

**UNIVERSITY OF VAASA**  
**FACULTY OF BUSINESS STUDIES**  
**DEPARTMENT OF ACCOUNTING AND FINANCE**

Ville Väliheikki

**SHORT-TERM OVERREACTION PHENOMENON IN GERMAN STOCK  
EXCHANGE:**  
**Comparative study of technology firms and traditional firms**

Master's Thesis in  
Accounting and Finance

Finance

**VAASA 2007**

<b>1. INTRODUCTION</b>	7
1.1 Purpose of the paper and approach	9
1.2 Background for industry classification	11
1.3 Previous researches on overreaction phenomenon	13
1.3.1 Researches supporting overreaction	14
1.3.2 Caveats for overreaction	16
1.4 Flow of research	17
<b>2. THEORETICAL BACKGROUND</b>	18
2.1 Random Walk and the Efficient Market Hypothesis	18
2.2 Portfolio theory	20
2.3 Market equilibrium and abnormal returns	23
2.3.1 The Capital Asset Pricing Model	23
2.3.2 The Arbitrage Pricing Theory	25
2.3.3 Estimation of abnormal returns in event studies	28
2.4 Theories from behavioral finance	30
<b>3. OVERREACTION THE NATURE OF THE PHENOMENON</b>	34
3.1 Overreaction phenomenon on different time intervals	34
3.2 Behavioral explanations for the overreaction phenomenon	36
3.3 Technical explanations and other related anomalies	39
<b>4. DATA AND METHODOLOGY</b>	42
4.1 Data description	42
4.2 Methodology	43
<b>5. EMPIRICAL RESULTS AND ANALYSIS</b>	47
5.1 Formulation of hypotheses	47
5.2 General findings	48
5.3 Effect of industry sector	50
5.4 Hypotheses and the results	53
<b>6. CONCLUSION</b>	55
<b>REFERENCES</b>	58



**APPENDIX**

Appendix 1: Table 4	66
---------------------	----

**FIGURES**

Figure 1: Stock price reaction to new information on efficient and inefficient markets	8
Figure 2: Capital Market Line in Portfolio Theory	21
Figure 3: The Capital Asset Pricing Model	24
Figure 4: The Arbitrage Pricing Line in one factor environment	27
Figure 5: A Hypothetical value function	31
Figure 6: The coexistence of the momentum effect and the overreaction phenomenon: an event window explanation.	35

**TABLES**

Table 1: Whole sample weekly abnormal profits	49
Table 2: Technology stocks sub sample weekly abnormal profits	51
Table 3: Classic stocks sub sample weekly abnormal profits	52
Table 4: Whole sample Winner and Loser weekly abnormal profits	66



---

**UNIVERSITY OF VAASA****Faculty of Business Studies**

**Author:** Ville Väliheikki  
**Topic of the Thesis:** Short-term Overreaction Phenomenon in German Stock exchange: Comparative Study of Technology Firms and Traditional Firms  
**Name of the Supervisor:** Timo Rothovius  
**Degree:** Master's Degree  
**Department:** Department of Accounting and Finance  
**Major Subject:** Accounting and Finance  
**Line:** Finance  
**Year of Entering the University:** 2000  
**Year of Completing the Thesis:** 2007 **Pages:** 66

---

**ABSTRACT**

The purpose of the thesis is to find out whether there is a possibility to earn short-term overreaction based abnormal returns in German Stock Exchange and test the market efficiency of German Stock Markets. In addition, the comparative study between the Technology firms and Traditional firms is conducted in order to make judgment whether the higher level of uncertainty pertaining to Technology stocks' prices increase the magnitude of possible overreaction based contrarian profits. The research period is 2002–2006.

Research data includes logarithmic return series of those stocks that are listed in Prime All Share Index and the market return is proxied by the return of the Prime All Share Index. The methodology of the thesis is similar to that of Lo and MacKinlay (1990) and Jegadees and Titman (1993). In addition to market wide analysis, stocks are examined in a sub sample environment in order to uncover possible differences in overreaction between the two industry classes.

According to the results contrarian strategy of buying prior losers and short-selling prior winners is not profitable in German Stock Exchange and German Stock Markets are weak form efficient. Arbitrage portfolios' returns are not statistically significant at any level and many of the formed arbitrage portfolios earn negative returns in stead of positive ones. Further analysis of Technology stocks and Traditional stocks in a sub sample environment does not reveal any abnormal returns that are, in terms of short-term overreaction, statistically significantly higher for the Technology stocks as it was originally hypothesized.

**KEYWORDS:** Overreaction phenomenon, Abnormal returns, Market efficiency, Technology stocks

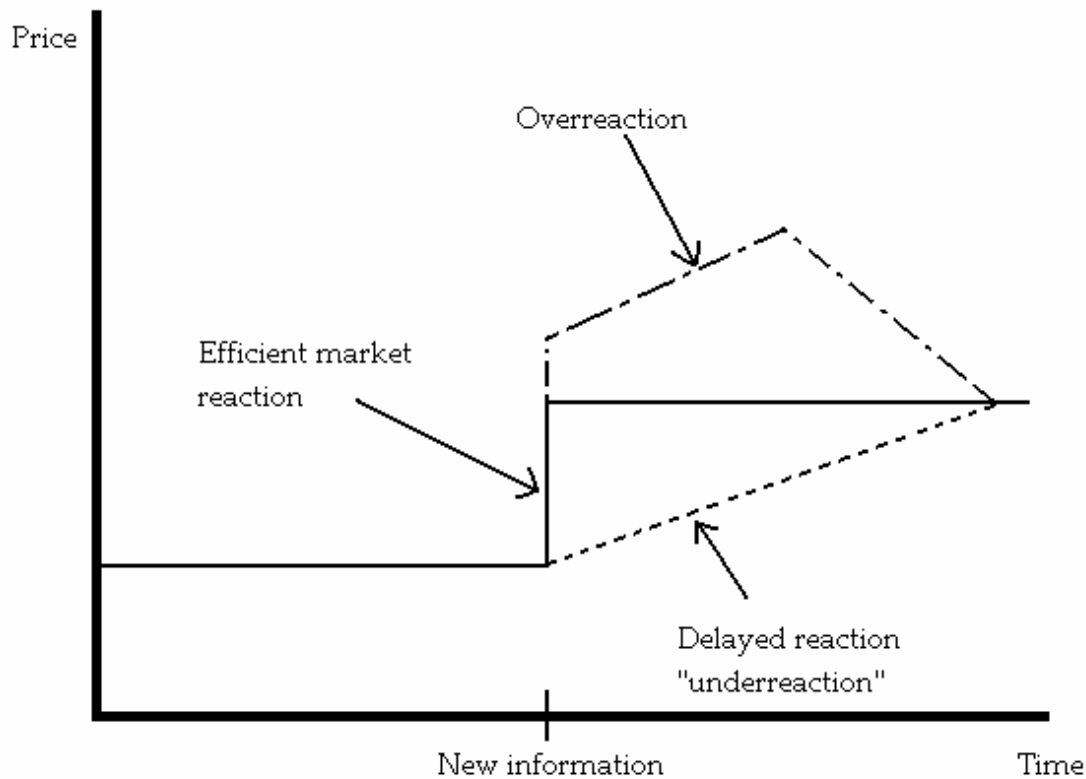


## 1. INTRODUCTION

For nearly seven decades economists and professionals in finance have been aware of the fact that stock prices do not always follow their fundamental values. These fundamental values refer to current stock prices that are derived by using different future dividends estimates which are based on rational expectations of the future market situation (ref. Sharpe, Alexander & Bailey 1999: 740–745). Even though the market efficiency and the randomness of stock price movements are standard concepts in contemporary finance, practitioners and researchers have identified many phenomena that seem to violate these concepts. Since these price deviations are persistent and they violate the statements of market efficiency regularly they are also known as anomalies (Nikkinen, Rothovius & Sahlström 2002: 86).

One particular phenomenon that has been identified by many researchers is an overreaction of stock prices. In a context of financial theory the term overreaction means that when important information arrives on the market, either at once or gradually, the asset price moves temporarily away from its fundamental value and reverts to the correct level some time after the initial price deviation (De Bondt & Thaler 1985; Nam, Pyun & Avarad 2001: 808). In a psychological context the overreaction means that individuals place too much weight on recent information relative to prior which causes them to react too drastically. By neglecting the base rate people discharge one of the basic concepts of statistics and are thereby apt to make errors in assessing the relative importance of the new information to stock prices (Kahneman, Solvic & Tversky 1982: 421). Figure 1 demonstrates the idea of an overreaction phenomenon and compares it to other types of market reactions. The length of the event window is ignored for the sake of simplicity.





**Figure 1.** Stock price reaction to new information on efficient and inefficient markets (ref. Ross, Westerfield & Jordan 2003: 404).

According to the figure 1 there are three different types of reactions to the arrival of the new information. The first one is in line with the market efficiency assumption that the new information should be incorporated into assets prices correctly and without any drift. The two alternative reactions are not in accordance with the efficiency assumption, first of which is the overreaction phenomenon. When the stock price overreacts it jumps temporarily over the efficient price level expressed by the solid line and reverts afterwards to the correct level. The second one is the delayed reaction where the stock price reaches the efficient price level but with a drift that is too long, that is, the stock price underreacts to the new information and fails to settle to the correct level fast enough to be classified as an efficient reaction. (Ross, et al. 2003: 403–404.)

In a field of finance the overreaction phenomenon establishes itself in an area of behavioral finance which concentrates to study and partially explain different financial phenomena based on psychological models and theories. Behavioral finance, however, uses models and theories that are largely derived from the traditional area of finance and its scientific contribution is quite modest. Furthermore, these behavioral based theories often fail to offer a unified theory of market operations (ref. Fama 1998: 285, 291). Given this, it is reasonable that an alternative and more common classification places the studies in behavioral finance in a class of market efficiency studies. In this light, the overreaction phenomenon does not differ from other anomalies that are explained by some sort of irrational behavior. The overreaction phenomenon offers, however, valuable additional information to the existing theories of the financial markets and, especially, those concerning the behavior of market participants.

The overreaction phenomenon is very interesting for at least four reasons. Firstly, it challenges the famous Efficient Market Hypothesis in that if stock prices overshoot systematically their reversals must be predictable to some degree which, of course, implies that historical data is predictive. Secondly, if historical data makes it possible to predict price reversals it means that there is a possibility to earn abnormal returns by following an investment process that exploits these systematic price movements. Thirdly, the interdisciplinary nature of the phenomenon calls for revision of the existing financial theory so that it would take better into account also the psychological features in investors' activities. This is particularly true when the underlying theory of decision making is in question. Fourth, by recognizing the overreaction phenomenon and its implications, investors are not only able to better understand the behavior of the markets, but their own behavior as well, which is very important in a light of self-development as a professional investor.

### **1.1 Purpose of the paper and approach**

This paper examines the possible existence of abnormal returns arising from a short-term overreaction phenomenon in German Stock Exchange (Deutsche Börse Group) and, simultaneously, tests the efficiency of German Stock Market. In addition, magnitudes of overreaction based abnormal profits are compared

between the technology firms and traditional firms in order to make judgment about the hypothesized dissimilarity between the two industry classes. The robustness of possible results supporting the overreaction are tested for size, seasonality and risk as well as market microstructures of trading volume and bid-ask bounce. Furthermore, to minimize issues concerning data mining, an out-of-the-sample test is performed.

In order to test the existence of short-term overreaction anomaly and the efficiency of German Stock Exchange following working hypothesis is formed:

**H1:** Overreaction based short-term abnormal profits exist in German Stock Exchange and German Stock Markets are not weak form efficient.

Related to the stated hypothesis above, the overreaction phenomenon is examined in sub sample environment to test the hypothetical dissimilarity of the two industry classes relative to the anomaly at hand. This translates into additional hypothesis of the form:

**H2:** The magnitude of the overreaction is stronger for technology firm's stocks than those of traditional firm's.

The basis for the hypothesized dissimilarity between the two industry classes in terms of short-term overreaction is the higher portion of intangible assets in technology firm's process of production. Since these intangible assets are more difficult to value than tangible ones, the number of overreaction triggering news events should be larger for technology firms than classic firms which should increase overreaction based profits (refer Chapter 1.2).

It is worth noting that, from statisticians view point, the first sample that contains all stocks, the second sample of technology stocks and the third sample of classic stocks are all different from one another. From traders perspective this means that if overreaction is present even in one of the two sub samples, there is a possibility to earn abnormal profits by investing in those stocks that are more sensitive to the phenomenon. The validation of the second working hypothesis would, therefore, automatically validate the first working hypothesis as well, since, even though the overreaction would not be a market

wide phenomenon, its presence even in one of the sub samples would make the earning of the abnormal returns possible and historical data predictive, which in turn would contradict the EMH.

The research is done as a time-series event study for Prime All Share Index listed stocks in German Stock Exchange between 1.1.2002 and 31.12.2006. The market returns and the returns of each individual stock are calculated from differences of logarithmic price quotations. Obtained return series take into account dividends and stock splits and all dividends are assumed to be reinvested at the time of their payment.

## **1.2 Background for industry classification**

One of the centerpieces of the overreaction hypothesis is the way the investors react to new information. It has been shown that when facing a risky choice people do not, however, behave according to Bayesian rule but overweight the new information (Kahneman et al. 1982: 421). More to the point, it has been noted that the more uncertainty there is associated with the future event the more difficult it is to make sound and unbiased decisions due to the inordinate weighting of personal risk assessments as well as mixed signals that are provided to decision maker (Viscusi 1997: 1657–1658). The information content of this orthodox statement lies in the way the risk is taken into account when the uncertainty increases, that is, the rational decision maker is very much aware of the uncertainty that is associated with his decision, where as, the opposite is true for the irrational decision maker. On stock markets financial analysts and investors are facing huge amount of value relevant information as well as noise signals of various sorts. The key for a rational and unbiased decision making for any stock market participant is to distinguish the information that is value relevant from the noise and sum up the value relevant information in a manner that is free from mentioned behavioral biases. This way it is possible to get a glimpse of the market consensus of tomorrow's prices *and* the risk that is associated with them.

