UNIVERSITY OF VAASA, FINLAND

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Antti Pukkinen

BEHAVIORAL BIASES AND THE MOMENTUM EFFECT: EMPIRICAL TEST OF THE PERFORMANCE OF WINNER AND LOSER PORTFOLIOS IN THE HELSINKI STOCK EXCHANGE FROM 2001 TO 2006

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UNIVERSITY OF VAASA
Faculty of Business Studies
Author: Antti Pukkinen

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Name of the Supervisor:	Professor Jussi Nikkinen
Degree:	Master of Business Studies
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ABSTRACT
Behavioral Finance argues that investor behavior influences stock prices, and it causes the security price deviate from its fundamental value. These irrational investors which influence asset prices by acting according to their feelings are called noise traders. Noise trading is about taking a position in a stock with false information and keeping that position even though there might some information in the markets about the stock which is more important and would state otherwise.

Behavioral finance is an argument against the efficient market hypothesis which states that the asset prices include all information there is in the markets. Behavioral finance relaxes the most important assumption of traditional finance theory, investor rationality. If psychological concepts such as heuristic simplification, mental accounting, reference effects, self-deception and self-control affect human behavior, should they not also affect investor behavior and the stock prices?

In this study the overreaction of the stock markets will be followed by forming two portfolios: the past losing stocks and the past winning stocks. The performance of these portfolios will be followed and analyzed in a four year period. It was discovered that the past losing portfolios outperform the winning portfolios in a short period of time (3-24 months after). However, 48 months after the portfolio formation, the winning portfolios were making far better returns.

KEYWORDS: Noise traders, Overreaction, Momentum effect, Heuristic-driven bias, Frame dependence, Inefficient markets.

1. INTRODUCTION

1.1. The beginning of behavioral finance

Irrational investors are called noise traders. Noise trading is the opposite of information and news in the formulation of trading strategies. Noise makes our observations of the real world imperfect. Noise is a diverse array of causal, unrelated elements to explain what happens in the real world. Thaler (1994) wrote that one way to think about noise is that it is the opposite of news. Rational traders make decisions on the basis of news (facts, forecasts, etc.). Noise traders make decisions based on anything else. Noise trading provides the essential missing ingredient to financial markets. People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading. Perhaps they think the noise they are trading on is information or perhaps they just like to trade. (Black 1986)

Noise trading is a part of behavioral finance. Behavioral finance was first established by Kahneman and Tversky in 1974, when they presented the principles of representativeness that is judgments based on stereotypes. Before their findings, Slovic (1972) had done a study of investor psychology, and it was published in The Journal of Finance. In 1979, Kahneman and Tversky developed prospect theory, which is a descriptive framework for the way people make choices in the face of risk and uncertainty. It provides evidence of frame dependence. Kahneman, Slovic and Tversky (1982) made another study where they presented the basics of behavioral finance. These authors' works play a central role in the field of behavioral finance. (Shefrin 2002: 7, 8)

Behavioral finance has become a major factor in the field of finance. Behavioral Finance means that investor behavior influences stock prices, and it causes the security price deviate from its fundamental value. The premise of behavioral finance is that conventional finance theory ignores how real people make decisions and that people make a difference. Behavioral finance is the study of how psychology affects financial decision making and financial markets. A growing number of economists have come to interpret the anomalies literature as consistent with several irrationalities individuals, so called noise traders, exhibit when making complicated decisions. These irrationalities stem from two main premises: first, that investors do not always process information correctly and therefore infer incorrect probability distributions about future rate of returns; and second, that even given a probability distribution of returns, investors often make inconsistent or systematically suboptimal decisions. (Bodie, Kane & Marcus 2005: 396)

Behavioral finance is an important and acknowledged part in the major areas of finance: portfolio theory, asset pricing, corporate finance, and the pricing of options. Practitioners, such as portfolio managers, financial planners and advisers, investors, brokers, strategists, financial analysts, investment bankers, traders, and corporate executives, are prone to committing specific errors. Behavioral finance can help practitioners recognize their own errors as well as the errors of others. Practitioners need to understand that both are important. (Shefrin 2002: 4-5.)

The efficient market hypothesis implies that prices usually are right and therefore there are no easy profit opportunities. Behaviorists, the supporters of behavioral finance, emphasize that two main implications, correct prices and no profit opportunities, can be severed: prices can be wrong, but still not give rise to easy profit opportunities. Thus, evidence that profit opportunities are scarce does not necessarily imply that prices are right. Virtually everyone agrees that if prices are right (i.e. price = intrinsic value), then there are no easy profit opportunities. Behavioral explanations of efficient market anomalies do not give guidance as how to exploit any irrationality. As investors, the question is still whether there is money to be made from mispricing, and the behavioral literature is largely silent on this point. To discover a model that predicts future stock prices and helps to use mispricing to your own advantage is a fascinating subject, but also perhaps impossible. (Bodie et. al. 2005: 400)

Some researchers believe that the efficient-market hypothesis ignores important aspects of human behavior. For example, psychologists find that people tend to place too much emphasis on recent events when they are predicting the future. If so, we may find that investors are liable to overreact to new information. It will be interesting to see how far such behavioral observations can help us to understand apparent anomalies. (Brealey et. al. 2003: 1000.) This is the reason why behavioral finance is really important nowadays. We need to understand the effects that human behavior has to volatility in stock prices. There is too much volatility in the markets, and it can not be solely explained by the amount of trading.

Most investors make their investment decisions based on their feelings. Employers often buy securities from their own firms; analysts tend to predict the future from the past; investors buy winners rather than losers; investors trade too much; to non-information there should be no movement in the price of a security; the underpricing of initial public offerings (IPO) and so on. These are all due to psychological phenomena, and it is necessary to further investigate the psychological nature of finance.

This study assumes that the anomalies, which irrational investors spread, have a significant affect to stock prices. Psychology will form a big part of this study. Shefrin (2002: 12) writes that the main themes of behavioral finance are heuristic-driven bias, frame dependence and inefficient markets. For example representativeness, overconfidence, anchoring and adjustment, aversion to ambiguity, cognitive limitations, hedonic editing, loss aversion, regret, mental accounting, and money illusion are the psychological areas of behavioral finance. These topics as well as stock valuation will form most of the theoretical part of this study.

After the introduction this study is divided into theoretical part and the empirical part. The second chapter is about the efficient market theory, and it will take a closer look at how stock prices can be calculated according to efficient market theory. The third section will describe what kind of investors there are in the financial markets. The fourth part is headlined as behavioral finance and it is the most important theoretical part. It tells about all the anomalies that noise traders spread. The fifth part is the empirical part in which this study will show the connection between investor behavior and stock prices. Finally the sixth part is the conclusion of all information collected. The last part is references and appendix.

1.2. Research problem and hypothesis

This study investigates the performance of winning and losing stocks in the Helsinki stock exchange in the years 2001-2006. There have been many revealing studies that past losers seem to outperform the past winning stocks. It is really interesting to see how the Helsinki stock exchange behaves in the 21st century.

De Bondt & Thaler (1985, 1987) found evidence of overreaction in the stock markets. They concluded that investors become overly pessimistic about past losers and overly optimistic about past winners. Thus this instance of heuristic-driven errors causes prices to deviate from fundamental values. Losers are undervalued and winners are overvalued for a while, but over time mispricing will correct itself. Hence losers will outperform the general market and winners will underperform. This finding is an explicit evidence for anomalies and noise trading in the stock markets. Their results also shed new light on the January returns earned by prior winners and losers. Portfolios of losers experience exceptionally large January returns as late as five years after portfolio formation. This study will take a closer look at this fact and the January effect on stock prices will be followed carefully, as well.

Unlike De Bondt et. al. (1985, 1987), Jegadeesh & Titman (1993) wrote that strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3- to 12-month holding periods. They argued that the results of De Bondt and Thaler can be explained by the systematic risk of their contrarian portfolios and the size effect. They added that in addition, since the long-term losers outperform the long-term winners only in Januaries, it is unclear whether their results can be attributed to overreaction. This overreaction can also be called momentum effect when investors are acting accordingly what the markets present at one point. Many people forget that the whole picture is a lot larger than just one day and single information.

It is hypothesized that past performance of stocks has a big influence to the future behavior of stock prices. This is because of investor overreaction. The opposite hypothesis is that it does not have any influence to stock prices and the winning stocks will still do better than the losing stocks. The interesting results will be shown in the research part.

1.3. Findings of empirical study

There have been many interesting studies about how noise traders affect to stock prices. Campbell and Kyle (1991) investigated the smart money and noise trader influence to stock prices. They found that the type of noise that appears to be empirically important is highly correlated with fundamental value. It is called overreaction, since it makes the stock price respond more to news about fundamentals than it otherwise would do. In their model where absolute risk is constant, a rise in the stock market which increases investor wealth will stimulate the demand for stocks by investors with declining absolute risk aversion. These investors follow “portfolio insurance” strategies, increasing their demand for risky assets with the price of risky assets. They pointed out that investment strategies of this sort increase stock market volatility, particularly in episodes such as the October 1987 stock market crash.

Kelly (1997) assumed that an individual’s probability of being a noise trader was diminishing in income, and conversely for the probability of being smart money. He found evidence that a strong participation level of the general population was negatively correlated with returns. Participation of very high-income households was strongly positively correlated with returns, and it changed in direct response to noise trader participation. His study showed quite clearly that high-income households are the one who make rational investment decisions.

De Long, Shleifer, Summers & Waldmann (1990) presented a simple overlapping model of an asset market in which irrational traders with erroneous stochastic beliefs both affect prices and earn higher expected return. They wrote that the unpredictability of noise trader’s beliefs creates a risk in the price of the asset that deters rational arbitrageurs from aggressively betting against them. As a result prices can diverge significantly from fundamental values even in the absence of fundamental risk. In the empirical part of the study, they found that the risk created by the unpredictability of unsophisticated investors reduces the attractiveness of arbitrage. Another interesting thing is that noise traders can earn higher expected returns even when they buy high and sell low. De Long, Shleifer, Summers & Waldmann (1991) made another study where they investigated the survival of noise traders in the financial markets. They presented a model of portfolio allocation by noise traders who form incorrect expectations chiefly about the variance of the return distribution of a particular asset. They showed that noise traders not only can earn higher returns than rational arbitrageurs but also can dominate the market in terms of wealth in the long run.

Trueman (1988) investigated the theory of noise trading in security markets. He found that noise trading should be more commonly observed in riskier assets, and as a result of this, the positive relation between fund turnover and performance should be weaker for those funds that specialize in riskier assets. Trueman claimed that this result may be useful for more detailed empirical work measuring the association between turnover and performance.

Palomino (1996) made a research in small markets. He found that in an imperfectly competitive market where investors are risk-averse, if the opinion of amateurs is unpredictable, amateurs may, on average, obtain higher utility relative to professional investors. Palomino stated, that this means that noise traders earn higher profits and this can not be attributed to pure luck. Nevertheless, the researcher admitted that noise traders may explain some anomalies in the markets. He also thought that noise traders bring an additional risk to the small markets, thus rational arbitrageurs rather trade on high liquidity markets.

Kahneman et. al. (1974, 1979) have shown empirically that people are irrational in a consistent and correlated manner. However, the case for the efficient market theory can be made even in situations where the trading strategies of investors are correlated. As long as there are some smart investors and arbitrage opportunities, they will exploit any mispricing and the irrational investors will lose money and eventually disappear from the market.

2. THE EFFICIENT MARKET HYPOTHESIS

2.1. Efficient markets

The basic theoretical case for the Efficient Market Hypothesis (EMH) rests on three arguments which rely on progressively weaker assumptions. First, investors are assumed to be rational and hence to value securities rationally. Second, to the extent that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices. Third, to the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices. (Shleifer 2000: 2)

The purpose of capital markets is to transfer funds between lenders and borrowers efficiently. Individuals or firms may have access to productive investment opportunities with anticipated rate of return that exceed the market-determined borrowing rate but not enough funds to take advantage of all these opportunities. However, if capital markets exist, they can borrow the needed funds. Lenders, who have excess funds after exhausting all their productive opportunities with expected returns greater than the borrowing rate, will be willing to lend their excess funds because the borrowing/lending rate is higher than what they might otherwise earn. Therefore both borrowers and lenders are better off if efficient capital markets are used to facilitate fund transfers. The stock markets work much with the same principal: investors buy the stocks of a company and they both benefit of this deal. Although the risk in the stock market is much higher than in the capital markets, but so are the possible earnings. (Copeland, Weston & Shastri 2005: 353).

When economists speak of capital markets as being efficient they usually mean that they view asset prices and returns as being determined as the outcome of supply and demand in a competitive market, peopled by rational traders. These rational traders rapidly assimilate any information that is relevant to the determination of asset prices and returns (e.g. future dividend prices) and adjust prices accordingly. Hence, individuals do not have different comparative advantages in the acquisition of information. This means that abnormal returns from trading should be zero. Thus, agents process information efficiently and immediately incorporate this information into stock prices. If current and past information is immediately incorporated into current prices then only new information or news should cause changes in prices. (Cuthbertson 2002: 93.)

