Information and Prices on a Betting Exchange:

- A Study of the Market Microstructure and the Efficiency of a Betting Exchange

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ABSTRACT

We study the market microstructure of betting exchanges and investigate whether this new betting market is efficient by looking at 50 561 transactions conducted by 214 traders. Given that betting exchanges have many characteristics in common with financial exchanges, we hypothesize an odds clearing equilibrium framework in order to study efficiency on this specific market. First, we find that the adverse selection problem inherent in the odds of regular betting markets still exists on the new betting exchange although it has decreased. Second, we find that a few informed professional bookmakers skim the regular noise bettors through adverse selection and market power. These "sitting-duck" bettors participate in the loosing zero-sum game being less informed and not possessing the skill of properly assessing the fair probability and odds (price) of an outcome. We argue that the reason for these bettors' demand for unfavorable odds is rooted in irrational behavioral factors such as a risk-loving utility curve, overconfidence and gambling with small amounts for pleasure. Hence, we conclude that the market is weak-form inefficient. Seeing as the benefits of the bookmaker position is open to anyone on the exchange, we suggest bettors and arbitrageurs to take advantage of our profitable trading strategies of betting on favorites and booking on underdogs. With increased competition among bookmakers, the market could become more efficient.

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1. INTRODUCTION

"I would be a bum in the street with a tin cup if markets were efficient," Warren Buffet[1]

Betting exchanges are one of the most recent opportunities for online wagering. Through the proliferation of Internet, international betting companies now reach an exponentially growing population of gamblers even to parts of the world where gambling is regulated such as for example Sweden. These companies attract customers by providing more money back to gamblers and by providing opportunities for tax-free profit. What differentiates betting exchanges from betting with regular fixed odds betting companies is that anyone can be the bookmaker. The bookmaker role is now not only open to the state, nor to some international betting companies – it is now open to anyone.

Betting exchanges provide bet matching between gamblers and makes it possible to resell a bet before maturity thus facilitating price discovery more than with traditional betting markets. Therefore, the betting exchange is in theory much like a market for bets, similar to a limit-order-book financial derivatives market with short maturities, where the equilibrium price will be the odds that equilibrates the supply and demand side of each bet. This makes the betting exchange an excellent arena for financial research.

Previous financial research proposes that in perfectly efficient markets, participants use all information available to form their expectations of future asset values and contracts, which is ultimately reflected in prices. According to the Efficient Market Hypothesis (EMH), there should at least not exist useful information in historical prices (week form efficiency) as stated by Fama (1970). However, markets are seldom as efficient as suggested by this hypothesis. According to for example Kahneman & Tversky (1978), this is explained by investors taking decisions under the influence of behavioral biases. Turning to the fixed odds betting market, the odds are the prices. If profitable strategies based on prices exist, this should be reflected in biases found in the odds and hence inefficiency.

Betting has fascinated people for centuries and many minds have been occupied, if not to say obsessed, with research on potentially profitable betting, or should we say trading strategies. The search for new innovative ways of profiting from betting without having to rely on pure luck appears endless. It should be well-known that average gamblers face negative expected values on their bets, since gambling companies charge for their service and gain profits. In odds betting, this is reflected by low odds.

Previous research on betting strategies, e.g. Thaler & Ziemba (1988), has been able to show some evidence of simple strategies that yield improved average returns to bettors. However, in most cases the return has still, due to the high spreads charged, not been possible to turn into actually profitable betting strategies, instead they have merely served to decrease the average loss of a bettor. With betting exchanges allowing gamblers to wager directly with each other, without charging any spreads through lower odds new opportunities arise. Traders on a betting exchange trade on both sides of the transaction in a competitive environment. If the odds are very favorable for the bookmaker side i.e. low, other bookmakers may enter and offer higher odds with less margin. Alternatively, the bettor could decide to switch side and trade as bookmaker instead.

[1] Quote published in book about Warren Buffet by Lowe (1997).

1.1 Purpose

The purpose of this thesis is twofold. First, we investigate the market microstructure of betting exchanges. Second, we analyze the efficiency of prices at the betting exchange and consequently investigate whether it is possible to construct simple trading strategies. More specifically we aim to answer the two following questions:

1. *What is the market microstructure of the betting exchange?*
2. *Is the betting exchange efficient?*

1.2 Contribution

Our thesis contributes to Finance research in two main ways:

- *A new field of research*. The betting market has with shifting success been used in financial research. However, to our knowledge we are the first to discuss the new type of betting market referred to as "betting exchange" in the light of financial markets. This market is more similar to financial markets than most other betting markets and it provides a natural and increasingly available setting for empirical research of investor behavior.

- *Unique dataset*. We exploit a dataset of approximately 50,000 wagers placed by over 200 bettors at an online betting exchange. Two aspects make this dataset different and unique: First and foremost, the betting data comes from a betting exchange. Second, in contrast to most previous betting studies our dataset not only includes information on prices – we also have access to quantities of bets placed by different actors.[2] This allows us to understand more about the participants in the trading game.

1.3 Outline

The thesis embarks on addressing the first research question by discussing the market microstructure of the betting exchange by giving a definition of the betting exchange and then discussing the various participants active on it. Further, we go on explaining how trading on the exchange actually is carried out and we hypothesize a framework for analyzing the betting exchange. The model is based on the four pillars: *Adverse Selection, Subjective Probability of Outcome, Market Power* and *Behavioral Factors* which are further explained. By having laid a foundation for the thesis and tackled the first research question we move on to introducing previous research in the field in order to address the second research question about whether the market is efficient. This is done by forming various hypotheses, which are based on the betting exchange market microstructure, our framework and previous research. The hypotheses are then investigated by analyzing the unique dataset and conclusions are drawn. Going forward, we present the results and analyze these. Finally, we give ideas of topics for further research based on what we have learned in the course of our research.

[2] The only exemption that we have identified is Levitt "How do markets function?: An Empirical Analysis of Gambling on the National Football league" (2002).

2. WHAT IS A BETTING EXCHANGE?

2.1 Definition

Betting exchange - a person to person gambling web site:

"A betting exchange is an Internet web site where people set odds and place bets against each other using the exchange as an intermediary."

2.2 Who are the Actors on the Exchange?

At the betting exchange people can register accounts and gamble with others. The betting exchange facilitates gambling by matching buyers and sellers of bets providing administration of gamblers' accounts. The betting exchange acts as a *broker* between parties placing bets (i.e. person to person gambling). The concept is similar to that of a limit-order-book derivatives exchange, where in this case the commodity being traded is a bet contract rather than a derivative. The type of events available on large betting exchanges range from all types of sports to political decisions, TV shows. The exchange requires both parties to have credit enough on the accounts for the worst possible outcomes, effectively reducing bettors' counter-party risk to the risk of exchange failure. In addition, the broker often speculates i.e. takes a role of *liquidity trader* in order to uphold liquidity on the exchange.

For a bet on a specific outcome to be placed and matched, two parties must agree on a stake (quantity of money) and odds (price). This is handled similarly to stock exchanges orders. For the purpose of this thesis we will refer to a trader that places a bet as *bettor* and one offering odds as *bookmaker*. The bettor wagering on a home team wins if the home team actually wins. The bookmaker then pays the stake times the odds. If the home team does not win, the bookmaker retains the stake collected from the bettor. At the betting exchange, the bettor is referred to as *back*, since he backs a team or outcome, whereas the bookmaker "laying" the odds is called *lay*. Back is traditional betting on a specific outcome (backing an outcome), while laying the odds is the role of the bookmaker. In financial markets, back would correspond to *going long* while lay would correspond to *going short*.

2.3 How to Trade on the Betting Exchange?

Most betting on a betting exchange is a form of fixed odds gambling. We therefore limit ourselves to describing only such betting and bookmaking. The two types of orders, commonly referred to as back and lay, that can be placed on the betting exchange are illustrated bellow:

Figure 1: An Example of Events Quoted on the Betting Exchange

The figure shows how the odds are presented for a football game on a betting exchange. The best available odds for bettors on the outcome Arsenal winning are 1.3, to which $200 can be matched directly. For actors interested in a bookmaker position, the best odds with direct matching of up to $350 are 1.4.

Figure 1 shows a real world example of the information related to a soccer game typically displayed on a betting exchange. The detailed view, here showing the depth in the market at second best odds level, is often available to the users of the betting exchange. However, in this example we have simplified the numbers and odds quoted. The ticks between odds are one tenth with no odds quoted for smaller tick size.

- Back is the best available bid price on each possible outcome of the soccer event: Arsenal vs. Aston Villla
- Lay is the best available ask price on each outcome of the event.
- Within parentheses the market depths at the best price (odds) is displayed, i.e. the maximum available stake.

2.3.1 Betting

A gambler can bet on any of three outcomes: Arsenal wins, Draw or Aston Villa wins. Consider "backing" Arsenal by placing a bet on Arsenal as winner. When backing an outcome, the gambler wins if the event turns out to be true. This is the traditional type of betting that most people are familiar with. In that case the odds in the *Back column* are to be considered. Such a bet can currently be placed at odds 1.3 and matched directly as long as the stake is up to €200 as shown in Figure 1.

A bet can be placed to match all of, or part of, the total stake shown. If one wants to bet more than €200 and get direct matching, one needs to accept the lower odds of 1.2 on the amount exceeding $200, but below $650. An order of €300 at odds 1.2 will be matched according to first come first served and best odds. Therefore, the gambler will get odds 1.3 on €200 and 1.2 on the remaining $100. Hence, the back column shows the odds available to bettors wanting to back an outcome and achieve direct matching. These back odds suggestions have been provided by exchange participants acting as bookmakers.

The betting exchange is all about competition. If someone feels that a superior odds should be available, he would not take the odds on offer, but would simply adjust his "ask" to a higher odds when backing, and hope someone would lay him the bet (i.e. hope that a bookmaker will be willing to take on the bet). If asking for odds between 1.3 and 1.4, it would be displayed in the best odds available in the *Lay column* to the right.

2.3.2 Bookmaking

Instead of "backing" one of the three outcomes (winning if the outcome comes true), a trader may act as a bookmaker and lay one of the outcomes – i.e. in principle *bet against one of the outcomes* and consequently win if the outcome does not come true. Acting the role of a bookmaker is commonly referred to as lay for "laying odds". If you find it unlikely that Arsenal will win, or at least given the odds find it attractive to bet against Arsenal winning, you may consider laying the outcome, i.e. acting as a bookmaker on the outcome. You then consider the odds in the Lay column showing best available ask prices (odds). In Figure 1 bettors in the market ask for odds of 1.4 and above. At odds 1.4 you may thus lay up to $350 and get it matched directly. When laying odds you will lose and pay out a sum depending on the odds if the outcome in question comes true, whereas you retain the stake of the opponent if it turns out to be false. Therefore, low odds are desirable when laying odds. If you do not find the odds satisfactory, you can place a lay order of some amount at some lower odds of your choice and hope that it eventually will become matched. The Lay column shows the odds available to bookmakers wanting to lay an outcome and achieve direct matching. These bet odds suggestions have been provided by exchange participants wanting to act the traditional bettor role, such as the case of a bettor wanting to back an outcome and not being satisfied with the, by bookmakers laying odds, currently offered odds.

2.3.3 Exchange Matching with FCFS and Best Execution

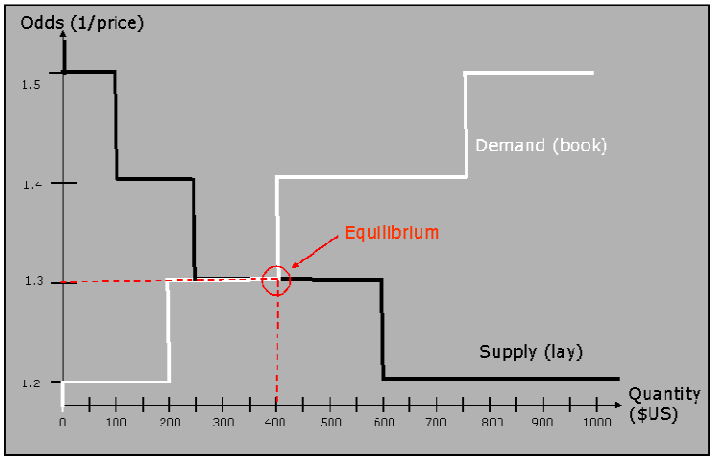
At the betting exchange a user's bet may be fully or partially matched with higher odds than asked for, when available. Thus, a large bet placed with lowest acceptable odds will still be matched with best odds possible until fully matched or until no more acceptable odds are available. This guarantees the best odds available at time of matching.

The stake of money available in the market view at each odds increment is a combination of one or more users' unmatched bets. Bets are, as mentioned, always matched at best odds and with the bet that was first placed, i.e. according to a *first come first served (FCFS) procedure*, which gives users incentives to offer odds early or offer odds better than those currently available.

The betting contracts not matched at maturity (the end date of the bet, normally some time before the event starts) are cancelled and the capital reserved is returned to the various market participants.

2.3.4 Equilibrium odds balancing supply and demand

Figure 2: Supply and demand of odds on the betting exchange



The figure depicts supply and demand for various odds on the betting exchange for the outcome of Arsenal winning vs. Aston Villa. At equilibrium bets with total stakes of $400 will be matched. There is still be more bookmakers wanting to book (lay) $200 at odds 1.3, but bettors require odds at 1.4.

In Figure 2 we see how the Arsenal vs. Aston Villa prices can be illustrated in an odds supply and demand schedule with the quantity being the stake amount and the price being the inverse of the odds. This is because odds in the traditional view of the bettor are more favorable the higher they are and vice versa. This inverts the supply and demand curves. In the figure, the equilibrium odds are the intersection of the supply and demand curves. The figure shows a market where the equilibrium odds of 1.3 results in bets of a total of 400 USD being placed in the market. There are still agents willing to lay at odds 1.3, but no more demand for placing bets on 1.3. Bettors who want to back the outcome demand odds of 1.4.

Demand: For gamblers the attractiveness of backing a certain outcome with a certain subjective probability increases with the odds ceteris paribus. The higher the odds, the more gamblers will find the bet of interest and they will be willing to bet more on the outcome. This is given that the expected subjective probability of the event does not change as odds change. One way to look at it is to say that as the odds go up, the stake at risk stays the same, implying that the price (the money at risk) relative to each unit of potential gain decreases. For example, if odds are 1.1, the potential gain of 0.1 comes at the risk of 1, i.e. a risk (cost) of 10 for each unit of gain being correct. If odds are 2, the potential gain of 1 comes at risk of 1, put in other words, when the price decreases (odds increases), the demand for a particular bet increases.

Supply: On the contrary, the attractiveness of laying a certain outcome increases with lower odds. When laying odds, the upside always retains hundred percent of the backing party's stake. The potential cost is the promised return being wrong (the stake times the odds minus the stake), which increases with the odds. Therefore, when odds increase, fewer and fewer will be willing to take the lay side of the bet, i.e. the supply of willing bookmakers and bookmaking amount will decline. This is illustrated in the supply demand diagram as seen in Figure 2.

Keeping the supply and demand concept in mind will be useful when analyzing the betting exchange data and explaining the dynamics of the exchange relative to traditional betting where the bookmaking side, laying odds, face little or no competition. There is a bargaining game with parties agreeing on odds. If one side has more power (e.g. less competition), it can take advantage of the other and biased odds can be set in a favorable or unfavorable manner.

2.4 What are the common characteristics of Betting and Financial Exchanges

There are many parallels between financial- and betting markets. Therefore a strand of Finance research has used betting markets as a type of natural experiment setting to learn about investor behavior and efficiency of prices. When comparing the new betting exchange with financial exchanges, we find an increased level of similarity that makes the betting exchange more useful than previous betting markets.

2.4.1 Similarities

Efficient Market Hypothesis: The idea of the efficient market hypothesis is useful and often discussed in betting as well as in financial markets. In an efficient market, the market price is an unbiased view of the "true" present value of some type of asset. In financial markets, the markets form expectations of future cash flows and the true value is typically not revealed, which causes efficiency tests to focus on asset return predictability. However, the efficient market hypothesis is also very applicable to many other competitive markets. In the betting market it is of interest whether the odds (price) show an unbiased expectation of the value of a bet, or if the bet is biased. If biases are present, bettors or arbitragers should be able to profit on such betting inefficiencies. Our view that stock trading and betting bear a strong resemblance is also corroborated by the fact that many stock traders and bettors have the same psychological traits, both making decisions under risk and facing problems with information and rationality. There are studies showing that stock traders often are frequent gamblers and hence that the participants are to some degree the same people (Govoni, Mann and Wynne (2004)).

Limit-order-book: The betting exchange has the same setup as a limit-order-book exchange. The betting exchange contrasts to betting markets with only one bookmaker quoting odds in a way similar to New York Stock Exchange in contrast to a quote driven exchange (OTC) such as NASDAQ where there are market makers providing the bid and ask quotes. The market makers usually charge a spread or a premium in order to compensate themselves for the risk of trading (betting) with better informed traders. There is always a risk that the market makers offering prices in both directions, buy/sell a financial asset or back/lay a bet, deal with better informed investors. Market makers that post prices or odds thus need to compensate for risk with a spread and closely follow the behavior of others frequently by continuously adjusting prices or odds as transactions are made. The same applies to the traditional bookmaker setup used at betting sites such as Unibet. On the betting exchange, any sellers (buyers) can place offers (bids) in the limit-order-book and wait until the orders are executed; or, alternatively, they can trade immediately by placing a market order against the existing bids (offers). And the large difference from traditional bookmakers is that other trader's positions are available to all actors creating more transparency.

Zero sum game: Just like in financial markets there is a trade-off between risk and return facing the investor. The activity on the betting exchange is similar to the "stock trading game", which as opposed to the "stock holding game", is a zero-sum game, seeing as the long run growth in the stock market has minimal effect over short periods. This ignores transaction costs, which are relatively higher at the betting exchange. Sport betting can therefore be compared to day-trading or trading in financial derivatives.

Subjective probability of outcome: A lot of lotteries and casino games are pure non-skills games. The skills possessed by the gambler cannot affect his chances of winning. Betting with fixed odds on the other hand is a skills game with analysis of information available about e.g. two teams that are to meet in a competition. Based on information, more and less educated guesses and probability estimates can be made. Similarly to a derivative, a fixed-odds betting event has a maturity date when it either pays out the amount at stake times the price (odds) or zero (the amount at stake is retained by the bookmaker).

Adverse Selection: On both financial and betting exchanges, investors with heterogeneous beliefs and information make decisions under risk by trading in an asset (at the betting exchange in bets instead of a commodity or currency) as uncertainty is resolved over time. The heterogeneity in information makes adverse selection problems possible on the market. For trading in stocks, the introduction of Internet and the following decrease in transaction costs meant a boom for private stock investments. Similarly, the higher pay-back ratios and availability of betting opportunities (no need anymore to find an ATG office, possible to play from home or work) nowadays provide a basis for a steadily and quickly growing betting market. This is likely to be taken advantage of by professional bettors (informed and skilled) as more and more uninformed ordinary bettors enter the market.

Arbitrage: Further, as is the case on OTC trading markets with several brokers, there are hundreds of betting exchanges and other alternatives that quote odds on the same games. Information and comparison is needed to get the best odds (price) available. This sometimes gives rise to the existence of arbitrage opportunities betting on the same event at shifting prices and same or all outcomes between sites as stated by Marshall (2005).