Given the nature of many technology firms it is relatively straightforward to claim that the valuation of technology firms is somewhat more difficult that

valuing of, say, companies in food industry. The reason for this is the high portion of Research & Development costs and other intangible assets, such as patents or knowledge, in firm's total inputs on its process of production (Barron, Byard, Kile & Riedl (2002: 289–290). For example Information Technology investments are the largest capital budgeting item in many U.S companies and, since it is only positive Net Present Value Investments that firms should undertake, these Information Technology Investments are of great interest to analysts who are trying to form a rational expectation of future profits (Tanriverdi & Ruefli 2004: 421). The valuation of intangible assets is, however, rather difficult. For instance, financial analysts' forecasts on high-intangible firms have a much lower degree of consensus than forecasts on those firms that invest more on tangible assets (Barron et al. 2002: 289). Further more conventional accounting systems have difficulties in capturing the rate of change in intangible assets which renders technology stock followers to more difficult valuation process over time (Shiu 2006: 356).

Researchers have identified that technology stocks exhibit unique price patterns and that the overreaction is stronger for the technology stocks. For example markets seem to be overly optimistic when valuing technology stocks. Further more stocks' seem to have some differences even among the broad category of technology stocks. Also the asymmetry of winner and loser stocks seems to be greater for technology losers. (Akhigbe, Larson & Madura 2003.)

In this paper the comparative study of technology firms and traditional firms is resting on an assumption that intangible assets are more difficult to measure than tangible ones. This adds an extra layer of complexity in already difficult decision making process of technology stock investors since e.g. Research & Development costs form a much higher proportion of technology stocks prices than those of traditional stocks. Because of the greater degree of uncertainty that is pertained to valuation of technology stock technology stocks investors are taken by surprise more often than those who follow companies that belong to the traditional industry sector (ref. Barron et al. 2002: 294; Akhigbe, Larson & Madura 2003: 142).

Overreaction hypothesis holds implicitly statement that the more there is uncertainty in expectation made by stock follower the more likely he is faced up

with dramatic news when the forecasted event plays it self out. This is so because it is precisely the new and dramatic events that people overreact to, and the less there are those prospects that the expectation was able to take into account in the first place, the more likely it is that of those prospects that remained unnoticed (read are new and surprising) some are interpreted as dramatic ones. When the inordinate weighting of personal risk assessments caused by the high level of uncertainty associated to the technology stocks is added in, the picture of the future prices and risk levels becomes quite different from what would be reasonable to expect

### **1.3 Previous researches on overreaction phenomenon**

**Williams** (1938) and **Keynes** (1964) were among the first to verify the existence of an overreaction. Based on their perceptions on fluctuation of different asset prices in short time-periods, they stated that market prices are too highly influenced by the expected returns on short-term investments. On the whole the history of the market efficiency recognizes the existence of an overreaction. Excess volatility, regression to the mean and different bubbles are all visible evidences of an irrational behavior of market participants and, although, it is only a small part of the bigger picture the overreaction phenomenon is clearly there. Along with its current definition it has been, however, only in a recent literature that the actual term "overreaction" is adopted to the jargon of finance.

Today, in a traditional area of finance, there are several studies on overreaction phenomenon on different markets, time-intervals, and conditions. Inconsistently, the empirical results on overreaction seem to be divided roughly in half either supporting it or rejecting it. In addition to this, alongside with an overreaction literature, a growing number of papers report that the markets have a tendency to underreact to the new information rather than overreact. Given that there is roughly an even split between the two anomaly in financial studies (Fama 1998: 284) and that the empirical findings of studies in both of these anomalies either support or reject it, the final judgment about the overreaction phenomenon and its existence is a hard one to make.

### 1.3.1 Researches supporting overreaction

**De Bondt & Thaler** (1985) were among the first to study the overreaction phenomenon on stock market more closely. According to their results portfolio formed from those NYSE stocks that had performed poorly (“Losers”) during the prior three years outperformed the market by, on average, 19,6 % three years after the portfolio formation. Similarly portfolio of prior “Winners” underperformed the market about 5 % during the same period.

In their follow up article De Bondt et al. (1987) concentrate to test the robustness of the overreaction phenomenon to the factors of size, January seasonality and time varying risk (beta in CAPM) factors. Authors control size by using market value as a predictor but their results do not erode the overreaction phenomenon. January seasonality is examined by comparing returns of Januaries to those of other months. Results indicate that, particularly for “Losers”, January returns are higher but taxes offer one explanation for this. To test the possibility of changes in risk, authors examine beta more closely. Differences are in fact observed, but the difference of 0,220 between the beta of the Winner portfolio and the beta of the loser portfolio is too small to explain the anomaly.

**Lo & Mackinlay** (1990), using weekly US stock prices, offer partly supporting partly adversary results for the overreaction phenomenon. Authors’ results show that cross-sectional correlations of stock returns form a big part of the short-term contrarian profits and that the size-sorted portfolios display lead-lag relation, that is, the returns of large stocks lead the returns of small stocks. Empirical results of their study account roughly 50 % of the overreaction profits to the cross-serial correlations among securities thus mitigating the relative importance of the overreaction phenomenon.

Employing an alternative methodology **Jegadeesh & Titman** (1995) examine the New York and American Stock Exchanges for the presence of weekly contrarian profits. Their decomposition of price movement to the two parts, one that is attributable to the reaction to the common factor and two, the part attributable to the reaction to the firm-specific information, enables them to make judgments about the lead-lag structure of short-term contrarian returns.

Contrary to the findings of Lo et al. (1990), authors find that reversal of the firm-specific component is the primary source of contrarian returns rather than the lead-lag component. Thus their results support the overreaction hypothesis.

**Cooper** (1999) examined the NYSE and AMEX large capitalization securities in order to uncover possible weekly overreaction. To correspond more to the psychological explanations offered for the overreaction phenomenon author impose several filters in portfolio formation and report greater reversal for stocks with low-volume. After the re-examination of the data in out-of-sample environment and after the controlling of size, volume, bid-ask spread and other microstructure characteristics, the results still support the overreaction.

**Mun, Vasconcellos & Kish** (2000) document, that short- and intermediate-term contrarian portfolios significantly outperform the market in US and Canadian stock markets. Instead of standard CAPM authors use the Multifactor CAPM as a model for capturing abnormal returns. In order to avoid problem of low predictive- and explanatory power arising from attempt to regress a non-stationary random walk with another non-stationary random walk, authors use non-parametric methodology to estimate the coefficients in multifactor CAPM. Authors' findings suggest that in the US short- and intermediate-term contrarian portfolios do earn excess returns and that the intermediate-term portfolio gives support to the overreaction in Canadian market.

Aside of momentum effect **Ihara, Kato & Tokunaga** (2004) study the overreaction phenomenon in Japanese Stock Exchanges. Test period from 1975 to 1997 uncovers significant return reversal one month after the portfolio formation period whereas no momentum effect is observed. Further analysis of industry classification, trading volume and arrival of new information at the end of the fiscal year shows that the overreaction is more pronounced with the low volume stocks that have done poorly, and that the fiscal year-end weakly supports the information arrival component of the total overreaction. Industry classification does not affect the returns.



### 1.3.2 Caveats for overreaction

**Kaul & Nimalendan** (1990) concentrate to study the variation in NASDAQ daily returns by taking into account the difference between the bid price and the ask price. Results show that at least half of the variation in daily returns can be explained by the bid-ask bounce. Further more, the results show that when the bid-ask bounce is controlled, the short term contrarian profits not only disappear but turn into loss, implying positive short-term autocorrelation in stock returns, that is, the NASDAQ stocks seem to express momentum effect in stead of overreaction.

Contradicting many previous results **Conrad & Kaul** (1993) note, that when measuring abnormal returns in any long-term strategy, the choice of a method to calculate returns is crucial. Particularly, when cumulative returns are used, obtained results can be biased and statistically insignificant due to the cumulation of the error term. Time series can thus be statistically significant by them selves, but when they are combined to form longer time series, results become unreliable as the error term cumulates. In this light, reported long-term returns are actually too unreliable to offer any definitive proof for the existence of the overreaction phenomenon.

Using a three factor model **Fama & French** (1996) test the robustness of the overreaction phenomenon on NYSE, AMEX and NASDAQ stocks. According to the results these stock markets do not express overreaction and it is impossible to earn abnormal profits by exploiting a long term overreaction. In addition test of short-term price behavior of listed stocks show return continuation instead of mean reverting. Authors' main argument against many previous studies on asset pricing anomalies, including long-term overreaction, focuses on the model and methodologies that researchers are using. More specifically, the reported abnormal returns tell only about the inefficiencies of the CAPM and not that of the market.

**Gaunt** (2000) examines the Australian stock Market from 1974 to 1997. To avoid significant transaction costs arising from monthly rebalancing author uses buy and hold method to calculate abnormal returns for contrarian portfolios. Results do not support the overreaction phenomenon for buy and hold

methodology. In rebalancing strategy positive abnormal returns of the loser portfolio reduced significantly after the risk was taken into account. Furthermore, illiquidity problems in Australia are too severe for the contrarian strategy to work.

#### **1.4 Flow of research**

This paper has two parts the theoretical one and the empirical one. The theoretical part deals with those theories that are in direct relationship with the overreaction phenomenon while the empirical part concentrates to explore the profitability of the phenomenon in German stock Exchange. After the introduction in the first chapter the research problem and approach is presented and working hypotheses are formulated. First chapter presents also previous studies on overreaction phenomenon and discusses about the difficulties in decision making process of the technology stock investor. Presented view point creates the background for the industry classification of this paper.

The second chapter creates the empirical frame of reference for the study covering the basic concepts of random walk, efficient market hypothesis and portfolio theory. Further more, The Capital Asset Pricing Model and the Arbitrage Pricing Theory are also presented and the theoretical background for abnormal return calculation is discussed. In addition to traditional finance the theoretical background is extended to cover also the psychological explanations that are offered by the behavioral finance. Third chapter examines the overreaction phenomenon in details scrutinizing the phenomenon on different time intervals and presents offered explanations for the phenomenon.

The fourth chapter starts the empirical part of the study presenting the data and the methodology used in this study. In this chapter formulas and econometrical models applied to uncover possible short-term overreaction are introduced and explained. The fifth chapter restates the formulated working hypotheses in testable form and gives an answer whether they should be accepted or rejected. In this chapter the empirical results are presented and their implications interpreted. The sixth chapter concludes the paper.

## 2. THEORETICAL BACKGROUND

Overreaction phenomenon is a broad concept that is related to many other observed market anomalies and traditional financial theories. In addition, due to its interdisciplinary nature, the overreaction phenomenon embodies theories also from psychology in a form of behavioral finance. Market equilibrium models and efficiency classifications are concepts of the former whereas the Prospect Theory, representativeness and overconfidence belong to the vocabulary of the latter.

### 2.1 Random Walk and the Efficient Market Hypothesis

**Maurice Kendall** (1953) examined 22 UK commodity and stock price series. He observed that it was impossible to show any predictable price patterns in those series and that the prices seemed to follow completely random paths, that is, the price of any given asset at any given time was as likely to increase, decrease or remain unchanged in subsequent period. Statistical definition to the randomness of asset prices means that there is no autocorrelation (or serial correlation) between the contemporaneous asset prices and their lagged prices (Dougherty 2002: 367). Also **Roberts'** (1959) findings corroborate the randomness of stock prices. According to his results time series generated from a sequence of random numbers were indistinguishable from a record of US stock prices. This unforeseeability of asset prices is known as a *random walk* theory and it is one of the building blocks of the contemporary market efficiency.

The Efficient Market Hypothesis (EMH) was formulated by **Eugen Fama** (1965) on the base of the preceding literature. According to the EMH the only thing that affects the stock prices is the arrival of new information, and since the information arrival on the market is random the price behavior of a stock is also deemed to be random (Nikkinen et al. 2002: 82). If there existed some model that would be able to predict the movements of stock prices the information of that model would already be fully priced on the market. The rationale for this is that the pursue of abnormal returns would instantaneously force the price to

the level predicted by the model since investors would allocate infinite amount of their wealth to those stocks that offer higher returns without a change in risks. (Bodie, Kane & Marcus 2005: 352)

Existing literature divides the EMH into three levels according to the level of information efficiency. (Copeland & Weston 1988: 332; Nikkinen et al. 2002: 83.)

1. *Weak* form market efficiency states that all information from historical price series is correctly priced by the market participants and that there is no lagged reaction to e.g. volume or price information of any previous trades. This implies that it is impossible to earn abnormal returns by examining historical price series. Thus, when weak form market efficiency holds, the use of a technical analysis such as contrarian strategy fails to earn abnormal profits.

2. *Semistrong* form market efficiency holds when all publicly available information, past or present, is correctly reflected in asset prices. Accordingly when information becomes public it is instantaneously and correctly incorporated into asset prices. It is thus, impossible to earn abnormal profits by using fundamental analysis since every price represents “a fair trade”.

3. *Strong* form market efficiency holds all elements of the previous two forms but in addition to their conditions all possible insiders’ information is also reflected in asset prices in a correct and timely manner.

In order to reflect the information in a way described above following underlying assumptions need to be filled on market. (Mossin 1966: 769–770; Malkamäki 1989: 31.)

- Investors aim to maximize their expected wealth at the end of the investment period.
- Only risk and expected returns affect the choices of investors.
- All market participants share the same view about the factors relevant to stock returns and their cross-sectional relations.
- All investors have the same investment period.
- All available information is accessible by all investors simultaneously and without any costs.

Based on the growing number of reported anomalies and the methodologies used to derive the results Fama revised the three level classification of the market efficiency in a year 1991. In his follow up article he suggests that the first level efficiency should be tested with the predictability power of publicly available information. Second level efficiency reports how timely and accurately information is transferred into asset prices, different event studies being the methodological viewpoint of this efficiency level testing. Third level efficiency tests concentrate on how insiders' information is able to generate abnormal profits, that is, profitability of trades performed by insider within a legal framework. (Fama 1991: 1576–1577.)