Statistical research has shown that to a close approximation stock prices seem to follow a random walk with no discernible predictable patterns that investors can exploit. Such findings are now taken to be evidence of market efficiency, that is, evidence that market prices reflect all currently available information. Only new information will move stock prices, and this information is equally likely to be good or bad news. If you are not sure what is meant by “random walk”, you might like to think of the following example: You are given $100 to play a game. At the end of each week a coin is tossed. If it becomes heads, you win 3 percent of your investment; if it becomes tails you lose 2.5 percent. Therefore, your capital at the end of the first week is either $103,00 or $97,50. At the end of the second week the coin is tossed again. Now the possible outcomes are: (Brealey et. al. 2005: 405. Bodie et. al 2003: 348)

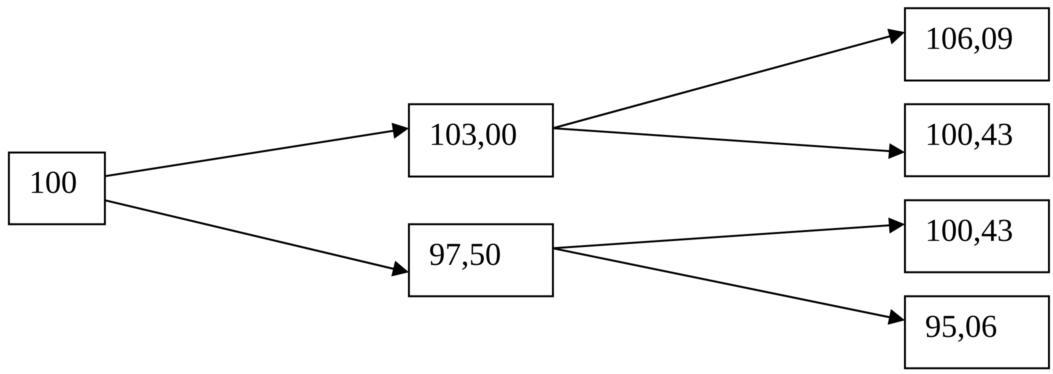

Figure 1. Coin tossing game is describing the random walk (Brealey et. al. 2003: 348)

The drift is equal to the expected outcome: (1/2) * 3 + (1/2) * (-2.5) = 0.25%

This process is a random walk with a positive drift of 0.25 percent per week. It is a random walk because successive changes in value are independent. That is, the odds each week are the same, regardless of the value at the start of the week or of the same pattern of heads and tails in the previous week. (Brealey et. al. 2003: 348)

Perfect capital markets:

- Every market participant thinks and acts rationally
- Every market participant can lend and borrow with same conditions and same market rate; there does not exist any discrimination and the markets are open for everybody
- Every market participant can get the necessary information freely and with no costs
- None of the market participants can not affect the price of a security, because the amount of market participants is so huge
- The market securities are totally real and liquid and they can be sold for the market price what ever the trance is
- There are not any bankruptcy costs in the market
- There are not any taxes in the market
- There are not any transaction costs in the market. (Leppiniemi 2000: 99-100)

2.2. Forms of efficiency

Eugene Fama has done many studies concerning market efficiency. Fama's works are the groundwork of efficient market hypothesis (EMH). As already stated, EMH implies that security prices accurately reflect all available information and respond rapidly to new information as soon as it becomes available. According to Fama EMH comes in three flavors, corresponding to different definitions of available information. The weak form, i.e. the random walk theory, says that prices reflect all information in past prices. The semistrong form says that prices reflect all publicly available information, and the strong form holds that prices reflect all acquirable information. (Brealey, Myers 2003: 996).

The weak-form hypothesis asserts that stock prices already reflect all information that can be derived by examining market trading data such as the history of past prices, trading volume, or short interest. This version of the hypothesis implies that trend analysis is fruitless. Past stock price data are publicly available and virtually costless to obtain. In other words this might imply that technical analysis is of no use. (Bodie et. al. 2005: 373).

The semi-strong form hypothesis states that the stock prices include all public information. This kind of information is for example financial statements, dividends, new products, prowess of the management, earnings predictions etc. The semistrong-form also embodies the weak form because the timelines of prices are public information. If the markets do not perform the semistrong-form conditions, an investor could act after the information has been announced and this way earn some abnormal return. In other words, neither fundamental analysis nor technical analysis can be used to achieve superior gains. (Nikkinen, Rothovius & Sahlström, 2002: 83).

The strong form of efficiency states that prices reflect not just public information but all the information that can be acquired by painstaking analysis of the company and the economy. In such a market we would see lucky and unlucky investors, but we would not find any superior investment managers who can consistently beat the market. In other words, even insider information is off no use. (Brealey et. al. 2003: 351).

2.3. Stock valuation models

The valuation of stocks is a difficult task. Many researchers have developed models that follow the market value of a stock quite closely, but since the beginning of capital markets, nobody has made-up a perfect model, which predicts the security prices precisely as they are in the market. The simplest model of stock market movements, which was generally accepted at least as an approximation until the early 1990's, is that the stock price equals the present value of expected future dividends, discounted at a constant rate. This model has been proved quite accurate even though it ignores all the basic foundations of finance. (Brealey et. al. 2003)

The valuation models are based on the calculation of discounted cash flows which the stockholders receive. The main point about these models is that they take into account the time value of money. The biggest problem and the factor that causes insecurity in defining a company's equity capital is that the shareholder's earnings depend on the future cash flows of the company. Because of this, when a stockholder is doing his investment decisions, it is uncertain how big cash flows does his investment involve, whereas there exists a big uncertainty compared to cash flows of bonds. (Nikkinen et. al. 2002: 148)

As already stated the dividend discount model is the simplest way to analyze stock prices. Free cash flow based method (FCF) and the economic value added (EVA) are also widely used methods to approximate the stock prices. Besides these, there are few techniques that are used. For example many investors look for peaks and bottoms of market indexes and stocks i.e. they use technical analysis to evaluate security prices. Fundamental analysis is also commonly used technique, because it uses financial statement data for analysis. This study will tell more about those methods in the next chapter.

2.3.1. Dividend discount model

The most common way to analyze stock prices is the dividend discount model. The method calculates the current price of a stock by discounting all the future dividend cash flows. Many researcher have found it to be the most efficient and accurate method to calculate the stock price. The Dividend Discount Model is also known as the "Gordon model" named after Professor Gordon who popularized the model in 1962. The dividend discount model is a broadly accepted stock valuation instrument found in most introductory finance and investment textbooks. The model calculates the present value of the future dividends that a company is expected to pay to its shareholders. It is particularly useful because it allows investors to determine an absolute or intrinsic value of a particular company that is not influenced by current stock market conditions. (Bodie et. al. 2005)

PV (Stock) = PV (Expected future dividends)

(1) $$S0 = \frac{Div1}{1+r} + \frac{Div2}{(1+r)\text{^}2} + ... = \frac{Div}{r}$$

Where

S_0 = Stock price
Div = Dividend price at time t
r = is the risk free interest rate

The equation above assumes that investors hold the stock for the life of the firm. However, Bodie et. al. (2005: 611) say that this equation is not very useful in valuing stocks because it requires dividend forecasts for every year into the indefinite future.

2.3.2. Free cash flow valuation

The free cash flow based model (FCF) means that instead of dividends you discount all future cash flows, which basically would be divided for shareholders, to present value. The advantage of FCF is that the company's dividend policy can not influence the model and the results as Modigliani & Miller (MM) concluded. Another benefit of using FCF, compared to methods which use earnings as a discount variable, is the fact that different kind of accounting figures are not able to manipulate the amount of cash flow. This way, for example accounting, practices or the changes which happen in these practices, can not have a lot of effect on the quantity of cash flows. (Nikkinen et. al. 2002)

(2) $$P_0 = \frac{FCF_1}{(1+r)} + \frac{FCF_2}{(1+r)^\wedge 2} + \frac{FCF_3}{(1+r)^\wedge 3}$$

Where,

P_0 = Price of the stock
FCF_t = Free cash flow of the company during time t
r = Risk free interest rate

The free cash flow valuation based method was first presented by MM. They claim that if we take as given a firm's future investments, then the value of its existing common stock is not affected by how those investments are financed.

Therefore, neither the firm's dividend policy nor its capital structure should affect the value of a share of its equity. (Bodie et. al. 2005: 634)

2.3.3. Economic value added (EVA)

Among the management tools EVA, in particular, emphasizes the interests of the owners. In other words, the owner's expect a maximum compensation over the cost of the capital invested in the firm. In line with the theory of finance the RI derivative EVA is commonly advocated as a management tool because the goal of the firm is to add to the value of the owners' wealth. In other words, the owners expect a maximum compensation over the cost of the capital invested in the firm. A central question concerning EVA is how sensitive this management tool is to the changes in its various components, management policies and external economic factors. (Salmi & Virtanen 2001)

EVA can be calculated as:

EVA = NOPAT - WACC * Capital

Where,

NOPAT = Net operating profit after taxes and
WACC = is the weighted average cost of capital.

Despite the unambiguous theoretical definition, applying EVA even in its pure, theoretical format is not straight-forward. EVA is defined as the difference between the firm's profit and cost of all capital employed, i.e. the weighted average cost of debt and equity. Measuring the profit of the firm and measuring the components of the cost of capital is problematic both in theory and in practice. In particular, measuring the cost of equity is a highly involved issue. (Salmi et. al. 2001)

2.3.4. Valuation ratios

Price/Earnings (P/E)

Much of the real-world discussion of stock market valuation concentrates on the firm's price-earnings multiple, the ratio of price per share to earnings per share, commonly called the P/E ratio. P/E ratio is widely used in the valuation of stocks. (Bodie et. al. 2005: 622.) Fuller et. al. (1987: 274) conclude that estimating an appropriate P/E ratio has long been a favorite approach among security analysts for deciding whether stocks are under- or overpriced.

Price-to-Book Ratio

This is the ratio of price per share divided by book value per share. Some analysts view book value as a useful measure of value and therefore treat the ratio of price to book value as an indicator of how aggressively the market values the firm. (Bodie et. al. 2005:632)

Price-to-Sales Ratio

Many start-up firms have no earnings. As a result, the price-earnings ratio for these firms is meaningless. The price-to-sales ratio (the ratio of stock price to the annual sales per share) has recently become a popular valuation benchmark for these firms. Of course, price-to-sales ratios can vary markedly across industries, since profit margins vary widely. (Bodie et. al. 2005:633)

2.4. Arbitrage

A textbook definition (Sharpe and Alexander 1990) defines arbitrage as the 'simultaneous purchase and sale of the same, or essentially similar, security in two different markets at advantageously different prices.' Scholes (1972) reasons that when arbitrage is needed to make markets efficient, individual stocks must have close substitutes for such arbitrage to work well. When close substitutes are available, arbitrageurs can sell expensive securities and buy cheap close substitutes, thereby equalizing their relative prices and bringing markets to efficiency. (Shleifer 2000: 4, 9.)

The central argument of behavioral finance states that, in contrast to the efficient markets theory, real-world arbitrage is risky and therefore limited. The effectiveness of arbitrage relies crucially on the availability of close substitutes for securities whose price is potentially affected by noise trading. For some so called derivative securities close substitutes are usually available, although arbitrage may still require considerable trading. Stocks do not have close substitutes, thus arbitrage does not help to pin down price levels. An arbitrageur who thinks that stocks as a whole are overpriced cannot sell short stocks and buy a substitute portfolio, since such a portfolio does not exist. The arbitrageur can instead simply sell or reduce exposure to stocks in the hope of an above-market return, but this arbitrage is not even close to riskless, especially since the average expected return on stocks is high and positive. (Shleifer 2000: 13, 14)

3. DIFFERENT TYPES OF INVESTORS

Investors can be divided into three groups: active investors, passive investors and noise traders. All these investors use different investment approaches to make profits. Active investors try to earn money with day trading and following the markets very closely. The most ordinary group of active investors is practitioners. Passive investors invest their capital into stocks and bonds, and they keep their positions for a long time. Passive portfolio management is especially common for example in retirement savings, when individuals try to earn profit with low risk. Noise trading, for one, is very universal phenomena and it happens in active investing as in passive investing. The most important part about noise is that you can find it everywhere. The deciding factor is that investors have to decide whether the information they have is significant or is it just a noise, which has nothing to do with the fundamentals. These phenomena confuse the capital markets all the time. (Grinold & Kahn 1995)

There are different methods to evaluate the future movements of stock prices. Main approaches are technical analysis and fundamental analysis. These two methods differ a lot from each other. Usually practitioners, such as analysts, use technical analysis to valuation. They are looking for peaks and bottoms and try to invest assets by following the market trend. Fundamental analysis, for one, is used when practitioners explore the financial statements of companies and try to predict the future movements of stock price by different figures.

3.1. Technical Analysis

Mostly professional investors use the technical approach to valuing stocks. Those who use technical analysis look for peaks, bottoms, trends, patterns and other factors affecting a stock's price movement and then make buy or sell decisions based on those factors. It is a technique many people attempt, but few are truly successful at it. Many people have claimed that they have done a lot of profit by buying stocks, which they have selected through technical analysis. In many cases these winners can be seen as pure luck and there is hardly anything to do with fundamentals. (Bodie et. al. 2005)

Trend types can be divided into three groups:

1. The primary trend is the long-term movement of prices, lasting from several months to several years.
2. Secondary or intermediate trends are caused by short-term deviations of prices from the underlying trend line. These deviations are eliminated via corrections, when prices revert back to trend values.
3. Tertiary or minor trends are daily fluctuations of little importance. (Bodie et. al. 2005: 374)

Technical analysts usually evaluate securities by taking into account past prices, market activity and volume. Technical analysts do not try to measure the intrinsic value of a stock; instead they look for stock charts for trends and cycles that will determine a stock's future performance. However many past studies have shown that it is almost impossible to predict the future performance of a stock from the past. Competition in technical research will tend to ensure that current prices reflect all information in the past sequence of prices and that future price changes cannot be predicted from past prices. (Brealey et. al. 2003)

3.2. Fundamental analysis

Financial statement analysis is the biggest part of fundamental analysis which is also known as quantitative analysis. Fundamental analysis uses earnings and dividend prospects of the firm, expectations of future interest rates and risk evaluation of the firm to determine proper stock prices. Ultimately, it represents an attempt to determine the present discounted value of all the payments a stockholder will receive from each share of stock. If that value exceeds the stock price, the fundamental analyst would recommend purchasing the stock.