2.4.2 Differences

The most fundamental difference between betting- and financial exchanges are that there is *no added value to society except entertainment* whereas financial markets and financial contracts normally serve a purpose in the economy – gambling add little of no such value to society. Betting is instead a type of entertainment, a source of excitement or a chance to fulfill a dream.

No fundamental underlying value: Another difference is that a bet does not have a fundamental underlying value from the beginning of the trade which is normally the case for a derivative. Betting is in that sense like an option which has some value when bought and it then possibly changes in value during the time span towards maturity depending on how the underlying instrument develops, or in this case the expectations on the outcome of the event. In contrast to a stock, but similar to a forward contract and stock options, a betting event does not have a perpetual life span. The life span of a bet with few exceptions is short, i.e. a week or a couple of days, whereas a company in theory could exist for ever and its underlying value is not revealed (underlying value of bets is always revealed at expiry). One could thus compare a betting contract to a weather derivatives contract.

Small bets: Regular unprofessional players typically gamble with small affordable stakes. In gambling, low stakes are commonly pooled together to very large prices changing the life of a lucky winner. However, such games consequently have very few winners - almost everyone lose 100% of their stake and risk increases with higher possible win (return if winning). Hence, bettors typically invest small amounts at very high risk. Small bets may lead to high relative cost of information, causing bettors to place bets with no or limited information. Placing small bets may also lead to a lack of interest (ignorance) in bets that can only give a tiny return, such as low odds in fixed odds betting.

Unskilled bettors: Betting is in contrast to trading in financial markets, easily available and requires a minimum of time and resources to enter. Anyone can quickly set up an account and transfer money from a credit card. Furthermore there are in most cases no tax and few or no contracts to sign. Almost everyone has some prior experience of games from ATG branch offices or other types of betting. This suggests that bettors on average are rather unsophisticated compared to actors on derivatives markets. Bettors are more like private people buying stocks.

Less liquidity: The betting exchange is affected by supply and demand. As the betting exchange is a rather new phenomenon, gamblers might initially be more comfortable going long as bettors rather than taking the, often perceived as more risky, bookmaking (short) position. A low supply of bookmakers could keep prices up i.e. odds down.

No natural need for hedging: In financial markets there are incentives for participation of natural hedgers. In betting markets we do not have natural hedgers. Bettors could possibly claim their participation is for an emotional hedging purpose betting on opponents of their favorite team.

2.5 Market regulation

The regulatory framework constitutes a key aspect of many types of markets. In particular financial markets are highly regulated. The market of financial institutions is one of the most regulated markets in the world. This is driven by the impact failures and fraud can have on the society on these markets. Likewise, gambling markets across the world are subject to heavy regulation. The Swedish gambling and lottery market is not an exception – it is regulated. Sweden has in principle a government monopoly on gambling. In some other parts of the world, gambling is even forbidden.

The regulations of a market determine what actors are allowed to do and can contribute to a better functioning market. However, it can naturally also introduce problems in the market. On the fixed odds betting market, government regulation affects the efficiency and quality of the market. This effect can be briefly examined by comparing prices on regulated markets with less regulated markets. On the Swedish gambling market, a betting exchange like the one studied in this thesis can in principle not function. First, Svenska Spel has monopoly on gambling. Second, Svenska Spel is not allowed pay-back ratios anywhere near those supplied on a betting exchange. Therefore if the government was to create a betting exchange with the current gambling legal setting, transaction costs on the exchange would most likely bring liquidity to zero and the market would dry up.

2.6 Summary of the Most Important Betting Exchange Characteristics

This chapter has laid the foundation for our further study of the betting exchange market microstructure as well as the efficiency of the market. We therefore summarize the most fundamental and pertinent characteristics that will have further bearing on answering our two research questions.

Table 1: Summary of betting exchange characteristics

- The betting exchange makes it possible to go long and short as both bettor and bookmaker increasing competition
- The betting exchange has a limit-order-book setup instead of quote driven trading
- Less regulation and more competition than in traditional bookmaker settings
- Betting is a skill game with a subjective probability of outcome
- Zero-sum game

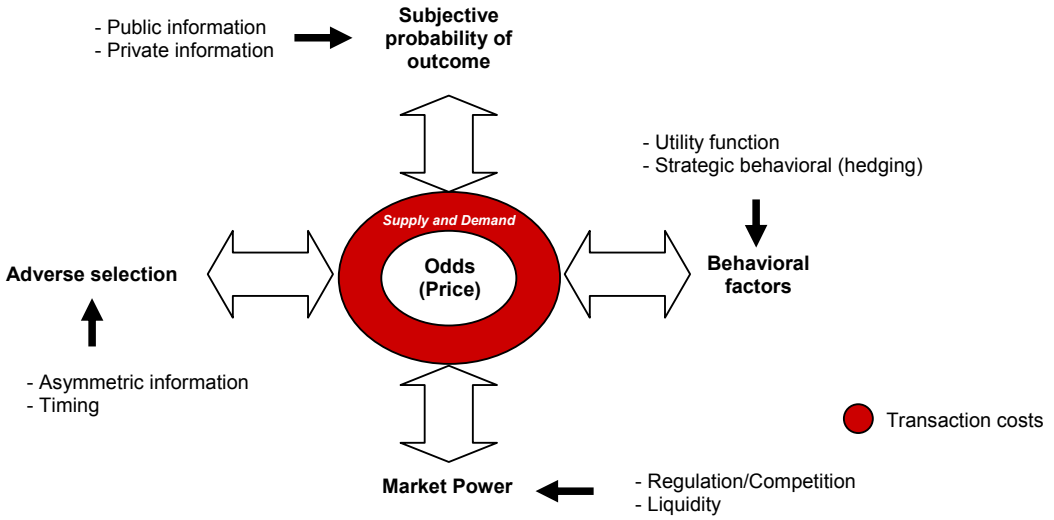
The betting exchange is structured in a limit-order-book setup and makes it possible to go both long and short, which increases competition in price setting. This together with deregulation would suggest that the betting exchange could be more efficient and display less adverse selection problems than the more traditional betting markets. The fact that betting is a skills game of assessing a probability and that most are unskilled traders makes it probable to suggest that some actors are more successful than other in a zero sum game. We now go forward to more in detail discuss the price setting mechanism on the betting exchange.

3. HOW ARE ODDS FORMED

What are odds? How are odds formed, interpreted, quoted, and how do bookmakers act? And more specifically how can we investigate whether the market is efficient? These are questions to be briefly discussed in the following sections. In order to answers our two research questions, we hypothesize a framework for the limit-order-driven betting exchange and try to explain how market prices arise from the interaction of a large number of anonymous traders, who arrive at the market at random times, can choose whether to trade immediately or to wait, and can behave strategically by changing their orders at any time.

Odds, just like derivative prices, are influenced by *supply and demand factors* and we have identified four areas of influence throughout our study that we find important to discuss in order to assess efficiency: *the subjective probability of outcome*, *adverse selection*, *behavioral factors and market power*.

Figure 3: Bongart & Conradsson Odds Clearing Equilibrium Model



The figure displays a hypothesized model for the factors affecting supply and demand setting the odds clearing equilibrium on a betting exchange. The four factor model should be interpreted in such that the four factors affect the price as well as each other trough supply and demand.

3.1 Subjective probability of outcome

Supply and demand is in part a function of how people perceive the quality of a commodity. In the betting context, odds are set subjectively and correspond to a price for the right to the outcome of an uncertain event. The more correct odds reflect the true probability of an outcome the better is the quality and hence the more efficient is the market.

Odds indirectly reflect the subjective probability of an outcome. High odds correspond to unlikely outcomes and low odds to likely outcomes. This subjective probability is derived from the participants' beliefs about the outcomes, which in turn often is derived from *historical data* such as the current standing in the league table, number of wins or losses lately etc. Secondly, *fundamental information* such as new signings, current team player skills etc are incorporated in odds. Thirdly, *inside information* like unreported injuries, bribed referees etc, which is only available to a limited number of persons play a role. The final odds thus will reflect at least these three sources of information and depend on the stakeholder's skill of assessing the right probability.

One can try to describe the subjective probability content in the odds more formally. First, assume a simple linear utility function U_i without regards to expected value volatility, only dependent on the dollar return on a bet (ignoring the value of the entertainment).

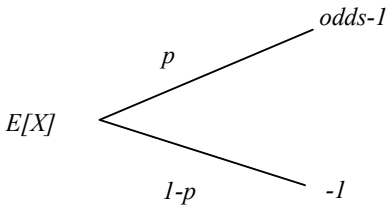
U_i = *dollar return on bet i*
E(U) = E(dollar return)

Further, assume a subjective probability p of team A beating team B in a game A vs. B. The required odds to (rationally) take the decision to bet on team A as winner will be such that expected value (utility) is at least zero.

Thus, on a $1 bet we require: $\overbrace{p*(odds-1)}^{probability\ weighted\ profit} + \overbrace{(1-p)*(-1)}^{probability\ weighted\ loss} \geq 0 \Rightarrow odds \geq 1+\frac{(1-p)}{p}$

Example: If (subjective) probability of team A winning is 0.5, the probability of team A not winning is $1-0.5=0.5$. *This leads to required odds of 2 on team A winning (*$odds = 1+\frac{1-0.5}{0.5}=2$*).*

Figure 4: Payoff scheme for a bettor position.



$$E[X] = X \cdot ((odds-1)\cdot p + (1-p)\cdot(-1)) = X(odds \cdot p - 1)$$
$$p = probability\ of\ outcome$$
$$X = value\ of\ bet$$

The figure shows the payoff scheme for a bettor position, meaning that the expected value is equal to the odds subtracted with one multiplied by the subjective probability on the upper branch and then added with the subjective probability subtracted with one and then multiplied by minus one (100% loss).

If a bet at a certain odds has the expected value of zero, one has a nice interpretation of the odds. Quoted odds of 1.10 should mean that in 10 out of 11 cases it comes true and one will gain 0.10, and in 1 of 11 cases one will lose 1.

In addition, the bookmaker can regularly adjust the odds according to the demand of different odds. If a bet is placed at 1.07 it signals that 1.07 might be favorable and it may be lowered to 1.06 and the other teams odds raised to 9.1 – to get bettors to bet on the other team as well. By setting odds a bit below reflecting only pure probabilities, the poster of the odds charge for risk and get return.

If a bet on a certain outcome for some reason is very popular, the strong *demand* for this particular outcome can drive up the price (down the odds). There might be a shortage of market makers interested to lay, causing odds to fall a lot. This will bias the odds and it will not anymore only reflect the probability of the event. When a bookmaker offers odds it is not necessarily his belief that the odds are fair. Determining the odds is a bargaining game where each party tries to get the best price – just like in any market. Therefore a bookmaker knowing that a game should have odds of 1.3 for a certain outcome may find it possible to get someone to accept his offer of 1.1. If so, there should be room for more competition on the bookmaker side.

3.2 Adverse selection

Supply and demand on financial markets are affected by adverse selection and even though this is a fundamental problem in markets one can argue that without some degree of adverse selection trading would not occur. The concept of adverse selection first appeared in insurance markets, describing the situation when people taking insurance are the more likely to make a claim than the population upon which the insurer sets the rates. The most famous use of adverse selection in finance stems from George Akerlöf (1970), who developed a model for the market of lemons. This was based on the used car market. People buying used cars do not know if the cars are "lemons" (bad cars) or "cherries" (good cars). Therefore they do not want to pay the full price of a good car, since there is a probability they may get a bad one.

In betting a bookmaker or bettor may have more and better information than the other party, which creates *asymmetry of information*. This occurs when one party have information that the other cannot obtain.

Another reason for adverse selection in betting is found in the difference of *timing*. The party first suggesting odds have less information than the one later accepting, since more information can be accumulated in the meantime before the accept. In addition to this, the party setting odds early does not have access to consensus estimates from multiple sources on the particular outcome. To put it simply, there are no or limited possibilities to benchmark the odds with views of other market participants. Therefore, it could be favorable to only trade in small quantities in the beginning to learn about where the market is. Any actor suggesting odds (prices) early on has the disadvantage of few comparisons, but given that he is well informed, it may be an advantage as those looking to accept may not be able to differentiate favorable from unfavorable odds by comparing different providers. Uninformed actors early in the process of odds determination are hence like "sitting ducks". Later on, when consensus odds have been established across markets on a certain event outcome, actors should face less risk of being used by more informed actors.

3.3 Behavioral factors

The Behavioral finance discourse accounts for how behavioral patterns affect financial markets and economic rationality. Like in financial markets, behavioral factors influence the determination of prices, i.e. the odds, in betting markets. Two factors to keep in mind trying to understand the process in which odds are determined are the subjective utility function and behavioral biases.

3.3.1 Utility function

Odds are determined in the interaction between individuals with certain needs and interest. What appears rational to one individual may not appear rational to others. One way of describing this is to say that agents have their own individual utility function that they maximize. Rationally maximizing expected utility may differ from maximizing expected monetary gain. When betting, participants value the excitement and the sense of at least having a probability of being a winner of some amount of money. Conceptually, the individual risk aversion plays an important role. Some people love taking risk, others (risk avert) hesitate even to take bets with positive expected values due to their aversion towards uncertainty/risk. At close examination, betting as well as lottery commonly has unfavorable expected monetary outcome. Still, people cannot resist gambling, suggesting that they value their participation not only in monetary terms.

3.3.2 Behavioral biases

Financial literature describes multiple examples of how different behavioral biases affect people's actions. The same is true in betting – behavioral patterns and biases are likely to influence the prices (odds). For example, so called positive illusion, egocentrism and framing of information may affect the judgment calls on how to place bets. In financial markets some invest for hedging purposes. This could also be true in betting markets meaning that when agents after more information becomes available want to cancel out bets made previously and/or rebalance their risk exposures. Overconfidence could be another behavioral

factor that impacts the odds. For example, after a big win people may think they are very good as it is hard to rationally and objectively differentiate luck from skill. All together, the behavioral factors can make the odds deviate from what would be suggested from a structured formal analysis/evaluation of bet win probabilities based on information.

3.4 Market power

When odds are formed, the market power of the odds setting participants plays an important role. In traditional betting such as fixed-odds betting with Svenska Spel in Sweden, one bookmaker has monopoly on laying odds. The bookmaker can hence solely determine the odds, but will take into account that odds need to be reasonably attractive to get anyone to place bets. In reality, Swedish bettors are not fully in the hands of Svenska Spel. Bettors can nowadays also bet on international betting web sites like Unibet or Ladbrokes. Since the bettor can choose to place a bet at the site offering the best odds, there is some competition on the bookmaking side of the bet. This flexibility is however limited by the bettors' ability and need to have accounts with several bookmakers. And one should not be too surprised finding that odds may be in similar ranges. On the new betting exchange, anyone can compete on the bookmaking side at one exchange and take the role that at present appears more favorable – bookmaker or bettor.

In the case of monopoly, the market power of the bookmaker typically the largest and the monopolist can set odds in his favor. As long competition is limited on the bookmaking side, bookmakers may be able to overcompensate for the risk of trading with an informed bettor and on average have positive returns. On the betting exchange, the competition would be expected to be high as anyone can take the bookmaking role if it appears favorable given the odds. On the other hand, there may still be the case that there is more people wanting to bet than book, and that those do not realize or care about the unfavorable conditions if odds are unfavorably low.

Furthermore, on a new market such as the betting exchange, professional bookmakers with large accounts may be able to buy up competitive bids, hedge their positions on other betting markets, and lay odds in their favor on the market for matching with uninformed average gamblers not knowing they are betting under unfavorable conditions.

On the regulated Swedish market, the monopolist must take into consideration the consequences and cost to society of non-responsible gambling and people becoming addicted to gambling. This is some of the rationale behind regulatory limitation on the pay-out ratio of Svenska Spel, which is not allowed to pay back 90-95% of stake to gamblers like that of international unregulated companies. Instead a substantial amount must be kept in order to make gambling less attractive and to cover for society's cost of irresponsible gambling. Svenska Spel can due to information asymmetry not see the difference between healthy gambling and irresponsible gambling.

Another issue related to market power is liquidity. Liquidity commonly increases with decreasing transaction costs. On a market with low spread and competition on both bookmaker and bettor side, bets are more liquid. Once you entered into a bet, you may later enter the opposite side of the bet and in practice cancel out your position. If odds have not moved, only the transaction cost will be the cost of this move. If odds have moved favorably, low transaction cost may induce an actor already in a bet contract to trade out of his position. This would be possible in a liquid market.

4. PREVIOUS RESEARCH

Betting has over the years caught the attention of everything from gamblers eager finding new betting strategies to serious academic researchers investigating betting markets and investment behavior. Research on betting market data has much been concerned with technical- and behavioral rules for betting. A large number of researchers have also pointed out similarities between transactions on betting markets and financial markets – similarities that we believe have become even stronger with the introduction of the betting exchange.

Many parts of the financial market efficiency related literature are equally applicable to sports markets and have been used repeatedly. Studies have explored the analogy between the markets at the empirical level and tried to establish whether the odds (prices) in betting markets reflect the true probabilities of specific outcomes of events.

Research into the efficiency of prices set by bookmakers in betting markets has provided a small but increasing contribution to the literature on the efficiency of financial markets. In order to answer our second research question: *"Is the market efficient?"*, we look deeper into financial research covering betting.

4.1 Subjective Probability of Outcome

In an efficient stock market, it should not be possible to systematically beat the market by stock picking. Something similar should apply in a betting market if odds are set in such a way that they reflect the true probabilities of an event.

4.2.1 Favorite Long Shot Bias

According to the in racetrack betting (Thaler & Ziemba, 1988) well-documented favorite long-shot bias, horses with short odds (favorites) offer higher expected payoff than horses with long odds (long-shots). It shows that favorites tend to be "under-backed" and long-shots tend to be "over-backed". The bias implies that a betting strategy that selects favorites will on average generate higher returns (or lower losses) than strategies betting on long-shots. As bets are placed on longer-priced horses, the average loss increases, which can be interpreted as a negative risk premium for such bets. An alternative theory, formulated by Griffith (1949), suggests that the bias might be due to the tendency of individual decision makers to overestimate small probabilities' events. Yet others are Weitzman (1965) and Ali (1977), who claimed that individual bettors are risk loving and are thus willing to accept a lower payoff when betting on the riskier long shots. Woodland & Woodland (1994) presented evidence of a reversal of the favorite-longshot bias in the MLB market, showing that actual returns betting on underdog (favorite) teams are significantly higher (lower) than expected returns. When re-examined by Gandar, Zuber, Johnson and Dare (2002), the conclusion was that there is insufficient evidence to call it a true anomaly.

4.2.2 Betting on Underdogs

Gandar et al (1988) proposed a series of tests including direct evaluation of returns by implementing technical trading rules, selecting bets purely on the basis of past team performance, and behavioral rules, which select bets in an attempt to make use of hypothesized behavioral patterns of the public. They found the behavioral rules betting on home teams and betting on underdogs to be profitable on NFL data, but not any technical rules. The idea is that if bettors believe strongly in e.g. favorite teams as winners they may bet excessively on those, although odds are low. As demand for odds on the favorite as winner is high, the bookmaking firm lowers the odds (increases the price) accordingly and increases the odds on the underdogs to balance the demand for bets between the different outcomes and thereby limit his risk and lock in profit.