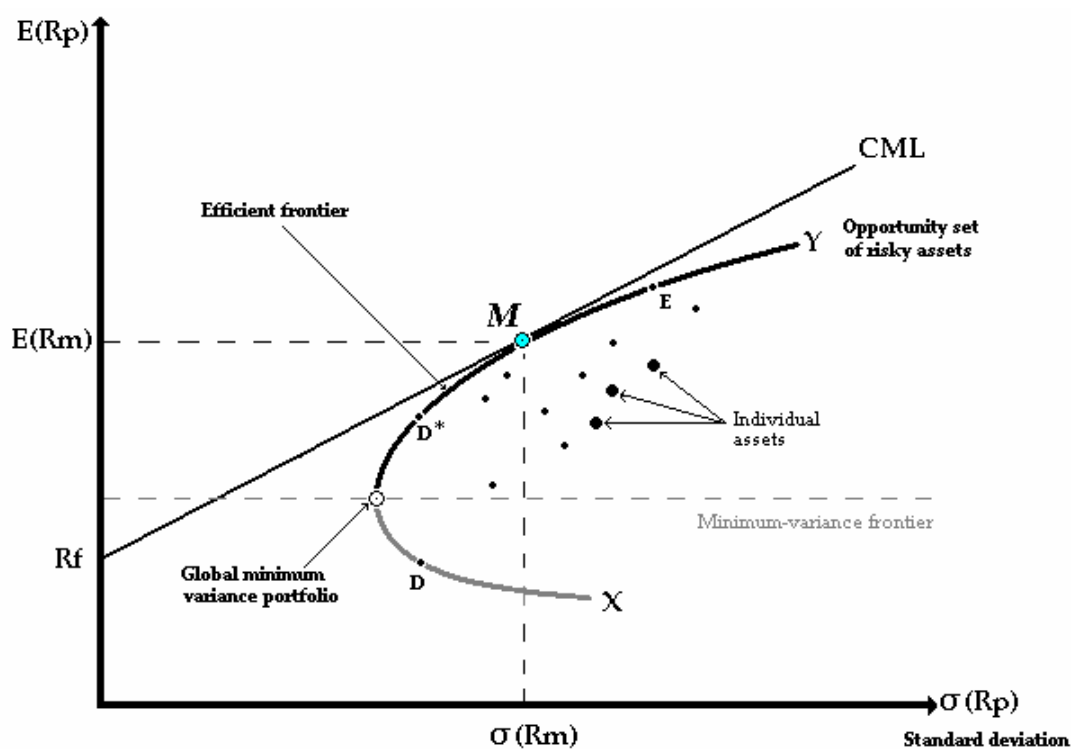
## 2.2 Portfolio theory

Foundation of the Portfolio Theory was laid in 1952 by **Harry Markowitz** and today it is the centerpiece of virtually all asset pricing models. In its simplicity the portfolio theory is based on an age-old wisdom offered already in The Holy Bible in a verse 2 of chapter 11 in Ecclesiastes which states “*Give portions to seven, yes to eight, for you do not know what disaster may come upon the land.*” (International Bible Society 1986). In a market place investors are faced with a certain amount of risk measured as a standard deviation of expected return of each asset. These returns are affected by number of factors such as business cycle, technological innovations, nature disasters etc. but the returns on different assets do not necessary move to the same direction than the returns on other assets. By investing in a large number of different assets investors are able to significantly reduce the risk of the expected return of their investments. This procedure of forming a portfolio that aims to reduce risk in a given level of return is called diversification (Ross et al. 2003: 427–429).

Diversification, however, does not eliminate the risk completely. The part of the risk that can be eliminated by using diversification is called unsystematic risk or diversifiable risk, where as, the part which cannot be eliminated is labeled as systematic risk or non-diversifiable risk. In determining what assets should be hold or taken into portfolio, the only thing affecting the decisions of investors is the systematic part of assets risk. (Brealey & Myers 2000: 169; Ross et al. 2003:

380.) In finance word risk refers in most cases to the systematic part of risk since there is no pay for risk that can be eliminated.

In accordance with the rationality assumption the only thing affecting the expected returns of portfolios is non-diversifiable risk. Thus, a rational investor would choose the portfolio which offers the highest return for a given level of risk or alternatively the lowest risk portfolio for a given level of return. This risk return trade-off is one of the main concepts in contemporary finance. In risk return trade-off the acceptable level of risk is affected by individual traits which are often represented by indifference curves (Copeland et al. 1988: 97–98).



**Figure 2.** Capital Market Line in Portfolio Theory (ref. Copelland et al. 1988: 196; Bodie et al. 2005: 220, 222, 226)

Figure 2 presents the risk return relationships for different assets and portfolios. Individual assets are depicted in the picture as small dots below the curve X to Y which represents the set of risky portfolios available to the investor. Of these individual assets one can form portfolios that have minimum variances. Examples of these minimum variance portfolios are those labeled D,  $D^*$  and E.

Portfolios that have a minimum variance at given level of return form together the opportunity set of risky portfolios. The rationality assumption, however, narrows the number of portfolios from which to choose to only those portfolios that lie above the Minimum-variance frontier. The argument for this is logical. Since portfolio  $D^*$  has much higher expected return than the portfolio  $D$  but exactly the same level of risk measured as a standard deviation of the expected return as the portfolio  $D$  any rational investor would choose the portfolio  $D^*$ . The portfolio  $D^*$  is said to dominate the portfolio  $D$  in terms of risk-return-trade-off. (Bodie et al. 2005: 222–226.)

The global minimum-variance portfolio in figure 2 is the one that has the lowest standard deviation available on the whole market and it is also the point of origin for the efficient frontier which represents all those portfolios that have the highest level of return for a given level of risk. The point  $M$  is the optimal risky portfolio for the investor who has certain preferences concerning the risk and return. No other portfolio in efficient frontier possess as appealing features to our example investor as the portfolio  $M$ . Given market efficiency the portfolio  $M$  must be the market portfolio, due to the equilibrium present on market. When lending and borrowing is allowed at the risk-free rate  $R_f$  one can form the optimal complete portfolio that contain the optimal risky portfolio and the risk-free asset in certain proportion. By varying these proportions according to the investors risk aversion it is possible to form the Capital Market Line (CML) which represents the combinations of all those complete portfolios that are feasible. By definition, the CML is tangent to the efficient frontier in point  $M$  since the optimal risky portfolio is a component in each optimal complete portfolio. (Copeland et al. 1988: 195–197; Brealey et al. 2000: 193; Bodie et al. 2005: 222–226.)

## 2.3 Market equilibrium and abnormal returns.

### 2.3.1 The Capital Asset Pricing Model

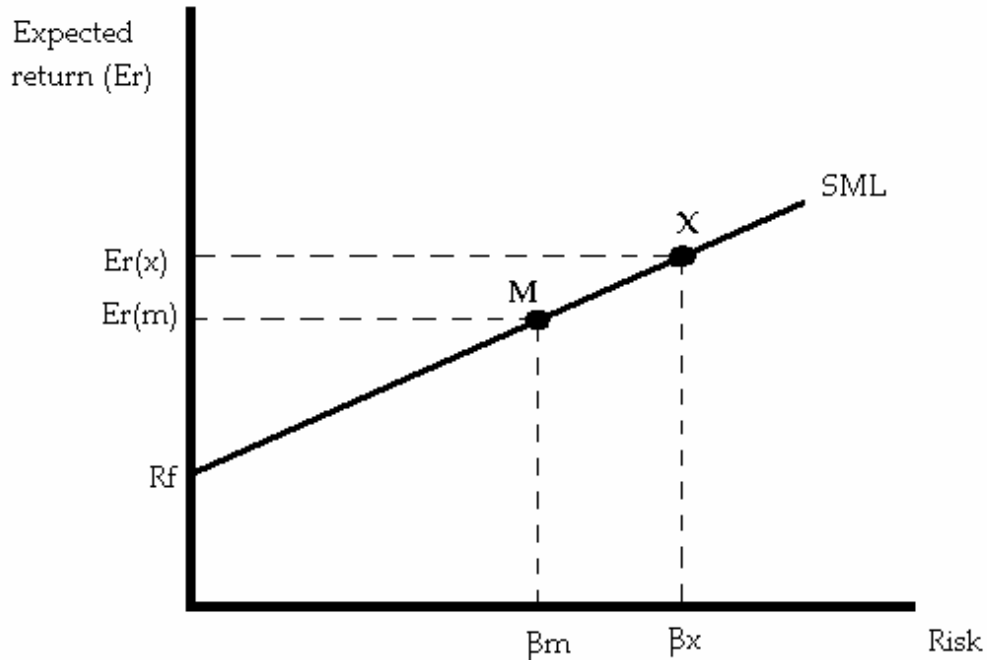
The Portfolio theory of Markowitz (1952) is the centerpiece of one of the simplest and most intuitively appealing models to calculate expected return known as the Capital Asset Pricing Model (henceforth CAPM). **Sharpe** (1964) and **Lintner** (1965) developed the CAPM, which states that the expected risk premium of an asset is directly proportional to its beta, and that the expected return is the sum of a risk-free asset return and the risk premium. The risk premium of an asset is calculated as the product of expected market return over the risk-free return and the correlation coefficient ( $\beta$ ) between the asset return and the return of the market. Given the directly proportional relationship of the beta and the risk premium, the relationship between the asset beta and the expected return can be expressed in a linear fashion by using a concept of Security Market Line (SML). The CAPM thus states that the expected return of every asset must lay on the SML, and that any deviations from it would result in abnormal returns contradicting the statement of market efficiency.

Mathematical formula for the CAPM is described in equation 1 (ref Sharpe et al. 1999: 235).

$$(1) \quad E(r_s) = r_f + \beta_s [E(r_m) - r_f],$$

Where  $E(r_s)$  is the expected return of a stock,  $r_f$  is the risk-free return,  $\beta_s$  is the beta of the stock and  $E(r_m)$  is the expected return of the market.





**Figure 3.** The Capital Asset Pricing Model (ref. Copeland et al. 1988: 197).

Graphical expression of the CAPM is presented in figure 3 which describes the linear relationship between the risk represented by the asset beta ( $\beta$ ) and the expected return ( $E_r$ ). As it can be seen the SML has its origin in the return of a risk-free asset which by definition has a zero beta. The SML slopes up from the point  $R_f$  showing the positive relationship between the risk and the return. The SML then runs through the point M which has exactly the same beta coefficient as the whole market, which is one. X is a stock or a portfolio that has a higher beta than the market, which means that its return oscillates more aggressively than that of the market, since its covariance with the market is above one.

Concerning the functionality and regulations of the markets, as well as the behavior of the market participants; the CAPM has the following underlying assumptions. (Vieru 1989: 83; Bodie et al. 2005: 282.)

- Investors can both lend and borrow money with risk-free rate.

- There are no transaction costs associated with the buying or selling of the securities.
- Investors are rational, that is they use the Markowitz portfolio selection method to select the assets in their portfolios.
- Investors can invest only on publicly available assets which are freely purchased and sold.

### 2.3.2 The Arbitrage Pricing Theory

One alternative market equilibrium model to the CAPM is based on the Arbitrage Pricing Theory (APT) developed by **Stephen Ross** (1976). This economic model is based on far less stricter assumptions about the functioning of the market and the behaviour of investors than the CAPM and is therefore more appealing in many cases. For example, where as the CAPM assumes that the conditions of Markowitz mean variance optimizations must holds for investors who operate on the market, the primary assumption of the APT is that each investor is an arbitrageur, that is, each investor would increase the expected return of his portfolio if it would be possible to do it without increasing the riskiness of the portfolio. This would be done by investing in arbitrage portfolios provided that they exist in the market. (Copeland et al. 1988: 219–220; Sharpe, et al. 1999: 283–284).

In addition to arbitrage nature of investors the APT imposes following four assumptions on the functioning of the markets and on the behavior of each individual investor. (Roll & Ross 1980: 1076; Huberman 1982: 189–190; Lehmann & Modest 1988: 215.)

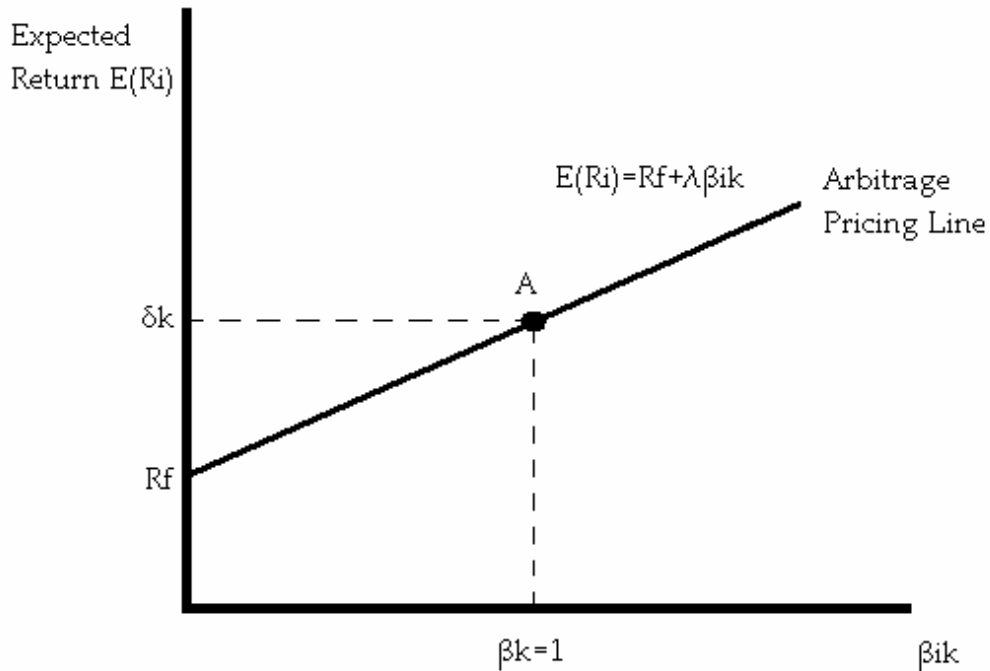
- Asset markets are perfectly competitive and frictionless.
- Investors are expected utility maximizers.
- The number of stocks is much greater than the number of factors in k-factor model.
- Investors believe homogenously that the random returns of securities are governed by k-factor model of the form:

$$(2) \quad R_{i,t} = E_i + \beta_{i1} \delta_1 + \dots + \beta_{ik} \delta_k + \varepsilon_i$$

$$i = 1, \dots, n.$$

where  $R_{it}$  is the return of the stock  $i$  at time  $t$ ,  $E_i$  is the stock's expected return,  $\delta_{kt}$  is the realization of the common factor  $k$ ,  $\beta_{ik}$  is the sensitivity of the return of stock  $i$  to the common factor  $k$ , that is, the factor loading and  $\varepsilon_{it}$  is the idiosyncratic return on the stock  $i$ . The idiosyncratic return is assumed to be sufficiently independent across stocks, and to have zero mean and finite variance so that the corresponding risk can be eliminated by using large and well diversified portfolios (Lehmann et al. 1988: 215).