Fundamental analysis is much more difficult than merely identifying well-run firms with good prospects. Discovery of good firms does an investor no good in and of itself if the rest of the market also knows those firms are good. If the knowledge is already public, the investor will be forced to pay a high price for those firms and will not realize a superior rate of return. The trick is not to identify firms that are good, but to find firms that are better than everyone else's estimate. Similarly poorly run firms can be great bargains if they are not quite as bad as their stock prices suggest. (Bodie et. al. 2005: 377)

3.3. Active investors

Investors who believe in active portfolio management do not follow the efficient market hypothesis. They believe it is possible to profit from the stock market through any number of strategies to identify mispriced securities. Active management is the opposite of passive management, to which this study will come up in the next section. The first necessary ingredient for success in active management is recognition of the challenge. Financial economists and quantitative researchers fall in three categories: those who think successful active management is impossible, those who think it is easy and those who think it is difficult. Despite the efficient market hypothesis, it is clear that markets cannot be perfectly efficient; hence there are reasons to believe that active management can have effective results. (Grinold et. al. 1995)

Individual investors who hold common stocks directly pay a tremendous performance penalty for active trading. Of 66 465 households with accounts at a large discount broker during 1991 to 1996, those that trade most earn an annual return of 11,4 percent, while the market returns 17,9 percent. The average household earns an annual return of 16,4 percent, tilts its common stock investment toward high-beta, small, value stocks and turns over 75 percent of its portfolio annually. This high level of trading can be at least partly explained by a simple behavioral bias: People are overconfident and overconfidence leads to too much trading. These figures quite clearly indicate that if an investor is practicing active management, he has to know all the facts. The knowledge of traditional finance theory is not enough; the behavioral finance is as important part of investing as the traditional side. Central message in this evidence is that trading is hazardous to your wealth. (Barber & Odean 2000)

3.4. Passive investors

From the perspective of the financial economist, active portfolio management appears an ordinary consideration, if not an entirely dubious proposition. Modern financial economics, with its theories of market efficiency, inspired the move over the past decade away from active management – trying to beat the market – to passive management – trying to match the market. Passive investment strategy is usually characterized by a buy-and-hold strategy. (Bodie et. al. 2005)

Passive portfolio management usually involves buying assets and keeping them for a long time. Several financial studies have shown that in the long run keeping your investments in the same securities proves to be more profitable than trading frequently. Overconfidence usually encourages people to trade and they might even think that they have superior information over some security. To address the puzzle of why so much trading occurs, it would be useful to understand what motivates trades and whether such motivations are rooted in behavioral hypotheses, such as an aversion to realizing losses, a misguided belief in contrarianism or momentum that might be evidence of overconfidence or a love of gambling. (Keloharju and Grinblatt 2001; Daniel, Hirshleifer and Subrahmanyam 1998)

3.5. Noise traders

Noise traders are those who falsely believe that they have special information about the future price of risky assets. A consequence of noise trading is that, if investors have short horizons and noise traders' misperceptions cannot be forecasted by arbitrageurs, then the fundamental risk is not the only source of risk in the market. In Black's basic model of financial markets, noise is contrasted with information. People sometimes trade on information in the usual way. They are correct in expecting to make profits from these trades. On the other hand, people sometimes trade on noise as if it were information. If they expect to make profits from noise trading, they are incorrect. However, Black stated, that noise trading is essential to the existence of liquid markets. (Black 1986; Palomino 1996)

Few will disagree with Black's assessment that real financial markets differ from their textbook counterparts in comprising noise traders as well as completely informed, Bayesian, expected utility maximizers. Although the idea that a subset of agents trade on the basis of extraneous information with no bearing on fundamentals have been formalized in a variety of intuitively reasonable models, most of the empirical evidence offered in support of these models is indirect. (Black 1986; Kelly 1997)

The effects of noise in the real world and our views of the world are profound. Noise in the sense of a large number of small events is often a causal factor much more powerful than a small number of large events can be. Noise makes trading in financial markets possible, and thus allows us to observe prices for financial assets. Noise causes markets to be somewhat inefficient, but often prevents us from taking advantage of inefficiencies. Noise in the form of uncertainty about future tastes and technology by sector causes business cycles, and makes them highly resistant to improvement through government intervention. Noise in the form of expectations that need not follow rational rules causes inflation to be what it is, at least in the absence of a gold standard or fixed exchange rates. Noise in the form of uncertainty about what relative prices would be with other exchange rates makes us think incorrectly that changes in exchange rates or inflation rates cause changes in trade or investment flows or economic activity. Most generally, noise makes it very difficult to test either practical or academic theories about the way that financial or economic markets work. We are forced to act largely in the dark. (Black 1986)

One of the fundamental concepts in finance is arbitrage, defined the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices. An important reason why arbitrage is limited is that movements in investor sentiment are in part unpredictable and therefore arbitrageurs betting against mispricing run the risk, at least in the short run, that investor sentiment becomes more extreme and prices move even further from fundamental value. As a consequence of such noise trader risk, arbitrage positions can lose money in the short run. (Shleifer 2000: 28; Barberis, Shleifer and Vishny 1998)

Arbitrage in a nutshell goes like this. If noise traders hold stocks when the price is above the fundamental value, then the smart money should sell these assets to the noise traders thus pushing down the price. As the price falls towards its fundamental value the noise traders lose money and tend towards bankruptcy while the smart money can if they wish buy back the stocks at the lower price. On the other hand, if the noise traders hold assets whose price is below the fundamental value, then the smart money should purchase such assets from the noise traders and they will then make a profit as the price rises towards the fundamental value. Hence the net effect is that the noise traders lose money and therefore should disappear from the market leaving only the smart money.

When this happens the prices should then reflect fundamentals. On the other hand, it is possible that noise traders can push the price of an asset even further from fundamentals and this way the smart money will lose money. (Cuthbertson 2002: 177)

4. THE PSYCHOLOGY OF INVESTING

As already stated, behavioral Finance is the study of how psychology affects finance and security prices. Psychology is the basis for human desires, goals and motivations, and it is also the basis for a wide variety of human errors that stem from perceptual illusions, overconfidence, over-reliance on rules-of-thumb and emotions. Errors and bias cut across the entire financial landscape, affecting individual investors, institutional investors, analysts, strategists, brokers, portfolio managers, option traders, currency traders, futures traders, plan sponsors, financial executives and financial commentators in the media. (Shefrin 2002: IX)

Behavioral finance relaxes the most important assumption of traditional finance theory, investor rationality. If psychological concepts such as heuristic simplification, mental accounting, reference effects, self-deception, self-control, dislike of ambiguity and social interactions affect (or plague) human behavior, should they not also affect investor behavior? This question should give a reasonable doubt to an investor whether or not he is rational in investment decision making. In an efficient markets all ‘players’ have access to the same information, they process the information in the same ‘rational way’ and all have equal opportunities for borrowing and lending. In the real world these conditions are unlikely to be met. For example, different investors may form different probability assessments about future outcomes or use different economic models in determining expected returns. (Cuthbertson 2002: 169)

Behavioral finance focuses on systematic irrationalities that characterize investor decision making. These “behavioral shortcomings” may be consistent with some of the efficient market anomalies uncovered by several researchers. By and large, the performance record of professionally managed funds lends little credence to claims that most professionals can consistently beat the market. (Bodie et. al. 2005: 406)

The next chapter will take a look at the main points in psychology of investing and the cognitive limitations that the practitioners spread. Behavioral finance is the application of psychology to financial behavior – the behavior of practitioners. Three main themes in behavioral finance are called heuristic-driven bias, frame dependence and inefficient markets (Shefrin 2002: 3-5. Linnainmaa 2003: 9)

This chapter concludes all the behavioral biases that subsist. These topics should all be thought of a same theme that live and survive separately and on the other hand coexist and interact with different ways in the formulation of behavioral errors and financial decision making. Financial decision making is not only about the numbers and financial statements. Sentiment is a big part of selection in everything.

4.1. Heuristic-Driven Bias

The dictionary definition for the word heuristic refers to the process by which people find things out for themselves, usually by trial and error. Trial and error often leads people to develop rules of thumb, but this process often leads to other errors. One of the great advances of behavioral psychology is the identification of the principles underlying these rules of thumb and the systematic errors associated with them. In turn, these rules of thumb have themselves come to be called heuristics. (Shefrin 2002: 13)

Investors' typical errors i.e. heuristic-driven bias:

- People develop general principles as they find things out for themselves
- They rely on heuristics, rules of thumb, to draw inferences from the information at their proposal
- People are susceptible to particular errors because the heuristics they use are imperfect
- People actually commit errors in particular situations. (Shefrin 2002: 14)

Availability bias is a good example of errors that investors exhibit. Availability refers to information which is in the open markets and it affects investors' decision making. Irrational investors analyze information in different ways and they appreciate information by their own non-logical methods. They usually ignore the information that contradicts their own prior beliefs and overweight the information they already have. (Shefrin 2002: 14)

4.1.1. Representativeness

One of the most important things that affect financial decision making is representativeness which states that decision making is based on stereotypes. The advantage of heuristics is that they reduce the time and effort required to make reasonably good judgments and decisions. Representativeness leads to very predictable biases in certain situations. The reason for focusing on biases rather than successes is that biases usually reveal more of the underlying processes than do successes. Virtually all current theories of decision making are based on the results of research concerning biases in judgment. (Plous 1993: 109)

For example, people often predict future uncertain events by taking a short history of data and asking what broader picture this history is representative of. In focusing on such representativeness, they often do not pay enough attention to the possibility that the recent history is generated by chance rather than by the model they are constructing. Investors may extrapolate short past histories of rapid earnings growth of some companies too far into the future and therefore overprice these companies. Representativeness leads to overreaction and overreaction to non-information might lead to price bubbles. (Shleifer 2000: 11)

Kahneman and Tversky (1982) acknowledged that people seem to make predictions according to a simple matching rule: the predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions. This rule-of-thumb, an instance of what Kahneman and Tversky call the representativeness heuristic, violates the basic statistical principal that the extremeness of predictions must be moderated by considerations of predictability. De Bondt (1985) found that there is also considerable evidence that the actual expectations of professional security analysts and economic forecasters display the overreaction bias.

A financial example illustrating representativeness is the winner-loser effect documented by De Bondt and Thaler (1985, 1987). They found that stocks that have been extreme past losers in the previous three years do much better than extreme past winners over the following three years. De Bondt (1992) explained that the long-term earnings forecasts made by security analysts tend to be biased in the direction of recent success. (Shefrin 2002: 16).

4.1.2. Overconfidence leads to overreaction

No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence. Due to their overconfidence, investors will trade too much. You can see overconfidence everywhere when people make decisions. They tend to be overconfident about their abilities and usually underweight the new significant information if it conflicts their own prior information. Shefrin et. al. (1994) and Odean (1999) concluded that noise traders do not understand that they are at an informational disadvantage, and thus make bad bets in the stock markets. The second reason is that investors trade too much, which is a clear evidence of overconfidence. Excessive trading leads to higher trading volume.

The overreaction hypothesis is an interesting part of behavioral finance. The obvious question is to ask: How does the anomaly survive the process of arbitrage? There has been considerable evidence that the existence of some rational agents is not sufficient to guarantee rational expectations equilibrium in an economy with some of what they call quasi-rational agents. Consistent with the predictions of the overreaction hypothesis, portfolios of prior losers are found to be to outperform prior winners. Thirty-six months after portfolio formation the losing stocks have earned about 25 % more than the winners, even though the latter are significantly more risky. The overreaction and momentum effect will be tested in the empirical part. (De Bondt et. al. 1985)

Gambler’s fallacy is described that investors are like gamblers and they have this erroneous belief about future stock price movements and they act according to their cognitive limitations. For example, if five tosses of a fair coin all turn out to be heads, what is the probability that the sixth toss will be tails? If the coin is fair, the right answer is one-half. Yet many people have a mental picture that when a fair coin is tossed a few times in a row, the resulting pattern will feature about the same number of heads and tails. Gambler’s fallacy arises because people misinterpret the law of averages; technically known as the “law of big numbers.” they think that the law of large numbers applies to small samples as well as to large samples. (Shefrin 2002: 17-18)

Rational investors trade only with stocks or buy information if it increases their expected income. An investor who is overconfident will decrease his earnings by trading too much. This is because he has an unrealistically positive picture of his own talent to choose the right stocks. These overconfident investors have even on average more risk in their portfolios than others. (Odean 1999)

How can overconfidence be reduced? People who are overconfident could learn to be better calibrated after making 200 judgments and receiving intensive performance feedback. Overconfidence also could be eliminated by giving subjects feedback after five deceptively difficult problems. There have been some studies which show that overconfidence can be unlearned, although their applied value is somewhat limited. Few people will ever undergo special training sessions to become well calibrated. The most effective way to improve calibration seems to be very simple: Stop to consider reasons why your judgment might be wrong. (Plous 1993: 227–228)

4.1.3. Mind games in investment decision making

Conservatism states that individuals are slow to change their beliefs in the face of new evidence. Individuals' subject to conservatism might disregard the full information content of earnings (or some other public) announcement, perhaps because they believe that this number contains a large temporary component, and still cling at least partially to their prior estimates of earnings. As a consequence they might adjust their valuation of shares only partially in response to the announcement. In particular, individuals tend to underweight useful statistical evidence relative to the less useful evidence used to form their priors. On the other hand they might be called being overconfident of their earlier information. (Barberis et. al. 1998).

Anchoring and adjustment is a psychological heuristic said to influence the way people estimate probabilities intuitively. It is difficult to protect against the effects of anchoring, partly because incentives for accuracy seldom work, and partly because the anchor values themselves often goes unnoticed. The first step toward protection is to be aware of any suggested values that seem unusually high or low. These are the anchor values most likely to produce biases in judgment. (Tversky et. al. 1974; Plous 1993: 151-152)

Another interesting behavioral phenomena is aversion to ambiguity. The main point about aversion to ambiguity is that people prefer familiar more than unfamiliar. People tend to show an availability bias, overweighting evidence that comes easily to mind, thereby allowing their decisions to be over-influenced by evidence that is more salient and attention-grabbing. (Shefrin 2002: 20)

Cognitive and emotional limitations exist everywhere in the financial sector. The recognition of your own as well as the others' mistakes is a beginning but it is not enough to earn free income. The goal of behavioral finance, the understanding of cognitive limitations and the decision-making process is to recognize the situations where it is possible to make a mistake. An investor has to be wary of his own as well as the other practitioners' mistakes. (Shefrin 2002: 21)

4.2. Frame Dependence

Frame dependence means that form is irrelevant to behavior. Proponents of traditional finance assume that framing is transparent. This means that practitioners can see through all the different ways cash flows might be described. Yet many frames are not transparent but rather are opaque. When a person has difficulty seeing through an unclear frame, his decisions typically depend on the particular frame he uses. Consequently, a difference in form is also a difference in substance. Behavior reflects frame dependence.