Demand may lower the odds of the favorite and drive up the odds of the underdog, creating a situation where it is profitable to systematically bet on the underdog, i.e. against the typical behavioral pattern. Several researchers have sought such evidence of inefficiencies in the form of systematic biases in bookmakers' odds, home-away team and favorite-long shot biases being two of the most frequent. Several other studies have also focused on the existence of profitable trading strategies. Golec and Tamarkin (1991), Vergin & Sosick (1999) Dare & Holland (2004) show a profitable strategy being to back home team underdogs in NFL games. Gandar, Zuber and Lamb (2001), however find little evidence of this in the Major League Basketball (MLB) and NBA games.

4.2 Adverse Selection and Market Power

A proposition for explaining the long shot bias comes from Ottaviani & Sörensen (2004 & 2005). They suggest that in fixed odds betting, the bias observed has an informational explanation in the long shots being subject to a worse adverse selection problem. Relative to favorites, long shots attract a relatively higher proportion of insiders and pay out more conditional on winning (since odds are high). To counteract this more severe adverse selection problem, competitive bookmakers quote relatively shorter odds on long shots, being equivalent to a larger bid-ask spread in the presence of more insider trading in a financial market setting. Due to the adverse selection problem being bigger on the long-shot than on a favorite, a favorite-long shot bias arises. Levitt (2004) shows that large positions with respect to the outcome of game make it possible for bookmakers to achieve substantially higher profits. As bookmakers are more skilled than bettors, they can systematically exploit biases by choosing prices that deviate from market clearing price. Hence they can use adverse selection in their favor.

4.3 Behavioral Biases

There are a number of attempts made to explain the biases by either existence of inefficiency in the market, i.e. biased expectations, or heterogeneous risk attitudes among bettors. The betting literature often considers the implementation of betting strategies that take advantage of the anomalies in the Efficient Market Hypothesis. Would it be efficient, gamblers should not be able to use e.g. historical data to systematically and repeatedly set up profitable betting schemes. As traditional bookmaking firms charge a spread from the bettors, the expected return of participation for a bettor should be negative if odds (prices) were efficiently reflecting underlying probabilities. Sports betting papers have so far mostly been focused on examining the market efficiency on the highly regulated Nevada betting markets. With studies made on the National Football League (NFL) and National Basketball League (NBA) games respectively, Gandar, Zuber O'Brien and Russo (1988) as well as Gandar, Dare, Brown and Zuber (1998) find that odds reflect the aggregate information in the betting market implying that betting markets are efficient. Gray & Gray (1997) find some sign of inefficiency on NFL data. In the case of association football (soccer) most previous research has focused on modeling home and away team scores. However, other studies on other markets have showed the existence of anomalies inconsistent with efficient markets on a number of betting markets. A very recent study by Goddard & Asumaphpoulos (2004) finds evidence against weak form market efficiency. Goddard and Asumaphpoulos successfully use past performance and other variables to predict the outcome of Premier League Football games.

4.4 Arbitrage

Arbitrage is a central concept in finance enforcing the law of one price and keeping markets efficient. In a traditional efficient market without frictions and with fully rational agents, any deviation of price from its fundamental value creates an attractive investment opportunity from which arbitrageurs can profit. Arbitrageurs buy and sell the same or similar securities at different prices making risk-free profits. Such activity should drive prices to their equilibrium and mispricing should only exist for a very short time. The existence of hundreds of Internet bookmakers simultaneously offering odds on the same sporting events, make examination of arbitrage opportunities very timely. Hausch and Ziemba (1990) suggested that it was possible to arbitrage by betting on the same horse on different race tracks, but attention has been limited despite the huge interest in gambling. The Hausch & Ziemba method required phone calls to the several bookmakers. In a recent paper Marshall (2005) examines a large set of arbitrage opportunities provided by

a company specializing in scanning bookmaker web sites. Marshall shows that average arbitrage revenues of 3.35% are possible. With relatively low transaction costs and within very short time, sport betting arbitrageurs can reinvest profits and potentially earn sizeable accumulated annual returns (see Appendix II for how this is done).

4.5 Summary of Previous Studies

The studies mentioned above almost all have corresponding analogies in financial literature and thus there seems to be a good possibility of learning more about human and investor behavior from the behavior in betting markets.

Table 2: Summary of previous financial research on betting

Authors	Main findings
Subjective probability	
Thaler & Ziemba (1988)	Found a favorite - long shot bias in racetrack betting. Short odds (favorites) offer higher expected payoff than horses with long odds (long shots).
Gandar, Zuber O'Brien and Russo (1988)	Spreads (odds) reflect the aggregate information in the NFL betting market. Some behavioral rules - betting on home team and betting on underdogs - were profitable on NFL data.
Griffith (1949)	Suggests that the long shots bias is due to the tendency of individual decision makers to overestimate small probabilities' events.
Goddard & Asumaphpoulos (2004)	Successfully use past performance and other variables to predict the outcome of Football games.
Woodland & Woodland (1994)	Presented evidence of a reversal of the favorite long shot bias in the MLB market, showing that actual returns betting on underdog (favorite) teams are significantly higher (lower) than expected returns.
Behavioral Biases	
Ali (1977)	Claimed that individual bettors are risk loving and thus willing to accept a lower payoff when betting on the riskier long shots.
Govoni, Mann and Wynne (2004)	Argued that well educated professional investors are as subjected to the same gambling behaviour and abuse as unprofessional gamblers.
Adverse Selection & Market Power	
Levitt (2004)	Shows that large positions with respect to the outcome of game make it possible for bookmakers to achieve substantially higher profits. As bookmakers are more skilled than bettors, they can systematically exploit biases by choosing prices that deviate from market clearing price.
Ottaviani & Sörensen (2004, 2005).	Informational explanation of the fixed odds long shot bias. Claims that long shots are subject to worse adverse selection problems, causing bookmakers to lower odds.
Arbitrage	
Marshall (2005)	Shows that average arbitrage revenues of 3.35% are possible at online bookmakers' web sites.
Hausch and Ziemba (1990)	Suggested that arbitrage was possible in race track betting on horses.

5. HYPOTHESES

In this chapter, we formulate five hypotheses for further analysis of the research questions:

1. What is the market microstructure of the betting exchange?

2. Is the betting exchange efficient?

In chapter 2 and 3, we introduced the betting exchange basics, including what actors are present and the process by which multiple gamblers trade with each other at the betting exchange. This makes up the basis of the market microstructure. In particular, the odds play the role of prices at the betting exchange. Odds have several sources of influence. Therefore, to analyze efficiency we formulate five hypotheses that aim to shed light of factors that arguably impact the prices and the efficiency of the market.

The first two hypotheses investigate existence of adverse selection characteristics on the betting market. According to the odds model presented in chapter 3 average odds/prices should reflect expected outcomes. However, due to adverse selection the odds may diverge from the "fair" price. Previous research has shown that bookmakers in betting markets are able to charge spreads from bettors and thus have higher returns. We hypothesize and investigate if that holds true also at the betting exchange, i.e. bookmakers also have higher returns than bettor on a betting exchange. Further, as a second hypothesis, we hypothesize that the element of bookmaker competition on the limit order book betting exchanges has decreased the problem previously experienced, implying higher odds for bettors.

As is commonly known, actors with market power can affect market prices as suggested in the chapter 3 odds equilibrium model. Hence, we analyze in hypothesis three whether there seems to be any presence of (large) market power actors on the betting exchange.

Another factor affecting prices is how traders act and to what degree they act rationality. In most betting markets and lotteries, effectively being zero-sum games, the majority of participants are unsuccessful when it comes to monetary return on investment. This is tested in hypothesis number four. The majority being unsuccessful allows a small number of big wins. Hence, participants pay a premium for having the possibility of a bigger win. Furthermore, we choose to hypothesize that traders change their behavior following a big win. Research on overconfidence, applied in a betting market context, would suggest that gamblers after a large win change their behavior. More specifically we expect them to become less successful, trade more often, and take more risk by placing bigger bets and bet on more uncertain outcomes (i.e. at higher average odds).

Finally, we test for existence of the so called long-shot bias. Previous studies have suggested that high-return strategies are betting on favorites, i.e. against underdogs. This could in the odds model be said to correspond to traders having subjective probabilities. Note however that the model suggests interplay between the factors. Subjective probabilities are also attributable to behavioral factors and vice versa. The model provides concepts for understanding what influence affects prices (odds).

The following table summarizes our hypotheses:

Table 3: Summary of hypotheses

Hypotheses:
Adverse Selection
H1: Bookmaking (going short) yields *higher* returns than betting (going long)
H2: The limit order book betting exchange has *higher* average odds than traditional bookmakers
Market Power
H3: Large market makers *overperform* average traders
Behavioral Factors
H4: Most traders are *unsuccessful*
H5: After a large win bettors:
a.) Trade with *lower* returns
b.) Trade to *higher* average odds
c.) Trade with *higher* stakes
d.) Trade *more* frequently
Subjective Probability
H6: High return trading strategies are:
a.) Betting (going long) on favorites (low odds)
b.) Booking (going short) on underdogs (high odds)

5.1 Adverse Selection

Hypothesis 1: *Bookmaking (going short) yields higher returns than betting (going long)*

On traditional betting sites, bookmakers quote the odds (prices) some time before bets are matched by bettors. According to Harris (2003), bettors may therefore enter into bets with more information to compensate themselves for the risk of trading with informed bookmakers, who in their turn incorporate a spread between 3-20%. The spread also reflects the profit that a bookmaker seeks to attain. We believe that still at the betting exchange, having competition between bookmakers, more or less professional bookmakers typically post odds first and these are later matched by bettors. We therefore believe that, due to information asymmetry, there exists a bias in the odds on a betting exchange favoring bookmakers and implying that bookmakers are more informed than bettors.

Hypothesis 2: *The betting exchange has higher odds than traditional bookmakers*

According to Fama (1970), competition is one prerequisite for the Efficient Market Hypothesis to hold. Due to the possibility of competition in setting odds and the possibility of either betting (going long) as well as booking (going short), we believe that betting exchanges have the framework for being more efficient despite still being the bookmakers market. We therefore expect to find superior odds for long position traders (i.e. bettors) at the betting exchange compared those markets where a single bookmaking firm has the monopoly on quoting odds (prices) and taking the short position in an outcome.

5.2 Market Power

Hypothesis 3: *Large market makers overperform average traders*

The role of the market maker, or bookmaker, is available to everyone on a betting exchange. The term market maker is appropriate to actors frequently laying odds on the betting exchange, providing a basis for attracting bettors. Market maker is, however, a role that a regular trader is less familiar with and might hesitate to take. This suggest that those acting as market makers are more informed and to a larger extent skilled and professional, quoting prices with some spread in their favor, which was also suggested by Levitt (2004). More specifically the perceived entry barrier of the bookmaking position (concept evaluation knowledge), might cause shortage of market makers. Hence, large market makers can benefit

from offering unfavorable odds to bettors who see no other ways of getting their bets matched. This is similar to Salomon Brothers' position in the bond markets during the 1980s.

5.3 Behavioral Factors

Hypothesis 4: *Most traders are unsuccessful*

As stated in section 2.4, a similarity with financial markets is that betting is a zero-sum game; however due to the spread component, i.e. the commission charged by the exchange, there ought to be a net loss for the whole sample of players. Seeing betting as an investment associated with high transaction (costs in the form of commission), we believe that these traders are on average unsuccessful. As a corresponding observation, regular traders in financial markets being unsuccessful have been showed in studies on stock trading by Anders Andersson (2004) and Barber & Odean (2000, 2001). If true, this suggests that other behavioral factors, such as value of excitement, come into effect and cause people to participate in market trading.

Hypothesis 5: *After a large win bettors:*

a.) Trade with lower returns
b.) Trade to higher average odds
c.) Trade with higher stakes
d.) Trade more frequently

According to modern research on decision-making investors are not fully rational, but let emotions influences their decisions. De Bondt and Thaler (1995) describe overconfidence as the "perhaps most robust finding in the psychology of judgment" and evidences of overconfidence have been found in numerous professions, ranging from attorneys, investment bankers to taxi drives. Evidences also indicate that overconfidence is more pronounced in situations where the tasks are ambiguous, rather than mechanical (Daniel et al. (1998)). When investors value securities and forecast long-term cash flows there is a substantial part of judgment involved, which subsequently makes the financial markets subject to high degrees of overconfidence. The similarities to betting on sports are many, which make us inclined to believe that also the betting market can be exposed to high degrees of overconfidence. Another psychological aspect contributing to overconfidence is self-attribution bias, which means that overconfidence grows when public information is in agreement with private information, but it does not fall proportionately when public information contradicts the private information (Daniel et al. (1998)). This implies that investors tend to credit themselves for past successes, while they blame external factors for failures (Taylor and Brown (1988)). We believe that also self-attribution bias might influence decision-making on the betting market and in particular we will examine whether large wins can make overconfidence grow stronger.

5.4 Subjective Probability

Hypothesis 6: *High return trading strategies are:*

a.) Betting (going long) on favorites (low odds)
b.) Booking (going short) on underdogs (high odds)

According to studies on favorite long-shot biases, such as Golec & Tamarkin (1991), there is evidence that suggests systematic biases in odds on favorites and underdogs. Further, according to prospect theory, people have a tendency to underestimate the likelihood of highly unlikely events. People conversely tend to overestimate likelihood of very likely events. This suggests inefficiency of odds on favorites and underdogs in betting markets. We therefore aim to investigate if this is the case on betting exchange data. If so, and if odds on average are higher, can this strategy allow positive returns of betting rather than just reducing loss? In any case, existence of the bias would suggest that there still is some way to go until we can speak of reasonable market efficiency.

6. DATA

In this section, we present our exchange betting data. First we describe the type of data and information contained in each observation. Secondly, we provide some descriptive statistics from the aggregate sample of the transactions. This provides an overview of the betting exchange, the gamblers and their behavior.

6.1 Type of Data and Source

Our main data consist of 50 416 player transaction records from 214 users on a betting exchange. The transactions were made during the period from August 2004 to March 2005 at the Betting Exchange. We have chosen not to disclose the source of the data provider due to the sensitivity of the findings.

The database consists of objects that we have chosen to call transactions. Each transaction is in itself a matched bet between two gamblers on a particular event including the agreed upon conditions. The information in a transaction is all that is needed to settle the bet. The transaction has the following data fields presented in Table 4 bellow:

Table 4: Transaction record of a matched bet

Match	Sochaux - Marseille	**Modification date**	1095022630
Back user	165	**Market id**	8349
Back country	Finland	**Bet type**	90 min Odds
Lay user	421	**Bet type id**	1
Lay country	Sweden	**Selection id**	901
Odds	3.2	**Result id**	901
Amount	200		

The *back user* and *lay user* variables are the identity numbers of the two gamblers that bet with each other in the transaction. The back user is the one that wins if the actual result is the same as the result bet on. The lay user is the bookmaker of the bet that keeps the money if the back user is wrong. The *odds* are the price at which the event outcome has been bought and the *amount* variable is the amount of money in Euro put on stake by the back user for the specified event. The *modification date* is the time when the transaction was performed expressed in seconds elapsed from year 1950. *Market id* stands for in which type of market the transaction has been conducted, for example Bundesliga, Champions League etc. *Bet type id* is the id of what type of event has been gambled upon. *Result id* is a coded number for the actual result of the event, for example 1, X or 2. *Match* stands for the event in question most often the teams playing against each other, for example Arsenal vs. Manchester. *Bet type* designates the product gambled upon such as 90 minutes football games, 60 minutes ice hockey games etc. *Back country* is the country origin of the user acting as bettor and *Lay country* is the country of origin for the user acting as bookmaker.

In addition to the betting exchange data, we collected data for comparison of odds between betting exchanges, bookmaking firms and the Swedish monopolist Svenska Spel. We manually collected 9738 observations of odds from the Internet for football matches from: the Betting Exchange we studied, from Betfair (the largest betting exchange) as well as the international bookmaking firms Unibet, Expekt and Ladbrokes along with Swedish Svenska Spel.

Table 5: Example of odds from different betting companies

Ice Hockey World Championships 2005, Saturday 14 May				
	1	**X**	**2**	
Sweden - Check Republic (full-time)	2.15	3.70	1.95	*Svenska Spel*
Sweden - Check Republic (full-time)	2.40	4.00	2.30	*Ladbrokes*
Sweden - Check Republic (full-time)	2.45	4.00	2.35	*Unibet*
Sweden - Check Republic (full-time)	2.68	4.145	2.37	*Betting Exchange**
Sweden - Check Republic (full-time)	2.76	4.20	2.42	*Betfair**

**Betting exchanges*

The table shows an example of the odds being significantly higher at the betting exchanges compared to what traditional betting firms offer.

At the Betting Exchange, the number of available games is small. As an example, on June 19 the Betting Exchange offers 100 games, whereas the standard bookmaking firms had a much greater supply of games (e.g. Unibet 919 games, Expekt 768 games and Ladbrokes over 2000 games). However, the large betting exchange Betfair also offers over 2000 games.

6.2 The Betting Exchange Descriptive Statistics

During the period of about 7 months from August 2004 to early March 2005, 50 461 bets were matched at the Betting Exchange amounting to 3.82 million Euro.

Table 6: Descriptive statistics over odds, amount, backuser and layuser

Number of Transactions	50 461
Time horizon	18 aug 2004 – 06 mar 2005
Total number of actors	214
Number of traders as bookmakers	90
Number of traders as bettors	212
Number of traders taking both sides	88
Number of originating countries	21
Most frequent countries	Sweden (75), United Kingdom (25) and Finland (18)
Median odds	2.08
Mean odds (unweighted)	3.12
Standard deviation odds (unweighted)	15.73
Amount-weighted mean odds	2.54
Mean amount/bet (unweighted)	€ 76.67
Median amount/bet	€ 21
Total turnover	€ 3 825 751
Commission	3% of net winnings

The table shows the size of the Betting Exchange and some of its main characteristics. Winners pay 3 percent commission to the exchange on their net wins.

There have been 214 active traders on the betting exchange during the period. Most of these, 212, have engaged on the bettor side of transactions, whereas only 42% (90 persons) have engaged on the bookmaker side of transactions. 88 participants have both acted bettors and bookmakers at least once. Geographically the market participants come from as much as 21 different countries across Europe with Sweden (75), Finland (18) and Britain (25) being the most frequent nations.

The typical bettor places bets that on average are as large as €76.67. However, it is obvious from the median amount (stake) of €21 that most amounts are smaller and a number of very large bets have had impact on the average odds. The bets are placed with mean odds of 3.12 and a high standard deviation of 15.73. The median odds are considerably lower, 2.08, which leads to the conclusion that some large odds have significantly impacted the mean.

The bets are placed on one of six available main types of bets: 90 minutes football games, 60 minutes ice hockey and handball games, Correct score of a game (number of goals), over or under 2.5 and/or 5.5 goals, Winner of a tennis game and a category we have named other.

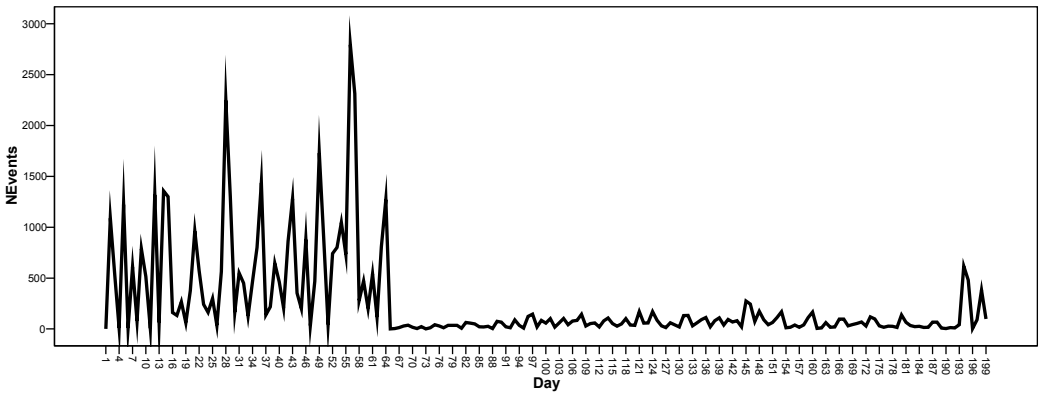
A majority of the bets placed at the Betting Exchange are placed on 90 minute and 60 minute odds. Such bets have only two or three different outcomes. Few outcomes available on a single event are often associated with lower average odds. The low average odds, as explained by the type of bet, also explain the relatively large amounts that are used in each of the bets placed.

