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MOMENTUM AND CONTRARIAN INVESTMENT STRATEGIES

Bachelor's Thesis

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1 INTRODUCTION

Functioning and efficiency of markets and pricing of assets has gained a lot of interest since decades and that paw seems to continue. The new era on a way of thinking began as early as year 1925 when Smith published book “Common Stocks as Long-Term investments” which claimed that price of investment did not have to be straight related to dividends share paid at the time. That meant that future growth had become an investment target, which could be speculated with. Ever since it has become more and more apparent that there are some anomalies in the markets which can be exploited in order to gain some excess return. Those anomalies and other different types of investment strategies have been researched by several authors, and knowledge of possibilities to gain excess returns has increased remarkably. That is also the main reason behind the fact that number of funds having some special investment style has increased so rapidly recent years.

Momentum and contrarian strategies are two opposite investment strategies which try to make excess returns investigating historical price/return data in order to forecast the future development of stock performance. Momentum strategy believes that stocks which have performed good will be doing so also in the future, so it buys stocks with good historical performance and sells stocks which have done worse. Contrarian strategy on the other hand believes that stocks whose historical performance is bad are going to do better in the future and historical winner stocks are going to come down, so it suggests buying losers and selling winners based on historical data. (Conrad and Kaul 1998) The empirical evidence of success of these both strategies is strong and extensive, and these results have gained a lot of interest also from institutional investors. For example, the momentum strategy has become a widely used investment strategy of many funds and other investors.

A number of papers have studied the performance of those strategies and determinants of their profitability. De Bondt and Thaler (1985) were one of the firsts arguing that contrarian strategy outperforms the market. Ever since the debate on that area has been strong, see e.g. Chan (1988), Lo and McKinlay (1990), Jegadeesh (1990), Chopra, Lakonishok and Ritter (1992), Lakonishok et al. (1994), Conrad and Kaul (1993 and 1998), and Larkomaa (1999). The first main work when momentum strategy is considered is Jegadeesh and Titman (1993). For further studies about momentum, see, e.g. Chan et al. (1996 and 1999), Rouwenhorst (1998 and 1999), Conrad and Kaul (1998), Moskowitz and Grinblatt (1999), Hong et al. (2000), Griffin et al. (2003), and Avramov and Chordia (2006). The evidence that both, momentum and contrarian, strategies can earn abnormal returns is strong.

However, the reasons behind these strategies are still very controversial. The aim of this study is to demonstrate the contrarian and momentum investment strategies, their profitability and reasons explaining their existence. This is done by introducing several studies which all present some different and interesting aspects of these strategies. Thus, test methodology used is qualitative in nature. In order to examine the different explanations given for the existence of these strategies, the studies are labeled as those of behaviorals and those that are risk-based. This classification can be rough, but it certainly helps to examine two different sides of these strategies and wide our knowledge of their real origins. It is also worth examining what is the development of these strategies: are they like other anomalies and are starting to disappear when the knowledge of them has increased, or do they still exist. The reasons which explain the success of these strategies are important to recognize because that is the only way to increase our knowledge of market efficiency and functioning of markets. One of the main questions is; are we talking about market anomalies that could be labeled as new risk-factors, or are markets just inefficient and investors behaving irrationally.

The remainder of this paper is organized as follows: The second Section introduces the concept of market efficiency concentrating only on those issues that are relevant for this study. The third Section introduces the concepts of contrarian and momentum strategies more carefully and reveals some of the most important test methodologies used to investigate them. Also, the empirical evidence of the existence of these strategies as well as the main theories and causes explaining them are concerned in the third Section. The fourth Section presents summary and conclusions of the previous Sections.

2 MARKET EFFICIENCY

2.1 Definition

Efficient market hypothesis (EMH) states that markets can be regarded as efficient when security prices fully reflect all available information. In order to that statement to be true all the information and trading costs, the costs of getting prices to reflect information, always have to equal to zero. (Grossman and Stiglitz 1980) That precondition is strong, and a weaker and economically more sensible version of the efficient market hypotheses says that prices have to reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs (Jensen 1978). Thus, it is impossible to consistently outperform the markets by using any information the market already knows, except through luck (Fama 1991).

Information in the EMH is defined as anything that may affect stock prices, is unknowable in the present and thus appears randomly in the future. This random information will be the cause of future stock price changes. The random walk hypothesis is closely related to efficient market hypothesis.[1] Hence, it can be said that in efficient market stock prices evolve according to a random walk and thus future prices cannot be predicted. (Elton et al. 2003, p. 405) It is notable that market efficiency alone is not testable. It must be tested jointly with some model of equilibrium, an asset pricing model (joint-hypotheses problem). That means, whether information is properly reflected in prices can be tested only in the context of a pricing model that defines the meaning of "properly". (Fama 1991)

Historically the efficient market hypothesis has been subdivided into three categories, each dealing with a different type of information. They are (1) weak-form tests, which test how well do past returns predict future returns, (2) semi-strong tests, testing how quickly do security prices reflect public information announcements, and

[1] Random walk hypotheses is a financial theory that states that stock prices evolve through a random walk and thus prices of stock markets cannot be predicted from past performance data. Thus, this is related to weak form efficiency especially.

finally (3) strong-form tests, which test do any investors have private information that is not fully reflected in market prices. If the markets are strongly efficient, they have to be efficient also on a weak- and semi-strong level. That was the original classification suggested by Fama (1970).