Prospect theory offered the first significant alternative to the expected utility paradigm that dominated research in finance until then. Prospect theory was based on experimental evidence about human behavior under uncertainty, and was built up to fit the evidence rather than embody an abstract sense of rationality. Prospect theory relies on evidence that when making economic decisions people are easily influenced by framing, that is by the context and ambience that accompany the decision problem. Part of this context is generated by the people themselves, as when they adopt arbitrary mental accounting of their financial circumstances. (Shefrin 2002; Shiller 2000).

4.2.1. Framing the investment decisions

The main point in loss aversion is that investors hate to lose and they are willing to do almost anything to avoid losing. In loss aversion, the function is steeper in the negative than in the positive domain; losses loom larger than corresponding gains. Diminishing sensitivity: the marginal value of both gains and losses decreases with their size. These properties give rise to an asymmetric S-shaped value function, concave above the reference point and convex below it, as illustrated in figure 3. (Tversky et. al. 1991)

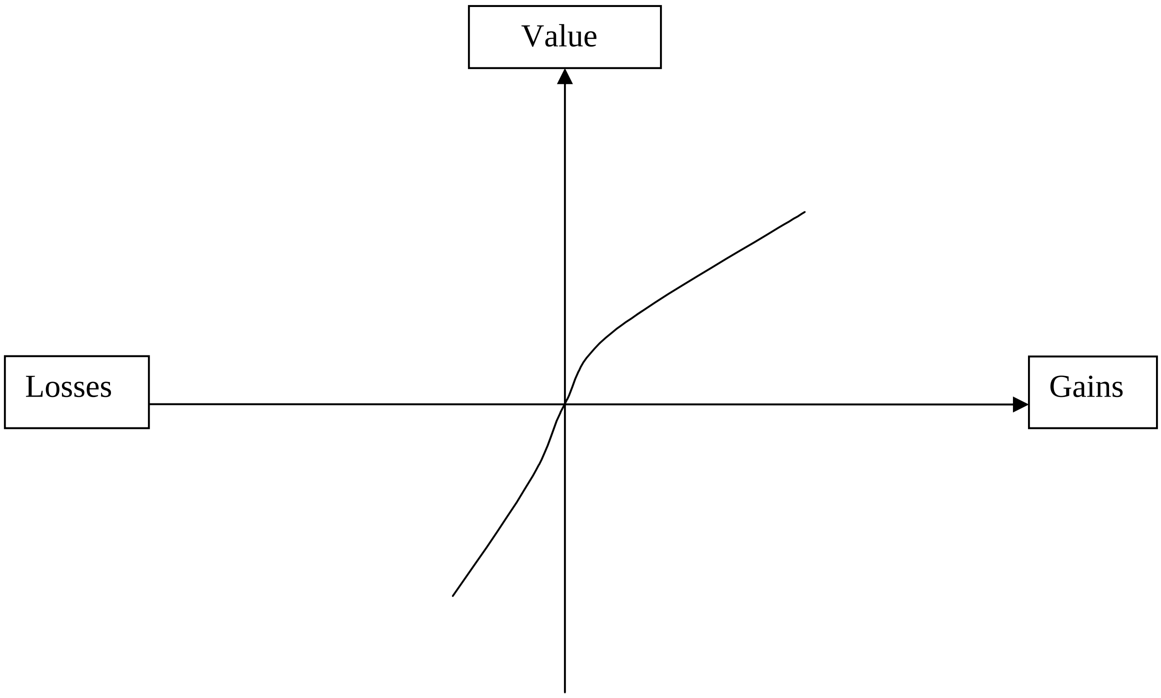

Figure 2. An illustration of a value function

From loss aversion investors usually get to get-evenitis. Here is a good example of get-evenitis: In 1995, Nicholas Leeson became famous for having caused the collapse of his employer, 232-year-old Barings PLC. He lost over 1,4 billion through trading. In 1992, Leeson began to engage in rogue trading in order to hide errors made by subordinates. Eventually he incurred losses of his own and get-evenitis set in. He asserted that he gambled on the stock market to reverse his mistakes and save the bank. (Shefrin 2002: 24)

Mental accounting is a specific form of framing in which people segregate certain decisions. For example, an investor may take a lot of risk with one investment account but establish a very conservative position with another account that is dedicated to her child's education. (Bodie et. al. 2005: 398) Statman (1997) argues that mental accounting is consistent with some investors' irrational preference for stocks with high cash dividends. Odean (1998) concludes that investors are more likely to sell stocks with gains rather than those with losses precisely contrary to a tax-minimization strategy.

The basic thing about hedonic editing is that investors prefer some frames to others. Investors are used to certain manners and one is that they do not like to lose. Realizing a loss would be a tough task for most people. For example it would be easier for people to accept a loss when a stockbroker says "transfer your assets". This way you can induce the client to use a frame in which he reallocates assets from one mental account to another, rather than closing a mental account at a loss. Basically this means that you disguise the loss in different words and it affects to the investor decision making. (Shefrin 2002: 26–27)

Prospect theory focuses on the way in which investors assess risk. This explanation, due to Barberis et. al. (1998), combines the Prospect Theory of Kahneman and Tversky (1979) with the idea that investors' willingness to gamble rises with their stock market winnings (Thaler and Johnson 1990). Because they are so much ahead of what they paid for their investments, their willingness to bear risk is extremely high.

Fear and regret are important factors, which influence the way investors make their decisions. Psychologists have found that individuals who make decisions that turn out badly have more regret (blame themselves more) when that decision was more unconventional. For example, buying a blue-chip portfolio that turns down is not as painful as experiencing the same losses on an unknown start-up firm. (Bodie et. al. 2005: 399)

The tendency of investors to hold losing investments too long and sell winning investments too soon is called the disposition effect. These investors demonstrate a strong preference for realizing winners rather than losers. Their behavior does not appear to be motivated by a desire to rebalance portfolios, or to avoid the higher trading costs of low priced stocks, nor is it justified by subsequent portfolio performance. For taxable investments, it is suboptimal and leads to lower after-tax returns. Tax-motivated selling is most evident in December. (Odean 1998; Shefrin & Statman 1985, 1987)

4.2.2. Money illusion

Frame dependence also impacts the way, people deal with inflation, both cognitively and emotionally. This is the issue of money illusion. People frame their beliefs of money so that they only think about the nominal value of money and ignore the real value. This way they structure their perspectives incorrectly and lose money by judging fundamentals wrong. Below is an example of money illusion: (Shafir, Diamond & Tversky 1997)

> If person A earns €40 000 per year and person B earns €40 000 per year as well. During the first year, when person A started working, there was not any inflation. When person B started working the inflation was 4 percent throughout the first year. After the first year A had €600 rise in salary and B had €1 500 rise in salary.
> a. Which one was doing better in the beginning of second year, A or B?
> b. Which one was happier in the beginning of the second year, A or B?
> c. Which one was more likely to leave his present job for another job, A or B?

When it comes down to money illusion, inflation has the biggest effects. Most people think about this situation in nominal values. It makes the majority of people to say that person B has a better salary, he is happier and person A is likely to look for another job, but in real values person A is making more money. People are not used to think about inflation and they ignore its effect for money. (Shefrin 2002: 32)

4.3. Inefficient markets and anomalies

The last 20 years have been very exciting for academic finance — perhaps almost as exciting as they were for financial markets. Among the many changes of views, the increased skepticism about market efficiency stands out. This skepticism derives from many sources, including the limitations of arbitrage, the accumulation of evidence on predictability of security returns, the observation of identical securities trading at different prices in different markets and the big movements in the stock markets, such as the 1987 and 2000 stock market bubbles. (Shleifer 2002: 175)

Fundamental analysis uses a much wider range of information to create portfolios than technical analysis. Investigations of the effectiveness of fundamental analysis ask, whether publicly available information beyond the trading history of a security can be used to improve investment performance, and therefore are tests of semistrong-form market efficiency. Surprisingly, several easily accessible statistics, for example a stock's price-earnings ratio or its market capitalization, seem to predict abnormal risk-adjusted returns. Findings such as these are often referred to as efficient market anomalies. (Bodie et. al. 2005: 388-389)

4.3.1. Small firm-in-January-Effect

The so called size or small-firm effect was originally documented by Banz (1981). The average returns on low-capitalization stocks are unusually high relative to those on large-capitalization stocks in early January, a phenomenon known as the turn-of-the-year effect. There has been evidence that the ratio of stock purchases to sales by individual investors displays a seasonal pattern, with individuals having a below-normal buy/sell ratio in late December and an above-normal ratio in early January.

The January effect is a widely discovered phenomenon. It is very common especially in small firm stocks. The January effect has become a paradox for models of equilibrium expected stock returns and the efficient market hypothesis. Besides this, there has been significant evidence that January returns were higher for small firms whose prices had declined the previous year. The possible explanation for January effect is the tax-loss selling. (Thaler 1987; Ritter 1988)

4.3.2. Neglected-Firm effect & Liquidity effect

Neglected-Firm effect and liquidity effect are other interpretations of the small-firm-in-January effect. Small firms tend to be neglected by large institutional traders; information about smaller firms is less available. This information deficiency makes smaller firms riskier investments that command higher returns. (Bodie et. al. 2005: 391)

4.3.3. Book-to-Market Ratios

Fama and French (1992) and Reinganum (1988) showed that a powerful predictor of returns across securities is the ratio of the book value of the firms' equity to the market value of equity. The dramatic dependence of returns on book-to-market ratio is independent of beta, suggesting either that high book-to-market ratio firms are relatively underpriced, or that the book-to-market ratio is serving as a proxy for a risk factor that affects equilibrium expected returns. In fact, Fama and French discovered that after controlling for the size and book-to-market effects, beta seemed to have no power to explain average security returns. This finding is a significant challenge to the notion of rational markets, since it seems to imply that a factor that should affect returns – systematic risk – seems not to matter, while a factor that should not matter – the book-to-market ratio – seems capable of predicting future returns. (Bodie et. al. 2005: 391-392)

4.3.4. Post-Earnings-Announcement Price Drift

Ball and Brown (1968) were the first to note that even after earnings are announced, estimated cumulative "abnormal" returns continue to drift up for "good news" firms and down for "bad news" firms. Foster, Olsen and Shevlin (1984) found that over the 60 trading days subsequent to an earnings announcement an investor can make abnormal returns of 25 % in stocks with unexpected earnings. Post-Earnings-Announcement price drift happens when significant news comes to the markets and investors overreact to this new information. Prices usually diverge from their real value for few minutes. Investors react to the earnings announcement and become aware of the full significance only as further information arrives.

There are two kinds of explanations for Post-Earnings-Announcement drifts. One class of explanations suggests that at least a portion of the price response to new information is delayed. A second class of explanations suggests that, because the capital asset pricing model (CAPM) used to calculate abnormal returns is either incomplete or misestimated, researchers fail to adjust raw returns fully for risk. As a result, the so-called abnormal returns are nothing more than fair compensation for bearing risk that is priced but not captured by the CAPM estimated by the researchers. (Bernard & Thomas 1989).

4.3.5. P/E-anomaly

Price/Earnings anomaly is a widely recognized phenomenon. P/E figure can be counted when you divide the share price by the earnings per share. P/E ratio is easy to calculate because you can find these two figures with no trouble. Portfolios of low price-earnings (P/E) ratio stocks have higher returns than high P/E portfolios. The P/E effect holds up even if returns are adjusted for portfolio beta. Is this a confirmation that the market systematically misprices stocks according to P/E ratio? This would be an extremely surprising and, to us, disturbing conclusion, because analysis of P/E ratios is such a simple procedure. Although it may be possible to earn superior returns by using hard work and much insight, it hardly seems possible that such a simplistic technique is enough to generate abnormal returns. (Bodie et. al. 2005)

4.3.6. Price bubbles

There are several examples of price bubbles. A price bubble occurs when the price of a stock keeps rising without any important news just because noise traders are chasing the trend. A most immediate example of such an apparent bubble is internet stocks in 1998. For example the stocks of Yahoo!, EBay and Amazon.com kept on rising although they had negative earnings and a little market power. Noise traders pushed the price up. A better description of noise trader behavior in such bubbles is positive feedback trading. Positive feedback investors buy securities after prices rise and sell after prices fall. This leaded to a stock market crash in the beginning of the year 2000. (Shleifer 2000: 154)

5. NOISE TRADER RISK IN THE FINANCIAL MARKETS

There has been different kind of opinions how noise traders affect stock prices. The first researcher, who argued about the irrational traders, was Milton Friedman (1953). Friedman concluded that irrational traders will consistently lose money, will not survive and therefore cannot influence long-run asset prices. Since his work, survival and price impact have been assumed to be the same. Kogan, Ross, Wang and Westerfield (2006) stated that survival and price impact are two independent concepts. The price impact of irrational traders does not rely on their long-run survival, and they can have a significant weight on asset prices even when their wealth becomes negligible. They also show that irrational traders' portfolio policies can deviate from their limits long after the price process approaches its long-run limit. The efficiency of financial markets is the principal motivation behind the interest in the survival of irrational traders. If irrational traders affect asset prices, then markets will not be efficient in any way.

De Long et. al. (1990) point out that the risk created by the unpredictability of unsophisticated investors' opinions significantly reduces the attractiveness of arbitrage. As long as arbitrageurs have short horizons and so must worry about liquidating their investment in a mispriced asset, their aggressiveness will be limited even in the absence of fundamental risk. They stated that in this case noise trading can lead to a large divergence between market prices and fundamental values. Moreover, noise traders may be compensated for bearing the risk that they themselves create and so earn higher returns than sophisticated investors even though they distort prices. Shleifer (2000: 28, 29) agree to this view by stating that if noise traders today are pessimistic about an asset and have driven out its price, an arbitrageur buying this asset must recognize that in the near future noise traders might become even more pessimistic and drive the price down even further. If the arbitrageur has to liquidate before the price recovers, he suffers a loss. Fear of this loss should limit his original arbitrage position. The same situation applies also conversely when there is a bullish market.

5.1. Traditional finance vs. Behavioral finance

Traditional finance theory ignores the aspects of behavioral finance. The supporters of traditional finance say that behavioral finance is no more than good stories which have been invented to cause confusion between practitioners. They rely on the studies of Fama and Scholes and are not willing to accept the possibility that there is some truth about investors' behavior and its effect on stock prices.