When compared to the CAPM, which explains the differences in stock returns with differences in their betas, the APT makes an assumption that stocks returns are explained by an unknown number of unknown factors (Sharpe et al. 1999: 283). Although, this may sound more complicated and less usable and intuitive than the CAPM the APT is a relatively straightforward and simple to use model. Of its core assumption that there are no riskless arbitrage profits Roll et al. (1980: 1074) say *"Its modest assumptions and its pleasing implications surely render the APT worthy of being the object of empirical testing"* Indeed, the CAPM and the APT are so close to each other econometrically that the former can be seen as a special case of the later when the return of the market portfolio is assumed to be the only relevant factor affecting the return of each stock (Copeland et al. 1988: 219). The similarity of the single factor APT and the CAPM can also be seen from the graphical illustration of the APT in figure 4.



**Figure 4.** The Arbitrage Pricing Line in one factor environment (ref. Copeland et al. 1988: 222).

where  $A$  is an example stock,  $k$  is the single stochastic factor that affects the return of any given stock  $i$ ,  $\beta$  is the stock's  $i$  sensitivity to the factor  $k$ ,  $\delta k$  is the expected return on a portfolio that has unit sensitivity to the factor  $k$ ,  $R_f$  is the risk-free rate of return, which by definition has a zero sensitivity to the factor  $k$  because its return is constant. Finally  $\lambda$  in picture's equation can be interpreted as the risk premium on a portfolio that has unit sensitivity to the  $k$  factor, that is, the expected return over and above the risk-free rate of a portfolio that moves in unison with the factor  $k$ .

In multifactor model Roll and Ross (1984) studied which possible factors affect the unexpected returns of a well diversified portfolio. According to the results unexpected changes in inflation, industry production, risk premium and interest rates were such possible factors. Also other possible factors were found but they all affect through the four mentioned factors.

### 2.3.3 Estimation of abnormal returns in event studies

Many of the event studies in finance involve the examination of stock returns around the event date. The goal for these studies is to make inferences about the effect of an event to the equilibrium price. What comes to overreaction, the definition of an event is a large price change since it is assumed that at least part of that change will be corrected in a subsequent period. Even though the actual realization of returns can be directly observed from the historical time series, the nature of an event study is forward looking, that is, by using a historical data economists are trying to find empirical relationships between the variables so that they can make more justifiable inferences about the future. This calls for models that can be used to measure returns. Although, there are various event studies and various methodologies proposed to discover abnormal returns around them, they all share one common component, that is, they all have to clearly define what *normal* returns are before any inferences about the abnormal returns can be made (Brown & Warner 1980: 207). There are various models created to give an answer to this question of correct returns, and although, all of them only proxy the correct returns analysts and economists are able to make an educated guess about the level of abnormal returns by using them. Perhaps the most commonly used models are the Market Adjusted Model, the Market Model and the Fama-French Multifactor Model.

The Market Adjusted Model is a statistical model since it does not impose any economic restrictions concerning the behavior of stock market participants like e.g. the CAPM. All that the model assumes is that the returns are in unison multivariate, normally and identically distributed thorough time. Further more, statistical frame work of this model can be easily modified so that it takes into account autocorrelation or heteroskedasticity (MacKinlay 1997: 17, 19). Kothari and Warner (1997) define abnormal return calculated for stock  $i$  at time  $t$  with the Market Adjusted Model as follows:

$$(3) \quad MAR_{i,t} = R_{i,t} - R_{m,t} ,$$

where,  $MAR_{i,t}$  is the market adjusted return of stock  $i$  at time  $t$ ,  $R_{i,t}$  is the return of the stock  $i$  at time  $t$  and  $R_{m,t}$  is the return of the market index at time  $t$ . That is, the abnormal return is the part of the stock return that is over and above the

return of the market portfolio. In this model ex ante expected returns are assumed to be equal across stocks, but not necessary constant for given stock (Brown et al. 1980: 208).

The Market Model is also a statistical model and in mathematical for it is written:

$$(4) \quad MMAR_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{m,t} ,$$

where  $MMAR_{i,t}$  is the market model abnormal return of stock  $i$  at time  $t$ ,  $R_{i,t}$  is the return of the stock  $i$  at time  $t$  and  $R_{m,t}$  is the return of the market index at time  $t$ .  $\alpha_i$  and  $\beta_i$  are regression coefficients obtained by regressing stocks  $i$  returns on market return prior the event (Kothari et al. 1997: 306) Estimation period for the alpha and beta coefficients in regression analysis depends on what returns are used in event study. For example, it has been suggested that estimation period of 24 months can be used when monthly returns are examined as well as period of 100 days in a case of a daily return analysis (Cox & Peterson 1994: 257; Kothari et al. 1997: 306). Market model has been proven to be very efficient in capturing abnormal returns since it removes the portion of the return that is related to variation in market's return from the equation, and there by reduces the variance of abnormal returns (MacKinlay 1997: 18). The market model is a very intuitive and easy to use model which "...performs well under a variety of conditions" as stated by Brown and Warner (1980: 205).

The Fama-French Three factor model is also one commonly used model to estimate returns. In this model abnormal returns are defined as follows:

$$(5) \quad FFMAR_{i,t} = R_{i,t} - R_{f,t} - \beta_{i1} (R_{m,t} - R_{f,t}) - \beta_{i2} HML_t - \beta_{i3} SMB_t ,$$

where  $FFMAR_{i,t}$  is the Fama-French Three-Factor model abnormal return of stock  $i$  at time  $t$ ,  $R_{i,t}$  is the return of the stock  $i$  at time  $t$  and  $R_{f,t}$  is the rate of return of a risk less asset at time  $t$ ,  $R_{m,t}$  is the return of the market index at time  $t$ . The coefficients  $\beta_{i1}$ ,  $\beta_{i2}$  and  $\beta_{i3}$  are stock's  $i$  sensitivities to market premium over risk-free rate factor, book-to-market factor and size factor respectively.  $HML_t$  is the high-minus-low book-to-market portfolio return at time  $t$  and  $SMB_t$  is the small-minus-big size portfolio return at time  $t$ . (Kothari 1997: 306).

In Three-Factor Model Beta coefficients are obtained by regressing stock's  $i$  returns on corresponding factors. Similarly to the previous two models the Three-Factor model is also a statistical model. The goal of adding a SMB portfolio to the model is to capture the apparent difference in variances of small and big companies' returns while HML portfolio's aim is to control the value effect (Fama & French 1992: 9). The ultimate goal in adding of extra factors is to increase the power of the regression. It has been argued, however, that adding of these extra factors have little if any significant value to R square numbers when compared to simpler models such as the market model (Brown et al. 1980: 249, MacKinlay 1997: 18).

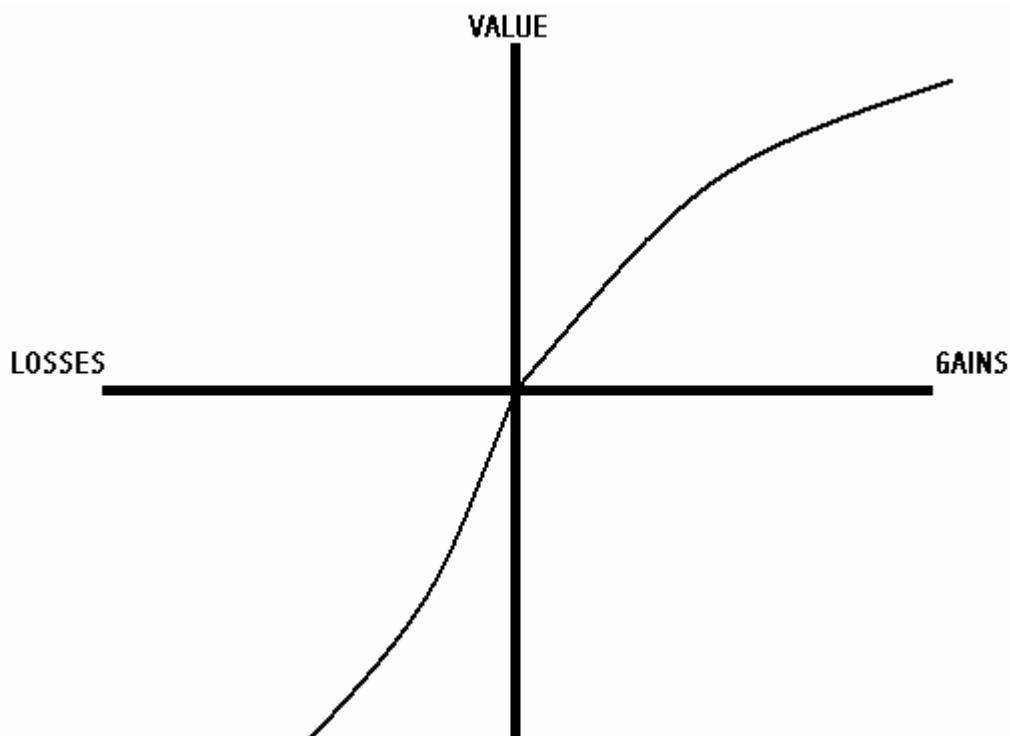
## **2.4 Theories from behavioral finance**

The actual term overreaction holds implicitly an assumption that there exists a reaction that is considered to be a correct one. One way to define the correct reaction is to use Bayes' rule which states that the solution to the problem (e.g. how much new information affects the stock price) should be based on both the probability given by the model and the new information. It is, however, well established fact that people do not behave according to this rule but, instead, tend to overweight the recent information relative to prior (see Keynes 1964; Arrow 1982; Kahneman et al. 1982). That is, people make predictions resting on heuristics such as representativeness and, therefore, select the predicted value so that its location in the distribution of outcomes matches its location in the distribution of their own beliefs (Kahneman et al. 1982: 416). This so called representativeness heuristic violates the rationality assumption of investors and contradicts the rational decision making process, which is based on statistical method of calculation of probabilities.

Base for the rationality in economics as well as in finance is the expected utility theory. According to this theory, when faced with multiple of choices, individual selects the one that has the highest expected utility at the lowest level of risk. This expected utility is a product of promised utility for an outcome and probability associated for this outcome to happen (Kahneman & Tversky 1979: 263–264). Thus, the expected utility theory does not leave any

room for illogical information processing or changing preferences when shifting from one problemset to another. In reality, however, it has been observed that people favor certain outcome over uncertain even when the later offers higher expected utility. Similarly, when individuals are making decision between the prospects, people discard components that are shared by all available choices under consideration. (Kahneman et al. 1979: 263.)

The Prospect theory formulated by Kahneman et al. (1979) offers alternative model for decision making. In prospect theory framework individuals use decision weights and gains or losses to form the shape of the value function. This is uncustomary compared to the traditional value function which is a product of probabilities and utilities. Another important aspect of the prospect theory is the shift of references which means that the actual outcome of the previous decision affects the way individuals see the subsequent set of choices. This coding of the choices is more apparent if a choice involves a high risk and is preceded by a negative experience. (Kahneman et al. 1979: 286–287.) Graphical expression of the hypothetical value function is described below.



**Figure 5** A Hypothetical value function (Kahneman et al. 1979: 279).



As it can be seen from the shape of the proposed value function people do not give equal weights for gains and losses. This is expressed by the steeper curve of the value function in down right corner of figure 5. This tendency of exaggerating the relative importance of losses is called the loss aversion (Tversky & Kahneman 1991: 1039).

Representativeness heuristic is one concept that is shown to contribute to the overreaction phenomenon. Representativeness gives rise to a tendency of an individual to see patterns in sequences which are actually random (Barberis, Shleifer & Vishny 1998: 316). More detailed description of representativeness is that *“people evaluate the probability of events by the degree to which these events are representative of a relevant model or process”* (Kahneman et al. 1982: 97) In a case of where a stock has experienced a positive past price development, investors can picture a beginning of a trend and extrapolate it too far into the future. That is, they became overly optimistic about the future price development of that particular stock and they fail to realize the fact that the historical growth rates tell only a little if anything about the future price development. Saliency of an event is an important element in this extrapolating. The more salient the past information releases are the more likely they are to be viewed as components in a pictured trend (Shefrin 2002: 103.)

In a field of psychology it is a well stated fact that most people think that they are above average what it comes to their own abilities (Kyle & Wang 1997: 2073–2075). This tendency is known as overconfidence. In addition, the degree of the overconfidence has been shown to increase when the new information is self acquired even though the additional value of this newly found information might be marginal (Kahneman et al. 1982: 292). To illustrate the overconfidence consider a trader who has a certain amount of information at hand to come up with an expectation of a future price level of some stock. Right at the beginning the trader forgets the fact that he does not possess all the information and, therefore, ignores the fact that, in essence, current stocks price represents the collective wisdom of the whole market. After calculations trader comes up with a number but fails to set the upper and the lower confidence intervals far enough so that the estimation would sufficiently take into account the

unavailable information and those factors that are missing from the model. This means that the confidence intervals for the estimate are set too close to each other, which renders trader to surprises. It follows that these surprises tend to revert and this, of course, is what overreaction is all about. (Shefrin 2002: 18, 41.)