In a more recent article Fama (1991) expands the definition of the first type efficiency. Now it does not concern only the forecast power of past returns, but covers also the more general area of tests for *return predictability*. That includes also the rapidly increasing work on forecasting returns with variables like dividend yields and interest rates. Since market efficiency and equilibrium-pricing issues are not separable, the discussion of predictability also considers the cross-sectional predictability of returns, to say, tests of asset pricing models and the anomalies (like the B/M and size effects) discovered in the tests. (Fama 1991) In this study is concentrated on weak-form market efficiency, because contrarian and momentum strategies are related to predictability of returns and thus, can be regarded as a challenge to weak-form market efficiency.

2.2 Empirical results

In recent years there has been a dramatic resurgence of academic interest and research on the predictability of stock returns, that is, the variation, rational or irrational, of expected returns through time. There is statistical evidence against random walk model of stocks prices, but the extent of predictability is unsolved. During the late 1970s, evidence started to accumulate against the then-accepted paradigm of market efficiency. Huge number of recent studies claims that returns are predictable from past returns, term-structure variables and dividend yields, and thus, abnormal returns can be earned by using these inefficiencies. However, these “abnormal” returns found by many researchers may not be reliable evidence against market efficiency if the equilibrium model adopted in the tests is incorrect. Before the efficient market hypothesis can be rejected one has to solve whether the return predictability reflects rational variation through time in expected returns, irrational deviations of price from fundamental value, or some combination of these two. (Fama 1991)

Typically the model that was used to define the “abnormal” excess market returns, and test return predictability and risk-related components of returns since 1970s until 1990s was the static CAPM-model of Sharpe (1962) and Lintner (1965) and Black (1972). CAPM-model is based on Markowitz (1952) portfolio theory and it offers intuitively pleasant way to measure risk and the relation between expected return and risk. According to the model, expected return of an asset *i* can be written as,

$$E(r_i) = r_f + \beta_{iM}\left[\left(r_M - r_f\right)\right] \tag{1}$$

where r_f is the risk free rate, r_m the return on market portfolio and β_{im} is the market beta of asset *i*. Beta measures the sensitivity of asset’s return relative to market return. When CAPM-model is used in time-series regressions for example to investigate excess returns or portfolio performance, the equation is,

$$r_{it} - r_{ft} = \alpha_i + \beta_{iM}\left(r_{Mt} - r_{ft}\right) + \varepsilon_{it} \tag{2}$$

If the average excess return of an asset *i* is completely explained by the CAPM-model, the intercept α_i should, on average, equal to zero when regarding the systematic part of changes of return. The random part of variation of returns is not explained by this model. Alfa is introduced by Jensen (1968). Intercept ε_{it} reflects the part of the returns that cannot be explained by the model. However, CAPM-model has gained lot of critic. For example the determination of market portfolio is very controversial. Since the late 1970s there has been several studies identifying some particular variables that seem to contradict the prediction of CAPM-model that market beta is able to describe the cross-section of expected returns. Because these patterns in average stock returns cannot be explained by the capital asset pricing models, they are called anomalies. (Fama and French 2004)

So called E/P-anomaly is suggested by Basu (1983), by showing that E/P ratios have marginal explanatory power and when controlling for beta, expected returns are positively related to E/P. Size-anomaly is found by Banz (1981), he shows that stock’s size (price times shares) helps to explain expected returns. Bhandari (1988) reveals that leverage is positively related to expected stock returns in tests that also include market beta. Chan, Hamao and Lakonishok (1991) and Fama (1991) on the other hand show that firm's book-to-market equity is positively related to expected returns. (Fama 1991)

Two anomalies that are under investigation in this study are the return reversal and medium-term return continuation. Long-term return reversal is introduced by DeBondt and Thaler (1985) who state that stocks with low long-term past returns tend to have higher future returns. In contrast, Jegadeesh and Titman (1993) show that stocks with higher previous twelve-month returns tend to have higher future returns, that is, short-term returns have tendency to continue. Cash flow per price (C/P) and past sales growth are also shown to be anomalous. CAPM-model of Sharpe (1962), Lintner (1965) and Black (1972), is not able to explain any of these anomalies, but that evidence can be seen either as an embarrassment of the model or the way it is tested rather than as evidence of market inefficiency. (Fama 1991)

Fama and French (1992) confirm all these problems and lacks CAPM-model has, and find them to be even more severe with more recent sample period. They state that there seems to be no relation between the average stock returns and conventionally estimated beta. Fama and French (1993), and Lakonishok, Schleifer and Vishny (1994) suggest that CAPM-model fails to explain returns, because univariate market betas show only little relation to BE/ME, E/P and C/P, which all are strongly related to average return. Thus, Fama and French (1993) propose a three-factor asset pricing model (FF three-factor model) that does seem to describe adequately the average excess stock returns. The expected excess return on a portfolio or stock *i* according to the three-factor model can be written as,

$$E(r_i) - r_f = \beta_{iM}\left[E(r_M) - r_f\right] + \beta_{iM} E(SMB) + \beta_{iM} E(HML) \qquad (3)$$

The model says that the expected return on a portfolio in excess of the risk-free rate [$E(r_i)$-r_f] is explained by the sensitivity of its return to three factors: (1) the excess return on a broad market portfolio (r_M-r_f); (2) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks firms (*SMB*, small minus big), (3) and the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (*HML*, high minus low). In the equation E(r_M)-r_f, E(SMB), and E(HML) are expected premiums, and the factor sensitivities or loadings, betas, are the slopes in the multiple regression. (Fama and French 1993) Their results show that the model captures much of the variation in the cross-section of average stock returns. Moreover, they claim that the model is equilibrium pricing model. In this view, SMB and HML factors mimic combination of two underlying risk factors, or reflect variables that investors should hedge against. The risk related to SMB factor may be due to risk that smaller firms are more likely to go bankruptcy compared to bigger firms during recession. The risk related to HML factor is that firms with high BE/ME ratio, called value stocks are more stable than those with low BE/ME ratio. (Fama and French 1996)