At end of the 1970's, the EMH was one of the great triumphs of twentieth-century economics. The economic theory, particularly the theory of arbitrage, predicted that financial markets were efficient. Mountains of empirical evidence based on some of the most extensive data available in economics, that on security prices, almost universally confirmed the predictions of the theory. Whenever researchers found small money-making opportunities, they could be easily explained away by an argument of failure to adjust properly for risk. Jensen's claim about the best established fact in economics was not all outrageous. (Shleifer 2000: 9–10). At that time, the rational expectations revolution in economic theory was in its first blush of enthusiasm, a fresh new idea that occupied the center of attention. The fact that speculative asset prices such as stock prices always incorporate the best information about fundamental values and that prices change only because of good, sensible information meshed very well with theoretical trends of the time. (Shiller 2002)

Fama (1998) concluded that market efficiency survives the challenge from the literature on long-term return anomalies. Consistent with the market efficiency hypothesis that the anomalies are chance results, apparent overreaction to information is about as common as underreaction, and post-event continuation of pre-event abnormal returns is about as frequent as post-event reversal. Most important, consistent with the market efficiency prediction that apparent anomalies can be due to methodology, most long-term return anomalies tend to disappear with reasonable changes in technique.

5.2. Behavioral finance vs. Traditional finance

Despite Fama's (1998) study to prove the markets efficient, there have been a lot of evidence of anomalies, and that stock prices deviate from fundamental values. Shiller (1981) and Leroy et. al. (1981) found evidence for too much volatility in the markets. They stated that stock prices seem to deviate more than just to be explained by the information for future dividends. The divergence from the efficient market hypothesis was so big, that it can not be explained by other factors, such as errors in data or problems in the price-index.

De Bondt et. al. (1985, 1987) concluded that research in experimental psychology has suggested that, in violation of Bayes' rule, most people overreact to unexpected and dramatic news events. The question then arises whether such behavior matters at the market level. They found significant evidence that the stock market overreacts especially on January and that buying losers rather than winners has a major impact on stock prices. In revising their beliefs, individuals tend to overweight recent information and underweight prior data.

Financial markets often exhibit sharply rising prices and subsequent declines that cannot be justified by fundamental or realistic economic assessments. But the recent dramatic rise and fall of Internet-related technology shares have demonstrated that such spectacles are not relegated to distant eras. The immediate availability of information about every publicly traded company, along with omnipresent media analysis, seems to have done nothing to diminish the magnitude of bubbles. (Caginalp, Porter & Smith 2001)

When investors' expectations for future earnings change so that they believe they can sell the stock in the future for more than they expected earlier, the market price of the stock will rise. If the rise of the stock derives from investor feelings, and there is no move in fundamentals, an asset bubble is born. The stock market crashes of 1987 and 2000 are due to irrational trading. Latest financial bubble in the year 2000 is a good example of a behavioral phenomenon. Despite the fact that the availability and diffusion of information had improved a lot, this most recent bubble attained price levels that were over 100 times their realistic valuation, even under the most optimistic estimates. There were not many professional investors that survived the technological bubble. This is a good indication of the function of the markets and the difficulty of investing. (Campbell & Kyle 1992)

5.3. Objections to rational and irrational ways of investing

According to Hirschleifer (2001) neither the rational nor the irrational models of finance should be totally rejected. Instead, he concludes that the methods should be affiliated in a sensible way. He presented the following arguments against both views:

Objection to Psychological Approach	Objection to Fully Rational Approach
Alleged Psychological biases are arbitrary Experiments that generate alleged psychological biases are not meaningful. It is too easy to go theory fishing for psychological biases to match data ex post. Rational traders should arbitrage away mispricing. Rational investors will make better decisions and get richer. Confused investors will learn their way to good decisions. Apparent return predictability is spurious, so psychological models of predictability are misguided.	Rationality in finance theory requires impossible powers of calculation. The evidence we possess does not support rational behavior. It is too easy to go theory fishing for factor structures and market imperfections to match data ex post. Irrational traders should arbitrage away efficient pricing. Irrational investors will bear more risk and get richer. Accurate investors will learn their way to bad decisions. Apparent return predictability is spurious, so rational models of predictability are misguided.

6. DATA AND METHODOLOGY

6.1. The markets in Finland

Organized security trading began in Finland already in the 1860's and the Helsinki Stock Exchange started its activity in the year 1912. The traditions of security trading are remarkably longer in many places. In London, security trading was in operation already in the end of 1500's. The most famous stock exchange in the world, New York Stock Exchange, started its securities trading in 1792. The Finnish stock market is one of the youngest and most illiquid markets in the world. (Pörssisäätiö)

The Helsinki stock exchange (HEX) was working as an independent exchange until the year 2005. On September 29, 2005, OMX presented its proposal for the OMX List, a common way of listing and presenting the portfolio of listed companies in the Nordic region. The OMX List replaced the current main list, I-List and NM- List in the Helsinki stock exchange. The local stock exchanges in the Nordic region will continue to be the listing venue and point of contact for already listed companies and future applicants to the OMX List. (OMX)

6.2. Data

Data will consist of stocks in the Helsinki stock exchange. The intention of this study is to follow the stock prices in the 21st century when the financial markets have grown to a new scale. The year 2000 was excluded from the examination because of the stock market crash of January 2000. The whole year was overly unstable and the market prices fluctuated unreliably. The period of data will be from 31.12.2000 to 31.12.2006.

OMX Helsinki and Bloomberg database are used to collect all required data. The final sample includes 60 stocks which will be separated into two different portfolios (each have 30 stocks). Table 2 shows the 30 stocks which were selected to the losing portfolio and table 3 provides the 30 stocks in the winning portfolio. Both portfolios include the biggest winners and losers in the selection period (31.12.2000-31.12.2002).

End of the month data will be used in each of the stocks. If it was not possible to get a price for a security in the end of the month, the price of the previous month will be used. This should not cause any difficulties to our research. Some stocks in the samples had a split during this examination period. Those stocks' prices have been adjusted according to the cumulative split adjustment factor which is from the Bloomberg database, as well. This should not cause any problems when making approximates about returns during different periods because the earnings of the securities are adjusted in the right ratio.

There are two anomalies that have to be taken into notice; the January effect and the small-firm-effect. This study does not separate the large firms and the small firms so it is possible that the results might include errors of small-firm-effects. The January effect is especially interesting because in the previous studies (De Bondt et al. 1985, 1987) were found that extreme past losers can have higher returns than winners in the beginning of the year and 3-12 months after. The stocks are also from different sectors which mean that there are for example technology companies and industry companies mixed in this sample.

Table 1 and table 2 include the stocks which are used in this research. Table 1 and table 2 also contain the asset prices in the end of each time series which is examined. These stocks are chosen by randomly and they are the biggest "losers" and the biggest "winners" from January 2001 to December 2002. Any companies' stocks which had gone to bankruptcy during the examination period were excluded from the data. All the stocks which have had a change in the series are excluded as well. This makes it easier to compare different time spans while every security in the data has a valuation on stock price during the whole examination period.

6.3. Model

This study will be closely related to De Bondt & Thaler (1985, 1987) and their study of does the stock market overreact. The model will calculate the extreme past losers and winners (from t-24 to t). Two portfolios will be formed and 3 time spans will be followed; t+24, t+36 and t+48. The intention is to find out whether extreme past losers will beat the stocks which were winners in the past. The main implication to this study is the overreaction bias which is well known among the supporters of behavioral finance. People overreact to new information no matter how relevant the new information is in reality. This can also be regarded as momentum effect when people are making approximates according to new information even though it might not be that relevant.

This study will first calculate the loser and the winner portfolios from January 2001 until December 2002 (24 months). Then 3 different time lines will be formed; from January 2003 until December 2004 (24 months), From January 2002 until December 2005 (36 months) and From January 2002 until December 2006 (48 months). Table 3 concludes the whole path of this study.

12/2000 = t-24	12/2002 = t	12/2004 = t+24	12/2005 = t+36	12/2006 = t+48
The stock prices in the Helsinki stock exchange will be followed	30 extreme past winning and 30 extreme past losing stocks during the last two years will be chosen Winning and losing portfolios will be formed	The performance of the portfolios will be noticed and analyzed	The performance of the portfolios will be noticed and analyzed	The performance of the portfolios will be noticed and analyzed

Table 1. The path of the study

Model:

(1) $P_{Portfolio} = P_{a1} + P_{a2} + ... P_{a30}$

Where,

$P_{portfolio}$ = Price of the Portfolio at time t

And

P_a = Price of the asset at time t

In the second part of the research part, earnings between different quartiles will be followed. This study will also follow the January effect, if there is any, in the Helsinki stock exchange. For this model we have a cumulative monthly earnings data from the Bloomberg database. Cumulative earnings will be calculated separately also between the losing and the winning portfolios. These results will be compared and analyzed carefully.

(2) $$P_{quarterly} = \frac{P_{a1_1} + P_{a1_2} + P_{a1_3} + P_{a2_1} + P_{a2_2} + ... + P_{a30_2} + P_{a30_3}}{30*3}$$

Where,

$P_{quarterly}$ = Price of the portfolio at the end of each quarter

And

P_{a11} = Price of the asset in the end of each month during quarter

7. EMPIRICAL RESULTS

In this section, results of the tests are reported. It is being examined whether stocks that are extreme past losers will outperform the stocks that are extreme past winners. In many previous studies this has been called the momentum effect when stock prices are behaving strangely because of new information or non-information at all. The statistical significance of this research will be tested in the end.

7.1. The performance of losing and winning portfolios

Jegadeesh and Titman (2001) concluded that momentum profits have continued in the 1990s, suggesting that the findings from the 1980s were not a product of data snooping bias. This empirical part tries to find if there is momentum in the 2000 century in the Helsinki stock exchange and results will prove if the is any profit to be make from mispricing.

Figure 3 shows how the value of the losing portfolio was decreasing during our examination period from January 2001 to December 2002 (from t-24 to t). The total downswing was 74,37 %. However, the following 24 months after the portfolio formation, the losing stocks got off to a flying start and the total profit was 80,35 % while the portfolio price climbed from 81,79 euros to 146,89 euros to the end of December 2004 (figure 3 and appendix 3). At the same time the stocks in the winning portfolio (figure 4 and appendix 4) were doing well despite of the market crash in January 2000. The total upswing from January 2001 to December 2002 was 40,06 %. A new portfolio of the winning stocks was then formed and value of the portfolio increases by 61,55 % during the next examination period (from January 2003 to December 2004). This result confirms the previous studies' findings that extreme past losing stocks seem to outperform the past winning stocks in a short period of time.

When looking at the next time sequence, it is clear what happens to the market prices. The stocks of the winning portfolio keep on increasing (t+36 = 106,92 %) while the "loser" portfolio's performance calms down (t+36 = 85,82 %). In a whole, the loser portfolio increases only 3,02 % while the winning portfolio has a performance of 28,09 % during the year 2005. The third year after the portfolio formation shows that the winning portfolios are making far better profit than the losing ones.

The last examination period is from January 2003 to December 2006 (from t to t+48). During this time the losing portfolio has increased by 60,42 % and the winning portfolio by 151,18 %. The loser portfolio has actually decreased in the year 2006 by -13,29 % and in the mean time the winner portfolio has increased by 21,39 %.

In a summary, the extreme past losing portfolios do not outperform the past winning portfolios in a long period of time. That can happen in shorter terms like 4-12 months after the portfolio formation. Many previous studies suggest that this can be viewed as markets correcting the prices closer to fundamental values. One reason for this is because by time overconfident investors (noise traders) and their actions have caused the divergence in market and fundamental values. These results confirm the previous findings which stated that in the end winning portfolios will outperform the losing ones.

Stocks have always been thought as an investment for a long period of time. It is really hard to make profit by acting according to momentum and single news about the firm. Taking a position in a stock and keeping that, say 5-10 years, has been proved in many studies to be the most efficient way to earn income. Noise traders especially seem to act when there is momentum and some kind of news release.