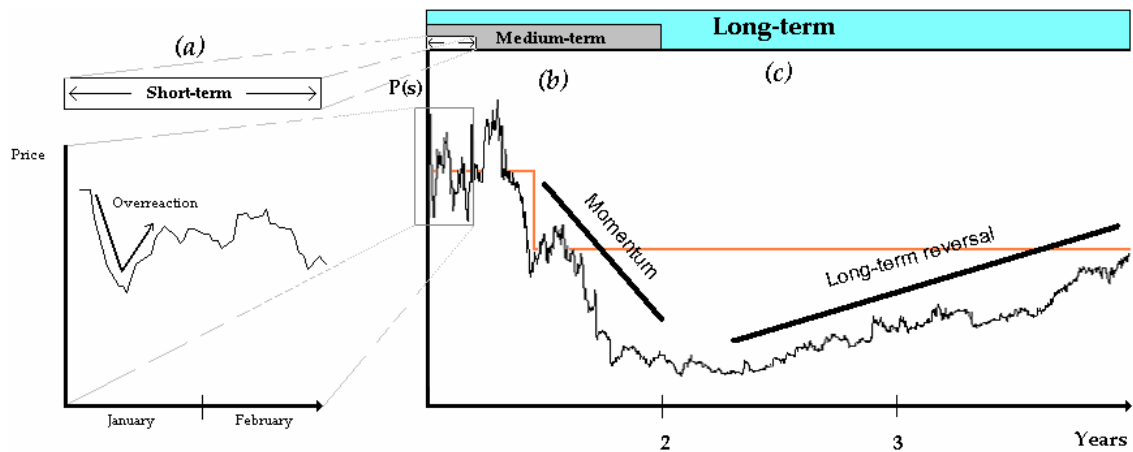
Biased self-attribution refers to the tendency of individuals to become more confident about themselves in a case where the external information supports their own private information and, at the same time, neglect the importance of contradicting public information (Daniel, Hirshleifer & Subrahmanyam 1998: 1844–1845). This psychological bias is related to the overconfidence in that when public information supports the private information individuals tend to become even more overconfidence about their abilities to pick stocks. Similarly self confirmation bias and illusion of validity are clearly related to the biased self-attribution since they predict that individuals downplay the importance of contradicting information and try to search supporting information (Shefrin 2002: 64, 204).

### 3. OVERREACTION THE NATURE OF THE PHENOMENON

The overreaction phenomenon has gained much interest over the past decades and, although, attempts have been made to explain it, it still remains rather elusive. The time frame, investors' psychology, the lack of efficiency in functioning of the markets as well as the technical explanations and other anomalies all constitute to the opaque phenomenon of overreaction. More to the point, the overreaction is so firmly tied to the underreaction that the separation of two anomalies from one another is unthinkable. After all, as Fama (1998) so adequately states it "... *apparent overreaction is about as common as underreaction*". Given this, it is still hard to say what exactly causes a particular investor simultaneously to overreact to some type of information and underreact to other. Regardless of this fact the overreaction phenomenon is still verified by many researchers and, even though the cause of the phenomenon is still largely unknown, it deserves its place on a list of those anomalies that requires further research.

#### 3.1 Overreaction phenomenon on different time intervals

Possibly the most plausible explanation for the coexistence of the hypothesized under- and overreaction is the apparent difference in the event windows of the two. It has been argued that at shorter time periods the stock markets tend to overreact where as at medium term momentum effect takes place (Bowman & Iverson 1998: 476; Kang, Liu & Ni 2002: 243, 263; Shefrin 2002: 85). Correspondingly when stock prices are monitored for a period over one year the overreaction seems to be the prevailing phenomenon. (Shefrin 2002: 85). Figure 5 describes what seems to be roughly the current understanding about the under and overreaction phenomena in terms of event window and lists references for each period.



(a) Short-term overreaction, refer e.g. Lehman (1990); Park (1995); Bowman et al. (1998); Lee, Chan, Faff & Kalev (2003) and Ihara et al. (2004).

(b) Momentum effect, refer e.g. Conrad & Kaul (1998); Lee & Swaminathan (2000); Jegadeesh et al. (1993, 2001) and Griffin, Ji & Martin (2003).

(c) Long-term reversal, refer e.g. De Bondt et al. (1985, 1987); Loughran & Ritter (1996); Gunaratne & Yonesawa (1997); Balvers, Wu & Gilliland (2000); Xiang, He & Cao (2002) and Chiao et al. (2005).

**Figure 6.** The coexistence of the momentum effect and the overreaction phenomenon: an event window explanation.

Even though the daily price fluctuations are not visible in Figure 6 it can still be seen that the stock price exhibits excess volatility and that the markets seem to concentrate too much on short-term investments and other ephemeral fundamentals of the company. This tendency is well stated fact and with a cursory observation one can verify it to be a universal phenomenon among securities (Keynes 1964; Arrow 1982). This overreaction to the transitory news is what drives the short-term overreaction of stock prices overshadowing the significance of long-term fundamentals. Indeed, when those pieces of news which are clearly of insignificant character cloud the more value relevant information, the result is the intermediate-term momentum where investors gradually understand the meaning of the shift in real fundamentals. This is very much in line with the Daniel et al. (1998) theory of continuous overreaction where the stock prices overreact to private information and underreact to public signals due to investors' overconfidence and biased self-attribution. In figure 6 the momentum effect is depicted by the downward sloping black line that intercepts the fundamental value line in the medium-term section of the time series.

In terms of long-term overreaction it has been argued that the past losers outperform the winners in subsequent two to five year period (see for example De Bondt et al. 1985, 1987 and Chiao & Hueng 2005). According to Daniels et al. (1998) theory this is triggered by the biased-attribution driven momentum effect which pushes the prices too far from the fundamental values. After the sufficient time period investors realize the bubble caused by the continuous overreaction (momentum) and correct the prices. Correspondingly Hong and Stein (1999) count the momentum effect as a cause for the long-term reversal. In figure 6 this long-term reversal is depicted by the black upward sloping line which has its origin around the middle point of the second year. This trend crawls steadily upward and can continue as long as five years with some small swings along the way. Regardless of the cause of both the underreaction as well as the overreaction the pattern of short-term overreaction, medium-term momentum and long-term overreaction is still verified by many authors. One possible answer to the coexistence is that allowing of transitory price swings in long irrationally interpreted cycles gives enough room to accommodate both of the two anomalies.

### **3.2 Behavioral explanations for the overreaction phenomenon**

Although, the offered behavioral explanations differ from one another, and often even substantially, they all share the same component concerning the assumptions made about the market participants and their behavior. Contradictory to the traditional finance's assumption of rational investor the behavioral finance rest on an assumption that investors can and do make mistakes and irrational decisions (Kahneman et al. 1982; Malkamäki 1989: 31). This stems from the fact that investors do not differ from other human beings in terms of psychological characteristics. Regardless of its triviality the statement is still true, since they are men and trading programs designed and supervised by men that form the markets. For example beliefs, emotions and adopted trading patterns are among the things that affect on investors decision making process. Investor's irrationality is a crucial deviation from assumptions behind the efficient markets and, thereby, constitutes one of the main disadvantages in research done in this field. (Olsen 1998: 10–17.)

Social biases differ from individual biases in that where the latter assigns biases to market participants individually, the former can assign different biases to different groups which can collectively exert a powerful enough buying and selling pressure to move the market prices (ref. Hong et al. 1999). This is a centerpiece in most of the behavioral based explanations for the overreaction phenomenon. The importance of this statement can be illustrated by noting that in a case of positive news, if one investor bets on a reversion whereas other bets on a momentum; the result is equilibrium when the momentum investor buys the stocks of the contrarian investor. Neither overbidding nor underselling is present in such equilibrium market. It has been argued, however, that individuals' biases are often systematical (Barber & Odean 1999: 41). Now when different groups react at different times and to different triggers, the market prices can oscillate due to the pressure caused by the trading activities of these groups.

Barberis et al. (1998) present a theory of representative investor who does not realize that the stock price follows a random walk. Instead, he uses two models, one for each return generating stock market regime, in determining whether to buy or sell. These models are Mean-reverting model caused by conservatism and Trending model driven by the representativeness heuristic. Of these two models the former is the return generating model of regime 1 and the latter is generating returns when the world is at regime 2. In Trending model the investor believes that that the pictured trend is going to continue and trades accordingly. This causes the overreaction when the investor strengthens the pictured trend and realizes the mistake later. Correspondingly, in Mean-reverting model the investor believes that the price is going to revert and trades accordingly, that is, buys after a price drop and sells after an increase thus smoothing the effect of sequential good or bad news to the price level. This, in turn, can be seen as momentum. Due to the slow learning and difficulty to shake off psychological biases the investor does not learn from the historical data so that he would change his model closer to a random walk. This leads to a continuous model with a fixed regime changing probabilities along with transitional probabilities in both models.

Another theory proposed by Daniel et al. (1998) links together both the underreaction and the overreaction by explaining the two anomalies with the two psychological biases, namely the overconfidence and the biased self-attribution. Since investors are heavily involved in information gathering process as well as in process where the validity of this information is determined they need to be aware of their own abilities to do this in a rational way. In this theory the biased self-attribution, however, prevents investors from correctly adopting the new public information when it is against their own estimations and, simultaneously, causes investors to become even more overconfidence when the supporting public information arrives. In their model, the overconfidence contributes to the long-term overreaction when overconfident investors, who rely too heavily on their private information, react to the public information too slow. Short- and medium-term momentum such as post earnings announcement drift is explained by this lagged adopting of new public information. After the series of public information releases price eventually revert to correct level.

Also Hong et al. (1999) offer a theory that takes into account both underreaction and overreaction. Authors begin by making three behavioral assumptions on investors who form the market. First one states that the market is formed by two different types of agents, the “newswatchers” and the “momentum traders”. First one makes stock price forecasts based on privately observed signals about the future fundamentals while the second one condition on past prices changes when he determines the correct price levels for the stocks. The second assumption concerns the ability of these two different investors to correctly process the information that they possess, namely, the newswatchers are not allowed to condition on past prices and the momentum traders who conditions on those prices has to do it with a simple model that ignores much of the public information. Thus both of the investors are boundedly rational. Third assumption states that the information diffuses gradually across the newswatchers population. Given these restrictions it follows that when negative news arrives on the market the newswatchers cause the price to go down but not enough, due to the graduate diffusion. This is noted by the momentum traders who correspondingly push the price below the long-term fundamentals. This is so because they do not know whether they are early or

late in the cycle. Eventually the price reverts to its correct level portraying the long-term overreaction.

### 3.3 Technical explanations and other related anomalies

In an area of market efficiency studies it is very common that the anomaly at hand is, at least to some extent, related to other anomalies and the overreaction is not an exception. The important thing in assessing the meaningfulness and validity of any anomaly is to distinguish those influencing anomalies that are strong enough to erode all abnormal profits from those that only reduce them. The same is true when the suitability of the methodology is examined, since many anomalies are sensible e.g. to the way that the abnormal returns are calculated, that is, the revealed abnormal returns disappear when the abnormal return calculation methodology is changed (Fama 1998: 285).

First on the list of technical explanations offered to explain the overreaction phenomenon is the so called bad-model problem which refers to the difficulty of creating good model to calculate the expected returns. One thing that illustrates the seriousness of this statement is the myriad of stock pricing models proposed to date by professors and economists. There is virtually one model for every anomaly proposed, since all one need to do to create a new stock pricing model is to add a factor or dummy variable that captures the found anomaly to the model that was used to discover it in the first place (ref. Chiao et al. 2005: 431, 441–444). These models, however, are often suitable only to the specific time frame and to the specific anomaly (Fama 1998: 285). The ubiquitousness of bad-model problem is crystallized by Fama (1998: 293) *“In short, bad-model problems are unavoidable, and they are more serious in tests on long-term returns.”*

The second thing that is crucial to keep in mind when the profitability of the overreaction anomaly is examined is the danger of data mining. In its broadest definition, the data mining refers to the occurrence of intensive search which is constantly going on among the professional investors and researchers of finding new events and investment processes that would generate abnormal returns. Basically, the data mining says that when one search for factors that are



assumed to forecast future returns one is bound to find them by change alone (McQueen & Thorley 1999: 61). Data mining is pervasive since it affects also those who are honestly forming and testing hypothesis, that is, it affects also to those who form the story before they start testing its profitability and significance. This is because e.g. in a field of behavioral finance there is a huge number of psychological traits which can seemingly explain virtually any phenomenon present in financial markets even though, in reality, they have nothing to do with the way the markets are operating (Fama 1998: 291).

Errors in econometrical and statistical procedures are the third technical explanation offered for many anomalies including overreaction. In this category falls for example issues concerning return metric calculation and their statistical significances. Joint test problem, for example, calls for revision of many anomalous patterns. This is so since the asset pricing models used to discover these patterns in the first place are silent in specifying the relevant interval for expected returns, that is, they do not tell the maximum time period that can be used to calculate the returns with them so that the results would still be meaningful and empirically tested. For instance, many author who report long-term abnormal performance for up to five years use monthly return models to calculate them, even though, the accuracy of the monthly return models in five year span is not tested. (Fama 1998: 294.)

From a statisticians view point existence of some anomalies is doubtful due to the statistical errors in methodologies. For instance, Buy-and-Hold methodology in calculation of long term returns is problematic due to the extreme skewness (Fama 1998: 295). Similarly summing up Abnormal Returns over long periods of time can be deceiving because also the error term cumulates (Conrad et al. 1993: 39, 41) This inherent danger of using CARs is also notified by Brown et al. (1980: 228–229) who state that *"Like any process which follows a random walk, the CAR can easily give the appearance of 'significant' positive or negative drift, when none is present."*

In addition to the technical explicatory factors mentioned above, there are also those who offer other anomalies as an answer to the cause of the overreaction phenomenon. For instance Zarowin (1990) argues that overreaction is caused by the size effect, which refers to the phenomenon where the small size firms

outperform the bigger ones. According to author's findings losers outperform winners in three year horizon after the portfolio formation period when they are smaller. Similarly, when winners are smaller than losers the portfolio of the former performs better than the later. When the size matched portfolio methodology is used for winners and losers, differential performance can only be observed in January. In line with the Zarrowin's findings Gaunt (2000) reports that the loser portfolio is dominated by the small firms indicating that the size effect has its role in explaining the overreaction anomaly.