Abnormal returns of anomaly portfolios using time-series data can be measured with equation,

$$r_{it} - r_{ft} = \alpha_i + \beta_{iM}\left(r_{Mt} - r_{ft}\right) + \beta_{is}\left(SMB_t\right) + \beta_t\left(HML\right) + \varepsilon_{it}, \qquad (4)$$

where the intercept α_i should, on average, equal to zero, if the model is able to explain the systematic variation of abnormal profits. Intercept ε_{it} is the error term reflecting the part of abnormal returns that cannot be explained by the model. By using this model Fama and French (1993 and 1996) are able to clear up almost all previous CAPM-model anomalies. When portfolios are formed on size and BE/ME, their model is a good description of returns (Fama and French 1993). Also, when portfolios are formed on E/P, C/P and sales growth, the three-factor model is able to capture the returns of the portfolios. The three-factor model is also able to explain long-term return reversal, a phenomenon that before FF (1996) had been thought to be unconnected to size and book-to-market factors. But anomaly that still remains unresolved by any existing pricing model is the short-term return continuation (momentum). (Fama and French 1996) That can be seen as a major challenge to weak-form market efficiency, but it also has inspired a huge work in order to make the existing equilibrium models better and to wide our knowledge about functioning of capital markets.

3 MOMENTUM AND CONTRARIAN INVESTMENT STRATEGIES

3.1 Definitions and theoretical background

Simple trading strategies have gained a lot of attention since the early days of stock trading. The most obvious trading strategies are those based on the past return pattern of stocks. Momentum and contrarian strategies are two opposite example of those. The momentum or contrarian profits could be explained by cross-sectional differences in expected returns of securities or by time-series predictability (continuation or reversal) of stock returns. Originally the literature has concentrated on time-series predictability but recently cross-sectional patterns have gained attention increasingly. (Lo and McKinlay 1990)

It is important to note that regardless of whether the strategy is momentum or contrarian, premise is that its success is based on the time-series behavior of asset prices. More precisely, a security's past performance relative to some benchmark (e.g. the average return of the portfolio of all securities). That is contrary to random walk model, and market efficiency. Therefore the study is intense, and attempt to find out the real, whether rational or irrational, reasons behind the profits of momentum and contrarian strategies is strong. One of the most interesting aspects of these strategies is that even though they are diametrically opposed, they appear to work "simultaneously", albeit for different time horizons. The main difference between these trading strategies is the time horizon used when they are investigated or used in practice. (Lewellen 2002) At first the majority of studies and interest concentrated on to investigate the contrarian strategy, but recently the momentum strategy is gaining more and more attention.

3.1.1 Contrarian strategy

The success of contrarian strategy has been investigated actively since 1970s. The foundations of this strategy are on a result of experimental psychology, which states that people do not behave rationally when making decisions because they tend to "overreact" to unexpected and dramatic news events. That has lead to a "stock market overreaction" hypothesis that maintains that a given stock decreases (increases) too far in price because of recent bad (good) news associated with the stock, but eventually returns to its fundamentals as investors realize that they have overreacted and thus, causes return reversals. Based on this belief, contrarian strategy is seen to be able to earn abnormal returns. (DeBondt and Thaler 1985)

DeBondt and Thaler (1985) were the first to present and investigate the return reversals in stock markets. In their study they formulate the overreaction hypothesis, and investigate whether such behavior affects stock prices, and make the experiments of profitability of contrarian strategies in the long-run. Formation period they use ranges from three to five years and holding period is three years long. (DeBondt & Thaler 1985) That study has become a benchmark of later studies. Since 1990s contrarian strategy has been examined also in very short time-horizon holding and formation periods equaling to one week or to one month.

Initially the negative autocorrelation of stock prices was seen as the main condition for return reversals. That is naturally a strong challenge against weak-form market efficiency, because it means that stock's future returns can be predicted from its past returns. The later research shows that also lead-lag effects, that is, positive serial correlation in portfolio returns, could cause part of the return reversals in the short term. The results are still very controversial. Most often contrarian strategy means particularly a strategy based on past returns, not prices or other fundamental values. At the time *t*, when weighted average wealth strategy (WRSS) method is used to form the portfolios, (see equation (8)) profit of contrarian strategy can be denoted as π_t,

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}\left(r_{i,t-1} - \bar{r}_{t-1}\right)r_{i,t} \tag{5}$$

where N is the number of stocks, r_i is the return of individual stock and $\bar{r}_{t-1}$ is the equal-weighted index return at time t-1. (Jegadeesh and Titman 1995)

3.1.2 Momentum strategy

Even though contrarian strategies received a lot of attention in the academic literature especially in 1980–1990s, the early literature on market efficiency focused more on strategies called relative strength strategies (momentum strategies) which buy past winners and sell past losers. Levy's (1967) study was one of the first studies about momentum, but its results are controversial. Despite the fact that contrarian strategy has been able to generate abnormal returns, many practitioners were still in 1990s and are still in 2000 using the relative strength as one of their stock selection criteria. For example, the Value Line rankings are known to be based mostly on past relative strength, also increasing number of mutual funds show a tendency to buy stocks that have increased in price over the previous quarter. (Jegadeesh and Titman 1993)