Table 7: Descriptive statistics over the different products supplied on the exchange

	90m	60m	Correct score	Over/under 2.5-5.5	Winner	Other
Turnover	2 399 575	380 149	4 391	287 582	79 453	708 765
Number of Transactions	34 855	2 372	969	2 932	740	8 101
Median bet amount	20	20	1	121	107	44
Mean bet amount	68	120	4.50	39	30	86
Mean odds (unweighted)	2.44	2.35	40	2.04	2.52	2.01
Mean odds (weighted)	2.61	3.20	28	2.01	2.01	1.97
Median odds	2.18	2.38	17.5	2.03	1.74	2.03

The Betting exchange facilitates betting mostly on 90 minute odds, i.e. soccer games. Besides the odds games on outcome 1X2 for football games, the Exchange also offers other games like betting on correct score, betting on number of goals, and betting on winner in other sports.

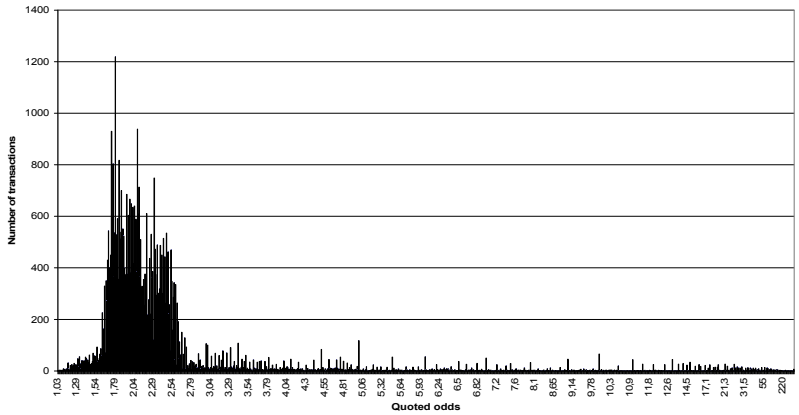
Figure 5: Number of daily matched wagers on the entire betting exchange (day 1 corresponds to the 18th of August 2004).



In the beginning of the period, trading was much more intense and volatile. Trading stabilized at a lower level after about one third of the period.

The graph above shows the liquidity of the exchange in terms of matched events. It appears that in the months of the launch of the exchange there was a substantial amount of trading which then after a while leveled out to about a 100 matched transactions per day. The graph below displays the frequency of transactions on different odds (prices).

Figure 6: Number of transactions for each odds category



The majority of bets are placed with odds around two, which is attributable to the type of games being 60 min and 90 minute odds (typically soccer and ice hockey).

7. METHODOLOGY

The first challenge was to better understand how the betting market and in particular betting exchanges work. Therefore, we tested betting on several different sites and compared what we found to be differences and similarities between traditional odds betting and exchange betting. We also investigated available literature on the betting subject as well as on financial/investment concepts, e.g. behavioral finance.

Following the initial betting, we came to hypothesize odds being better at the exchange. However, our performance also (as expected) suggested that there were no free lunches out there, at least not for beginners.

Still millions and millions of people participate in the market. We therefore continued with analysis of what causes people to gamble and in effect how more or less efficient prices are formed in the interplay between actors on the exchange. The new thing about betting exchanges is the increase in competition leading to more competitive odds compared to traditional monopolies, where the bookmaker set odds assuring them to lock in sizable risk-free profits. Ideally, "fair" prices would reflect the average public expectations on probabilities of the different outcomes. Also, as the exchange's commission is limited to around 3% of net wins, it seemed more likely that systematic trading strategies could not only reduce losses, but perhaps yield positive average returns.

The outcome of the first qualitative study was an introduction to how the betting exchange works. After gaining access to real data from a betting exchange, we also could derive descriptive statistics over the betting exchange such as: the number of transactions, total turnover, number of bettors and bookmakers, mean and median odds to mention a few measures. These are presented in the data section.

When we finally had a grasp of the data, we were able to proceed to a more formal hypothesis approach and we performed statistical testing where we found it to be applicable. The following section describes how we performed empirical analysis of the data to analyze and evaluate our hypotheses.

7.1 Selecting Data for Hypotheses Testing

A majority of the bets placed at the Betting Exchange are placed on 90 minute and 60 minute odds. Such bets have three different possible outcomes. Tennis games have two outcomes and for example "correct score" has a large (or in theory unlimited) number of possible outcomes. For relatively close games, the average odds by nature become comparably low. If only two possible outcomes, both may have odds slightly below two. If three equally possible outcomes, they may in theory all have odds close to three. Supply and demand factors may also affect these odds, but the more possible outcomes the less likely each outcome (on average) gets and the higher the odds. Heavily backed favorites by nature have low odds, implying high odds on the disparate unlikely outcome(s). It is also possible that the gamblers on different types of sports differ from each other. We therefore find it reasonable to study different types of games separately. The football odds, the 90 minutes odds, have a large number of transactions, whereas the other types of games have much fewer. We therefore limit our study to the set of 90 minutes odds where the odds are of same type and on average relatively low.

When considering very high odds, such as 1000, it is necessary to have a far greater amount of data, as such events should come true only a little more than one out of a thousand times. Small odds outcomes occur frequently and statistical significance can be found in smaller sets of data. We therefore only used 60 and 90 minute odds, having lower odds, in our analysis.

7.2 Methods for Hypotheses Testing

In order to answer **Hypothesis 1:** *Bookmaking (going short) yields higher returns than betting (going long)* was evaluated by performing two tests: one being to measure the ex post return that would have been realized by acting bookmaker on all outcomes with a stake of 1, and in the second we translated odds into implied win 'probabilities' and compare the average with the actual average frequency of wins.

Return: First we aggregated the returns from the transactions according to the formulas in Appendix I taking the 3% transaction cost on net winnings into account. By programming in SPSS syntax language we were able to compare outcomes and extract the resulting outcomes for bookmakers and bettors. We calculated the mean and median returns as well as total profit for all the transactions corresponding to the two groups of traders, bettors and bookmakers. The results are presented in section 8.1.

Truncated distribution of returns: Plotting the returns on the stake (money) at risk show that about half of the returns for bookmakers as well as bettors is -100%, the rest of the returns are depending on odds ranging from zero to hundreds of percent positive return. Returns are hence not normally distributed. However, since we have a very large number of transaction, we approximate the returns to be normally distributed based on the central limit theorem. More sophisticated methodologies could have been used to transform the return distribution before performing tests.

Check of probabilities:[3] It seems reasonable to assume that both, the bettor or the bookmaker, sets odds to reflect his subjective probability estimate for each particular outcome. Odds are set and fixed some time before a bet is matched. Therefore, when the counterpart enters the bet he or she may have more information. The one who posted the odds faces a risk that the posted odds are more favorable than they should be if posted at the time of the matching. Therefore, a margin should be charged to reflect and compensate for the expected variance of the new information which accrues after odds are posted. We believe that in the general case, bookmakers quote odds at the betting exchange, just like bookmaking firms, and bettors then enter into the bets. Bettors also quote odds, but we believe matching usually occurs at the bid price - the odds offered by bookmakers. Therefore, from the perspective of the bookmaker, the odds (φ_i) on match could be modeled as depending on the perceived probability of the outcome of the event *i* occurring (p_i) and a margin (λ_i) in the following manner:

$$\varphi_i = \frac{1}{odds} = p_i + \lambda_i \quad (1)$$

We can see φ_i as the direct "probability" contained in the odds, e.g. odds 1.1 should mean a direct probability of 10/11 as that would yield zero expected return. Then, if the bookmaker did not want to earn any profit by offering odds and if no new information was released after odds were posted, the margin λ_i would be zero and the directly implied probability would be the subjective probability of the bookmaker. In practice, it appears reasonable that the party posting odds first (which we think is the bookmaker) can be assumed to earn a positive margin, i.e. $\lambda_i \geq 0$ and $\varphi_i \geq p_i$.

Size and distribution of margins: We examine the (hypothesized positive) size of the margin of the bookmakers in our sample by comparing the average value of the inverted odds (on each outcome) $\overline{\varphi}$, with the proportion of the sample for which the outcome bet on was realized μ. The ex post mean value of the margin can be expressed as:

$$\lambda = \overline{\varphi} - \mu \text{ . (2)}$$

Secondly, for **Hypothesis 2:** *The betting exchange has higher odds than traditional bookmakers*, we collected 9736 odds on events from six betting markets. We then compared the betting exchange odds with other betting

[3] This measurement of margin is corresponds to the method used by Goddard & Asumaphpoulos (2004).

odds, recalculating the betting exchange odds to reflect commission charged by betting exchanges[4]. We did not consider any tax differences as these may be illegal.

Illustration of effective difference in odds between the Betting Exchange and other source such as Svenska Spel, Unibet etc.:

$$Diff = \frac{Odds\ From\ Other\ Source}{0.97 * (Betting\ Exchange\ Odds - 1) + 1} - 1. \quad (3)$$

Further, we also looked at the availability of games on the various markets in comparison to our betting exchange data in order to see if the availability of games differed at the exchange. The results are presented in section 8.2.

Thirdly, **Hypothesis 3:** *Large market makers overperform average traders,* was investigated by selecting the largest actors in terms of number of transactions as well as turn-over. These numbers where calculated by programming in SPSS syntax language and derived from our data. We then aggregated the data to include various characteristics of these actors such as their booking and betting returns, number of days active etc. The return measures where calculated according to the formulas in Appendix I taking the 3% transaction cost into account. The results are presented in section 8.3.

Further, **Hypothesis 4:** *Most traders are unsuccessful* was inferred by performing a one sided non-parametric sign test. We thus counted the number of actors with positive and negative returns respectively. The returns where calculated by programming in SPSS syntax language using the formulas presented in Appendix I taking the 3% transaction cost into account. Further, we also performed an unparametric Mann-Whitney ranking test as well as a t-test of the mean returns for sub samples of bettors, bookmakers and traders overall, which revealed large outliers. Since the normality assumptions can be questioned for the sample due to few very large outliers, we removed 5% of the worst outliers to test our hypothesis. The results of the test are presented in section 8.4.

Furthermore, **Hypothesis 5:** *After a large win bettors: a.) Trade with lower returns, b.) Trade to higher average odds, c.) Trade with higher stakes, d.) Trade more frequently* was answered by performing an event study. Firstly, the days in the sample with highest absolute profit were identified and classified as possible "triggers" for changes in gambling behavior. The reason for choosing absolute profit instead of return is that gamblers in most cases reference their performance to absolute profit.

Secondly, the trading pattern after these large wins were compared to the trading pattern before in order to see whether it was more speculative in terms of *higher bets*, *higher odds*, and *more frequent gambling*. We also looked at differences in *return*.

We used an event window of 5 event days before and after the event. The reason for choosing 5 event days was that transactions for players can be dispersed in time and thus calendar days would not capture the sought effect. Further, the size of the window was chosen to 5 event days as it seemed reasonable that a trader would start to forget the triggering event after a certain amount of transactions. As the number of daily transaction varied quite substantially it was a good proxy to capture most of the effect. We argue this as very frequent gamblers will trade several times every day while more careful ones will only place bets from time to time.

Moreover, before extracting the daily values we had to transform each player's transactions to daily values, which were done by aggregating the mean and median of the sought variables. It turned out that the mean

[4] The Betting Exchange charges a commission of 3% on net wins. Betfair charges up to 5%, but has a bonus system that can give rebate. However, as quite substantial bets each week are required, we approximate a rebate of 0% for Betfair. As an example, if the odds on an outcome was 1.1, a winner with a stake of $100 would be charged 3% of the $10 win, effectively reducing the effective odds to 1.097. Since commission only is paid on net wins on a market, this reduction will overestimate the actual commission, but should work as a good approximation.

and median where basically identical. Further, the differences before and after the wins were calculated for each and one of the investigated variables for all bettor series.

Finally, we performed a Wilcoxon rank test as well as a t-test. The Wilcoxon rank test is a non-parametric test, which is necessary when working with matched pairs and in this case, dependent observations and thus the t-test assumptions of normality can not be taken for granted. The results are presented in section 8.5.

The above procedure is summarized in the following formula for the means:

$$\overline{\psi}_k = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=0}^{T}(\alpha_{t+1} - \alpha_{t-1}), where\ \alpha = \frac{1}{M}\sum_{j=1}^{M}\beta_j \qquad (4)$$

The formula states that for the mean of each investigated variable $\overline{\psi}_k$, we calculated the daily (α) average of the β_j transactions that day. Then we calculated the difference between the days before and after ($\alpha_{t+1}, \alpha_{t-1}$) the triggering event at t=0 in our event window (5 days i.e. T=4). We finally calculated the mean for all the 214 traders. The procedure for the Wilcoxon test is similar, however one has to rank the differences and assign the correct sign to each difference. Finally, one can calculate the Wilcoxon statistic with the following formula:

$$Z_{Wilcoxon} = \frac{Min(W^+, W^-) - 0{,}5 - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \sim \text{Normal distributed} \qquad (5)$$

The above formula means that we take the smallest of the positive and negative ranks W^+ and W^- and subtract with half of the total sum of the ranks and then divide by an approximation for the standard deviation.

The next hypothesis, **Hypothesis 6a:** *High return strategies are betting (going long) on favorites (low odds)*, was answered by creating trading portfolios by programming in SPSS syntax language. We define favorites to consider in 90 minutes odds as outcomes with odds below 1.50, but we look at various levels of odds to investigate differences.

For each portfolio, we selected games with odds in specific intervals and calculated the ex post mean and median return one would have yielded by investing one unit of capital in these games by taking either the bookmaker position (short position) or bettor position (long position). For example, we would calculate the return one would yield by investing in all odds lower than 1.20 as either bookmaker or bettor. Positive returns indicates that it would on average have been profitable to bet on all matches in the group and if the idea would have been present ex ante the profit opportunity could have been exploited. We also created portfolios of investing in all odds as either bookmaker (going short) or bettor (going long). The results are presented in section 8.6.

With the purpose of answering **Hypothesis 6b:** *High return strategies are booking (going short) on underdogs (high odds),* the same approach as in Hypothesis 6a was used. However, here we would create portfolios by selecting odds that we considered high. We regarded underdogs as teams having odds higher than 3.00 for winning. To the underdog category we also added draws with odds over 3.00, as we were concerned with outcomes that few people believe in and thus yields high odds. For example we then calculated the return one would yield by investing in all odds higher than 5.00 as either bookmaker or bettor. The results are presented in section 8.6.

The methodology of the two hypotheses can be summarized into the following formulas:

Long position

$$\bar{r}_{bet} = \frac{1}{N} \sum_{i=1, X<odds<Y}^{N} \begin{cases} win, & (odds_i - 1) \\ loss, & -1 \end{cases} \quad (6)$$

Short position

$$\bar{r}_{book} = \frac{1}{N} \sum_{i=1, X<odds<Y}^{N} \begin{cases} win, & -1 \\ loss, & \dfrac{1}{(odds_i - 1)} \end{cases} \quad (7)$$

Combined position (short and long)

$$\bar{r}_{book \bigcap bet} = \frac{1}{N} \left(\sum_{i=1, X<odds<Y}^{N} \begin{cases} win, & -1 \\ loss, & \dfrac{1}{(odds_i - 1)} \end{cases} + \sum_{i=1, X<odds<Y}^{N} \begin{cases} win, & (odds_i - 1) \\ loss, & -1 \end{cases} \right) \quad (8)$$

X is the lower bound and Y the higher bound of the specific odds interval chosen. The mean return, $\bar{r}$ for either taking the bet or bookmaker position is equal to the return according to Appendix I, i.e. when going long you get the odds minus one when choosing the event turning out to be true and -100% when you choose the wrong answer. For the short position you lose 100% in return when choosing the event turning out to be true and earn one divide by the odds minus one when the event turns out to be false. By then choosing a specific odds interval as defined by X and Y we can investigate the return of various intervals.

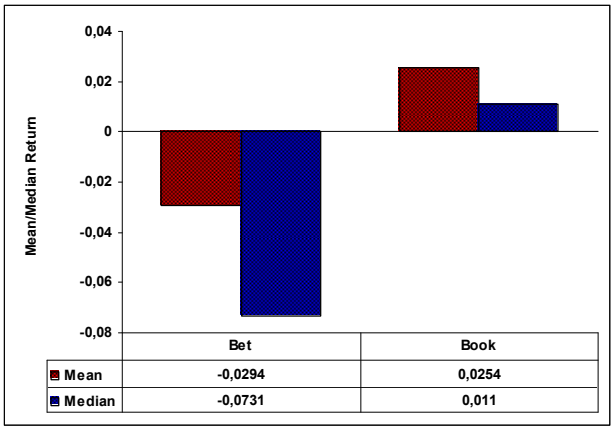
8. EMPIRICAL FINDINGS

8.1 Bookmaking Yields Higher Returns than Betting

In Figure 7 and Table 7, we see that the returns of bookmakers are not only higher than of bettors, they are positive. We therefore ***do not find any reason to reject*** *the null hypothesis* that *"Bookmaking yields higher returns than betting".*

The presented numbers take transaction costs into account, thus showing that bookmakers on average make a positive return on each transaction whereas average bettors have negative returns. This reflects that betting €1 on average leads to a loss of 2.9 cents, whereas booking same risk leads to a gain of 2.5 cents. The average returns are lower and higher than zero and significant on the 3 and 5% levels respectively. This shows that bettors average loss is comparably low, which is due to a low commission charged at the betting exchange. One should note that we have weighted each bet equally despite differences in the stake. In reality, different stakes are used by traders for different bets.

Figure 7: Statistics on odds collected from different sources relative The Betting Exchange.



The figure shows that bookmakers profit on the average transaction, even taking transaction costs into account. Consequently the bettors pay for this and realize significant losses.

Table 7: Average and median returns on betting and bookmaking

Return	Bet	Book
Average*	-0,0294	0,0254
Significance level (of average)	0.020	0.038
Median*	-0,0731	0,0110
Total profit (€)	-97,000	-23,500

* Unweighted. All transactions matter equally

Table 8 shows that bettors on average lose 2.9% on each EURO at risk, whereas bookmakers on average gain 2.5% on each Euro at risk at the betting exchange. The returns are significant on the 5% level.