January seasonality is another anomaly that is proposed to explain the overreaction phenomenon. For example Pettengill and Jordan (1990) report that losers' returns increased on January. Also Rosita, Chang, McLeavey and Rhee (1995) observe the January effect. In their findings January returns are higher than the returns of other months for both losers and winners, although the returns are not large enough to explain the whole anomaly. Zarrowin (1990), however, report that in loser portfolios 80 percent of cumulative returns realize on months of January and when matched portfolios are used only January returns are different for winners and losers. Thus the January effect seems to explain the entire overreaction phenomenon along with the size effect. It is however worth of noting that many studies report statistically significant returns on contrarian strategies even when the size effect and January seasonality is taken into account.

## 4. DATA AND METHODOLOGY

### 4.1 Data description

The data is obtained from the Thomson Financial database and it comprises all those German Stock Exchange stocks that are listed in Prime All Share index between 1.1.2001 and 31.12.2006. The difference between the length of the test period 1.1.2002–31.12.2006 and the length of the data arises from the abnormal return estimation model prerequisite, since the Market Model is used in this study. For each individual stock the following daily information is extracted: the bid price, the ask price, the closing price and the volume. Yearly information for each stock contains the net sales and the total number of shares outstanding in a year. Prime All Share index is used as a component in abnormal return calculation to proxy the market return. All returns series are logarithmic and take into account dividends and stock splits. Dividends are assumed to be reinvested at the time of their payment. Total length of price series for each stock is 1260 trading days, so even the strategy that has the longest formation and holding period accumulates enough observations so that the test for its statistical significance can be conducted.

Totally 246 stocks are included in the sample of which 97 belong to the group of technology stock leaving 149 to the control group of “traditional stocks”. Three from original one hundred technology stocks were removed from the sample due to high concentration of missing observations in extracted price series. Furthermore, those stocks that have price quotation under one Euro are not included in the sample, since the inclusion of low-priced stocks might give the appearance of overreaction phenomenon even though none is present (Bowman et al. 1998:481). That is, the inclusion of these “penny stocks” might increase the probability that the results would be driven by few stocks that exhibit only minor price changes in Euro amount but huge swings percentagewise. Large percentual bid-ask spreads of these low-priced stocks is another motive in exclusion of them from the sample.

The German Stock Exchange is a marketplace organizer which offers high level of liquidity and low transaction costs. Its electronic trading platform XETRA started in November 1999 and is today one of the largest cash market in the world. XETRA has currently over 10700 securities on offer. On average there are more than 4500 traders and around 420000 transactions done on a day, which translates into average daily turnover of more than 10 billion euros. With its 96 percent market share of German equities XETRA offers an extensive view of German stock markets and thus gives a complete and easy to access database for market efficiency studies in German stock markets. (German Stock Exchange 2007.)

## 4.2 Methodology

Methodology used in this paper is similar to the one proposed by Lo and MacKinlay (1990) and later applied and worked over by Jegadeesh and Titman (1995) and, with slight modifications, Lee et al. (2003). This contrarian investment strategy involves buying and selling stocks based on their returns in predetermined time period and holding the stocks to the end of the subsequent tracking period. Weights of the stocks in this contrarian portfolio are inversely proportional to the stock's excess returns. Instead of Market Adjusted Model used by the authors excess returns are estimated using the Market Model where the market return is proxied by the Prime All Share Index. What comes to the ability to capture the pronounced reversion element of overreaction the methodology is very much in line with De Bondt et al. (1985) finding that *"the more extreme the initial price movement, the greater will be the subsequent adjustment."*, since it places greater weights on those stocks that have experienced largest excess returns. Thus the contrarian portfolio formed with this methodology should capture overreaction profits better than portfolio that uses equal weighting.

Mathematically the weight of an individual stock in contrarian portfolio can be written as follows (ref Jegadeesh et al. 1995: 977):

$$(6) \quad w_{i,t} = -\frac{1}{N} (r_{i,t} - \alpha_{i,t} - \beta_{i,t} r_{m,t}) ,$$

where,  $w_{i,t}$  is the weight of stock  $i$  at time  $t$ ,  $N$  is the total number of stocks in the portfolio,  $r_{i,-t}$  is the return on stock  $i$  at time  $-t$ ,  $\alpha_{i,-t}$  and  $\beta_{i,-t}$  are the Market Model parameters for the stock  $i$  at time  $-t$  and, finally,  $r_{m,-t}$  is the return on market index at time  $-t$ . This strategy is self financing, that is, the total investment at any time is zero. Actual dollar amount of the strategy can, however, vary in short and long sides of the portfolio depending on the return realization of the stocks at time  $-t$ .

This paper examines the profitability of total sixteen short-term trading strategies. The methodological base for the different test periods is that of Jegadeesh and Titman (1993) with slight modifications. Authors trading strategies involves formation of portfolios based on 1, 2, 3 or 4 quarters and holding them 1 to 4 quarters subsequently, where as, in this paper the maximum length of holding period is one month. Following authors example all stocks are ranked into decile portfolios. In each strategy the stocks are included in portfolio based on their one, two, three or four trading week returns and are hold either one, two, three or four trading weeks subsequently, depending on a strategy. The decile portfolio with the highest stock returns is defined as the winner portfolio. Analogously the decile portfolio with the poorest performing stocks is the loser portfolio. Arbitrage portfolio is formed from the winner and loser portfolios by short selling the winner stocks and investing the obtained proceeds to the loser portfolio. This way the possible returns of the arbitrage portfolio are available without initial investments and the return of the portfolio equals the possible excess returns on a given holding period.

Returns of the winner and loser portfolios are defined logarithmically. This approach is backed up by the notion that logarithmic returns follow better standard distribution than absolute returns. Returns for each stock can be calculated with the following function:

$$(7) \quad R_{i,t} = \log(P_{i,t}) - \log(P_{i,-t}) ,$$

where  $R_{i,t}$  is the logarithmic return of the stock  $i$  at time  $t$ ,  $P_{i,t}$  is the price of the stock  $i$  at time  $t$ ,  $P_{i,-t}$  is the price of the stock  $i$  at time  $-t$  and  $\log$  is the natural logarithm.

profits from the strategy can now be calculated with the equation 8 (ref Jegadeesh 1995: 978). Let:

$$(8) \quad \pi_t = -\frac{1}{N} \sum_{i=1}^N (r_{i,-t} - \alpha_{i,-t} - \beta_{i,-t} r_{m,-t}) r_{i,t} ,$$

where,  $\pi_t$  is the profit of the portfolio at time  $t$ ,  $N$  is the total number of stocks in the portfolio at time  $t$ ,  $r_{i,-t}$  and  $r_{i,t}$  is the return on stock  $i$  at time  $-t$  and  $t$  respectively.  $\alpha_{i,-t}$  and  $\beta_{i,-t}$  are the Market Model parameters for the stock  $i$  at time  $-t$ .  $r_{m,-t}$  is the return on market index at time  $-t$ .

As it can be seen from equations 6 and 8 the excess return calculation method in this study is the market model formally written:

$$(9) \quad MMAR_{i,t} = R_{i,t} - \alpha_{i,t} - \beta_{i,t} R_{m,t} ,$$

where,  $MMAR_{i,t}$  is the **Market Model Abnormal Return** of stock  $i$  at time  $t$ ,  $R_{i,t}$  is the return of the stock  $i$  at time  $t$  and  $R_{m,t}$  is the return of the market index at time  $t$ .  $\alpha_{i,t}$  and  $\beta_{i,t}$  are the market model parameters for the stock  $i$  at time  $t$ , which are obtained by regressing the stock's return against the return of the market index 250 days prior the extreme price movement.

Returns of the Winner and Loser portfolios are calculated using the Cumulative Abnormal Return Model. First step is to calculate stocks' cumulative abnormal returns over the various holding periods (ref. Conrad et al. 1993:42) which, for every stock, are of the form:

$$(10) \quad CMMAR_{i,t} = \sum_{i=1}^N MMAR_{i,t} ,$$

where  $CMMAR_{i,t}$  is the **Cumulative Market Model Abnormal Return** of the stock  $i$  at time  $t$ ,  $MMAR_{i,t}$  is the market model abnormal return of stock  $i$  at time  $t$ . Because the holding periods in strategies vary from one to four weeks the cumulative abnormal return for each observation has to be adjusted for the length of the cumulation period or else the profits from various strategies are not comparable (ref. Conrad et al. 1993: 42). The second step is to calculate stock's weekly average excess return with the formula:

$$(11) \quad CMMAR_{i,t}(k) = \frac{1}{k} \sum_{i=1}^k MMAR_{i,t} ,$$

where  $CMMAR_{i,t}(k)$  is the **Cumulative Market Model Abnormal Return** of the stock  $i$  at time  $t$  adjusted for the cumulation over  $(k)$  weeks,  $MMAR_{i,t}$  is the market model abnormal return of stock  $i$  at time  $t$  and  $k$  is the number of weeks over which the abnormal returns are cumulated.

After the abnormal returns are estimated for each stock as described above the average abnormal weekly returns are calculated for both winner and loser portfolios. These are simply the arithmetic averages of those stocks' abnormal returns that belong to the particular portfolio. In equation form this can be written:

$$(12) \quad AMMAR(P_{i,t}) = \frac{1}{N} \sum_{i=1}^N CMMAR_{i,t}(k),$$

where  $AMMAR(P_{i,t})$  is the **Average Market Model Abnormal Return** of the portfolio  $i$  at time  $t$ ,  $N$  is the number of stocks in portfolio.  $CMMAR_{i,t}(k)$  is as is described in the equation (x). Finally, in order to make inferences about the strategies overall performance and statistical significances these returns are averaged over the entire test period (Conrad et al. 1993:43). Final step is to test the obtained results for the statistical significance with the one tailed t-test. Based on the p-value associated to the t-test, strategies returns are tested for the statistical significances at the levels of one, five and ten percent.

## 5. EMPIRICAL RESULTS AND ANALYSIS

### 5.1 Formulation of hypotheses

According to the first working hypothesis overreaction based short-term abnormal profits exist in German Stock Exchange and German Stock Markets are not weak form efficient. If this hypothesis is accepted it would mean that the return of the arbitrage portfolio formed by shorting the winners and buying the loser would be positive. This translates into testable hypothesis of the form:

$$\mathbf{H1_0} : R(P_a) = 0$$

$$\mathbf{H1_1} : R(P_a) > 0$$

According to the first null hypothesis return of the arbitrage portfolio  $R(P_a)$  is equal to zero which would mean that overreaction hypothesis is not true and that there are no abnormal profits available for those who try to exploit short-term contrarian strategy in German Stock Exchange. It would also mean that German Stock Markets would be weak form efficient. Counter hypothesis would, comparably, mean that the return of the arbitrage portfolio would be positive and statistically significant which, in turns, means that German Stock Markets would not be weak form efficient since historical data would be predictive.

Second working hypothesis is that the magnitude of the overreaction is stronger for technology firm's stocks than those of traditional firm's. This is due to the higher portion of intangible assets, which are difficult to value. This hypothetical dissimilarity of the two industry classes in terms of overreaction would mean that, if the hypothesis is true, the overreaction based profits would be larger for the technology contrarian portfolio than the portfolio formed from those stocks that belong to the group of classic stocks. The second testable hypothesis is formed as follows:

$$\mathbf{H2_0} : R(P_{\text{Tech}}) = R(P_{\text{Classic}})$$

$$\mathbf{H2_1} : R(P_{\text{Tech}}) > R(P_{\text{Classic}})$$



This means that according to the second null hypothesis return of the Technology contrarian portfolio  $R(P_{Tech})$  is equal to the return of the Classic contrarian portfolio  $R(P_{Classic})$  and that there are no differences in abnormal returns between the two industry classes in favor of technology stocks. Therefore, the second working hypothesis should be rejected. Analogously, the validation of the counterhypothesis would mean that the returns of the technology stocks contrarian profits would be larger.

## 5.2 General findings

Table 1 presents the results for the whole sample contrarian portfolios' returns for the sixteen different trading strategies over the whole test period of 1.1.2002–31.12.2006. The returns of the arbitrage portfolios are obtained by subtracting the profits of the loser portfolio from the profits of the winner portfolio where winners are defined as the top decile stocks and losers as the bottom decile stocks respectively.

**Table 1.** Whole sample market model adjusted weekly abnormal profits over the years 2002–2006. T-test associated p-values are expressed in parenthesis for the arbitrage portfolio. \*\*\* indicates statistical significance at the level of one percent and \*\* and \* mean five and ten percent significances respectively.

<b>Formation</b>		<b> Holding Period</b>			
<b>Period</b>	<b>Portfolio</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1</b>	Winner	0,21 %	0,13 %	0,10 %	0,08 %
	Loser	0,31 %	0,19 %	0,16 %	0,13 %
	<b>Arbitrage</b> (p-value)	<b>-0,10 %</b> (0.275)	<b>-0,06 %</b> (0.324)	<b>-0,06 %</b> (0.320)	<b>-0,05 %</b> (0.330)
<b>2</b>	Winner	0,21 %	0,12 %	0,10 %	0,08 %
	Loser	0,17 %	0,12 %	0,11 %	0,09 %
	<b>Arbitrage</b> (p-value)	<b>0,05 %</b> (0.483)	<b>0,00 %</b> (0.438)	<b>-0,01 %</b> (0.424)	<b>-0,01 %</b> (0.425)
<b>3</b>	Winner	0,14 %	0,09 %	0,07 %	0,06 %
	Loser	0,03 %	0,08 %	0,08 %	0,06 %
	<b>Arbitrage</b> (p-value)	<b>0,11 %</b> (0.462)	<b>0,00 %</b> (0.388)	<b>-0,01 %</b> (0.375)	<b>0,00 %</b> (0.386)
<b>4</b>	Winner	0,21 %	0,11 %	0,06 %	0,05 %
	Loser	0,17 %	0,15 %	0,10 %	0,08 %
	<b>Arbitrage</b> (p-value)	<b>0,04 %</b> (0.444)	<b>-0,04 %</b> (0.408)	<b>-0,03 %</b> (0.412)	<b>-0,03 %</b> (0.413)

It becomes very clear from the table 1 that the results of the whole sample do not support short-term overreaction hypothesis on German Stock Exchange over any examined interval. First of all, ten of sixteen short-term arbitrage portfolios express *negative* returns in stead of positive ones. Secondly, three of remaining six portfolios have average weekly returns equally to zero which leave only three portfolios to the group of those arbitrage portfolios that have, on average, expressed positive returns over the years 2002–2006. Thirdly, none of the sixteen arbitrage portfolios returns are statistically significant at any level.