That quarrel between contrarian and relative strength strategies may have inspired Jegadeesh and Titman (1993) to start to study the momentum effect more carefully. They are the first to show clear evidence that momentum strategy is able to generate economically and statistically significant abnormal returns. That study has become a benchmark in more recent research on stock momentum and their methods and time horizons are actively used ever since. Since 1990s the research on that area has increased remarkably and momentum as an investment strategy has become more popular, especially among institutional investors. (Jegadeesh and Titman 2001)

In the literature the momentum effect is defined as cross-sectional covariance of the successive returns of a sample of stocks. The momentum effect is typically defined as a positive relation between the return of a stock in a certain period with its lagged return, both relative to the cross-sectional sample mean. (Jegadeesh and Titman 2001) The definition of individual stock momentum can be presented by equation

$$E\left\{\frac{1}{N}\sum_{i=1}^{N}\left(r_{i,t-1}-\bar{r}_{t-1}\right)\left(r_{i,t}-\bar{r}_{t}\right)\right\}>0, \qquad (6)$$

where $r_{i,t}$ is the return of stock i in period *t*, $\bar{r}_t$ the average return of the sample, and N the number of stocks. The momentum strategy is more pronounced and investigated on a medium-term, formation and holding periods ranging from 3 to 12 months. (Jegadeesh and Titman 1993)

3.1.3 Test methodology

3.1.3.1 Contrarian strategy

One of the most remarkable methodologies to test the profits of contrarian strategy is that employed by DeBondt and Thaler (1985). It can be described as a two-step procedure. In the first step, at the beginning of the test period, the winner and loser stocks are determined in order to form the winner and loser portfolios. The portfolios are usually formed according to cumulative market-adjusted returns of stocks over the formation period. Some studies use risk-adjusted returns. Market-adjusted abnormal return (*u*) can be written as,

$$u = r_{i,t} - r_{m,t} \tag{7}$$

where $r_{i,t}$ is the realized return of stock i in month t and $r_{m,t}$ is the market return in month t. The length of that formation period depends on the chosen time period; usually it is from 3 to 5 years, one week or a month. The cumulative market-adjusted abnormal returns are ranked from high to low and portfolios are formed. Firms in the top 35 stocks (or the top 50 stocks or the top decile) are assigned to winner portfolio W, and firms in the bottom 35 stocks (or the bottom 50 stocks or the bottom decile) to the loser portfolio L. For the portfolio formation dates DeBondt and Thaler choose December-end dates, which they note, is "essentially arbitrage". When other months are chosen, the returns of contrarian strategy become significantly smaller (Ball, Kothari and Shanken 1995).

The second step involves measuring the performance of winner and loser portfolios in each test or investment period. The length of test period ranges from 1 to five years, or equals to one week or one month. First, the market-adjusted returns (equation 7) to each stock i in the winner (loser) portfolio are determined in the first, second, and up to *m*-months or years in the portfolio evaluation period. This step is repeated for all subsequent test periods. Cumulated abnormal returns (CARs) are then obtained by adding up these abnormal returns. Then, these CARs are used to calculate the average cumulated abnormal returns (ACARs) in each k, where k=1,….,m, during the test period. The $ACAR_w(k)$ ($ACAR_L(k)$) indicates how much cumulated abnormal returns stocks in the winner (loser) portfolio earn on average during k-months or years in the test period. The overreaction hypotheses predicts $ACAR_w(k) < 0$ and $ACAR_l(k) > 0$, and especially, $ACAR_l(k) - ACAR_w(k) > 0$. (DeBondt and Thaler 1985) Usually, test period returns are also risk-adjusted in order to investigate the risk related to the returns. This is done by adjusting the returns to the CAPM-model (equation 2) or to the FF three-factor model (equation 3). Recent studies suggest, that FF three-factor model should be used because both market- and CAPM-adjusted returns are biased upward and do not take into account the relevant factors proposed by FF three-factor model. (Antoniou et al. 2006)

However, this cumulative abnormal returns -method has gained critic, and Konrad and Kaul (1993) claim that that method is flawed in that it spuriously inflates the return to the arbitrage portfolio by cumulating short-term (monthly) returns to each stock in both winner and loser portfolios. They argue that single-period returns are upwardly biased due to measurement errors in observed prices due to bid-ask errors, non-synchronous trading etc., and these single period biases are then cumulated with the true returns, and the results are overly positive. So, they suggest that *holding period returns* (HPR) should be used instead of cumulated abnormal returns (CARs) as performance evaluation measure. In HPR-method years are used instead of months to calculate the abnormal returns. (Conrad and Kaul (1993) However, also this method is criticized. Loughran and Ritter (1996) state, that this holding return method suffers from survivorship bias, since winner and loser portfolios include only those firms that survive into test periods. Despite the critic, the holdings period returns are mostly used in stead of cumulative returns in several more recent studies, for example in Baytas and Cakici (1999) and Dahlquist (2000).

3.1.3.2 Momentum strategy

There are several research methods proposed in the literature also in order to investigate the existence of momentum effect. These methods differ somewhat in their implementation and hence, can influence the empirical outcomes. The method used by Jegadeesh and Titman (1993) is based on equally weighting of stocks and is actively used in literature. In that method, a strategy that selects stocks on the basis of returns over the past *J* months (*J* is the formation period of 3, 6, or 12 months) and holds them for *K*-months (*K* is the holding period of 3, 6, or 12 months), is constructed as follows: At the beginning of each month *t* the securities are ranked in ascending order on the basis of their returns in the past *J* months. Based on these rankings ten decile portfolios are formed that equally weight the stocks contained in the top decile, the second decile, and so on. The top decile portfolio is called the "winners" decile and it contains the best 10% of sample firms and the bottom decile is called the "losers" decile and it contains the worst 10% of the sample. In each month *t*, the strategy sells the loser portfolio and buys the winner portfolio, holding this position for *K* months. In addition, the strategy closes out the position initiated in month *t – K*.