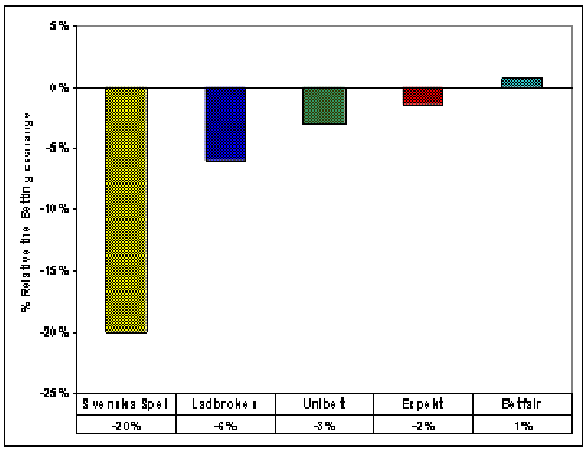
In the return calculations, we have assumed that the same amount was gambled on all outcomes. This implies a bias in the odds causing returns to favor the bookmakers. Even if transactions are weighted with the amounts actually bet, bookmakers still win from bettors. During the sample period, bettors lost €97,000, whereas bookmakers only lost €23,500. The total loss of participants of €120,500 was according to our calculated commission to be charged by the exchange. As groups, both bookmakers and bettors lost from their gambling. Bettors lost more. Bookmakers lost in absolute monetary terms not due to unfavorable odds, but due to large stakes on unfortunate positions and commission. A bookmaker with €1 in all matched bets would have made a profit.

When it comes to the margins that bookmakers charged on top of subjective probabilities, we estimate the margin λ to be 1.35% on all odds, 0.4% on the 90 minutes odds. Margins are significant on the 3% and 5% level respectively. The average probability was $\overline{\varphi}$ =46.4% with standard deviation 11.5%. This is in line with the return findings, but the margin is small for the 90 minute odds.

8.2 Comparing the Betting Exchange with Traditional Betting Markets

In Figure 8, we see that the odds on betting exchanges are clearly higher than at Svenska Spel. The differences from the Betting Exchange for Svenska Spel, Landbrokes, Unibet, Expekt are all statistically significant on the 1% level, whereas the difference from Betfair is not significant at any reasonable significance level.[5] The traditional betting web sites show much smaller differences than Svenska Spel. Hence, we ***do not reject*** *the null hypothesis* that *"The betting exchange has higher odds than traditional bookmakers".*

Figure 8: Statistics on odds collected from different sources relative The Betting Exchange.



The odds at Svenska Spel are 20% lower than the odds at the Betting Exchange taking into account the transaction cost of the exchange (else the difference is larger). The international betting sites show much more competitive odds, but the betting exchanges still remains the superior arena.

At the Betting Exchange, the number of available games is small. As an example, on June 19 the Betting Exchange offers 100 games, whereas the standard bookmaking firms had a much greater supply of games (e.g. Unibet 919 games, Expekt 768 games and Ladbrokes over 2000 games). However, the large betting exchange Betfair also offers over 2000 games. This reflects that our betting exchange is not very established and has fewer opportunities for bettors.

Another disadvantage with betting exchanges is that sometimes the depth of odds at certain games is small. Occasionally there may only be possible to gamble a small amount at the announced best odds. One could therefore discuss whether the best odds are fairly representing the exchange. At standard bookmaking firms no limit is visible to bettors, however there is of course always a limit on how much they are willing to accept - reflecting the risk management of the firms. A principal difference is that on a betting exchange, in contrast to a standard betting market, there must be gamblers willing to act bookmakers on all results, otherwise the market can suffer from low liquidity and dry up.

5 Since the number of observations is over 1000, we find it reasonable to approximate differences to be normally distributed in accordance with the central limit theorem. The observed t stats for one-sided t tests on the paired samples are -17, -9, -11, -7 and 0.3.

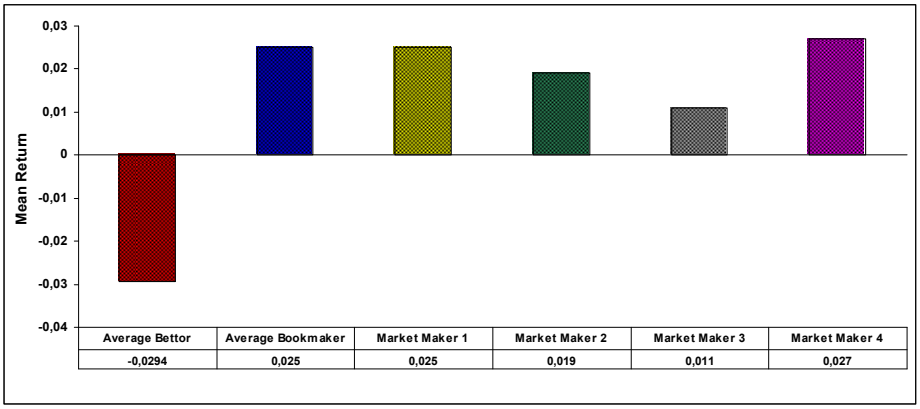
8.3 Large Market Maker Returns

We now study the largest market makers (bookmakers) with the aim to investigate whether they possibly influence and move the market.

Filtering all transactions for large market makers left us with four actors that together were involved in over 50% of transactions on the Betting Exchange. They also represented over 50% of bookmaking turnover. In Figure 9 and Table 9 we see characteristics of these large market makers. We can note that they have shifting returns. One market maker is more profitable than bookmakers in general (0.027 vs. 0.025), a second is in line with, and two underperform the average bookmaker (0.019 and 0.011). Compared to the average return for bookmakers of 0.025 the market makers show no significant difference, but clearly market makers overperform average bettor return of -0.029. It seems as if large market makers have better returns than the average traders. Thus, *we* ***do not reject*** *the null hypothesis* that *"Large market makers overperform average traders"*. Large market however do not seem to overperform other bookmakers, but if having market power they may be able to determine odds levels.

Other characteristics of the large market makers are that they have been active over most of the time period. They have also been active placing some bets, which might be a way of hedging. Only one of them (1005) was profitable in absolute terms of €9,101 and all of them had negative average returns on their bets. The market makers median bookmaking odds ranged from 2 to 2.32, being clearly lower for the most successful market maker.

Figure 9: Average and median returns on betting and bookmaking



In Figure 9, one sees that in the data the average bettors are worst off, losing money to bookmakers. The large bookmakers all make sizeable and positive returns, suggesting that they can influence prices towards for them advantageous levels.

Table 9: Data on large market makers and average bettors

User	Bet Median Odds	Book Median Odds	Bet Mean Odds	Book Mean Odds	Days Active	Normalized Mean Bet return	Normalized Mean Book Return
1005		2,00		2,03	363		0,025
489		2,32		4,62	365		0,019
421		2,31		3,59	362		0,011
240		2,25		2,75	341		0,027
Average bettor	3,63		3,04		89	-0,0294	

Table 9 shows that four bookmaker together act bookmaker role in over 50% of the transactions. They seemingly act liquidity providers and they earn returns far exceeding those of regular bettors.

8.4 Most Betting Exchange Participants Are Unsuccessful

Looking at whether exchange participants are successful, the majority lose from their participation. The results are found in Table 10. Among the 212 Betting Exchange bettors less than half (98) were profitable at the end of the sample period. The bookmakers did better and 48 of 90 were profitable. 92 out of 214 participants were profitable in the sample period.

We performed a two-sided sign test with the null hypothesis of an equal number of profitable players to unprofitable players in order to see if most traders are unsuccessful on our market. The results are presented in the table bellow:

Table 10: Summary of Sign Test of returns for bettors and bookmakers

	Sign Test		
	Profitable	**Unprofitable**	**Sig**
Number of Bettors	98	**114**	0,151
Number Bookmakers	**48**	42	0,701
Traders overall	92	**122***	0,047

* Significant at the 5 % level

Table 10 shows that the majority of bettors lose from their actions on the betting exchange, which is as expected. Since most participants act as bettors, most of them lose, whereas the picture for bookmakers is not clear.

The sign test suggests that there are more unprofitable bettors than profitable, but it is not significant. Traders overall however significantly underperform, driven by most of them being bettors. Among bookmakers there seems to exist a few more profitable than average.

The conclusion of our results is hence that at least traders overall seem to be unsuccessful and have negative returns. Bookmaker returns are also negative on average when removing extreme outliers although higher than bettor returns and thus more in line with the actual spread of 3% being charged at the exchange. We can therefore say that most betting exchange participants are unsuccessful and thus do not find any reason why ***not to reject*** *the null hypothesis* that *"Most traders are unsuccessful"*.

8.5 Bettors trade more aggressively and less successfully after a large win

The event study of how bettors react to a large win gave significant results for all variables but the mean returns for the t-test and significant results for all variables for the Wilcoxon test. The results from the t-test show that after large win bettors bet on events with about 0.40 higher odds per day with about €65 per day higher stakes on average during the 5 day period after the large win. Bettors also bet on about 0.45 more events per day on average. The Wilcoxon test gave the same indications as the t-test. When looking at the actual returns we did not get significant results for the returns with the t-test even though there seems to be a negative trend. The Wilcoxon test gave significant results both for mean and median of negative returns. In interpreting the results one has to lean to the Wilcoxon test as the daily betting returns can not be assumed, unlike daily stock returns, being normally distributed due to the negative pay-off that every bettors is facing.

Table 11: Summary of t- and Wilcoxon test of changes in bettors daily mean return, mean odds, mean amount and mean number of transactions

Daily	t-test				Wilcoxon test					
	t	**df**	**mean**	**sig**	**Z**	**N**	**W+**	**W-**	**Difference**	**sig**
Mean Return	-0,561	183	**-0,040**	0,575	-1,964	175	6382	-9018	**Neg***	0,050
Median Return	-0,803	183	**-0,062**	0,423	-1,975	166	5706	-8155	**Neg***	0,048
Mean Odds	2,381	181	**0,4659***	0,018	-3,383	178	10294	-5637	**Pos****	0,000
Median Odds	2,193	181	**0,3960***	0,030	-3,190	172	10785	-6157	**Pos****	0,001
Mean Amount	3,197	183	**63,379****	0,002	-3,119	177	10768,5	-6223,5	**Pos****	0,002
Median Amount	3,107	183	**70,385****	0,002	-3,217	162	8515,50	-4678,50	**Pos****	0,001
Mean Number of Transactions	3,204	181	**0,4895****	0,002	-3,964	160	8766,50	-4113,50	**Pos****	0,000
Median Number of Transactions	2,724	181	**0,4066****	0,007	-2,651	129	5320,00	-3065,00	**Pos****	0,008

* Significant at the 5 % level
** Significant at the 1 % level

The table shows that after a big win, bettors change their behavior significantly and bet at higher odds and with higher stakes, which suggests that they become overconfident.

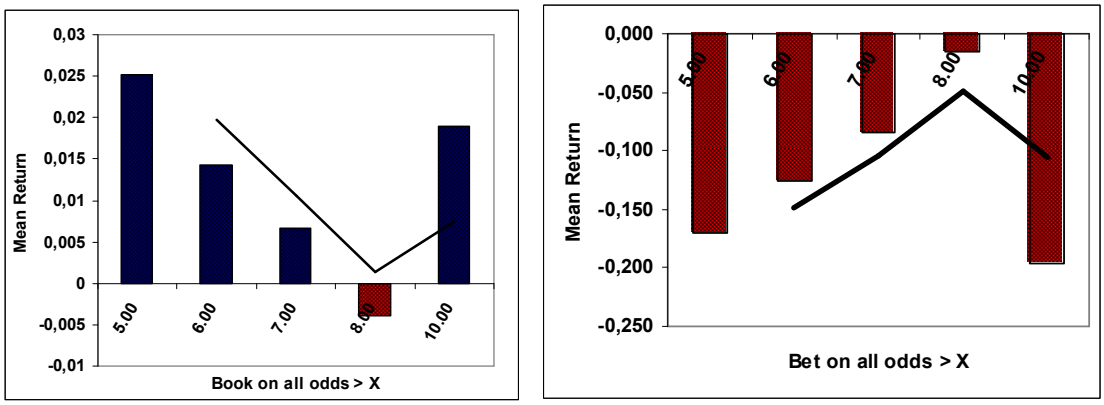
We find that bettors seem to become less successful in terms of daily returns after a large win; however we can not say how large this decrease is due to the insignificant t-test. The other tested variables show a significant positive trend. We therefore ***do not reject*** *the null hypothesis* that *"After a large win, bettors trade to higher average odds, with higher stakes and on average trade more often.*

Concluding, one can say that after a large win, a bettor trades more often with higher stakes to higher odds indicating lower returns possibly due to overconfidence i.e. increased risk taking in terms of betting more frequently on higher odds (representing riskier outcomes) with higher capital stakes.

8.6 Betting on Favorites and Bookmaking on Long-shots Yields Better Returns

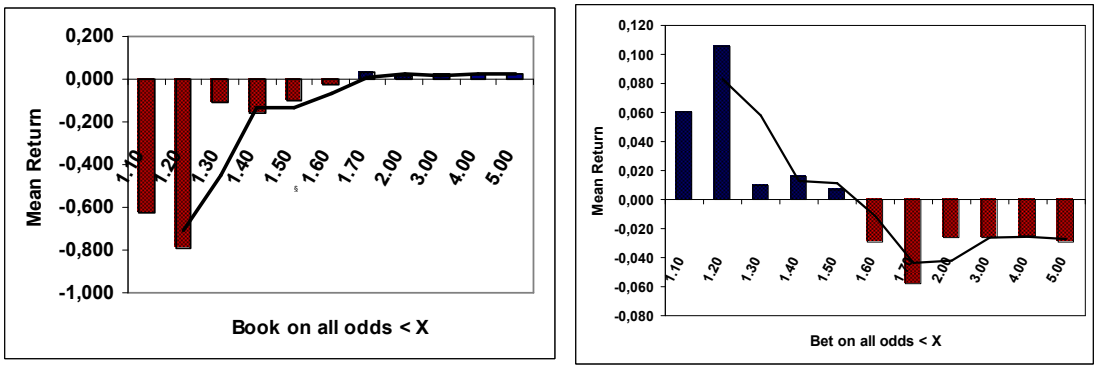
The observations of returns on betting and bookmaking in a number of different odds categories are summarized in Figure 10 and 11. What we can see in the figures is that, on average, the returns on bet positions on low odds are positive, whereas the returns on high odds are negative. The bookmaking side returns are almost the reverse. The pattern is relatively clear and supports the existence of long-shot – favorite bias, i.e. betting strategies with good returns are betting on favorites and bookmaking on unlikely outcomes. Transaction costs on wins have a slightly adverse effect on all returns. Note that the return measure does not take into account whether a large or small bet was put on a particular outcome. Instead all bets on favorites e.g. bets with odds ranging up to 1.2 are treated equally.

Figure 10: Higher odds show characteristics of Long-shot bias – returns in favor of bookmakers



In the figure we can see that the mean return for the bookmakers on high odds (>5) on average is positive, whereas the bettors lose a significant share of their stake. This suggests that bookmakers make their profits mainly on high odds, where the level of uncertainty is large.

Figure 11: Low odds show Favorite bias characteristics – betting on low odds gives significantly better average return



In the figure we can see that the mean return for the bettor position of odds below 1.5 on average is positive, whereas higher odds typically lead to negative bettor return. This suggests betting on low odds to be favorable for the bettor and less attractive for bookmakers.

The returns in betting are by nature not normally distributed, since the bettor (ignoring commission) either gets an amount of zero or of the odds times the stake back (and vice versa for the bookmaker). The distribution of returns will hence be truncated with numerous of minus 100 percent returns and other returns spread from zero and upwards. This unfortunately makes standard t-testing not applicable.

A difficulty is also that very small odds such as 1.05, and below, require a large number of observations to determine whether or not they systematically may be profitable to bet on. These outcomes most often come true, which also may induce a gambler to place a single, or very few, big bet(s) on this outcome. When we get to higher odds around 1.30, we find it more interesting as the sample is larger and returns remain negative. Betting odds on favorites up to 1.50 actually appear to give clearly better returns +0.69% compared to the average odds at which the average bettor return is -2.9% (see Appendix IV for more information) on a sample that is large.

The best strategy would be bookmaking on high odds. If bookmaking on all odds above 3.00, an average return of 3.61% with standard error 0.87% would have been realized. This is to be compared to the return of 2.5% on average bookmaking. For odds above 3.00, the odds and associated outcomes in out dataset generally have favored the bookmakers, although there is a weakening in return for the odds between 8 and 10. The overall picture of bookmakers gaining on high odds is in line with the idea of more asymmetric information problems with very unlikely outcomes. The weakening for the odds 8-10 is on a relatively limited number of transactions and on transactions with high odds. This sheds light on the high risk faced by bookmakers on high odds, but is not strong support against the average profitability of bookmaking in high odds. Seeing that bookmakers have relatively much to lose on high odds, it is the opposite situation on low odds; bettors risk the entire stake for a tiny return. Therefore, the situation is in a sense more or less the opposite with bettors facing low returns but high downside on low odds and they actually succeed to compensate a little, but not as well as bookmakers on high odds.

We can note that the on the games with odds between 1.60 and 1.70, the outcomes have greatly favored the bookmakers, whereas games with lower odds have been relatively better for bettors. The odds over 1.70 up to three again on average leads to small losses also for the bookmaking side of the transaction, but the bettors are worse off.

Another way to describe if betting and bookmaking strategies yield different average returns is to look at whether, or not, bookmakers (or bettors) are able to charge a positive margin above the fair price for a bet on a particular outcome. Bookmakers like Unibet should as mentioned be expected to assess probability of a particular outcome and then charge a margin in their favor on top when setting the price (odds). Bookmakers would be expected to set odds somewhat lower than what they predict would be fair given their outcome probability assessment, else they would not expect any profit and probably not enter the bet. Strategic bettors on the other hand would be expected to do the opposite and require odds that they find favorable relative to their assessment of outcome probability. The margin would provide compensation for uncertainty and profit.

When looking at the margins for bookmakers implied by actual outcome frequencies and odds, for odds 1.50 and below, odds up to 3.00 and odds above 3.00 respectively, we find the results summarized in Table 12 below. It is the case that bookmakers manage to charge comparably quite large margin on small probability (high odds) bets, whereas the margin on high probability (low odds) is negative, which means that bets are in the favor of bettors (bettors are able to charge a margin from bookmakers on these bets). This assumes that the subjective probability estimates of bookmakers on average are in line with actual frequencies, or in other words that bookmakers on average are not worse than bettors in their assessments, which would not appear unreasonable.

Table 12: Summary of average margins that bookmakers have been able to add on top of actual probabilities

Odds	Average bookmaker return	Standard error
<=1.50	-0.10	0.067
<=3.00	0.023	0.006
>3.00	0.036	0.019

In the table we see that bookmakers on average realize losses on low odds, whereas they have significant returns on high odds bets. The contrary is true for bettors – they lose when betting on high odds and win on low odds.

Turning back to Hypothesis 6a: "*Betting on favorites (low odds) yield better returns"*, we can conclude that we ***cannot reject*** the hypothesis. Betting on low odds outcomes yields significantly better return, although they are on average still negative.

The related Hypothesis 6b, "*Bookmaking on Underdogs Yields Better Returns",* ***cannot be rejected*** either as bookmaking on underdogs provides significantly better returns compared to bookmaking on lower odds, i.e. bookmakers manage to charge a margin on underdog bets. It is even the case that bookmakers on average achieve profitable returns after taking transaction costs into account.