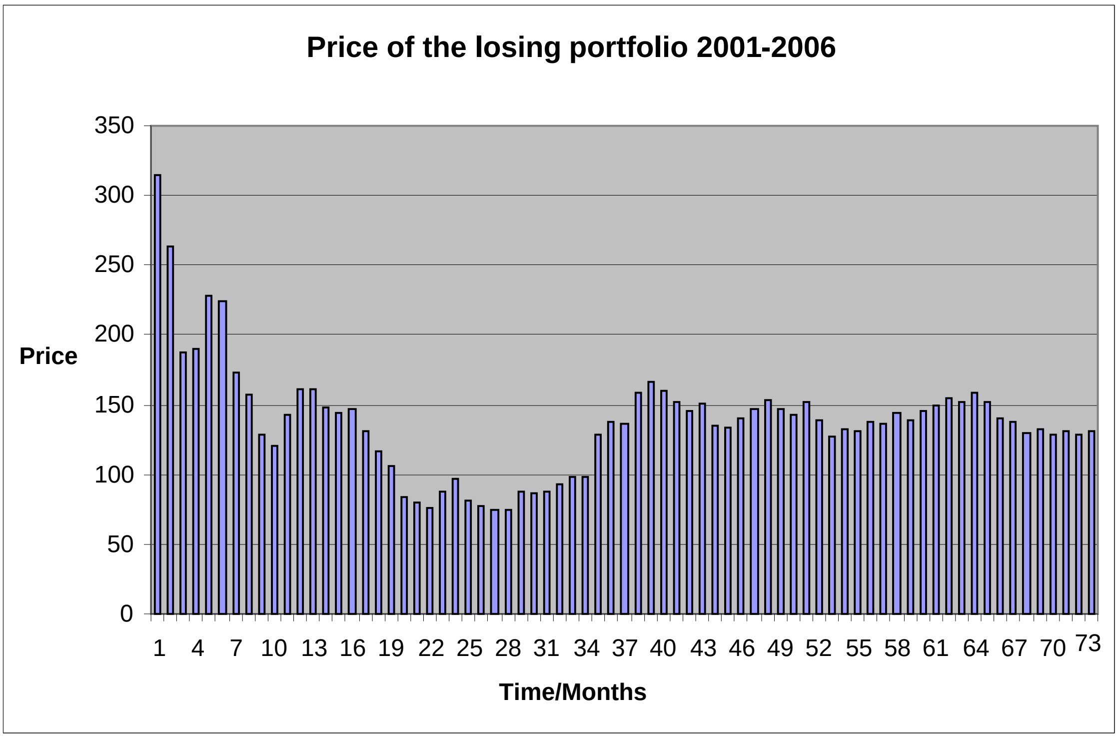

Figure 3. The performance of the losing portfolio

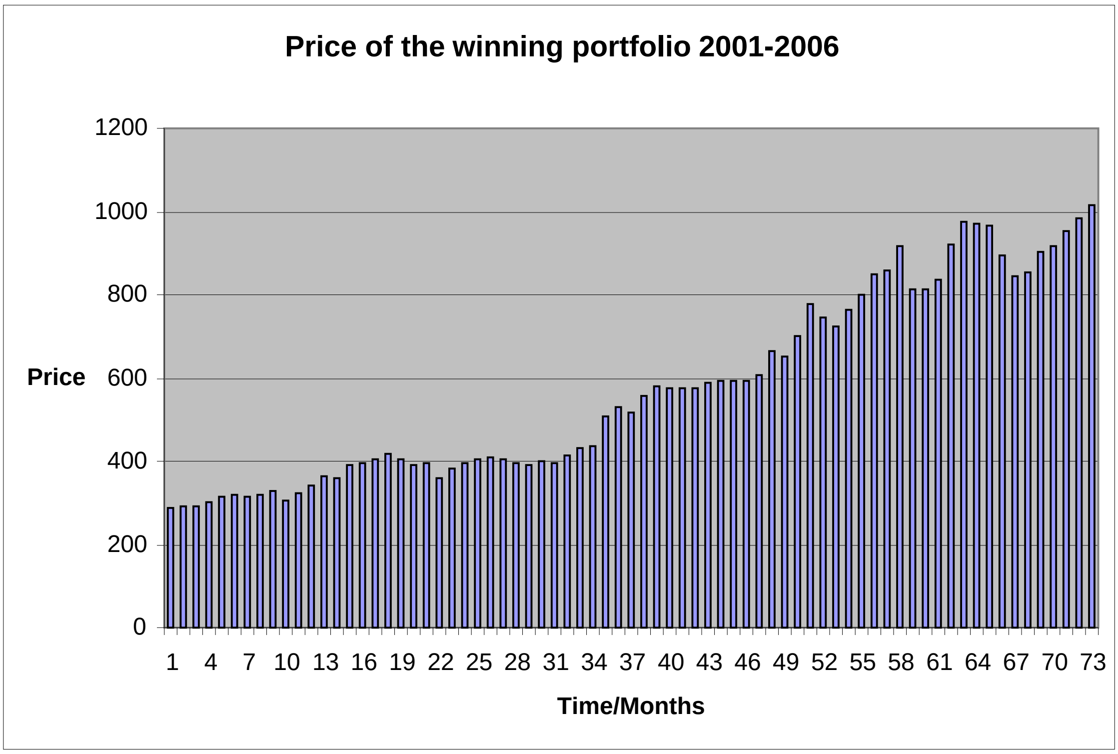

Figure 4. The performance of the winning portfolio

Name	Short name	Price t-24	t	t+24	t+36	t+48
Aspocomp Group Oyj	ACG1V	30,00	6,25	9,72	7,50	3,56
Aldata Solution Oyj	ALD1V	6,57	0,88	1,11	1,85	1,77
Proha Oyj	ART1V	2,95	0,52	0,45	0,36	0,40
Biohit Oyj B	BIOBV	6,20	1,41	2,06	2,15	2,03
Benefon S	BNFSV	8,15	0,72	0,12	0,25	0,22
Cencorp Oyj	CNC1V	4,62	0,36	0,66	1,23	0,44
Comptel Oyj	CTL1V	15,35	1,00	1,86	1,64	1,80
Elektrobit Group Oyj	EBG1V	2,58	0,29	0,56	0,19	0,21
Efore Oyj A	EFO1V	6,80	1,54	24,96	14,32	9,60
Elisa Communications Oyj A	ELI1V	22,93	5,72	11,86	15,65	20,75
Elcoteq Network Oyj A	ELQAV	33,50	10,80	17,89	20,15	9,78
Evox Rifa Group Oyj	ERG1V	0,22	0,06	0,10	0,07	0,08
Evia Oyj	EVI1V	2,69	1,08	1,10	1,33	1,11
F-Secure Oyj	FSC1V	5,20	0,75	1,81	2,04	2,25
Incap Oyj	ICP1V	4,50	2,01	1,90	1,87	2,51
Nokia Oyj	NOK1V	47,50	15,15	11,62	15,45	15,48
Okmetic Oyj	OKM1V	5,16	2,30	2,44	1,78	3,69
Oral Hammaslääkärit Plc	ORA1V	0,81	0,02	1,92	1,37	3,02
Perlos Oyj	POS1V	22,00	6,01	11,77	8,95	3,51
Ruukki Group Oyj	RUG1V	0,07	0,03	0,04	0,06	0,12
Satama Interactive Oyj	SAI1V	1,26	0,50	0,88	1,04	1,00
Scanfil	SCF1V	10,50	3,30	4,58	4,38	2,37
Stonesoft Oyj	SFT1V	15,37	0,55	0,58	0,51	0,47
SSH Communications Security Oy	SSH1V	15,40	0,75	1,28	1,23	1,15
TietoEnator Oyj	TIE1V	30,30	13,00	23,40	30,85	24,44
Tieto-X Oyj	TIX1V	4,29	1,96	3,95	3,76	4,63
TJ Group Oyj	TJT1V	1,14	0,14	0,16	0,06	0,05
Tekla Oyj A	TLA1V	5,18	1,58	1,87	3,42	7,88
Talentum Oyj	TTM1V	6,55	2,86	5,90	7,40	6,58
Turvatiimi	TUT1V	1,35	0,25	0,34	0,46	0,31

Table 2. Stocks of the losing portfolio

Name	Short name	Price t-24	t	t+24	t+36	t+48
Amer-Yhtymä Oyj A	AMEAS	28,00	34,90	38,55	47,19	50,04
Aspo Oyj	ASU1V	5,00	8,94	15,30	10,35	10,20
Atria Oyj A	ATRAV	4,29	7,70	11,30	17,99	18,29
Citycon Oyj	CTY1S	0,94	1,10	2,44	3,11	5,05
EQ Online Oyj	EQO1V	1,21	1,50	2,06	2,50	4,84
Fortum Oyj	FUM1V	4,35	6,25	13,62	15,84	21,56
HK Ruokatalo A	HKRAV	1,60	5,95	7,36	9,86	14,50
Huhtamäki Oyj	HUH1V	28,40	38,20	47,48	55,64	59,52
Ilkka-Yhtymä 2	ILK2S	18,40	22,50	29,92	43,80	51,35
Interavanti Oyj	INA1S	1,53	2,21	3,51	5,50	5,31
J. Tallberg-Kiinteistöt Oy B	JTKBS	4,20	5,40	9,78	13,04	18,70
Kasola Oyj A	KASAS	1,30	1,50	1,75	2,55	3,40
Kesla A	KELAS	4,25	5,00	9,18	20,94	8,46
Kemira Oyj	KRA1V	5,40	6,55	10,16	13,48	17,03
Keskisuomalainen Oyj A	KSLAV	28,00	38,00	71,16	85,72	72,80
Larox B	LARBS	5,12	7,50	13,98	18,30	27,00
Lemminkäinen Oy	LEM1S	12,35	16,00	15,74	30,50	36,10
Marimekko	MMO1V	5,00	14,30	39,19	43,30	39,06
Neomarkka Oyj B	NEMBV	3,80	5,50	7,35	7,75	7,76
Nokian Renkaat Oyj	NRE1V	17,90	33,99	111,80	106,50	155,20
Norvestia Oy B	NVABV	11,70	14,20	13,06	17,10	18,58
Olvi Oyj A	OLVAS	17,20	21,00	26,34	42,20	80,00
Panostaja Oyj B	PNABS	2,70	4,26	7,80	11,76	19,08
Sponda Oyj	SDA1V	3,95	5,45	7,18	7,95	12,00
Oy Stockmann Ab A	STCAS	11,39	13,84	21,10	32,38	36,40
Oy Stockmann Ab B	STCBV	10,40	13,80	21,70	32,53	36,48
Stromsdal Oyj B	STM1V	1,20	2,90	1,96	1,46	0,71
Tamfelt Oyj Abp etu	TAFPS	17,98	29,00	23,94	24,15	31,95
Tulikivi Oy A	TULAV	17,45	20,00	31,60	40,80	70,20
YIT-Yhtymä Oy	YTY1V	13,60	16,79	36,72	72,26	83,80

Table 3. Stocks of the winning portfolio

7.2. January returns and monthly return data

One of the interesting results in previous papers (De Bondt et. al. 1987; Reinganum 1988) was that a large portion of the excess returns occurs in January. Using the cumulative logarithmic earnings data from Bloomberg, we will now explore this curious fact. These earlier findings link these January returns either to tax code or to seasonality in the risk-return relationship. Tax-code happens in the end of the year when people realize losses to get them deducted in their taxation.

In this research, it is visible that the losing portfolio (table 4) is getting, in average, excess returns in January more so than in the coming months after that (1,18 %). The winning portfolio (table 5) is making abnormal returns in January, as well (10,44 %). This indicates that the January excess returns of both, winners and losers, show significant short-term reversals. For losers these reversals may reflect tax-loss selling pressure. For winners, the short-run reversals are consistent with a capital gains tax lock-in effect (De Bondt et. al. 1987).

Cumulative logarithmic montly return data				Losing portfolio		
Year	January	1-3 months	4-6 months	7-9 months	10-12 months	Total/year
2001	-3,40	-16,12	-2,67	-14,53	7,23	-26,10
2002	-0,63	-2,13	-10,27	-10,16	0,06	-22,50
2003	-1,10	-3,47	8,88	6,81	6,98	19,20
2004	4,48	1,90	-1,92	-1,58	-0,80	-2,40
2005	-0,53	1,08	0,15	1,74	-2,38	0,59
2006	2,36	3,99	-3,19	-1,84	0,01	-1,03
Total/quarter	1,18	-14,76	-9,01	-19,56	11,10	
Mean	0,20	-2,46	-1,50	-3,26	1,85	

Table 4. Logarithmic return data of the losing portfolio

Cumulative logarithmic montly return data Winning portfolio

Year	January	1-3 months	4-6 months	7-9 months	10-12 months	Total/year
2001	1,30	2,37	0,94	0,03	4,87	8,21
2002	1,69	4,52	0,58	-2,08	2,37	5,39
2003	0,47	-0,55	1,46	3,75	1,98	6,64
2004	1,86	3,29	0,65	0,51	-0,80	3,65
2005	2,15	3,80	1,69	3,12	0,03	8,64
2006	2,96	4,01	-3,19	0,82	4,08	5,72
Total/quarter	10,44	17,44	2,14	6,15	12,53	
Mean	1,74	2,91	0,36	1,02	2,09	

Table 5. Logarithmic return data of the winning portfolio

It is interesting to notice that the losing portfolio is making highest returns in average from October to December (11,10 %). The winning portfolio's abnormal return is 12,53 % during the same time. Grinblatt et. al. (2001) argue that investors are reluctant to realize their losses except in December, when the urge to realize large losses for tax purposes tends to eliminate this fact. Tax-loss selling is one of the biggest motivators in realizing a loss and selling the asset.

If you take a closer look at the year after the portfolio formation (2003), it is noticeable that the loser portfolio's earnings quarterly are -3,47 %, 8,88 %, 6,81 % and 6,98 %, respectively. This indicates quite clearly that the market is correcting its prices after the big decrease during the examination period and it is happening between 4-12 months. Are these corrections because of investor overconfidence is another question. Some previous studies consider that to be the case.

The winning portfolio's performance during the test and the valuation period does not vary much. This is against the proposal that the past winners should perform worse than the past losers. When you compare the winning and the losing portfolios four years after the portfolio formation, it is clear that the winning stocks have totally outperformed the losing ones.

7.3. OMX Helsinki Benchmark and portfolio performance

This section will compare the development of losing and winning portfolios to OMX Helsinki Benchmark index (OMXHB) which includes 50-70 biggest and most traded stocks in OMX Helsinki. OMX Helsinki Benchmark has a wide variety of stocks included so it presents closely how the markets are performing during the test period. OMXHB shows how the markets are behaving in average while these portfolios in the research are the extreme stocks in the OMX Helsinki stock exchange. Table 6 shows that the extreme portfolios' (when the worst and the best performing stocks are chosen) performance percentages are a lot more volatile than the index.

During the first examination period OMXHB has decreased 55,88 % while the losing portfolio has declined 74,37 % and the winning portfolio has increased 40,06 %. As already stated, the portfolios in this study contain the extreme stocks and these results confirm the fact. If you follow each of the examination periods you discover that the portfolios are performing in percentage terms a lot differently than the OMXHB. Even after the period 2001-2002, the markets are declining and mean while the portfolios in this study are increasing heavily.

This proves the fact that putting your funds to winning stocks is a good investment while it looks like the losing portfolio is getting good results as well comparing to OMXHB. The losing portfolio is obviously a lot more risky and thus more volatile than the market index. It would be interesting to see the results of these portfolios after 10 years after the portfolio performance. Previous studies suggest that the differences between the performances would in average calm down and performance of the portfolios would be closer to the market index.

OMX Helsinki Benchmark

Date	OMXHB change%	Losing Portfolio change%	Winning Portfolio change%
31.12.2000			
31.12.2002	-55,88 %	-74,37 %	40,06 %
31.12.2004	-5,23 %	79,59 %	61,55 %
31.12.2005	23,10 %	85,01 %	106,92 %
31.12.2006	43,68 %	60,42 %	150,44 %

Table 6. OMX Helsinki Benchmark index and portfolio performance

7.4. Statistical significance of the research

If the t value that is calculated is above 0,05, then the null hypothesis that the two groups do not differ is rejected and on the other hand the opposite hypothesis which typically states that the groups do differ is accepted.