So, under this trading strategy the weights on 1/*K* of the securities in the entire portfolio are revised in any given month and carried over the rest from the previous month. This strategy is usually referred as *J*-month/*K*-month strategy. These strategies usually include portfolios with overlapping holding periods. That means, in any given month *t*, the strategies hold a series of portfolios that are selected in the current month as well as in the previous *K-1* months, where *K* is the holding period. In this method portfolios are overlapping but the returns are not. This should improve the robustness. (Jegadeesh and Titman 1993) This method has also the advantage that extreme weighting schemes are excluded and that portfolio weights of the stocks are the same throughout the analysis. Including one week or one month interval between the formation and holding periods improves the robustness of results. It helps to avoid contaminating the momentum strategy with the very short-term reversals and to avoid some microstucture problems. (Grundy and Martin 2001) The returns used for both the portfolio formation and testing period can be either market-adjusted returns (equation 7) or CAPM- or FF three-factor model –adjusted. Similar to contrarian strategy, multifactor-adjusted returns should be used (Antoniou et al. 2006).

Another approach to detect momentum effect and to form the winner and loser portfolios is based on a sample analogue of the momentum effect of equation (6) and is referred to as the weighted average wealth strategy (WRSS). According to this strategy portfolios are formed in a way that assets are held in proportion to their market adjusted returns. Thus, *weight* of an asset *i* in a portfolio in month *t* is,

$$w_{i,t} = \frac{1}{N}\left(r_{i,t-1} - \bar{r}_{t-1}\right), \tag{8}$$

where $r_{i,t-1}$ equals the return of an asset *i* at time *t*-1, $\bar{r}_{t-1}$ equals the return on the equal-weighted index at time *t*-1, and *N* is the total number of stocks. Whether a stock belongs to a winner or loser portfolio depends on its previous performance during the formation period. This strategy has the advantage that profits can be easily tied to the autocorrelation of returns, and thus, it is possible to examine the different sources of momentum profits more carefully. (Lewellen 2002) Originally this method was used to form the short-term contrarian portfolios and to investigate their origins by Lo and McKinley (1990). Profits from this strategy, denoted as π_i, can be expressed as,

$$\pi_t = \sum_{i=1}^{N} w_{i,t} r_{i,t} = \frac{1}{N}\sum_{i=1}^{N}\left(r_{i,t-1} - \bar{r}_{t-1}\right) r_{i,t} \tag{9}$$

However, WRSS method may suffer from lack of robustness, because stocks that have outperformed the market by a large amount are dominant stocks in the momentum strategy regardless of their market capitalization. Thus, WRSS could lead to long and short positions that contain only the smallest stocks listed. In addition, the large idiosyncratic components in WRSS portfolios might reduce reliable inference. In order to reduce the influence of these idiosyncratic returns, many papers use the stepwise weighting scheme in which the top 10% of the stocks in the ranking on past returns form the winner portfolio and the bottom 10% form the loser portfolio. (Swinkels 2004) However, all the methods presented here have their advantages and disadvantages, and they all are used in literature. As a consequence the results vary marginally. When the momentum strategy is concerned, the variations in returns are however insignificant. (Swinkels 2004)

Return decomposition

Since 1990s there have been several studies which try to explain the determinants of momentum and contrarian profits by decomposing the cross-section of portfolio returns. One way to decompose the WRSS profits (equation 9) to different components is that presented originally by Lo and MacKinley (1990) who investigate the sources of short-term contrarian profits. The model has also been used, among others, by Jegadeesh and Titman (2002) and Conrad and Kaul (1998) to investigate the sources of momentum profits. The equation of the model is

$$\pi_t = -\operatorname{cov}\left(\bar{r}_t, \bar{r}_{t-1}\right) + \frac{1}{N}\sum_{i=1}^{N} \operatorname{cov}\left(r_{i,t}, r_{i,t-1}\right) + \sigma_\mu{}^2 \tag{10}$$

This decomposition model says that momentum or return reversal can arise in three ways. The first term on the right hand side is the negative of the first-order autocovariance of the return on the equal-weighted market portfolio, and is almost completely determined by cross-serial covariances of individual security returns. That implies that returns of one firm can predict returns of the other.[2] The second term is the average of first order autocovariances of the *N* individual securities, and it implies that return of a firm is predictable from its past returns. The third term denotes the cross-sectional variance of expected returns, and it suggests that stocks with the highest unconditional expected returns also have the highest realized returns. The sum of the two first components represents the time-series predictability effect, and if they are responsible for the momentum (contrarian) returns, the weak-form market efficiency is challenged. Lo and McKinley (1990) concentrate on these first two terms similar to Jegadeesh and Titman (1995)[3] in order to examine the contrarian profits. Lewellen (2002) investigates them as source of momentum, and Conrad and Kaul

[2] Negative cross-serial covariance here signifies that a firm with a high return today predicts that other firms will have low returns in the future, that is also referred as a lead-lag effect.

[3] Jegadeesh and Titman (1995) criticize this method, and investigate its significance more carefully. However, the method of Lo and McKinley (1990) is still very commonly used in literature.