8.7 Summary of Empirical Findings

In this section we wrap up our empirical findings and present them in Table 13 below:

Table 13: Summary of empirical findings on hypotheses

Hypotheses:	
Adverse Selection	
H1: Bookmaking (going short) yields *higher* returns than betting (going long)	*Not rejected*
H2: The limit order book betting exchange has *higher* average odds than traditional bookmakers	*Not rejected*
Market Power	
H3: Large market makers *overperform* average traders	*Not rejected*
Behavioral Factors	
H4: Most traders are *unsuccessful*	*Not rejected*
H5: After a large win bettors:	*Not rejected**
a.) Trade with *lower* returns	*Not rejected*
b.) Trade to *higher* average odds	*Not rejected*
c.) Trade with *higher* stakes	*Not rejected*
d.) Trade *more* frequently	*Not rejected*
Subjective Probability	
H6: High return trading strategies are:	
a.) Betting (going long) on favorites (low odds)	*Not rejected*
b.) Booking (going short) on underdogs (high odds)	*Not rejected*

* t-test was insignificant, however Wilcoxon test showed significance to not reject

9. ANALYSIS AND CONCLUSIONS

In this chapter we will develop and discuss our empirical findings. First we briefly cover selected parts of the market microstructure and its relevance in Finance. We then analyse the nature of the four forces that, according to our odds equilibrium (chapter 3), have an effect on the betting exchange odds. Based on our evaluation of the market on these four pillars, we can draw conclusions about the questions initially posed, i.e. *"What is the market microstructure of the new betting exchange?"* and *"Is the betting exchange efficient?"*.

9.1 The New Market Microstructure of the Betting Exchange

9.1.1 Interesting for Financial Research

When investigating and comparing the characteristics of betting- and financial exchanges, we found many similarities. In general, one can say that some derivatives markets are highly similar to betting exchanges in the short-run in terms of market dynamics. However, two significant differences prevail at the betting exchange: *less skill is required to trade* and there is *no underlying value* of a betting contract. Betting exchanges in contrast to financial exchanges, only serve as the role of entertainment and do not add economic value to society in terms of growth and risk management in their current framework. We conclude that the betting exchange market dynamics bears strong resemblance with financial exchanges and has good potential for increased use in financial research, both for understanding of investor behavior and market efficiency. By studying betting exchanges we can also learn more about whether behavior found in markets could be inherent to humankind.

9.1.2 Adverse selection problem reduced: Higher odds, but still the bookmakers' market

Adverse selection and information asymmetry on the betting exchange
One pillar of influence on the betting market prices is the existence of adverse selection problems. The Swedish regulated betting market and to lesser extent the oligopoly of betting sites have very low or low payback ratios, reflected in low odds for bettors. This we argue is related to adverse selection problems. We can compare these markets to quote-driven financial exchanges with lack of competition.

One reason for the problem is that the evaluation of prices becomes difficult as traders only have one source of prices and therefore have a difficulty of getting an overview of what the market prices really should be. This leads to a situation where betting on average yields highly negative returns for bettors. Participation will therefore require less informed actors that do not realize that the price is unfair and the expected value much lower. Alternatively the bettor must have strong incentives beside the expected return on the outcome to take the bet i.e. a strong liking of the team or a risk-loving behavior.

Bookmakers on the other hand seem to be mostly professional, four of them making up the majority of transactions, and participate to consistently lock in profits, whereas bettors seem to largely participate on the basis of entertainment and pleasure. Thus, we have a case with informed bookmakers taking advantage of bettors i.e. bets being lemons with excessively high prices.

When comparing the returns of bettors and bookmakers on the Betting Exchange data, we again find that bookmakers have higher average returns than bettors. The finding is a bit surprising as bettors wanting to gamble have the equivalent options of betting on an outcome, or to act bookmaker on the mutually exclusive other outcome(s). This should lead to more competition as more people can take the attractive role of a bookmaker. As a comparison, the change from quote-driven financial markets over to digital limit-order book exchanges has lead to spreads coming down and margins for market makers (investment banks) being squeezed. Similarly, we would expect bets to be subject to commoditization as competition increases and the price information becomes increasingly available to everyone with best execution.

So why is not this case for our Betting Exchange? With bettors being able to take the reverse positions, bettor and bookmaker returns should have evened-out and prices should move to reflect the true probabilities of outcomes, but that is not the case. Bookmakers being more professional and more informed do not appear unlikely as bookmakers may follow the market and the teams more closely and consequently have more knowledge about the game, thereby able to benefit from better probability estimates. More importantly, bookmakers appear to be better at evaluating the prices relative to probability of outcomes. If one considers a bet on Arsenal to beat Villa, one will naturally want to gamble on Arsenal. But would one do it at any odds? What if one, if being right, got 1% extra back per 1 Euro at stake? Then one would hardly want to take on the bet. There is a tradeoff between upside and probability of the outcome, which is not easily accessible if not used to think in similar expected value terms. For gamblers who have learned about Texas Holdem poker, this is similar to the use of so called "pot odds" to motivate betting.

If bettors are less informed and to lesser extent consider the conditions they get, they on average are deemed to lose. We find that it is not straightforward to take on and fully understand the bookmaker's position. The position has not been possible for sports betting very long. Therefore, it is still complicated for users to understand the return characteristics properly, as well as actually carrying out the transaction on the website. We found indications in our data that the most traders were bettors, which indicates that fewer people are willing to take on the bookmaker's position. It could also be the case that only a few bookmakers manage to set the odds at competitive levels, others not fully understanding the position may have put out uncompetitive bookmaking orders to the exchange that never were matched.

Bookmakers being more skilled is in line with the findings of Levitt (2002, 2004) and others. This being true on monopoly and oligopoly markets is however not as surprising as it being true also on the betting exchange open to competition. One possible explanation could be that the exchange is a relatively new institution and that skilled actors still are reluctant to participation in odds betting, preferring other types of games, e.g. poker, over betting. If so, the exchange may be on the way to become more competitive.

Timing is also a source of information asymmetry in betting markets. The party first suggesting terms of a bet will need to accept that additional information will accrue until the time of the bet being matched. To compensate for the risk of missing important information, the quote posted should intuitively be set somewhat favorable. If bet matching commonly happens following bettors accepting bookmaker suggestions, the matching process procedure itself may give rise to slightly better bookmaker return compensating for risk associated with delayed matching.

Another aspect of average return is the risk structure of participation. If participating bookmakers on average take higher risk, one could easily argue they should be compensated with higher expected return. That would be an argument for bookmakers to have more favorable returns on high odds bets compared to low odds bets. On low odds, the bookmaker can only lose a very small fraction of the stake, implying that amount possible to win is many times the potential loss. For the bettor it is the other way around. Thus, the probability-weighted volatility of the outcome will be the same, but the downside risk relative to the potential upside for bookmakers will be the largest on high odds and smallest on low odds. For bettors the largest absolute downside risk will be on small odds, e.g. odds of 1.1 imply possibility of 10 percent return at the cost of possibility of loosing 100 percent. Looking at the data set at hand, we find that most bets are on odds above 1.5 and up to 4. In this range, most bets have ratios of upside to downside return exceeding one, i.e. relatively more limited bookmaker downside. It can therefore be a way of explaining that participants in the market hesitate to take the potentially larger downside in the bookmaking position. The consequence being that supply of odds goes down and price comes in favor of the few bookmakers offering odds with incomplete competition.

But odds are higher on the exchange

When comparing the odds of two betting exchanges and to the odds of traditional bookmakers, it is clear that the betting exchange offers better odds. The odds at the betting exchange are on average as much as 20% better than the odds at the monopolist Svenska Spel. This is of course due to the fact that Svenska Spel's prices are the only available and that bettors cannot compare them to other information available as time goes by in contrast to the betting exchange where this is possible due to the limit-order-book setup.

Betting with Svenska Spel and on traditional betting markets, leaves the bettor with a single fixed odds quote to consider.

Even the large online bookmaking firms such as Unibet, Expekt and Ladbrokes have lower odds than betting exchanges, but the differences are much smaller (3%, 1.5% and 6%) taking commission charged on wins into account. Note that we still have not taken any tax effects into account, which could occasionally be a consideration when gambling at Svenska Spel in contrast to gambling offshore. We conclude that betting exchanges have superior odds to regular betting markets.

The reason for the higher odds at exchanges is undoubtedly that anyone can be a bookmaker and competition for bets to be matched lowers the spread (or margin) that traditional bookmakers otherwise charge (to earn more or less sizable profits). In Sweden the law stipulates that the betting company Svenska Spel cannot pay back more than a certain percentage to bettors, effectively making expected return of betting fall below minus 20%. By betting at international betting web sites, bettors can improve their expected returns to around minus 7-13%. Finally, bettors may enter betting exchanges and perhaps improve their returns yet another small step.

We found that the most successful traders seem to be more informed and have learned how to use the bookmaker's position. It could therefore be concluded that the betting exchange currently serves the purpose of more professional gamblers. As time goes by and gamblers become more accustomed and willing to taking on the bookmaker's position, betting exchanges may become more liquid and thus prevail even over standard betting markets with small spreads.

Another benefit that online bookmaking firms have over Svenska Spel is that odds are fixed at the time of the bet. At Svenska Spel the bettor does not exactly know his odds until after the game. This allows Svenska Spel to minimize their risk and adjust odds to balance their accounts.

To make a full comparison of the actual financial returns between bookmakers and bettors, it would be necessary to understand the monopoly/ oligopoly bookmakers' (Svenska Spel/ Unibet, Ladbrokes etc.) cost of offering the gambling opportunity to bettors. The betting exchange works differently – bookmakers do not handle the betting service provisioning, instead all participants pay an equal percentage commission on wins. Returns on bets are therefore fully comparable. Then, if bookmaker actors and betting actors are equally good at assessing bets and would evaluate bets based on assessing probabilities and maximizing expected returns, fair prices would on average yield same returns for bettors and bookmakers.

With the upsides mentioned above, why have gamblers then still not left the traditional betting markets and especially Svenska Spel in favor for the seemingly attractive betting exchanges?

First of all, the trend over the last year clearly shows that bettors actively leave the Swedish monopolist Svenska Spel to wager at more favorable conditions at other bookmaking firms. We see no reason for this trend to turn as long as the conditions for betting at other firms are extremely favorable. However, as gambling overall has grown, Svenska Spel has maintained a large turnover finding new customers and having the benefit of local branches and a strong brand.

Betting exchanges have some obvious problems, one being that they suffer from low liquidity in terms of both depth and the number of events and products offered. For example, as opposed to standard betting markets, there is not always someone willing to take on one's position. At the standard betting market the bookmaking firm normally takes on all bets as long as the stakes are not excessively high. However, at the betting exchange, winners gambling with larger stakes will always be welcome to try to get their bets matched. At the betting exchange only a certain amount is available at best bid price. This is not different from the bookmaking firms, since they adjust their quoted odds as bets come in. Also, bookmaking firms do not allow bets of any size – large bets must be made over the telephone at agreed upon terms.

Summing up, the betting exchange provides a superior arena for betting with new opportunities for betting against outcomes available to gamblers. The odds are highly competitive, although some of the traditional online actors almost reach similar levels.

9.1.3 Market power: Sign of market power as the large market makers show good returns

Prices on the betting exchange may, as in other markets and as suggested in the odds model, be affected by actors utilizing their market power to achieve some benefits.

Studying the data set for bookmakers involved in a large number of transactions, we found that there were four large market makers that participated in a very substantial share (over 50%) of the matched bets. They might even have some special relation with the betting exchange to quote prices and provide liquidity. These four should have some control over the prices, be more professional and informed. For example they could take on some fair or unfavorable odds in order to clear the relatively illiquid exchange order book from competitive odds to be matched and thereby get their own favorable odds exposed to a majority of trading participants who only use the betting position of the transaction.

Looking at return on bets, the large market makers appear to be better off than average participants and bettors. We note that the single most significant market maker has an average return on book transactions in line with average book return, whereas the others have good returns, though lagging the leader. Relative to average bettors, the four market makers have better returns. The large market makers therefore support the hypothesis of them having some market power that they can utilize to achieve superior returns, at the cost of an adverse impact on market efficiency.

The fact that so few other traders act bookmakers is surprising as the bookmaker side is more profitable. The reason may be that gamblers have not yet become used to the strategies and learned to be bookmaker. Therefore, if the regular bettor would get more insights, the returns of bookmakers would be pushed further down to parity with bettors' returns. For now, it is the bookmakers market.

9.1.4 Market Behavioral biases: Bettors show signs of overconfidence and lose from their gambling

The third aspect of the price formation at the betting exchange that we wanted to further understand is the participants' motivation for trading and rationality of behavioral.

As expected, the data set shows that the majority of participants on the Betting Exchange lose money. Traders that on average lose from participation is in line with results of Andersson (2004) and Barber & Odean (2000) pertaining to day trading on financial markets. Moreover, since the exchange itself charges commission and betting is a zero-sum game, the aggregated outcome over all participants is a loss, representing the commission charged by the exchange on wins. Bookmakers being better off implies that they are more informed agents, better at predicting outcomes accurately and setting terms of bets, implicating a bias in the odds. The commonly suggested explanation would be that people bet for entertainment – like participants in lottery. Gambling adds excitement and dreams it adds to everyday life. The chance of a big win has therefore utility allowing for a possibility of the bettor being able to change his life or fulfill a dream. In the case of fixed odds betting, low odds do not provide opportunity for big wins – at least as long as stakes are limited. This suggests lower non-monetary utility of betting at low odds, which may be one of the reasons to why, as we shall see, bookmakers do not manage to get as favorable conditions on low odds as on higher odds.

However, as opposed to lottery betting has an element of skill in assessing a winner. Therefore, participants can motivate a bet if they believe that they are better than others on the market in assessing the winner. If so, participants rationally try to maximize their monetary gain by betting. As illustrated, bettors are not particularly successful and consistently perform worse than bookmakers, which reflect suboptimal assessments of bets taken. If the subjective probability assessment of an outcome if too high, a

loss will on average materialize. This shows that average individuals have problems in assessing probabilities and correctly evaluating what odds to require when taking a bet, i.e. they are overconfident in their beliefs of who will win, and suffer a negative return as consequence. In line with this, Griffith already 1947 suggested that individuals have tendency to overestimate the probability of unlikely outcomes.

Another parallel to the situation on the betting market we find in the financial markets when we consider the type of participants/gamblers. We can assume that gamblers mostly are private individuals and very seldom large organizations or institutions. Therefore, the gamblers are in some sense similar to private stock investors testing their luck on the stock markets. Several studies have shown that private individuals invest heavily in (relatively risky) high-tech stocks and therefore seem to have an exaggerated appetite for risk. We could use similar reasoning for describing bettors' interest in unlikely high odds (risky) outcomes, representing an extraordinary appetite for risk. Weitzman (1965) and Ali (1977), suggested the risk-loving behavior of individuals to be the reason for accepting lower payoff when betting on unlikely outcomes. As we shall see in the next section, bettors accordingly have particularly bad payoffs when betting on low probability (high-odds) outcomes.

Further, we found that bettors become more aggressive after a large win and change their behavior to trade on higher odds, more frequently and with higher stakes. This is a behavior that bookmakers directly or indirectly profit from. This behavior seems to be in line with what has been observed on stock exchanges with people losing money due to overconfidence as they credit themselves for their success (Daniel et al. (1998)).

The findings of this section suggest that successful bookmakers are taking advantage of biases in the behavior of bettors, such as overconfidence and difficulties to assess low probabilities and evaluate bet conditions for monetary consequences.

9.1.5 Subjective probability of outcome

Having found that the bookmaker side of the exchange is overall more profitable, we here look closer at betting on higher and lower odds – outcomes with smaller and higher implied probabilities. As we shall see, the odds observed suggest that bettors and bookmakers have biased subjective probability estimates with differences for high vs. small probability outcomes (favorites vs. long-shots). The betting exchange characteristics therefore suggest that a simple profitable strategy could be formed to benefit from the biases.

Starting with a comparison between bookmakers and bettors, bookmakers have on the data set at hand better implied probabilities of their position – illustrated by better average returns on each bet. This suggests that they have better information and are more professional. Estimating probabilities is a difficult art, where active bookmakers seem to have developed their tools further. Bettors may to lesser extent know how to conceptually deal with analysis of odds and given that gambling may be for fun and normally small sums, the approach could naturally be expected to be less professional.

Professional market makers in financial assets (compare e.g. OTC markets) charge the "bid-ask spread" to earn money for their work and to compensate for risk of trading with more informed (Harris (2003)). Bookmakers facilitating liquidity at the betting exchange would also want to compensate for risk of trading with informed investors (bettors), described as charging a margin. To see if bookmakers actually lock in profits and take advantage of bettors across the board of bets, we looked at returns in different odds categories – higher and lower odds – odds on less and more likely outcomes. According to the literature on the long-shot bias we expected some bias in returns for the betting bookmakers, whereas financial market makers should be expected to show relatively stable returns at the level of the margin charged. The findings in Figure 5 and 6 illustrate that average returns for bettors and bookmakers varies substantially depending on odds level. On low odds (<1.5), bettors have clearly better returns, whereas the opposite was true on higher odds. The picture is a bit blurred from odds above 1.6 showing highly negative returns, but overall picture fits very well with expectations. We can conclude that the most successful bettor returns are with trades on low odds, while the most successful bookmakers trade to higher odds. This suggests that the implied subjective probability estimates of bookmakers were more in

their favor on high odds and unfavorable on low odds, or that they managed to charge margin on top of their probability estimate only on high odds. In literature, one suggested explanation to the bias comes from Ottaviani & Sörensen (2004), who attribute higher odds higher level of information asymmetry and adverse selection, which in turn require bookmakers to charge a risk premium when laying odds.

In accordance with the favorite and long-shot bias, we formed strategies to read off ex-post returns. By placing €1 bets on all low odds (<1.5) outcomes we managed to get a betting return of 0.7% compared to the negative -2.9% betting average return. Bookmaking high odds outcomes yielded a positive return of 3.6%. This shows that there is a systematic bias in the odds. This weak form market inefficiency is the same as observed on other data such as racetrack betting and NFL.

9.2 The betting market is inefficient

Gandar et al (1988), Golec and Tamarkin (1991), Vergin & Sosick (1999), Dare & Holland (1996) and others have already found that several betting markets appear to have some degree of inefficiency, commonly illustrated with profitable betting strategies based on expected behavioral patterns. We have in the previous sections looked at a four key aspects of the new betting exchange. All in all that leads us to believe that, although it is in many ways superior to bookmaking sites, the Betting Exchange is still not efficient.

There are a number of reasons to why the exchange appears to be inefficient and why bookmakers systematically earn less on low outcomes and more on high odds outcomes (existence of long-shot bias).

9.2.1 Degree of asymmetric information

Despite new characteristics of betting due to the limit-order book betting exchange, an asymmetry of information between bettors and bookmakers prevails. Betting with Svenska Spel and on traditional betting markets, leaves the bettor with a single fixed odds quote to consider. Since it is hard to determine fair odds and no simple comparison can be made, such structure opens up for adverse selection and high spreads. In financial markets, there has been a somewhat corresponding development with the introduction of electronic exchanges replacing OTC markets, which has lowered adverse selection. With the order driven limit-order book betting exchange, the commonly less informed bettors get best execution from several bookmakers, and if not satisfied they can post their own odds. At the betting exchange, the spread is overall lower, i.e. odds better, for bettors. Bettors with more information will enter due to the better conditions and reduce overall information asymmetry.

One more way to view potential information asymmetry impact on odds, is to consider the component of the bid ask spread relating to the risk of trading with a more informed counterpart (i.e. a counterpart with better probability assessment). In high odds outcomes, there is commonly a team involved that is less known to the public, have lower standings in the league tables and has more room for information asymmetry problems. High odds also make high returns, attracting participants with insider information. Therefore the risk of trading with a more informed counterpart could be higher, causing a need for bookmakers to compensate through quoting lower odds.