The thing that can be said about the returns of the winner and loser portfolios is that, even though they all are positive and about the equal size, none of the returns are statistically significant (refer APPENDIX 1). So, in a light of these results, all who contemplate investing in partial contrarian portfolios on

German Stock Exchange should reject the idea and look for better investment opportunities.

### **5.3 Effect of industry sector**

The test of the third hypothesis was conducted by dividing the original sample into two sub samples. The first sub sample contains all those stocks that belong to the Technology Industry Sector of the General Industry Classification (GIC) standard used by the German Stock Exchange. The second sub sample comprises all other stocks of the whole sample. Each stock in the second sub sample belongs to one of the various other GIC industry sectors.

Tables 2 and 3 presents the results for the Technology stocks sub sample and the Classic stocks sub sample respectively. Contrarian portfolios' returns are calculated for the sixteen different trading strategies over the whole test period of 1.1.2002–31.12.2006. Again, the returns of the arbitrage portfolios are obtained by subtracting the profits of the loser portfolio from the profits of the winner portfolio.

**Table 2.** Technology stocks sub sample market model adjusted weekly abnormal profits over the years 2002–2006. T-test associated p-values are expressed in parenthesis for the arbitrage portfolio. \*\*\* indicates statistical significance at the level of one percent and \*\* and \* mean five and ten percent significances respectively.

<b>Formation</b>		<b>Period</b>			
<b>Period</b>	<b>Portfolio</b>	<b>Holding Period</b>			
		<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1</b>	Winner	0,74 %	0,47 %	0,35 %	0,30 %
	Loser	0,94 %	0,48 %	0,46 %	0,40 %
	<b>Arbitrage</b>	<b>-0,21 %</b>	<b>-0,01 %</b>	<b>-0,12 %</b>	<b>-0,10 %</b>
	(p-value)	(0.297)	(0.443)	(0.308)	(0.319)
<b>2</b>	Winner	0,80 %	0,50 %	0,41 %	0,33 %
	Loser	0,30 %	0,29 %	0,31 %	0,24 %
	<b>Arbitrage</b>	<b>0,50 %</b>	<b>0,22 %</b>	<b>0,10 %</b>	<b>0,09 %</b>
	(p-value)	(0.219)	(0.389)	(0.468)	(0.474)
<b>3</b>	Winner	0,51 %	0,30 %	0,25 %	0,23 %
	Loser	0,10 %	0,29 %	0,29 %	0,18 %
	<b>Arbitrage</b>	<b>0,41 %</b>	<b>0,01 %</b>	<b>-0,05 %</b>	<b>0,05 %</b>
	(p-value)	(0.334)	(0.403)	(0.367)	(0.427)
<b>4</b>	Winner	0,76 %	0,41 %	0,27 %	0,21 %
	Loser	0,64 %	0,59 %	0,36 %	0,29 %
	<b>Arbitrage</b>	<b>0,12 %</b>	<b>-0,18 %</b>	<b>-0,09 %</b>	<b>-0,08 %</b>
	(p-value)	(0.481)	(0.366)	(0.394)	(0.394)

As in the case of whole sample stocks, none of the sixteen different trading interval arbitrage portfolios exhibit statistically significant returns. T-test associated p-values settle between the best value of 0,219 and worst value of 0,481 indicating that the results have no statistical value. Further more, half of the arbitrage portfolios earned negative returns on average, which is a clear implication of pure randomness in return generating processes of the portfolios.

**Table 3.** Classic stocks sub sample market model adjusted weekly abnormal profits over the years 2002–2006. T-test associated p-values are expressed in parenthesis for the arbitrage portfolio. \*\*\* indicates statistical significance at the level of one percent and \*\* and \* mean five and ten percent significances respectively.

<b>Formation</b>		<b> Holding Period</b>			
<b>Period</b>	<b>Portfolio</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1</b>	Winner	0,20 %	0,11 %	0,08 %	0,07 %
	Loser	0,36 %	0,24 %	0,18 %	0,14 %
	<b>Arbitrage</b> (p-value)	<b>-0,16 %</b> (0.202)	<b>-0,13 %</b> (0.219)	<b>-0,10 %</b> (0.262)	<b>-0,08 %</b> (0.288)
<b>2</b>	Winner	0,16 %	0,08 %	0,07 %	0,06 %
	Loser	0,25 %	0,16 %	0,13 %	0,10 %
	<b>Arbitrage</b> (p-value)	<b>-0,09 %</b> (0.361)	<b>-0,08 %</b> (0.365)	<b>-0,06 %</b> (0.379)	<b>-0,04 %</b> (0.397)
<b>3</b>	Winner	0,15 %	0,09 %	0,06 %	0,04 %
	Loser	0,05 %	0,09 %	0,08 %	0,06 %
	<b>Arbitrage</b> (p-value)	<b>0,10 %</b> (0.456)	<b>0,00 %</b> (0.386)	<b>-0,03 %</b> (0.367)	<b>-0,02 %</b> (0.373)
<b>4</b>	Winner	0,18 %	0,09 %	0,05 %	0,04 %
	Loser	0,14 %	0,12 %	0,08 %	0,06 %
	<b>Arbitrage</b> (p-value)	<b>0,04 %</b> (0.444)	<b>-0,02 %</b> (0.416)	<b>-0,03 %</b> (0.413)	<b>-0,02 %</b> (0.418)

Analysis of the price behaviour of Classic stocks reveal the same pattern of randomness that is eminent in Technology stocks as well as in whole stocks samples. In table 3 thirteen out of sixteen arbitrage portfolios earned negative returns, two portfolios had positive returns and one strategy had arbitrage returns equal to zero. As indicated by the results of the previous two analyses, none of the arbitrage portfolios returns, whether they are positive or negative, are statistically significant at any level. Cursory look at the results show that abnormal returns in Technology stocks sample are higher than those of Classics. The lack of the statistical power, however, prevents any speculations concerning the second hypothesis.

#### 5.4 Hypotheses and the results

According to the first null hypothesis the return of the short-term arbitrage portfolio would be equal to zero in German Stock Exchange. Counter hypothesis is that the returns would be positive, which would indicate that the use of the overreaction based contrarian strategy would be beneficial in economic sense. Contradicting the first hypothesis, however, the results give clear and substantial indications that the first counter hypothesis should be strongly rejected in favour of null hypothesis of zero arbitrage portfolio returns, since weekly arbitrage returns have no statistical significances and many of the strategies, provided that they were significant in statistical view, earn negative returns.

Since the first null hypothesis of zero returns for short-term overreaction based arbitrage portfolios is accepted, the German Stock Markets can be said to be weak form efficient in terms of short-term overreaction phenomenon. In a light of the results in all of the three samples, there is not a single case out of the total 48 different combination of arbitrage strategies that would warrant the rejection of the first null hypothesis. Thus, in economical sense, short-term abnormal profits cannot be earned by using an overreaction strategy of shorting the prior winners and buying the prior losers over any pricing scheme. As stated by the weak form condition of EMH, analysis of past price series does not give advantage in German Stock Markets and investment process that condition on large price changes is not beneficial.

According to the counter hypothesis number two there should be a difference in strategies' abnormal profits between the two industry classes in favour of Technology stocks. In German Stock Exchange this hypothesis is false and rejected. Results from the analysis have no statistical significances that would challenge the second null hypothesis. Technology firms do not seem to possess any unique characteristics in a way that the pricing of their stocks would be more error prone and more likely to portray overreaction.

Since none of the results support the existence of short-term overreaction in German Stock Exchange there is no need for further robustness checks of size,

seasonality, risk or market microstructures of trading volume and bid-ask bounce.

The goal of this paper was to find out whether short-term overreaction based abnormal profits exist in German Stock Exchange, simultaneously test the EMH relative to the anomaly at hand and make judgement about the hypothesized dissimilarity of the Technology stocks and Classic stocks in terms of short-term overreaction. Given the results of the previous chapter, there is one sentence that gives answer to all of these questions. Short-term overreaction phenomenon does not seem to exist in German Stock Market and weak form efficiency hold for both Traditional stocks as well as for Technology stocks.

## 6. CONCLUSION

The overreaction phenomenon, where the price of an asset shifts temporarily away from its fundamental value in response to new and dramatic information is one of those anomalies that have been under a lot of testing in past few decades. Although, attempts have been made to explain the phenomenon it still remains rather elusive. For example, the cause of the anomaly is still largely unknown and the results of the previous studies are not consistent with each other. Particularly, the Finance vs. the Behavioral finance setting brings up quite different explanations for the anomaly. Proponents of the Behavioral finance explain the anomaly by the irrational behaviour of the market participants, whereas the proponents of the traditional view see it as a rational response to the continuous information flow or only as a random deviation from efficient price level together with the underreaction anomaly (Fama 1998: 283, 284–285; Ross et al. 2003: 406–407).

Regardless of its cause the anomaly is still present on market and many studies report statistically significant abnormal returns for the portfolios designed to exploit the anomaly. In this thesis the purpose was to find out whether short-term overreaction based abnormal profits exist in German Stock Exchange. Further comparison of Technology stocks and Traditional stock was motivated by the higher degree of uncertainty associated to the valuation of technology stocks. In terms of overreaction the higher level of uncertainty increases the number of the value relevant prospects that remain unnoticed. This in turns leads to an increased number of overreaction triggering dramatic news events which should, on average, be reflected in return series of technology stocks as an increased volatility and increased number of identifiable and exploitable overreaction events.

In order to be exploitable, the contrarian investment strategy should be able to predict the return reversals by using historical prices. Thus, in a case of a short-term overreaction phenomenon, ephemeral price fluctuations should be detectable on stock markets. From the perspective of the EMH this would mean that the German Stock Markets would not be efficient at weak form since short-term abnormal profits would be available for the contrarian investors who base



their strategies on historical prices. In this thesis the nature of the examined phenomenon challenges the EMH and thereby this study is also a market efficiency study of the German Stock Exchange.

According to the results of the empirical part of this thesis it is impossible to earn positive abnormal returns by exploiting short-term overreaction phenomenon in German Stock Exchange. None of the total 48 different trading strategy arbitrage portfolios' returns were statistically significant at any level and 35 of them earned negative abnormal returns or had returns equally to zero. Therefore, in a light of the EMH the German Stock Markets are efficient at weak form what comes to investors ability to predict the price movements by using a short-term contrarian models.

Comparison of the Technology stocks and the Traditional stocks was conducted by analyzing contrarian profits in a sub sample environment. Contradictory to the second working hypothesis, no differences were observed between the two industry classes in favour of Technology stocks. Arbitrage portfolios' returns were all statistically insignificant for both of the sub samples in a case of every trading strategy, even though the returns of the Technology sub sample seemed to be a bit higher.

Based on numerous previous studies the expectation was to find statistically significant returns on at least some of the examined trading strategies but. As it is already stated, none were found. It is difficult to give a definitive answer to the absence of short-term overreaction profits in German Stock Exchange. Perhaps the markets have become more efficient with the launch of XETRA trading platform in 1999 or, given that the returns are very sensitive to the methodology used, perhaps it is the choice of the methodology that explains the results. After all, simple but still often used Market Adjusted Model for the abnormal return estimation can give spurious contrarian returns which disappear when the Market Model is used, since it ignores the individual characteristics of the stocks and assumes that all stocks have the same risk premium as the whole market.

In my opinion, in the light of the results, there might be a reason to think that perhaps the market participants are not that irrational as claimed by the

proponents of the Behavioral finance. After all, it is precisely the irrationality assumption of the Behavioral finance that opens up the Pandora's Box. When the degree of the investors' irrationality is allowed to go high enough the result is that one can explain virtually every phenomenon that exists on market, even though, in reality, it's only noise. This is so because from the myriad of psychological traits one can always find those that are suitable to explain the coined anomaly. To illustrate, what might happen when one discharges the common sense and starts to search explanation too far, consider a study by Daniel and Titman (1999). In their paper authors raise the overconfidence as a strong reason why the markets are not efficient. As an explanation for the overconfidence and as a basis for the bias authors, however, propose following:

"If a theory of asset pricing is to be based on a suspected behavioral bias, it is important to have strong basis for why such a bias is likely to persist. Two related criteria must be considered. First, biases that distort decisions with no offsetting benefits are likely to have been eliminated over a long period of time by natural selection... Although clear disadvantages are associated with overconfidence, some offsetting benefits suggest that, overall, overconfidence may have increased the chances of individuals passing on their genes. The evolutionary theories suggest that those individuals who *appear* to be the strongest and the smartest are more likely to attract mates and reproduce."

Although the investors' overreaction has not yet been explained by the evolution theory, in order to make the point stronger, by paraphrasing McQueen and Thorley (1999) one can say that – since, in one sense, the market price represents the collective wisdom of all investors, theories or explanations based on the idea that market participants are dumb, lazy, myopic or descendants of apes are not to be trusted.

The first main finding of this study is that there are no possibilities to earn abnormal returns by investing in short-term contrarian portfolios in German Stock Exchange and that the German Stock Markets are weak form efficient what comes to the ability to use historical data to predict the short-term price reversals. The second finding is that the contrarian returns of the Technology stocks are not higher than the contrarian returns of the Traditional stocks, that is, in terms of short-term overreaction Technology stocks do not possess any unique characteristics. Both hypotheses are strongly rejected in favour of their null hypotheses.