(1998), and Jegadeesh and Titman (2002) concentrate on the last term as source of momentum effect.

In general, there are several variations of these decomposition models, and the interpretations vary accordingly. Therefore it is very challenging to make conclusions about the sources of momentum or contrarian strategies based on these profit decompositions. Simpler way to investigate the determinants is to use asset pricing models which can tell how big a part of profits could be explained by cross-sectional variation versus time-series variation of returns. (Jegadeesh and Titman 2002)

3.2 Empirical results

3.2.1 Contrarian strategy

DeBondt and Thaler (1985) show the first evidence that contrarian strategy can earn abnormal profits in the long-term. Their data consists of all common stocks traded in NYSE (New York Stock Exchange), and period under investigation is from January 1926 to December 1982. The portfolios of losers and winners are formed using formation periods of 3- to 5-years, and the holding period is three years. Their results show that previous losers outperform the market by, on average, 19.6% thirty-six months after portfolio formation, whereas winner portfolio earns about 5% less than the market. Thus, the overreaction effect is very asymmetric being much larger for loser portfolios. Accordingly, the difference in cumulative average residual between extreme portfolios equals 24.6% (t-statistic: 2.20) for three years.

Their findings state also that most of the returns are realized in January, which refers to January anomaly. Further, the January effect is observed as late as five years after portfolio formation. Mostly the overreaction phenomenon occurs during the second and third year of the test period. For a formation period as short as one year, no reversal is observed. (DeBondt & Thaler 1985) Their following study (1987) shows further, that return reversals are statistically significant only in Januaries (DeBondt & Thaler 1987). Similar findings that long-term losers outperform long-term winners report also Chopra, Lakonishok and Ritter (1992).

However, these findings have faced a lot of critic. Conrad and Kaul (1993) suggest that the results provided by DeBondt and Thaler (1985) framework are not valid, because the reported excess returns are due to cumulating bias of single period returns. When this is taken into account, and a buy-and-hold performance measure is used instead of cumulative, the profits from contrarian strategy become insignificant for non-January months. They use a sample of NYSE listed stocks over the 1926–1988 period and find that, the appropriate holding period average return of loser minus winner portfolio is -1.7% per month. (Conrad and Kaul 1993) Also, when Ball et al. (1995) use June-end dates, instead of original December-end dates, for as portfolio formation dates, the returns of contrarian strategy drop significantly. Explanations for this drop are various, but all the same, it casts doubt on the robustness of DeBondt and Thaler's (1985) results. Moreover, Ball et al. (1995) report that both, raw and abnormal returns, suffer from severe measurement problems. Because contrarian strategies invest in very low price loser stocks, these problems become more severe, and bias the returns upwards.

Kryzanowski and Zhang (1992) suggest that positive profits resulting from the use of the contrarian investment strategy are limited to the U.S. stock market. When they apply the DeBondt and Thaler (1985) framework to the Canadian stock market, contrarian strategy is not able to produce favourable results. In fact, instead of finding significant price reversals, Kryzanowski and Zhang find that the Canadian stock market exhibits significant price continuation behaviour. (Kryzanowski and Zhang 1992)

Similar results and international evidence is shown by Baytas and Cakici (1999) as they test contrarian strategy in seven industrialized countries, namely in US, Canada, UK, Japan, Germany, France and Italy. Instead of DeBondt and Thaler's (1985) cumulative returns they use the holding period returns method. Their evidence seems to favor long-term contrarian strategies in all countries except the US, also for Canada the evidence is notably weak. That is consistent with Conrad and Kaul (1993). The average raw yearly return to the arbitrage portfolio of losers minus winners is only 12.4% in Canada, while in Japan it is 94.5%, in France 62.9%, in UK 58.5%, in Germany 50.5% and in Italy 21.6%. (Baytas and Cakici 1999)

More recent study of Conrad and Kaul (1998) suggests further that in the US the contrarian strategies net statistically significant profits only during the “unusual” 1926–1947 subperiod. On other periods, even though statistically significant price reversals are being observed, the profits emanating from the reversals are typically neutralized by the losses due to the large cross-sectional variance in mean returns. (Conrad and Kaul 1998) Also Jones (1993) replicates DeBond and Thaler (1985), and finds that the profitability of contrarian portfolios is a pre-WW II phenomenon.

Larkomaa (1999) investigates contrarian effect in Finnish stock market during the period 1975-1996 and finds that contrarian strategy is able to produce both, market- and CAPM-adjusted, abnormal returns with holding and testing periods ranging from three to five years. However, compared to previous international evidence the return reversals in Finnish stock market are very weak. Though, this might just reflect the differences in the length of the data samples used. Like mentioned above, large variation in arbitrage returns has been reported as a function of time. In Finland, the contrarian profits (profits of loser minus winner portfolios) seem to focus on the portfolios formed in the middle as well as subsequent part of the 1980’s. This could be related to the boom period that took place in Helsinki Stock Exchange in the second half of the 1980’s. Moreover, the contrarian effect in Finland seems to be at least partly connected to January effect. This is consistent with previous international evidence. (Larkomaa 1999, p. 66–69, 71)