9.2.2 Market power influences

There are four big bookmaker actors on the Betting Exchange. Their mere existence and above average returns are strong signs of market power forces. If big actors can affect prices and gain from it, it is a sign of market inefficiency. In our case we can conclude that there are reasons to believe that these four could have market power.

9.2.3 Behavioral biases

Most of the participants on the exchange are bettors. Since they on average lose, they have reasons for participation beyond positive average returns. Some can be risk-loving and willing to bet just to have the

possibility, though tiny, to win. Bettors also tend to be overconfident. In particular after big wins, they change their behavior and risk appetite and gamble to higher odds and higher stakes, which is likely to lead to worse performance. Some of the behavior can be explained with the size of stakes often being small, so the approach is not that of a really important investment for individuals.

9.2.4 Assessment of subjective probabilities and small probabilities bias

Estimating probabilities is a difficult art, in which bookmakers are superior to bettors. Bookmakers are more informed or may have more experience and skill in estimating probabilities of outcomes and odds that will equalize supply and demand.

If probabilities are small, a single probability percentage point can make a big difference on the odds. For the bookmaker, the extreme payouts and risk in the high odds games therefore becomes a reason to compensate with higher return – spread. Being able to set lower odds to compensate is, at least partly, explained by lack of competition (or even oligopoly) among bookmakers. On low odds however, the potential win-loss structure is the other way round – bettors can lose a substantial amount (the full stake) relative to the small potential upside (perhaps a few percentage), and hence bettors should try require the same premium illustrated by much better returns for betters on low odds.

9.2.5 Unfavorable preferences for high odds

In the data we see that bettors do not place any substantial amounts of bets on low odds, where they have better returns. Instead, they ask for bets on outcomes with higher odds. Hence, bookmakers can set for them favorable levels on high odds and bettors lose from their risk-loving high-odds preference. It might not come as a surprise that the most popular games to bet on are those with very high first prices, even though these games have low probabilities of winning. Bettors may hence not regard only the expected monetary value of their games, but instead excessively set value on a small probability to win big over a good probability of a small win (despite better expected value).

9.2.6 Lack of arbitrageurs

If bettors were as informed and skilled as bookmakers, they would be able to realize that they should place positions equivalent to bet positions by backing the other outcomes, thereby competing with bookmakers as long as the bookmaker position appears more favorable. With more such actors, the difference in success between bettors and bookmakers should even out. However, the market currently does not seem to be competitive enough – there are too few actors making use of the bookmaker role. Put in other words, although competition among bookmakers has increased with the introduction of the new betting exchange, there is still not enough competition to facilitate an efficient market. This is because market efficiency requires a large number of competing market participants with heterogeneous beliefs and information. In our data set, individual actors, i.e. large bookmakers, can influence the prices and earn superior returns at the cost of bettors.

The findings thus suggest that the Betting Exchange is weak form inefficient and that the most informed and successful participants take advantage of the biases observed in the odds at the Betting Exchange. Information in odds can be used to predict returns on the Betting Exchange.

9.3 Discussion of data

The main data sample used to study the betting exchange comes from one single betting exchange. It would have been beneficial to get data from more exchanges to investigate whether results generalize on other exchanges and in other types of odds betting, in view of the fact that in our sample, we find only that the 90 minutes odds have enough observations to draw any conclusions with reasonable significance. Other betting exchanges, however, were not willing to, or did not have time to, leave out their databases.

An important consideration for our data sample is that the betting exchange is recently established and has a limited number of actors as well as traders. Therefore it could be that the situation has not stabilized and has not reached equilibrium. Inefficiency could much likely arise initially due to a lack of traders fulfilling the competition conditions for an efficient market.

As to our empirical study, we have found several results with shifting levels of significance. This should be seen as indicatory and results could be linked to the type of bettors and bookmakers that initially have found their way to the betting exchange. When betting exchanges become more known and attract the broad public, new studies may provide more robust results that with ease can be generalized to other markets. However, as similar findings have been made on established betting markets, we find that we have contributed to support them with our observations from the betting exchange.

9.4 Conclusions

Table 14: Summary of findings

- The Betting Exchange is in many ways similar to financial exchanges and limit-order book, and is consequently frequently used among finance researchers
- Although adverse selection problems are reduced, they still exist on the betting exchange
- Despite better odds to bettors, bookmakers still are the winners on the market
- Large bookmakers represent majority of bookmaker activity
- Bettors lose from their participation and must have other motivations than expected value
- After big wins, bettors unsuccessfully change their behavior
- Sign of long-shot bias - betting of favorites yields better returns than betting on long-shots
- The betting exchange is weak form inefficient

We conclude that the betting exchange bears strong resemblance to financial exchanges. Betting markets have after the introduction of betting exchanges even more in common with financial markets, and a good potential for increased use in financial research. Many researchers have already shown interest in betting markets, but more is surely to come as betting exchanges show many similarities with financial exchanges.

Compared to other types of fixed odds betting, the betting exchange provides gamblers with the new opportunity of *betting against outcomes – going short*, something previously limited to bookmakers. This type of market reduces the adverse selection problem and gives participants the possibility of best execution and matching of odds better than initially asked for by the bookmaker. The odds at the betting exchanges are superior to other betting markets, even taking commission into account. In comparison to betting with the Swedish betting company Svenska Spel, conditions for betting on the exchange are outstanding with over 20% better returns for traditional betting. However, on the downside one should keep in mind that some exchanges regularly suffer from low liquidity.

As expected, traders on the betting exchange still significantly lose on average of their participation. The bettors are the biggest losers, whereas bookmakers have better and positive returns. This leads us to conclude that bookmakers are more informed agents, whereas bettors must be betting with more reasons than rational expectations on return, e.g. betting for entertainment. Bettors do not appear to be able to, or care to, assess fair odds given their subjective assessments of the probability of outcomes. Hence, there are still adverse selection problems although smaller. The fact that four big bookmakers represent over half of bookmaking transactions also leads us to believe that these actors are large enough to influence prices on the different markets, e.g. by being first to quote a price and lead the market to favorable odds levels.

Not only do bettors bet although they lose, they also become aggressive if they win. After a large win they tend to trade on higher odds, trade more frequently and to trade with higher stakes. This is a behavior that bookmakers directly or indirectly profit from. Seeing similarities in financial markets and other betting markets, we can conclude that the bettors' behavior, with demand for unfavorable odds, can be

understood as being due to bias of overconfidence, difficulties of assessing small probabilities, levels of risk aversion gambling with small wagers and adverse selection.

Finally, we conclude that there is a profitable trading strategy in betting on low odds outcomes (favorites) and bookmaking on high odds outcomes (underdogs), i.e. betting on favorites and betting against underdogs, in accordance with the in betting markets frequently observed favorite long-shot bias.
With these findings in mind, we answer our research questions by *concluding that the betting exchange market is inefficient*. Despite the promising reduction of the adverse selection problem with competition on the bookmaking side, the information asymmetry still exists. As the bookmaker position is not fully understood and utilized, the supply of odds is adversely affected and bookmakers have much better returns than bettors. The effect is partly due to bettors betting more on high odds where they lose more.

As people learn to evaluate the bookmaker role, we believe that the betting exchange is on the track to more competition on bookmaker side and more efficient odds to lesser extent favoring bookmakers. The bookmaker role is open to everyone and we expect arbitrageurs and bettors to start taking advantage of the favorable bookmaker side of bets and especially the long-shot favorite bias. The most important conclusions are summarized in Table 14.

10. SUGGESTIONS TO FURTHER RESEARCH

During the course of our study we have run into a multitude of prospects for further research. The academic use of betting markets is still under development and it is our firm belief that there is yet much more to come and a potential for many interesting theses within this area. By exploring betting market data we believe that there is a good chance of further understanding the concept of market efficiency as well as the behavioral finance strand. Reading more about the 2002 Noble Price Winners Kahneman & Tversky should be a good source of inspiration. We would suggest the following to be subjects that could prove interesting to investigate further.

- *Real time odds:* Analyze the information content/impact on prices (odds). E.g. look at injuries and other information prior to mach starts. It is generally thought that odds, especially online odds, are updated very infrequent. This should be expected to give rise to potential arbitrage or profit opportunities. Are there any signs of over or under reaction?

- *Arbitrage:* Are there significant arbitrage opportunities available using betting exchanges? This is likely to be the case due to the higher odds offered and the expected involvement of non-professional market makers (regular agents).

- *Event studies:* Similarly to finance studies of the effect on CEO changes on asset returns, the importance of key players to game outcomes could be examined using statistical methods. For example, players missing from their teams due to games with their national teams could provide basis for such studies. In the sports setting, the advantage is that we can separately examine the markets' view of the importance of a key player (as reflected in the odds) and the actual importance (as reflected in the effect on actual winning percentages). In regular finance settings, market perceptions and real effects are almost impossible to separate as the true value of the firm is not revealed.

- *Weather effects:* Are there any weather effects on the betting market, i.e. is the weather correlated with betting returns? For example, on rainy days people might be less self-confident and hesitate to place bets.

- *Well-known teams:* There are reasons to believe that gamblers act seemingly irrationally, perhaps under the collusion of psychological biases. It could for example be the case that bettors bet excessively on certain well-known teams (due to a reference point of them winning often and being good teams), not fully considering probability estimates, but using limited rationality when they evaluate their decisions and the information contained in the odds (in the price). Therefore we could have an effect on the betting market similar to the neglected firm effect in financial markets, with bookmaking on well-known teams as a profitable strategy.

- *Media coverage and importance of information:* Do large events with significant media expose (e.g. Football championships, Eurovision Song Contest) attract more noise bettors (traders) that lose to more informed agents.

- *Gambler behavior studies:* How do gamblers react after a large loss or win? Do gamblers trade more often? Do they take more risk, e.g. by betting at higher odds? Do they bet on more types of games? Do they become more successful?

- *Timing Effects:* When looking at the daily median odds one can clearly see that during some time periods the median odds seem to be higher on average. What signifies these periods? Are there major events such as particular tournaments affecting the odds?

11. APPENDIX

Appendix I. Betting return calculation

Figure 12: Profit, Payoff and Return Table of Back and Lay Position for either Win or Loss

	Profit Back (Bettor)		**Profit Lay (Bookmaker)**	
Chelsea **wins**	$(odds-1)\bullet wager$	**(1)**	$-(odds-1)\bullet wager$	**(3)**
Chelsea **does not win**	$-1\bullet wager$	**(2)**	$1\bullet wager$	**(4)**
	Payoff Back (Bettor)		**Payoff Lay (Bookmaker)**	
Chelsea **wins**	$(odds-1)$	**(5)**	$-(odds-1)$	**(7)**
Chelsea **does not win**	-1	**(6)**	1	**(8)**
	Return Back (Bettor)		**Return Lay (Bookmaker)**	
Chelsea **wins**	$\frac{(odds-1)\bullet wager}{wager}=(odds-1)$	**(9)**	$\frac{-(odds-1)\bullet wager}{(odds-1)\bullet wager}=-1$	**(11)**
Chelsea **does not win**	$\frac{-1\bullet wager}{wager}=-1$	**(10)**	$\frac{1\bullet wager}{(odds-1)\bullet wager}=\frac{1}{(odds-1)}$	**(12)**

In Figure 12, the wager is the stake that a bettor wants to bet on the outcome of Chelsea winning a football game. Return calculations take the possible payoff for each trader relative to the money at risk if losing the bet.

Profit
The profit for a bettor is the amount wagered times the odds minus the amount wagered in case of a positive outcome according to (1), i.e. the bettor chooses the right event outcome. In case of choosing the false event outcome the bettor loses 100% of his wager according to (2).

The bookmaker's profit is the opposite of the bettor's profit i.e. when booking (shorting) an event that turns out to be true, the bookmakers loses the amount wagered times the odds minus one according to (3). When the bookmaker books an outcome that does not come true he earns the money put on stake i.e. 100% of the wager according to (4).

Payoff
The payoff is thus just the above expressions divided with the wager according to (5), (6), (7) and (8).

Return
Returns are finally calculated by dividing the profit in (1), (2), (3) and (4) by the amount put on stake i.e. the amount on risk. For the bettor this is straightforward as the money on risk is the amount wagered, thus the return for a bettor is equal to the payoff according to (9) and (10).

The returns for a bookmaker are slightly more complicated as the money put on risk by the bookmaker equals the wager times the odds minus one. We therefore derive that a bookmaker has -100% in returns when he books on event that turns out to be true according to (11). When he books an event that turns out to be true his returns are one dived by one minus the odds according to (12).

Discussion
In reality, the traders at the betting exchange sometimes bet more money, sometimes less. Returns are therefore also a matter of timing of big stakes to the ones that actually payoff. This may or may not be a

question of luck. However, it seems reasonable that a bettor or a bookmaker before each transaction evaluates the downside rise (the stake) in relation to the potential upside dictated by the odds and the subjective probability of being correct. That would imply that a good gambler has good returns. However, the amount at stake in certain event may indicate to what extent that bet was perceived as beneficial. Thus amount weighted returns are also of interest.

Appendix II: Identifying Arbitrage Opportunities

At a stock exchange and similar market places, only one price is quoted. However, at betting markets prices (odds) are often quoted simultaneously by several sources. Currently tens or hundreds of web sites offer odds on the same events. This is similar to OTC trading and trading in stocks that are listed at several different exchanges. According to the law of one price, the price of the same asset should be the equal across different places of trading. One price is enforced by arbitrageurs who buy where it is cheap and sell where it is more expensive.

When individual bookmakers post odds that are sufficiently different, arbitrage opportunities are created. An arbitrage opportunity is the case if it is possible to buy and sell the same security profitable at the same time locking in a risk-free profit. In theory, one could with arbitrage earn an infinite amount of money with putting no money at risk.

To determine arbitrage opportunities on betting markets is thus a frequently discussed topic. The way to go about this is somewhat different depending on how many possible outcomes are available; the easiest case is when having two outcomes A and B of an event. Then, to determine if a betting market arbitrage opportunity exists, one compares the longest (highest) odds offered by a range of bookmakers on outcome A with the longest odds offered by a range of bookmakers on outcome B. We shall here present how to utilize arbitrage opportunity as described by Ben Marshall (2005):

First, the bettor calculates the so called Arbitrage Possibility (AP). If the AP is less than one, an arbitrage opportunity exists. Please note that the two outcomes must be disparate and collectively exhaustive.

$$AP = \frac{1}{HO_{Ai}} + \frac{1}{HO_{Bj}}, \quad \textit{where } AP = \textit{Arbitrage Possibility}$$

HO_{Ai} *is the highest odds available on team A* (*European format*)

HO_{Bj} *is the highest odds available on team B* (*European format*)

$$\textit{Total revenue per bet } \$1 \textit{ is} : \mathrm{R} = \frac{1 - AP}{AP}, \quad \textit{where } AP \textit{ subject to } AP < 1$$

To take advantage of an arbitrage opportunity (gain whatever the outcome of the event), the arbitrageur should bet proportionally on team A and B according to the following:

$$\textit{Proportion on team A} = \frac{\frac{1}{HO_{Ai}}}{\frac{1}{HO_{Ai}} + \frac{1}{HO_{Bj}}}, \quad \textit{Proportion on team B} = \frac{\frac{1}{HO_{Bj}}}{\frac{1}{HO_{Ai}} + \frac{1}{HO_{Bj}}}$$

Figure 13: An example of taking advantage of arbitrage between betting sites.

Example: On the 28th of August 2003 the following odds were on offer for a Major League Baseball (MLB) match between Boston Red Sox and Oakland Athletics:

Boston Red Sox to Win at Stan James at 1.83
Oakland Athletics to Win at ToteXpress at 2.38

$$AP = 1/1.83 + 1/2.38 = 0.5464 + .4202 = 0.9666 < 1 \Rightarrow \textit{Arbitrage opportunity exists!}$$ AP=1/

To take advantage of the opportunity and earn a risk-free profit, the arbitrageur must bet *(1/1.83)/(1/1.83+1/2.38)= 56.53%* of his total bet on Boston Red Sox and *(1/1.83)/(1/1.83+1/2.38)= 43.47%* on the Oakland Athletics.

Based on these bets, the return per $1 bet is:

$$R = \$(1 - 0.9666)/0.9666 = \$0.0346$$

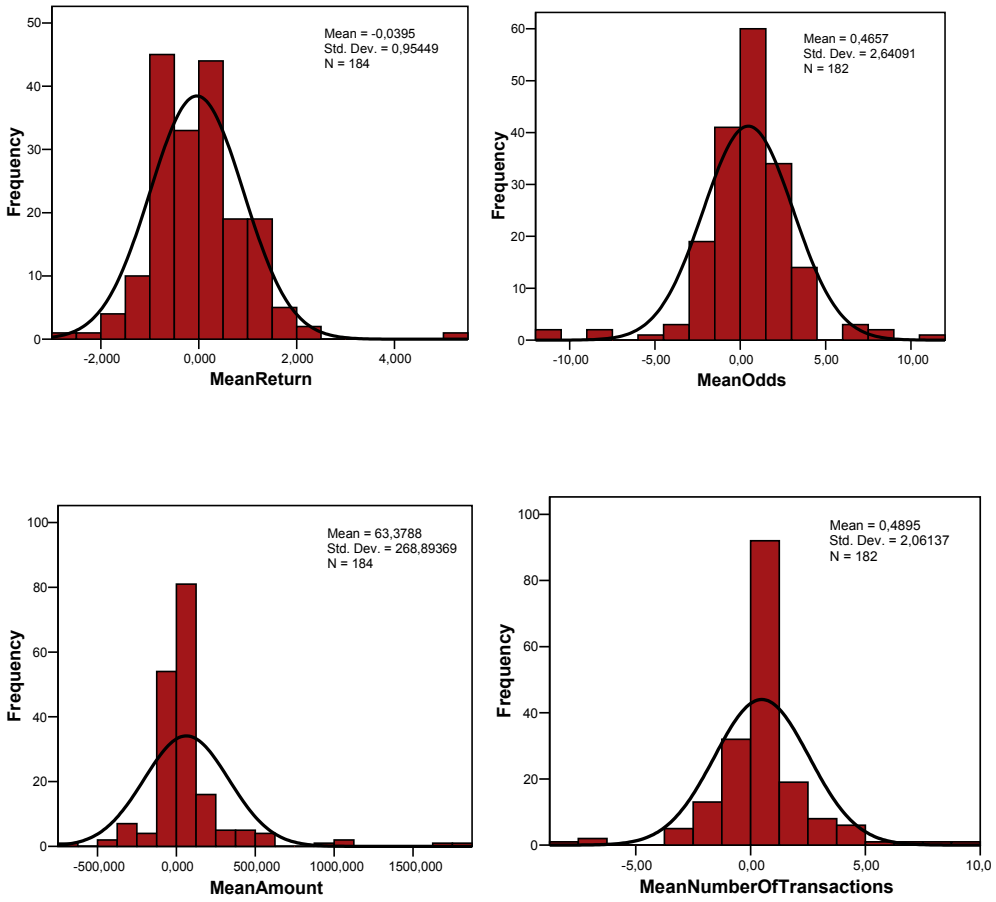
So, by committing e.g. $1000, the arbitrageur receives $34.6.