To test the statistical significance of the study, a t-test is used. The t-test assesses whether the means of two groups are statistically different from each other. The t column (see appendix 1 and appendix 2) displays the observed t statistic for each sample. It is calculated as the ratio of the difference between sample means divided by the standard error of the difference. Appendix 1 and 2 provide descriptive statistic of the winning and losing portfolios. The means of the losing portfolios in the end of each research year 2000, 2002, 2004, 2005 and 2006 are 10,64; 2,77; 4,90; 5,04 and 4,37 respectively and for the winning portfolios 9,62; 13,47; 21,77; 27,88 and 33,85 respectively. The difference in the average stock prices between the two samples is not significant at the 0,05 level (t = 0,703; 0; 0; 0 and 0 respectively). The t-value of 0,703 between the samples in the year 2000 asserts that the means do not differ that much. However, when you consider the t-statistic in the rest of the samples (t = 0), this quite clearly shows that the means are totally different between the winning and the losing portfolios.

Levene's analysis tests the null hypothesis that the variances in the samples are equal. If the resulting values of Levene's test is less than 0,05 (confidence level in this research), the obtained differences in sample variances are unlikely to have occurred based on random sampling. Thus, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the sample. The statistic of this examination state that Levene’s value is 0,222 for the prices in the beginning of 2001 between loser and winner portfolios. This proves that the variances are not totally different but differ anyway since the value is close to 0,05 confidence level. The significance of the rest of the prices in the year end have a value of 0,00, which concludes in certainty that the variances between losing and winning portfolios are entirely different.

When testing the means of the returns of January and different quartiles, we discover that these are not that significant in a 0,05 confidence level. We found this kind of results: January t-statistic is 0,224, from January to March t-statistic is 0,108 and from July to September t-statistic is 0,225. The means of these sample periods differ pretty certainly from each other, even though they are not at the 0,05 confidence level. The second quartile from April to June has a t statistic of 0,496 and the fourth quartile from October to December has a t-statistic of 0,904. These figures show evidence that the earnings of losing and winning portfolios do not seem to differ that much in the year end. The biggest differences in the earnings seem to come in the beginning of the year and the third quartile.

Looking at the possibility of equality of variances in earnings between different quartiles, we discover that the variances differ for sure in January and the third quartile (sig. = 0,036 and 0,030). The significance level in the first (0,11), the second (0,157) and the fourth quartile is very close to the 0,05 confidence level as well. By conclusion, we can confirm that the variance levels between the losing and winning portfolios differ and thereby the losing and winning portfolios are not dependent on each other.

8. CONCLUSIONS

The main implications of this study were noise traders, the momentum affect and the overreaction hypothesis. Among the supporters of behavioral finance it is generally believed that noise traders are the cause and effect to the overreaction of security prices. This study does not really prove the fact that this is to be the case but from the previous papers it is possible to find some indications that this can indeed be true. The performances of stocks have been widely examined during the last hundred years. Many revealing studies have been written and new stock valuation models have been invented. This study continued the same route which these previous studies have set.

When comparing the first two years after the portfolio formation it was discovered that the losing stocks do indeed top the winning stocks. Actually this phenomenon happens already during the first year after the portfolio formation. The main explanation for this phenomenon might be that the markets are correcting themselves. The divergence of prices has probably been set off by the overconfidence bias which irrational investors spread while they are making false approximates of the future returns of the stock. Finally, markets are correcting the price differences closer to their fundamental values. Manu professional investors call this the momentum effect when investing to stocks which have been losers in the previous 2 years.

The key finding of this study was that the extreme past winners outperform the extreme past losers in a longer period of time (3-4 years after the portfolio formation) in the Helsinki stock exchange. The prices of the losing portfolio are very stable after the correction effects and there does not seem to be any leaps up or down. On the other hand the winning portfolio is increasing very firmly during the whole examination period. While this is a small liquidity market place it would be interesting to see what kind of results one can obtain with these methods from bigger stock exchanges.

The cumulative logarithmic monthly return data from Bloomberg database proves more precisely what is happening to the stock prices between different quartiles and January. There seems to be excess income for both portfolios in January. Previous studies have found this to be January effect when markets are generally rising. The results in this study agree to this view while on average losing portfolio is making slightly positive earnings on January and winning portfolio has a mean of 1,74 euros during the examination period. In fact, the fluctuations seem to very modest in January when comparing to other quartiles.

It is generally believed that investors sell their losing assets in the end of the year because they can cut those losses in taxation. This study provides evidence of this as the losing portfolio has a lot of abnormal returns in the final quarters of each year or at least is performing better than in other quartiles. Even though irrational traders are unwilling to realize losses, the tax effect seems to be a great motivator for selling the asset in a loss.

Noise trading is a very unifying phenomenon. It is the cause to many things in the financial markets as well as in every day life; 90 pro cents of people think their driving skills are better than others, 80 pro cent of the poker players think that their skills are above average although all the time 50 per cent of the players at least have to be losing players (probably higher). These are very curious facts which should without a doubt prove that these biases exist also in the financial markets.

REFERENCES

Banz, Rolf (1981). The Relationship between Return and Market Value of Common Stock. *Journal of Financial Economics* 9, 3–18.

Barber, Brad M. & Terrance Odean (2000). Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance* LV: 2, 773-806.

Bernard, Victor L. & Jacob K. Thomas (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research* vol. 27: 1-36.

Barberis, Nicholas, Andrei Shleifer & Robert Vishny (1998). A model of investor sentiment. *Journal of Financial Economics* 49: 3, 307–343.

Black, Fischer (1986). Noise. *The Journal of Finance* 41: 3, 529-543.

Bodie, Zvi, Alex Kane & Alan J. Marcus (2005). *Investments*. 6th edition. Boston etc.: McGraw-Hill Inc. 1090 p. ISBN 0-07-286178-9.

Brealey, Richard A. & Stewart C. Myers (2003). *Principles of Corporate Finance.* 7th edition. New York etc.: McGraw-Hill Inc. 1071 p. ISBN 0-07-115144-3.

Caginalp, Gunduz, David Porter & Vernon Smith (2001). Financial Bubbles: Excess Cash, Momentum and Incomplete Information. *The Journal of Psychology and Financial Markets* 2: 2, 80-99.

Campbell, John Y. & Albert S. Kyle (1993). Smart Money, Noise Trading and Stock Price Behaviour. *Review of Economic Studies* 60: 1, 1-34.

Copeland, Thomas E, J. Fred Weston & Kuldeep Shastri (2005). *Financial Theory and Corporate policy*. Pearson Education, Inc. 1000 p. ISBN 0-321-22353-5.

Grinold, Richard C. & Ronald N. Kahn (1995). *Active Portfolio Management*. The McGraw –Hill Companies Inc. 388 p. ISBN 1-55738-824-5.

Cuthbertson, Keith (2002). *Quantitative Financial Economics: Stocks, Bonds and Foreign Exchange.* John Wiley & Sons Ltd. 470 p. ISBN 0-471-95359-8.

Daniel, Kent, David Hirshleifer & Avanidhar Subrahmanyam (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance* 53: 6, 1839-1886.

De Bondt, Werner F. M. & Richard H. Thaler (1985). Does The Stock Market Overreact? *The Journal of Finance* 40: 3, 793-805.

De Bondt, Werner F. M. & Richard H. Thaler (1987). Further Evidence of Investor Overreaction and Stock Market Seasonality. *The Journal of Finance* 42: 3, 557-581.

Fuller, Russell J. & James L. Farrell, Jr. (1987). *Modern Investments and Security Analysis.* McGraw-Hill. 666 p. ISBN 0-07-022621-0.

Hirschleifer, David (2001). Investor Psychology and Asset Pricing. *The Journal of Finance* Vol. LVI, No.4: 1533-1597.

Jegadeesh, Narasimhan & Sheridan Titman (2001). An evaluation of Alternative Explanations. The Journal of Finance Vol. 56, No. 2. pp. 699-720.

Kahneman, Daniel, Paul Slovic & Amos Tversky (1982). *Judgment Under Uncertainty: Heuristics and Biases.* New York: Cambridge University Press.

Kahneman, Daniel & Amos Tversky (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology* 3: 430–454.

Kahneman, Daniel, & Tversky, A. (1973). On the psychology of prediction. *Psychological Review* 80: 237-25l.

Kahneman, Daniel & Amos Tversky (1979). Prospect Theory: An Analysis of Decision under Risk, *Econometrica* 47: 2, 263-292.

Kelly, Morgan (1997). Do Noise Traders Influence Stock Prices? *The Journal of Money, Credit and Banking* 29: 3, 351-363.

Kogan, Leonid, Stephen A. Ross, Jiang Wang & Mark M. Westerfield (2006). The Price Impact and Survival of noise Traders. *The Journal of Finance* Vol. LXI, No. 1: 195-229.

Leppiniemi, Jarmo (2000). *Rahoitus*. Helsinki. WSOY. 358 p. ISBN 951-0-24526-7.

Leroy, Stephen F. & Richard D. Porter (1981). Stock Price Volatility: Tests Based on Implied Variance Bound. *Econometrica* 49: 1, 97-113.

Linnainmaa, Juhani (2003). *Essays on the Interface of Market Microstructure and Behavioral Finance.* Helsinki School of Economics. 112 p. ISBN 951-791-782-1.

Nikkinen, Jussi, Timo Rothovius & Petri Sahlström (2002). *Arvopaperisijoittaminen*. Helsinki. WSOY. 244 p. ISBN 951-0-26627-2.

Odean, Terrance (1998). Are Investors Reluctant to realize their losses? *The Journal of Finance* 53: 5, 1775-1797.

Odean, Terrance (1999). Do Investors Trade Too Much? *The American Economic Review* 89: 5, 1279-1298.

OMX Helsinki Stock Exchange. Available in World Wide Web: http://www.omxnordicexchange.com.

Palomino, Frédéric (1996). Noise Trading in Small Markets. *The Journal of Finance* 51: 4, 1537-1550.

Plous, Scott (1993). *The Psychology of Judgment and Decision Making*. McGraw-Hill, Inc. 302 p. ISBN 0-07-050477-6.

Pörssisäätiö. Available in World Wide Web: www.porssisaatio.fi.

Reinganum, Marc R. (1988). The Anatomy of a Stock Market Winner. *Financial Analysts Journal*, March-April: 272-284.

Ritter, Jay R. (1988). The Buying and Selling Behavior of Individual Investor at the Turn of the Year. *The Journal of Finance* 43: 3, 701–717.

Salmi, Timo & Ilkka Virtanen (2001). Economic Value Added: A Simulation Analysis of the Trendy, Owner-oriented Management Tool. Acta Wasaensia, No. 90. Business Administration 35. Accounting and Finance.

Shefrin, Hersh (2002). *Beyond greed and fear: understanding behavioral finance and the psychology of investing.* Oxford University Press, Inc. 368 p. ISBN 0-19-516121-1.

Shefrin, Hersh & Meir Statman (1994). Behavioral Capital Asset Pricing Theory. *The Journal of Financial and Quantitative Analysis* 29: 3, 323-349.

Shiller, Robert J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Review* 71: 3, 421-436.

Shiller, Robert J. (2000). *Irrational exuberance.* Princeton university Press. 312 p. ISBN 0-691-05062-7.

Shiller, Robert J. (2002). From Efficient Market Theory to Behavioral Finance. Available in World Wide Web: <URL: http://cowles.econ.yale.edu/P/cd/d13b/d1385.pdf>

Shleifer, Andrei & Lawrence H. Summers (1990). The Noise Trader Approach to Finance. *The Journal of Economic Perspectives* 4: 2, 19-33.

Shleifer Andrei (2000). *Inefficient markets.* Oxford university press. 216 p. ISBN 0-19-829228-7.

Slovic, Paul (1972). Psychological Study of Human Judgment: Implications for Investment Decision Making. *The Journal of Finance* 27: 4, 779-799.

Statman, Meir (1997). Behavioral Finance. *Contemporary Finance Digest*, 5-22.

Thaler, Richard H. (1994). Psychology and Savings Policies. *The American Economic Review* 84: 2, 186-192.

Thaler, Richard H. (1987). Anomalies: The January Effect. *Economic Perspectives* 1: 1, 197–201).

Thaler, Richard H. & Eric J. Johnson (1990). Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on risky Choice. *Management Science* Vol. 36, No. 6, 643-660.

Trueman, Brett (1988). A Theory of Noise Trading in Securities Markets. *The Journal of Finance* 43: 1, 83-95.

Tversky, Amos & Daniel Kahneman (1974). Judgement under Uncertainty: Heuristics and Biases. *Science* 185: 4157, 1124-1131.

Tversky, Amos & Daniel Kahneman (1991). Loss Aversion in Risk less Choice: A Reference-Dependent Model. *The Quarterly Journal of Economics* 106: 4, 1039–1061.

