140
0,85-0,9	14,571%	7	0,020	19,392***
0,9-0,95	0,000%	0	0,000	0,000
Total/weighted average	**3,234%**	**261**	**0,597**	**0,876**