For those interested in betting arbitrage there is a British company, Zero-risk-arbitrage.com, that identifies sports betting arbitrage opportunities in the odds quoted by Internet sports bookmakers. Zero-risk-arbitrage.com uses software to scan bookmaker web sites in real-time. When opportunities are identified, an email or SMS message is sent to the subscribers so that they are alerted about the opportunity as soon as possible. Zero-risk-arbitrage.com focuses on arbitrage opportunities in sporting events with two or three outcomes such as NBA, NFL, NHL, Soccer, Tennis etc. Arbitrage opportunities have been shown to occur thousands of times per year with persistence ranging from seconds to hours, days and weeks.

Appendix III: Distribution of Differences of Tested Variables after a Large Win

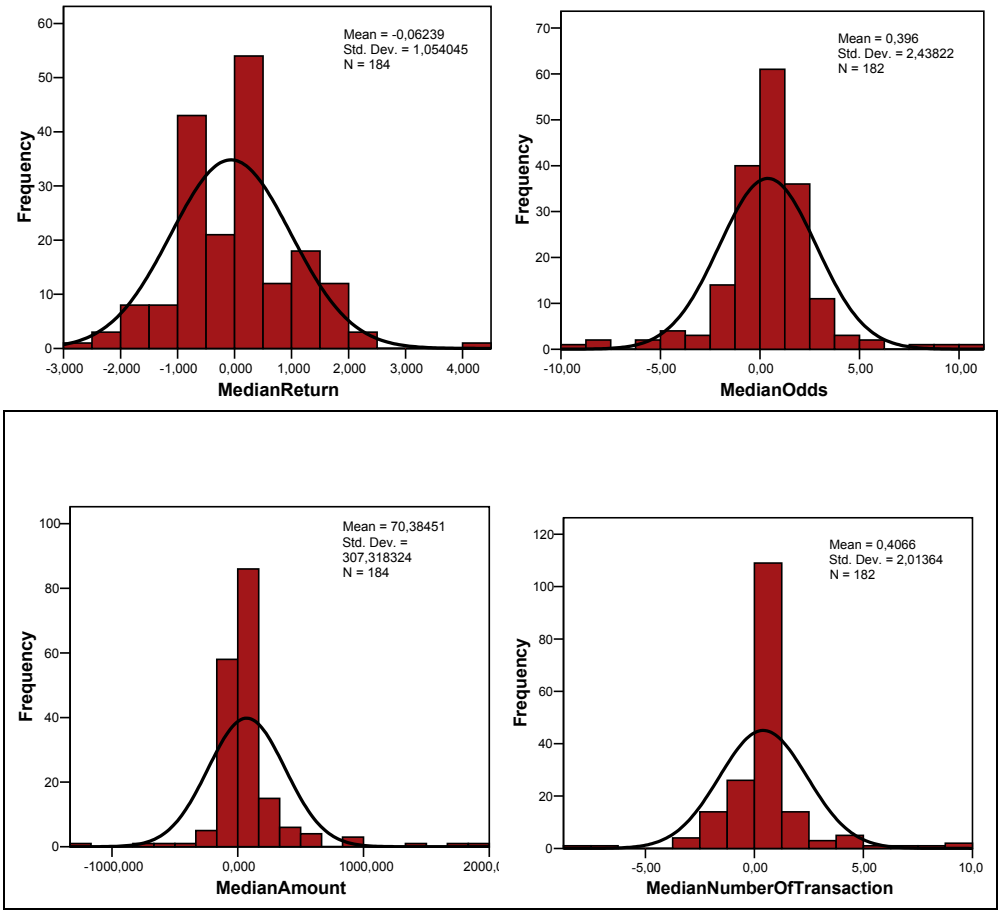
Change in Mean

Figure 14: Change in mean return, odds, amount and number of transactions following a large win.



Change in Median

Figure 15: Change in median return, odds, amount and number of transactions following a large win.



Appendix IV: Tables over betting strategy portfolios

Table 15: Portfolios on 90 min odds involving all odds intervals

Position	Condition	No. transactions	Average
Bet	-	34 855	**-0.029**
Book	-	34 855	**0.025**

Table 16: Portfolios on 90 min odds involving differing odds intervals

Position	Condition	No. transactions	Average	Std. Error
Bet	Odds < 1.10	28	**0.061**	0.008
Bet	Odds < 1.20	61	**0.106**	0.027
Bet	Odds < 1.30	198	**0.010**	0.033
Bet	Odds < 1.40	365	**0.016**	0.026
Bet	Odds < 1.50	608	**0.007**	0.023
Bet	Odds < 1.60	979	**-0.029**	0.021
Bet	Odds < 1.70	2 772	**-0.058**	0.014
Bet	Odds < 2.00	14 434	**-0.026**	0.007
Bet	Odds < 3.00	31 250	**-0.028**	0.006
Bet	Odds < 4.00	32 931	**-0.029**	0.006
Bet	Odds < 5.00	33 584	**-0.029**	0.006
Bet	Odds > 5.00	1 220	**-0.17**	0.075
Bet	Odds > 6.00	930	**-0.13**	0.093
Bet	Odds > 7.00	660	**-0.084**	0.114
Bet	Odds > 8.00	478	**-0.015**	0.085
Bet	Odds > 10.00	290	**-0.197**	0.091

Table 17: Portfolios on 90 min odds involving differing odds intervals

Position	Condition	No. transactions	Average	Std. Error
Book	Odds < 1.20	61	**-0.795**	0.14366
Book	Odds < 1.30	198	**-0.115**	0.13734
Book	Odds < 1.40	365	**-0.158**	0.0924
Book	Odds < 1.50	608	**-0.104**	0.06724
Book	Odds < 1.60	979	**-0.024**	0.04964
Book	Odds < 1.70	2 772	**0.033**	0.02558
Book	Odds < 2.00	14 434	**0.015**	0.00958
Book	Odds < 3.00	31 250	**0.023**	0.00568
Book	Odds < 4.00	32 931	**0.028**	0.00544
Book	Odds < 5.00	33 584	**0.025**	0.00535
Book	Odds > 5.00	1 220	**0.025**	0.01028
Book	Odds > 6.00	930	**0.014**	0.01124
Book	Odds > 7.00	660	**0.007**	0.01258
Book	Odds > 8.00	478	**-0.004**	0.01439
Book	Odds > 10.00	290	**0.019**	0.01454

Appendix V: SPSS programming code

```
**********************************************************************.
```

```
* What we do in life echoes in eternity.
```

```
* Copyright (c) 2005 Robert Bongart  & Johan Conradsson
*****************************************************************************.
PRESERVE.
GET FILE ='c:\betting1.sav'.
COMPUTE
date=DATE.YRDAY(2004,((modificationdate/(60*60*24*365)+1970)-
2004)*365).
COMPUTE day=XDATE.JDAY(date).
COMPUTE week=XDATE.WEEK(date).
COMPUTE month=XDATE.MONTH(date).
DO IF (selectionid=resultid).
        COMPUTE betProfit=(odds-1)*0.97.
        COMPUTE bookProfit=-(odds-1).
        COMPUTE betProfitNoSpread=(odds-1).
        COMPUTE bookProfitNoSpread=-(odds-1).
        COMPUTE exchangeProfit=(odds-1)*0.03.
ELSE.
        COMPUTE betProfit=-1.
        COMPUTE bookProfit=0.97.
        COMPUTE betProfitNoSpread=-1.
        COMPUTE bookProfitNoSpread=1.
        COMPUTE exchangeProfit=amount*0.03.
END IF.
SAVE OUTFILE ='c:\data.sav'.
*****************************************************************************.
*                       Testing Efficiency with portfolios.
*****************************************************************************.
GET FILE ='c:\newdata.sav'.
DEFINE macdef (arg1= !TOKENS(1) /arg2 = !TOKENS(1) /arg3=
!TOKENS(1))
!DO !i = !arg1 !TO !arg2 !BY !arg3.
DO IF (selectionid=resultid).
        COMPUTE portfolio1=(odds-1)*0.97.
        COMPUTE portfolio1_notrans=(odds-1).
        DO IF (odds<(1+!i/100)).
                COMPUTE portfolio3=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.05).
                COMPUTE portfolio5=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.10).
                COMPUTE bet110=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.20).
                COMPUTE bet120=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.30).
                COMPUTE bet130=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.40).
                COMPUTE bet140=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.50).
                COMPUTE bet150=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.60).
                COMPUTE bet160=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.70).
                COMPUTE bet170=(odds-1)*0.97.
        END IF.
        DO IF (odds<2).
                COMPUTE bet200=(odds-1)*0.97.
        END IF.
        DO IF (odds<3).
                COMPUTE bet300=(odds-1)*0.97.
        END IF.
        DO IF (odds<4).
                COMPUTE bet400=(odds-1)*0.97.
        END IF.
        DO IF (odds<5).
                COMPUTE bet500=(odds-1)*0.97.
        END IF.
        DO IF (odds>5).
                COMPUTE BET50=(odds-1)*0.97.
        END IF.
        DO IF (odds>6).
                COMPUTE BET60=(odds-1)*0.97.
        END IF.
        DO IF (odds>7).
                COMPUTE BET70=(odds-1)*0.97.
        END IF.
        DO IF (odds>8).
                COMPUTE BET80=(odds-1)*0.97.
        END IF.
        DO IF (odds>10).
                COMPUTE BET100=(odds-1)*0.97.
        END IF.
        DO IF (odds<1.5).
                COMPUTE BET5000=(odds-1)*0.97.
        END IF.
ELSE.
        COMPUTE portfolio1=-1.
        COMPUTE portfolio1_notrans=-1.
        DO IF (odds<(1+!i/100)).
                COMPUTE portfolio3=-1.
        END IF.
        DO IF (odds<1.05).
                COMPUTE portfolio5=-1.
        END IF.
                COMPUTE BOOK50=1/(odds-1)*0.97.
        DO IF (odds<1.10).
                COMPUTE bet110=-1.
        END IF.
        DO IF (odds<1.20).
                COMPUTE bet120=-1.
        END IF.
        DO IF (odds<1.30).
                COMPUTE bet130=-1.
        END IF.
        DO IF (odds<1.40).
                COMPUTE bet140=-1.
        END IF.
        DO IF (odds<1.50).
                COMPUTE bet150=-1.
        END IF.
        DO IF (odds<1.60).
                COMPUTE bet160=-1.
        END IF.
        DO IF (odds<1.70).
                COMPUTE bet170=-1.
        END IF.
        DO IF (odds<2).
                COMPUTE bet200=-1.
        END IF.
        DO IF (odds<3).
                COMPUTE bet300=-1.
        END IF.
        DO IF (odds<4).
                COMPUTE bet400=-1.
        END IF.
        DO IF (odds<5).
                COMPUTE bet500=-1.
        END IF.
        DO IF (odds>5).
                COMPUTE BET50=-1.
        END IF.
        DO IF (odds>6).
                COMPUTE BET60=-1.
        END IF.
        DO IF (odds>7).
                COMPUTE BET70=-1.
        END IF.
        DO IF (odds>8).
                COMPUTE BET80=-1.
        END IF.
        DO IF (odds>10).
                COMPUTE BET100=-1.
        END IF.
        DO IF (odds<1.5).
                COMPUTE BET5000=-1.
        END IF.
END IF.
DO IF (selectionid<>resultid).
        COMPUTE portfolio2=1/(odds-1)*0.97.
        COMPUTE exchange2=1/(odds-1)*0.03.
        COMPUTE portfolio2_notrans=1/(odds-1).
        DO IF (odds<(1+!i/100)).
                COMPUTE portfolio4 = 1/(odds-1)*0.97.
        END IF.
        DO IF (odds>10).
                COMPUTE portfolio5=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<10).
                COMPUTE book=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.10).
                COMPUTE book110=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.20).
                COMPUTE book120=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.30).
                COMPUTE book130=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.40).
                COMPUTE book140=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.50).
                COMPUTE book150=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.60).
                COMPUTE book160=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<1.70).
                COMPUTE book170=1/(odds-1)*0.97.
        END IF.

        DO IF (odds<2).
                COMPUTE book200=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<3).
                COMPUTE book300=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<4).
                COMPUTE book400=1/(odds-1)*0.97.
        END IF.
        DO IF (odds<5).
                COMPUTE book500=1/(odds-1)*0.97.
        END IF.
        DO IF (odds>5).
        END IF.
```

```
                DO IF (odds>6).
                        COMPUTE BOOK60=1/(odds-1)*0.97.
                END IF.
                DO IF (odds>7).
                        COMPUTE BOOK70=1/(odds-1)*0.97.
                END IF.
                DO IF (odds>8).
                        COMPUTE BOOK80=1/(odds-1)*0.97.
                END IF.
                DO IF (odds>10).
                        COMPUTE BOOK100=1/(odds-1)*0.97.
                END IF.
                DO IF (odds>3).
                        COMPUTE BET5000=1/(odds-1)*0.97.
                END IF.
                DO IF (odds>3).
                        COMPUTE BETOR500=1/(odds-1)*0.97.
                END IF.
ELSE.
                COMPUTE portfolio2=-1.
                COMPUTE portfolio2_notrans=-1.
                DO IF (odds<(1+!i/100)).
                        COMPUTE portfolio4=-1.
                END IF.
                DO IF (odds>10).
                        COMPUTE portfolio5=-1.
                END IF.
                DO IF (odds<1.10).
                        COMPUTE book110=-1.
                END IF.
                DO IF (odds<1.20).
                        COMPUTE book120=-1.
                END IF.
                DO IF (odds<1.30).
                        COMPUTE book130=-1.
                END IF.
                DO IF (odds<1.40).
                        COMPUTE book140=-1.
                END IF.
                DO IF (odds<1.50).
                        COMPUTE book150=-1.
                END IF.
                DO IF (odds<1.60).
                        COMPUTE book160=-1.
                END IF.
                DO IF (odds<1.70).
                        COMPUTE book170=-1.
                END IF.
                DO IF (odds<2).
                        COMPUTE book200=-1.
                END IF.
                DO IF (odds<3).
                COMPUTE book300=-1.
                END IF.
                DO IF (odds<4).
                        COMPUTE book400=-1.
                END IF.
                DO IF (odds<5).
                        COMPUTE book500=-1.
                END IF.
                DO IF (odds>5).
                        COMPUTE BOOK50=-1.
                END IF.
                DO IF (odds>6).
                        COMPUTE BOOK60=-1.
                END IF.
                DO IF (odds>7).
                        COMPUTE BOOK70=-1.
                END IF.
                DO IF (odds>8).
                        COMPUTE BOOK80=-1.
                END IF.
                DO IF (odds>10).
                        COMPUTE BOOK100=-1.
                END IF.
                DO IF (odds>3).
                        COMPUTE BET5000=-1.
                END IF.
                DO IF (odds>3).
                        COMPUTE BETOR500=-1.
                END IF.
END IF.
DESCRIPTIVES VARIABLES=portfolio1, portfolio2, portfolio5,bet110, bet120,
bet130, bet140, bet150, bet160, bet170, bet200, bet300, bet400, bet500,
BET50,
BET60, BET70, BET80, BET100, book110, book120, book130, book140,
book150,
book160, book170, book200, book300, book400, book500, BOOK50,
BOOK60,
BOOK70,BOOK80,BOOK100,BETOR500,BET5000  /STATISTICS=ALL.
!DOEND
!ENDDEFINE.
MACDEF arg1=100  arg2=100 arg3=10.
```

```
*************************************************************************.
*                                Overall statistics.
*************************************************************************.
GET FILE ='c:\data1.sav'.
COMPUTE day=XDATE.JDAY(date).
COMPUTE week=XDATE.WEEK(date).
COMPUTE month=XDATE.MONTH(date).
DO IF (selectionid=resultid).
        COMPUTE betProfit=(odds-1)*0.97.
        COMPUTE bookProfit=-1.
        COMPUTE betProfitNoSpread=(odds-1).
        COMPUTE bookProfitNoSpread=-1.
        COMPUTE exchangeProfit=(odds-1)*0.03.
ELSE.
        COMPUTE betProfit=-1.
        COMPUTE bookProfit=1/(odds-1)*0.97.
        COMPUTE betProfitNoSpread=-1.
        COMPUTE bookProfitNoSpread=1/(odds-1).
        COMPUTE exchangeProfit=1*0.03.
END IF.
*Overall statistics per time*********************************************************.
AGGREGATE OUTFILE='c:\overall_per_time_aggr.sav' /BREAK=week
/NEvents = NU(betProfit)
/NEventsWithoutResult = NU(odds)
/totalBookProfit=SUM(bookProfit)
/meanBookProfit=MEAN(bookProfit)
/medianBookProfit=MEDIAN(bookProfit)
/minBookProfit=MIN(bookProfit)
/maxBookProfit=MAX(bookProfit)
/stdBookProfit=SD(bookProfit)
/totalBetProfit=SUM(betProfit)
/meanBetProfit=MEAN(betProfit)
/medianBetProfit=MEDIAN(betProfit)
/minBetProfit=MIN(betProfit)
/maxBetProfit=MAX(betProfit)
/stdBetProfit=SD(betProfit)
/maxOdds=MAX(odds)
/minOdds=MIN(odds)
/meanOdds=MEAN(odds)
/medianOdds=MEDIAN(odds)
/stdOdds=SD(odds)
/totalAmount=SUM(amount)
/maxAmount=MAX(amount)
/minAmount=MIN(amount)
/meanAmount=MEAN(amount)
/medianAmount=MEDIAN(amount)
/stdAmount=SD(amount)
/totalBetProfitNoSpread=SUM(betProfitNoSpread)
/maxBetProfitNoSpread=MAX(betProfitNoSpread)
/minBetProfitNoSpread=MIN(betProfitNoSpread)
/meanBetProfitNoSpread=MEAN(betProfitNoSpread)
/medianBetProfitNoSpread=MEDIAN(betProfitNoSpread)
/stdBetProfitNoSpread=SD(betProfitNoSpread)
/totalBookProfitNoSpread=SUM(bookProfitNoSpread)
/maxBookProfitNoSpread=MAX(bookProfitNoSpread)
/minBookProfitNoSpread=MIN(bookProfitNoSpread)
/meanBookProfitNoSpread=MEAN(bookProfitNoSpread)
/medianBookProfitNoSpread=MEDIAN(bookProfitNoSpread)
/stdBookProfitNoSpread=SD(bookProfitNoSpread)
/differentProducts=NU(bettype)
/maxExchangeProfit=MAX(exchangeProfit)
/minExchangeProfit=MIN(exchangeProfit)
/meanExchangeProfit=MEAN(exchangeProfit)
/medianExchangeProfit=MEDIAN(exchangeProfit)
/totalExchangeProfit=SUM(exchangeProfit)
/stdExchangeProfit=SD(exchangeProfit).
GET FILE='c:\overall_per_time_aggr.sav'.
COMPUTE relStdBookProfit = stdBookProfit/meanBookProfit.
COMPUTE relStdBetProfit = stdBetProfit/meanBetProfit.
COMPUTE relStdOdds = stdOdds/meanOdds.
COMPUTE relStdAmount = stdAmount/meanAmount.
COMPUTE relStdBetProfitNoSpread=stdBetProfitNoSpread/meanBetProfitNoSpread.
COMPUTE relStdBookProfitNoSpread=stdBookProfitNoSpread/meanBookProfitNoSpread.
COMPUTE relStdExchangeProfit=stdExchangeProfit/meanExchangeProfit.
SAVE OUTFILE='c:\overall_per_time_aggr.sav'.
TSPLOT totalBookProfit.
TSPLOT totalBetProfit, totalBookProfit, totalExchangeProfit.
TSPLOT meanBetProfit, meanBookProfit, meanExchangeProfit.
TSPLOT totalExchangeProfit.
```

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