Appendix 1. T-Test for the performance of winning and losing portfolios

Group Statistics

	Type	N	Mean	Std. Deviation	Std. Error Mean
Price00	Losing portfolio	30	10,64	11,80	2,15
	Winning portfolio	30	9,62	8,55	1,56
Price02	Losing portfolio	30	2,73	3,92	0,72
	Winning portfolio	30	13,47	11,46	2,09
Price04	Losing portfolio	30	4,90	6,91	1,26
	Winning portfolio	30	21,77	23,30	4,25
Price05	Losing portfolio	30	5,04	7,31	1,33
	Winning portfolio	30	27,88	25,79	4,71
Price06	Losing portfolio	30	4,37	6,12	1,12
	Winning portfolio	30	33,85	33,28	6,08

Independent Samples Test		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Price00	Equal variances assumed	1,523	0,222	0,383	58	0,703	1,01767	2,65990	-4,30671	6,34204
	Equal variances not assumed			0,383	52,870	0,704	1,01767	2,65990	-4,31773	6,35306
Price02	Equal variances assumed	24,198	0,000	-4,861	58	0,000	-10,74800	2,21102	-15,17384	-6,32216
	Equal variances not assumed			-4,861	35,684	0,000	-10,74800	2,21102	-15,23353	-6,26247
Price04	Equal variances assumed	11,529	0,001	-3,802	58	0,000	-16,87133	4,43720	-25,75335	-7,98931
	Equal variances not assumed			-3,802	34,065	0,001	-16,87133	4,43720	-25,88817	-7,85449
Price05	Equal variances assumed	22,690	0,000	-4,667	58	0,000	-22,83767	4,89356	-32,63319	-13,04214
	Equal variances not assumed			-4,667	33,630	0,000	-22,83767	4,89356	-32,78661	-12,88872
Price06	Equal variances assumed	23,438	0,000	-4,771	58	0,000	-29,47200	6,17790	-41,83841	-17,10559
	Equal variances not assumed			-4,771	30,962	0,000	-29,47200	6,17790	-42,07253	-16,87147

Appendix 2. T-Test for the logarithmic monthly return data

Group Statistics

	Type	N	Mean	Std. Deviation	Std. Error Mean
January	Losing portfolio	6	0,20	2,79	1,14
	Winning portfolio	6	1,74	0,83	0,34
JanuaryToMarch	Losing portfolio	6	-2,46	7,22	2,95
	Winning portfolio	6	2,91	1,84	0,75
AprilToJune	Losing portfolio	6	-1,50	6,19	2,53
	Winning portfolio	6	0,36	1,79	0,73
JulyToSeptember	Losing portfolio	6	-3,26	7,82	3,19
	Winning portfolio	6	1,03	2,13	0,87
OctoberToDecember	Losing portfolio	6	1,85	4,17	1,70
	Winning portfolio	6	2,09	2,21	0,90

Independent Samples Test		**Levene's Test for Equality of Variances**		**t-test for Equality of Means**						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
January	Equal variances assumed	5,834	0,036	-1,298	10,000	0,224	-1,542	1,18793	-4,18855	1,10522
	Equal variances not assumed			-1,298	5,888	0,243	-1,542	1,18793	-4,46184	1,37850
JanuaryToMarch	Equal variances assumed	3,074	0,110	-1,763	10,000	0,108	-5,365	3,04341	-12,14614	1,41614
	Equal variances not assumed			-1,763	5,649	0,131	-5,365	3,04341	-12,92557	2,19557
AprilToJune	Equal variances assumed	2,337	0,157	-0,706	10,000	0,496	-1,858	2,63205	-7,72292	4,00625
	Equal variances not assumed			-0,706	5,831	0,507	-1,858	2,63205	-8,34424	4,62757
JulyToSeptember	Equal variances assumed	6,386	0,030	-1,295	10,000	0,225	-4,285	3,30968	-11,65943	3,08943
	Equal variances not assumed			-1,295	5,740	0,245	-4,285	3,30968	-12,47333	3,90333
OctoberToDecember	Equal variances assumed	4,847	0,052	-0,124	10,000	0,904	-0,238	1,92476	-4,52697	4,05030
	Equal variances not assumed			-0,124	7,604	0,905	-0,238	1,92476	-4,71742	4,24076

Appendix 3. The return data for the losing and winning portfolios

CODE	Market price 29.12.2000	Market price 30.12.2002	Change in value	Change in value %	Market price 30.12.2004	Change in value	Change in value %	Market price 30.12.2005	Change in value	Change in value %	Market price 29.12.2006	Change in value	Change in value %
	t-24	t	From t-24 to t		t+24	From t to t+24		t+36	From t to t+36		t+48	From t to t+48	
ACG1V	30,00	6,25	-23,75	-79,17 %	9,72	3,47	55,52 %	7,50	1,25	20,00 %	3,56	-2,69	-43,04 %
ALD1V	6,57	0,88	-5,69	-86,60 %	1,11	0,23	26,14 %	1,85	0,97	110,23 %	1,77	0,89	101,14 %
ART1V	2,95	0,52	-2,43	-82,37 %	0,45	-0,07	-13,46 %	0,36	-0,16	-30,77 %	0,40	-0,12	-23,08 %
BIOBV	6,20	1,41	-4,79	-77,26 %	2,06	0,65	46,10 %	2,15	0,74	52,48 %	2,03	0,62	43,97 %
BNFSV	8,15	0,72	-7,43	-91,17 %	0,12	-0,60	-83,33 %	0,25	-0,47	-65,28 %	0,22	-0,50	-69,44 %
CNC1V	4,62	0,36	-4,26	-92,21 %	0,66	0,30	83,33 %	1,23	0,87	241,67 %	0,44	0,08	22,22 %
CTL1V	15,35	1,00	-14,35	-93,49 %	1,86	0,86	86,00 %	1,64	0,64	64,00 %	1,80	0,80	80,00 %
EBG1V	2,58	0,29	-2,29	-88,76 %	0,56	0,27	93,10 %	0,19	-0,10	-35,52 %	0,21	-0,08	-28,97 %
EFO1V	6,80	1,54	-5,26	-77,35 %	24,96	23,42	3041,56 %	14,32	12,78	829,87 %	9,60	8,06	523,38 %
ELI1V	22,93	5,72	-17,21	-75,06 %	11,86	6,14	107,34 %	15,65	9,93	173,60 %	20,75	15,03	262,76 %
ELQAV	33,50	10,80	-22,70	-67,76 %	17,89	7,09	65,65 %	20,15	9,35	86,57 %	9,78	-1,02	-9,44 %
ERG1V	0,22	0,06	-0,16	-72,77 %	0,10	0,04	66,67 %	0,07	0,01	16,67 %	0,08	0,02	33,33 %
EVI1V	2,69	1,08	-1,61	-59,84 %	1,10	0,02	1,85 %	1,33	0,25	23,15 %	1,11	0,03	2,78 %
FSC1V	5,20	0,75	-4,45	-85,58 %	1,81	1,06	141,33 %	2,04	1,29	172,00 %	2,25	1,50	200,00 %
ICP1V	4,50	2,01	-2,49	-55,34 %	1,90	-0,11	-5,47 %	1,87	-0,14	-6,97 %	2,51	0,50	24,88 %
NOK1V	47,50	15,15	-32,35	-68,11 %	11,62	-3,53	-23,30 %	15,45	0,30	1,98 %	15,48	0,33	2,18 %
OKM1V	5,16	2,30	-2,86	-55,43 %	2,44	0,14	6,09 %	1,78	-0,52	-22,61 %	3,69	1,39	60,43 %
ORA1V	0,81	0,02	-0,79	-97,53 %	1,92	1,90	9500,00 %	1,37	1,35	6750,00 %	3,02	3,00	15000,00 %
POS1V	22,00	6,01	-15,99	-72,68 %	11,77	5,76	95,84 %	8,95	2,94	48,92 %	3,51	-2,50	-41,60 %
RUG1V	0,07	0,03	-0,04	-57,53 %	0,04	0,01	33,33 %	0,06	0,03	110,00 %	0,12	0,09	300,00 %
SAI1V	1,26	0,50	-0,76	-60,31 %	0,88	0,38	76,00 %	1,04	0,54	108,00 %	1,00	0,50	100,00 %
SCF1V	10,50	3,30	-7,20	-68,57 %	4,58	1,28	38,79 %	4,38	1,08	32,73 %	2,37	-0,93	-28,18 %
SFT1V	15,37	0,55	-14,82	-96,42 %	0,58	0,03	5,45 %	0,51	-0,04	-7,27 %	0,47	-0,08	-14,55 %
SSH1V	15,40	0,75	-14,65	-95,13 %	1,28	0,53	70,67 %	1,23	0,48	64,00 %	1,15	0,40	53,33 %
TIE1V	30,30	13,00	-17,30	-57,10 %	23,40	10,40	80,00 %	30,85	17,85	137,31 %	24,44	11,44	88,00 %
TIX1V	4,29	1,96	-2,33	-54,32 %	3,95	1,99	101,53 %	3,76	1,80	91,84 %	4,63	2,67	136,22 %
TJT1V	1,14	0,14	-1,00	-87,72 %	0,16	0,02	14,29 %	0,06	-0,08	-57,14 %	0,05	-0,09	-64,29 %
TLA1V	5,18	1,58	-3,60	-69,50 %	1,87	0,29	18,35 %	3,42	1,84	116,46 %	7,88	6,30	398,73 %
TTM1V	6,55	2,86	-3,69	-56,33 %	5,90	3,04	106,29 %	7,40	4,54	158,74 %	6,58	3,72	130,07 %
TUT1V	1,35	0,25	-1,10	-81,49 %	0,34	0,09	36,00 %	0,46	0,21	84,00 %	0,31	0,06	24,00 %
Losers	**319,14**	**81,79**	**-237,35**	**-74,37 %**	**146,89**	**65,10**	**80,35 %**	**151,32**	**69,53**	**85,82 %**	**131,21**	**49,42**	**60,42 %**

CODE	Market price 29.12.2000	Market price 30.12.2002	Change in value	Change in value %	Market price 30.12.2004	Change in value	Change in value %	Market price 30.12.2005	Change in value	Change in value %	Market price 29.12.2006	Change in value	Change in value %
	t-24	t	From t-24 to t		t+24	From t to t+24		t+36	From t to t+36		t+48	From t to t+48	
AMEAS	28,00	34,90	6,90	24,64 %	38,55	3,65	10,46 %	47,19	12,29	35,21 %	50,04	15,14	43,38 %
ASU1V	5,00	8,94	3,94	78,79 %	15,30	6,36	71,14 %	10,35	1,41	15,77 %	10,20	1,26	14,09 %
ATRAV	4,29	7,70	3,41	79,47 %	11,30	3,60	46,75 %	17,99	10,29	133,64 %	18,29	10,59	137,53 %
CTY1S	0,94	1,10	0,16	17,00 %	2,44	1,34	121,82 %	3,11	2,01	182,73 %	5,05	3,95	359,09 %
EQO1V	1,21	1,50	0,29	24,04 %	2,06	0,56	37,33 %	2,50	1,00	66,67 %	4,84	3,34	222,67 %
FUM1V	4,35	6,25	1,90	43,70 %	13,62	7,37	117,92 %	15,84	9,59	153,44 %	21,56	15,31	244,96 %
HKRAV	1,60	5,95	4,35	272,00 %	7,36	1,41	23,70 %	9,86	3,91	65,71 %	14,50	8,55	143,70 %
HUH1V	28,40	38,20	9,80	34,51 %	47,48	9,28	97,17 %	55,64	17,44	45,65 %	59,52	21,32	55,81 %
ILK2S	18,40	22,50	4,10	22,28 %	29,92	7,42	32,98 %	43,80	21,30	94,67 %	51,35	28,85	128,20 %
INA1S	1,53	2,21	0,68	44,40 %	3,51	1,30	58,82 %	5,50	3,29	148,87 %	5,31	3,10	140,27 %
JTKBS	4,20	5,40	1,20	28,58 %	9,78	4,38	81,11 %	13,04	7,64	141,48 %	18,70	13,30	246,30 %
KASAS	1,30	1,50	0,20	15,38 %	1,75	0,25	16,67 %	2,55	1,05	70,00 %	3,40	1,90	126,67 %
KELAS	4,25	5,00	0,75	17,64 %	9,18	4,18	83,60 %	20,94	15,94	318,80 %	8,46	3,46	69,20 %
KRA1V	5,40	6,55	1,15	21,30 %	10,16	3,61	55,11 %	13,48	6,93	105,80 %	17,03	10,48	160,00 %
KSLAV	28,00	38,00	10,00	35,71 %	71,16	33,16	87,26 %	85,72	47,72	125,58 %	72,80	34,80	91,58 %
LARBS	5,12	7,50	2,38	46,48 %	13,98	6,48	86,40 %	18,30	10,80	144,00 %	27,00	19,50	260,00 %
LEM1S	12,35	16,00	3,65	29,55 %	15,74	-0,26	-1,63 %	30,50	14,50	90,63 %	36,10	20,10	125,63 %
MMO1V	5,00	14,30	9,30	185,99 %	39,19	24,89	174,06 %	43,30	29,00	202,77 %	39,06	24,76	173,13 %
NEMBV	3,80	5,50	1,70	44,76 %	7,35	1,85	33,64 %	7,75	2,25	40,91 %	7,76	2,26	41,09 %
NRE1V	17,90	33,99	16,09	89,89 %	111,80	77,81	228,92 %	106,50	72,51	213,33 %	155,20	121,21	356,60 %
NVABV	11,70	14,20	2,50	21,36 %	13,06	-1,14	-8,03 %	17,10	2,90	20,42 %	18,58	4,38	30,85 %
OLVAS	17,20	21,00	3,80	22,09 %	26,34	5,34	25,43 %	42,20	21,20	100,95 %	80,00	59,00	280,95 %
PNABS	2,70	4,26	1,56	57,81 %	7,80	3,54	498,59 %	11,76	7,50	176,06 %	19,08	14,82	347,89 %
SDA1V	3,95	5,45	1,50	37,95 %	7,18	1,73	31,74 %	7,95	2,50	45,87 %	12,00	6,55	120,18 %
STCAS	11,39	13,84	2,45	21,51 %	21,10	7,26	52,46 %	32,38	18,54	133,96 %	36,40	22,56	163,01 %
STCBV	10,40	13,80	3,40	32,68 %	21,70	7,90	57,25 %	32,53	18,73	135,72 %	36,48	22,68	164,35 %
STM1V	1,20	2,90	1,70	141,83 %	1,96	-0,94	-32,41 %	1,46	-1,44	-49,66 %	0,71	-2,19	-75,52 %
TAFPS	17,98	29,00	11,02	61,30 %	23,94	-5,06	-17,45 %	24,15	-4,85	-16,72 %	31,95	2,95	10,17 %
TULAV	17,45	20,00	2,55	14,62 %	31,60	11,60	58,00 %	40,80	20,80	104,00 %	70,20	50,20	251,00 %
YTY1V	13,60	16,79	3,19	23,46 %	36,72	19,93	118,70 %	72,26	55,47	330,38 %	83,80	67,01	399,11 %
Winners	**288,61**	**404,23**	**115,62**	**40,06 %**	**653,03**	**248,80**	**61,55 %**	**836,45**	**432,22**	**106,92 %**	**1015,36**	**611,13**	**151,18 %**