Several more recent studies provide evidence of shorter-term return reversals. Howe (1986), who confirms the findings of DeBondt and Thaler (1985) finds that significant portion of returns realized by using the contrarian strategy appears to occur within a short period of time after the large initial price increase. More recently, Jegadeesh (1990) and Lehman (1990) were one of the firsts showing that contrarian strategies that select stocks based on their returns in the previous week or month generate significant abnormal returns in the US. Jegadeesh (1990) investigates this using sample period of 1963–1990, and all the firms traded on NYSE and American Stock Exchange. Results show, that the difference between abnormal returns on the loser and winner portfolios that are formed on a basis of one month lagged returns, is 1.99% per month, when the abnormal returns are estimated under the CAPM-model. (Jegadeesh 1990) Antoniou et al. (2006) suggest similar results of short-term reversals when investigating short term contrarian strategy in London Stock Exchange. The short-term contrarian profits are though smaller in the UK than in the US. (Antoniou et al. 2006)

3.2.2 Momentum strategy

Momentum strategy is, contrary to contrarian strategy, most profitable in medium time horizon. The study of Jegadeesh and Titman (1993) shows that strategy of buying past winners and selling past losers over the 1956 to 1989 period realizes significant abnormal returns, when formation and holding periods range from 3 to 12 months. When formation and holding periods both are 6 months, the market-adjusted return of winner minus loser portfolios (that is, zero-cost strategy) is 0.95% per month (t-statistic: 3.07). The most profitable zero-cost strategy is the one having a formation period of 12 months and holding period of three months. In that case, the difference between extreme portfolios is 1.49% (t-value: 4.28) per month in all months except January. In January the losers significantly outperform the winners. When returns are adjusted to the CAPM-model they stay somewhat the same. (Jegadeesh and Titman 1993) Conrad and Kaul (1998) test six-months/six-months strategy using WRSS method and they show monthly return of 0.36% (t-value: 4.55). Thus, the difference in returns when portfolio formation method is changed is obvious. However, both studies show abnormal returns that are statistically very significant.

Using the US data over the 1990 to 1998 sample period, Jegadeesh and Titman (2001) find that the momentum strategies tested in their previous work (1993) continue to be profitable. The past winners outperform the past losers about the same magnitude as in the earlier period. During the period 1990–1998 the monthly return for the winner minus loser portfolio is 1.39 (t-value: 4.96). That proof provides assurance that momentum profits are not entirely due to data snooping bias. The risk-adjusted returns when CAPM-model is used are 1.24% per month (t-value: 6.50), and 1.36% per month (t-value: -7.04) when FF three-factor model is used. This difference is due to the fact that loser portfolios are more sensitive to FF factors. When examining the portfolios separately, it shows that the winner portfolio outperform the equal-weighted index by 0.56% per month, whereas loser portfolio underperforms the index by 0.67% per month. These results suggest that both winners and losers contribute about equally to momentum profits.

The profitability of momentum strategies is not restricted only to US evidence, but similar findings have been found also by using international data. Rouwenhorst (1998) studies momentum outside the US using sample that consists of 2190 firms from 12 European countries and the sample period is from 1978 through 1995. Study shows that return continuation and success of momentum strategy is not due to country momentum, it is pervasive and not restricted to a few individual markets. When six-months/six-months strategy is used the excess return of winners over losers is 1.16 % (t value: 4.02) per month. When investigating 12 European countries separately, Rouwenhorst finds significant return continuation in 11 out of 12 countries.

Griffin et al. (2003) investigate the momentum effect around the world using methods similar to Jegadeesh and Titman (1993) with six-months/six-months strategy, and confirm the results of earlier studies. The average monthly raw return for zero-cost portfolio is 1.63% for Africa, 0.78% for Americas (excluding the US), 0.32% for Asia and 0.77% (about 9.24% per year) for Europe, and these profits are highly significant for all regions except for Asia. Profits for Asia are dramatically smaller than those for other regions, especially when compared to Europe. When investigating emerging markets and developed markets (excluding the US), the results show statistically insignificant average profits of 0.27% per month (3.24% per year) for emerging markets and statistically significant average profits of 0.73% per month (8.74% per year) for developed market. These results concerning emerging markets are consistent also with Rouwenhorst (1999). All this international evidence confirms the fact that momentum effect is not a result of data snooping bias.

All this empirical evidence clearly states that momentum effect is very strong and pervasive, and not restricted to a specific sample period or geographic area. The high t-values indicate that returns are statistically significant. The evidence of profitability of contrarian strategies is not so strong; at least it is more controversial and dependent on the test method used. However, it can be said that both of these strategies earn profits that excess the market index used.

3.3 Sources of momentum and contrarian profits

If there is no reasonable explanation for the profitability of a contrarian or momentum strategy, the pattern of profits observed in the past could be a statistical fluke. If that is the case, then the trading strategies are unlikely to be profitable in the future. On the other hand, if the pattern is a result of systematic biases in the way investors process information, or compensation for risk, then their profitability should continue. Empirical evidence seems to favor this presumption. When trying to understand the existence and exploitability of contrarian or momentum strategy it is important to understand the sources of the excess returns they are generating more preciously. Basically, the explanations behind both the contrarian and momentum strategies can be divided as behavioral, on market inefficiencies based, models, and risk-based models which defend the market efficiency. (Swinkels 2004)

3.3.1 Behavioural explanations

The first studies about causes behind the contrarian and momentum effects concentrated mostly on the market inefficiencies and imperfections of information diffusions. It is well recognized that there does not exist a rational asset pricing model which could explain the profits of momentum strategies, and also the ability of FF three-factor model to explain the return reversals has been questioned by many authors. That has lead to a spur of several irrational models which try to explain abnormal profits of trading strategies based on past returns. As overreaction is seen as the main behavioral bias that explains the profitability of contrarian strategies, underreaction, along with positive autocorrelation, is traditionally seen as a driving force of momentum. Three most recognized behavioural models that have been developed to explain underreaction and overreaction of stock markets are those proposed by Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999).