## REFERENCES

- Akhigbe, A., S. Larson & J. Madura (2003). Market Underreaction and Overreaction of Technology Stocks. *The Journal of Psychology and Financial Markets*. 3:3, 141–151.
- Arrow K. (1982). Risk Perception in Psychology and Economics. *Economic Inquiry*. 20:1, 1–9
- Balvers, R., Y. Wu & E. Gilliland (2000) Mean Reversion across National Stock Markets and Parametric Contrarian Strategies. *The Journal of Finance*. 55:2, 745–772.
- Barber, M. & T. Odean, (1999). The Courage of Misguided Convictions. *Financial Analysts Journal*. 55:6, 41–55
- Barberis, N., A. Shleifer & R. Vishny (1998) A Model of Investor Sentiment. *Journal of Financial Economics*. 49:3, 307–343.
- Barron, O., D. Byard, C. Kile & E. Riedl (2002) High-Technology Intangibles and Analysts' Forecasts. *Journal of Accounting Research*. 40:2, 289–312.
- Bodie, Z., A. Kane & A. Marcus (2005). *Investments*. 6 ed. New York. The McGraw-Hill Companies, Inc. 1090 p. ISBN 0-07-123820-4.
- Bowman, R. & D. Iverson (1998). Short-run overreaction in the New Zealand stock market. *Pacific-Basin Finance Journal*. 6, 475–491.
- Brealey A. & S. Myers (2000) *Principles of Corporate Finance*. 6. ed. New York: The McGraw-Hill Companies, Inc. 1093 p. ISBN 0-07-709843-9.
- Brown, S. & J. Warner (1980). Measuring security price performance. *Journal of Financial Economics*. 8:3, 205–258.

- Chiao, C. & J. Hueng (2005). Overreaction effect independent of risk and characteristics: evidence from the Japanese stock market. *Japan and the World Economy*. 17:4, 431–455.
- Conrad, J. & G. Kaul (1993). Long-Term Market Overreaction or Biases in Computed Returns? *The Journal of Finance*. 48:1, 39–63.
- Conrad, J. & G. Kaul (1998). An Anatomy of Trading Strategies. *The Review of Financial Studies*. 11:3, 489–519.
- Cooper, M. (1999). Filter Rules Based on Price and Volume in Individual Security Overreaction. *The Review of Financial Studies*. 12:4, 901–935.
- Copeland, T. & F. Weston (1988). *Financial Theory and Corporate Policy*. 3 ed. Addison-Wesley Publishing Company, Inc. 732 p. ISBN 0-201-10648-5
- Cox, D. & D. Peterson (1994). Stock Returns following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance. *The Journal of Finance*. 49:1, 255–267.
- Daniel K., D. Hirshleifer & A. Subrahmanyam (1998). Investors Psychology and Security Market Under- and Overreaction. *The Journal of Finance*. 53, 1839–1885.
- Daniel, K. & S. Titman (1999). Market Efficiency in an Irrational World . *Financial Analysts Journal*. 55:6, 28–40.
- De Bondt, W. & R. Thaler (1985). Does the Stock Market Overreact? *The Journal of Finance*. 40:3, 793–805.
- De Bondt, W. & R. Thaler (1987). Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance* 42:3, 557–581.
- Dougherty, C. (2002). *Introduction to Econometrics*. 2 ed. New York: Oxford University Press Inc. 409 p. ISBN 0-19-877643-8.

- Fama, E. (1965). The Behavior of Stock Market Prices. *Journal of Business*. 38:3, 793–805.
- Fama, E. (1991). Efficient Capital Markets: II. *The Journal of Finance* 46:5, 1575–1617.
- Fama, E. & K. French (199). Common risk factor in the returns of stocks and bonds. *Journal of Financial Economics*. 33: 3–56.
- Fama, E. & K. French (1996). Multifactor Explanation of Asset Pricing Anomalies. *Journal of Finance*. 51, 55–84.
- Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49, 283–306.
- Gaunt, C. (2000). Overreaction in the Australian equity market: 1974–1997. *Pacific-Basin Finance Journal*. 8:3, 375–398.
- German Stock Exchange [online] (2007). XETRA [Cited 23.2.2007] Available on World Wide Web <URL: [http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb\\_navigation/home](http://deutsche-boerse.com/dbag/dispatch/en/kir/gdb_navigation/home)>
- Griffin, J., X. Ji & S. Martin (2003). Investing and Business Cycle Risk: Evidence from Pole to Pole. *The Journal of Finance*. 58:6, 2515–2547.
- Gunaratne, P. & Y. Yonesawa (1997). Return reversals in the Tokyo Stock Exchange: A test of stock market overreaction. *Japan and the World Economy*. 9:3, 363–384.
- Hong, H., J. Stein (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance*. 54:6, 2143–2184.
- Huberman, G. (1982). A Simple Approach to Arbitrage Pricing Theory. *Journal of Economic Theory*. 28:1, 183–191.

- Ihara, Y., H. Kato & T. Tokunaga (2004). The winner-loser effect in Japanese stock returns. *Japan and the World Economy*. 16:4, 471–485.
- International Bible Society (1986). *The Holy Bible, New International Version*. Michigan: USA. The Zondervan Corporation. 923 p. ISBN 0-310-90652-0.
- Jegadeesh, N. & S. Titman (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*. 48:1, 65–91.
- Jegadeesh, N. & S. Titman (1995). Overreaction, Delayed Reaction and Contrarian Profits. *The Review of Financial Studies*. 8:4, 973–993.
- Jegadeesh, N. & S. Titman (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance*. 56:2, 699–720.
- Kahneman, D., P. Slovic & A. Tversky (1982). *Judgement Under Uncertainty: Heuristics and Biases*. London: Cambridge University Press. 562 p. ISBN 0-521-28414-7
- Kahneman, D. & A. Tversky (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*. 42:2, 263–292.
- Kang, J., M. Liu & S. Ni (2002). Contrarian and momentum strategies in China stock markets: 1993–2000. *Pacific-Basin Finance Journal*. 10:3, 243–265.
- Kaul, G. & M. Nimalendan (1990). Price Reversals: Bid-ask Errors or Market Overreaction. *Journal of Financial Economics*. 28:1&2, 67–93.
- Kendall, M. (1953). The Analysis of Economic Time Series, Part 1: Prices. *Journal of the Royal Statistical Society*. 96
- Keynes, J. (1964). *The General Theory of Employment, Interest and Money*. London: Harcourt Brace Jovanovich.
- Kothari, S.P. & J. Warner (1997). Measuring long-horizon security price performance. *Journal of Financial Economics*. 43:3 301–339.

- Kyle, A. & A. Wang (1997). Speculation Duopoly with Agreement to Disagree: Can Overconfidence Survive the Market Test? *The Journal of Finance*. 52:5, 2073–2090.
- Lee, C. & B. Swaminathan (2000). Price Momentum and Trading Volume. *The Journal of Finance*. 55:5, 2017–2069.
- Lee, D., H. Chan, R. Faff & P. Kalev (2003). Short-term contrarian investing—is it profitable? ... Yes and No. *Journal of Multinational Financial Management*. 13:4–5, 385–404.
- Lehman, B. (1990). Fads, Martingales and Market Efficiency. *The Quarterly Journal of Economics*. 105:1, 1–28.
- Lehman, B. & D. Modest (1988). The Empirical Foundations of the Arbitrage Pricing Theory. *Journal of Financial Economics*. 21:2, 213–254.
- Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics*. 47:1 13–37.
- Lo, A. & C. MacKinlay (1990). When are Contrarian Returns Due to Stock Market Overreaction? *The Review of Financial Studies*. 3:2, 175–205.
- Loughran T. & J. Ritter (1996). Long-Term Market Overreaction: The Effect of Low-Priced Stocks. *The Journal of Finance*. 51:5, 1959–1970.
- MacKinlay, C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*. 35:1, 13–39.
- Malkamäki, M. (1989). Rahoitusmarkkinoiden tehokkuuskäsitteet. In book: *Rahoitusmarkkinat*. Published by. Malkamäki & Martikainen, Weilin+Göös. 28–44. ISBN 951-35-4983-6
- Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*. 7:1, 77–91.

- McQueen, G. & S. Thorley (1999). Mining fool's gold . *Financial Analysts Journal*. 55:2, 61–72.
- Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*. 34:4, 768–783.
- Mun, J., G. Vasconcellos & R. Kish (2000). The Contrarian/Overreaction Hypothesis: An analysis of the US and Canadian stock markets. *Global Finance Journal*. 11, 53–72.
- Nam K., C. Pyun & S. Avard (2001). Asymmetric reverting behavior of short-horizon stock returns: An evidence of stock market overreaction. *Journal of Banking & Finance*. 25, 807–824
- Nikkinen, J., T. Rothovius & P. Sahlström (2002). *Arvopaperisijoittaminen*. 1. ed. Vantaa: Werner Söderström Osakeyhtiö. 244 p. ISBN 951-0-26627-2.
- Olsen, R. (1998). Behavioral Finance and its Implications for Stock-Price Volatility. *Financial Analyst Journal*. 54:2, 10–18.
- Park, J. (1995). A Market Microstructure Explanation for Predictable Variations in Stock Returns following large Price Changes. *Journal of Financial and Quantitative Analysis*. 30:2, 241–256.
- Pettengil, G. & B. Jordan (1990). The Overreaction Hypothesis, Firm Size and Stock Market Seasonality. *Journal of Portfolio Management*. 16:3, 60–64
- Roberts, H. (1959). Stock Market "Patterns" and Financial Analysis: Methodological suggestions. *The Journal of Finance*. 44, 1–10.
- Roll, R. & S. Ross (1980). An Empirical Investigation of the Arbitrage Pricing Theory. *The Journal of Finance*. 35:5, 1073–1103.
- Roll, R. & S. Ross (1984). The Arbitrage Pricing Theory Approach to Strategic Portfolio Planning. *Financial Analyst Journal*. 40:3, 14–26.



- Rosita, P., D. Chang, S. McLeavey, & G. Rhee (1995). Short-term Abnormal Returns of the Contrarian Strategy in the Japanese Stock Market. *Journal of Business Finance & Accounting*. 22:7, 1035–1048.
- Ross, S., R. Westerfield & B. Jordan (2003) *Fundamentals of corporate finance*. 6. ed. McGraw-Hill Companies, Inc. 892 p. ISBN 0-07-115102-8.
- Roll, S. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*. 13:3, 341–360.
- Sharpe, W. (1964). Capital Asset Prices: A theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*. 19:9, 425–442.
- Sharpe, W., O. Alexander & J. Bailey (1999). *Investments*. 6. ed. Prentice-Hall International, Inc. 962 p. ISBN 0-13-011507-X.
- Shefrin, H. (2002). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Oxford University Press Inc. 384 p. ISBN 0-19-516121-1.
- Shiu, H. (2006). The Application of the Value Added Intellectual Coefficient to Measure Corporate Performance: Evidence from Technological Firms. *International Journal of Management*. 23:2, 356–365.
- Tanriverdi, H. & T. Ruefli (2004). The Role of Information Technology in Risk/Return Relations of Firms. *Journal of the Association for Information Systems*. 5:11-12, 421–447.
- Tversky, A. & D. Kahneman (1991). Loss Aversion in Riskless Choice: A Reference-Dependent Model. *The Quarterly Journal of Economics*. 106:4, 1039-1061.
- Vieru, M. (1989). Rahoitusmarkkinoiden tasapainomallit. In Book: *Rahoitusmarkkinat*. Published by Malkamäki & Martikainen, Weilin+Göös. 79–97. ISBN 951-35-4983-6.

Viscusi, K. (1997). Alarmist Decisions with Divergent Risk Information. *The Economic Journal*. 107:445, 1657–1670.

Williams, J. (1938). *Theory of Investment Value*. Amsterdam: North Holland, 1956 (reprint of 1938 edition).

Xiang, J., J. He & M. Cao (2002). Continuous overreaction, insiders trading activities and momentum strategies. *Journal of Multinational Financial Management*. 12:4–5, 429–449.

Zarowin, P. (1990). Size, Seasonality, and Stock Market Overreaction. *Journal of Financial and Quantitative Analysis*. 25:1, 113–125.

## APPENDIX

**Table 4.** Whole sample Winner and Loser market model adjusted weekly abnormal profits over the years 2002 – 2006. T-test associated p-values are expressed in parenthesis for the arbitrage portfolio. \*\*\* indicates statistical significance at the level of one percent and \*\* and \* mean five and ten percent significances respectively.

<b>Formation</b>		<b> Holding Period</b>			
<b>Period</b>	<b>Portfolio</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>
<b>1</b>	<b>Winner</b>	0,21 %	0,13 %	0,10 %	0,08 %
	(p-value)	(0.216)	(0.340)	(0.394)	(0.430)
	<b>Loser</b>	0,31 %	0,19 %	0,16 %	0,13 %
	(p-value)	(0.104)	(0.247)	(0.294)	(0.336)
<b>2</b>	<b>Winner</b>	0,21 %	0,12 %	0,10 %	0,08 %
	(p-value)	(0.359)	(0.444)	(0.466)	(0.486)
	<b>Loser</b>	0,17 %	0,12 %	0,11 %	0,09 %
	(p-value)	(0.403)	(0.446)	(0.454)	(0.476)
<b>3</b>	<b>Winner</b>	0,14 %	0,09 %	0,07 %	0,06 %
	(p-value)	(0.486)	(0.448)	(0.434)	(0.426)
	<b>Loser</b>	0,03 %	0,08 %	0,08 %	0,06 %
	(p-value)	(0.408)	(0.445)	(0.445)	(0.425)
<b>4</b>	<b>Winner</b>	0,21 %	0,11 %	0,06 %	0,05 %
	(p-value)	(0.479)	(0.474)	(0.454)	(0.448)
	<b>Loser</b>	0,17 %	0,15 %	0,10 %	0,08 %
	(p-value)	(0.497)	(0.493)	(0.469)	(0.461)