Barberis et al. (1998) build their model on two types of heuristics that they assume investors use when making financial decisions. These heuristics are *representativeness* and *conservatism*. Representativeness means that people view events as typical or representative of some specific class and ignore the laws of probability in the process. That kind of behavior leads to overreaction and profitability of contrarian strategy. On the other hand, conservatism is defined as slow updating of a model in the face of new evidence and leads to underreaction*,* which causes the momentum effect. Further, their model implies negative autocorrelation in the long run, leading to reversals, and positive correlations in the shorter run, as a cause of momentum effect. This is consistent with previous literature. (Barberis et al. 1998)

Daniel et al. (1998) also present a single agent model, but they base their model on two other well-known psychological biases, namely investor *overconfidence* about the precision of private information, and biased *self-attribution*. Biased self-attribution means that people too strongly attribute events that confirm the validity of their actions to high ability, and events that disconfirm the action to external noise or sabotage. This self-attribution adds momentum effect in the short-run but causes return reversals in the longer-run. Overconfidence on private information causes initial overreaction, which leads to momentum in stock returns. Investors underreact to public signals about firm value, and thus, the reversal is caused afterwards. Also, according to Daniel et al. momentum is explained by positive autocorrelation of stock returns in the short run through continued overreaction. They show that positive return correlation can be a result of continuing overreaction. This is followed by long-run correction. Thus, short-run positive autocorrelation can be consistent with long-run negative autocorrelations. This is contrary to model of Barberis et al. (1998), which states that underreaction is the main cause of momentum. However, it could be possible, that both of these sets of investor assumptions play role in investment behavior. (Daniel et al. 1998)

Hong and Stein (1999) present a model based on gradual-information-diffusion. They try to explain the anomalous trading strategies by examining the interaction between heterogeneous agents, and less the cognitive biases investors face. Their model is based on three main assumptions. First of all they suggest that markets are populated by two groups of boundedly rational agents: *"newswatchers"* and *"momentum traders"*. Newswatchers make forecasts based on signals that they privately observe about future fundamentals, but they fail to extract other newswatchers' information from prices. Momentum traders do condition on past price changes but their limitation is that their forecasts must be "simple", also univariate functions of the history of past prices. The last assumption is that information diffuses gradually across the newswatcher population.

They show that under these assumptions, when only newswatchers are active, prices adjust slowly to new information, thus there is underreaction but never overreaction. The momentum traders on the other hand try to exploit this underreaction with a simple arbitrage strategy. They manage to eliminate it only partially, and by doing so, create an excessive momentum in prices that inevitably culminates in overreaction. Thus, Hong and Stein claim that both underreaction and overreaction get out of just one primitive type of shock: Gradually diffusing news about fundamentals. (Hong and Stein 1999) Hong, Lim and Stein (2000) show results consistent with this study when using firm size and analyst coverage as a proxy for the rate of information diffusion. They suggest that gradual information diffusion is indeed a driving force of momentum effect. (Hong, Lim and Stein 2000)

Evidence to support the behavioral models is presented by Jegadeesh and Titman (2001) who examine the postholding returns of momentum portfolios. They examine the returns of loser and winner stocks in the 60 months following the formation date, and found that momentum portfolio yields significant positive returns in the first 12 months after portfolio formation, whereas the cumulative returns in months 13 to 60 on average are negative. That is consistent with the behavioral models which predict that the momentum profits will eventually reverse. But it is remarkable to note that the evidence of return reversals is strong only for small firms, and most of it takes place in January. Moreover, the return reversal is significant only in the period 1965–1981, during the subperiod 1982–1998 postholding returns are only -0.01% per month. When momentum returns are regarded there is not such a difference. These facts suggest that, even though the overall results of postholding returns are consistent with the behavioral models, this evidence should be tempered with caution. (Jegadeesh and Titman 2001)

Also Griffin et al. (2003) show international evidence that momentum returns reverse quite soon after the investment period and over long horizon they become negative, as predicted by behavioural models. Outside the US the reversal returns are almost entirely not driven by negative January returns (unlike the returns shown by

Jegadeesh and Titman 2001). They point out however, that in most behavioural models there is no specified time horizon, which makes it difficult to compare the results, even though this evidence seems to be strongly inconsistent with the risk-based models. (Griffin et al. 2003) Further, Cooper et al. (2004) find that momentum returns do reverse in the long-run, as predicted by the overreaction theories.

However, without unambiguous predictions about undetected trading patterns or price dynamics that can subsequently be tested, scepticism about quality of the behavioural models will most likely remain strong. Thus, these models remain, nothing but, highly descriptive in analyzing which type of behavior might cause momentum or return reversal. (Swinkels 2004) Further, Fama (1998) argues that, the ability of Barberis et al. (1998) and Daniel et al. (1998) to explain momentum and contrarian effects is not surprising, because that is what they were designed to do. Their ability to explain other anomalies is however embarrassing, and thus, that also casts doubt on their reliability. (Fama 1998)

3.3.1.1 Contrarian strategy

Even though there is not a complete behavioural model that could explain the contrarian effect, a lot of work has been done to examine components of contrarian abnormal returns in order to find some evidence of market inefficiencies. Initially the profitability of contrarian strategies was seen as a result of stock market overreaction. The fist studies show results suggesting that overreaction is predictive, and that adjustments of profits to the CAPM-model could not explain the abnormal results. Also, they show that portfolios based on market-adjusted excess returns do not systematically differ with respect to either market value of equity, dividend yield or financial leverage. So, these results challenged the hypothesis of weak-form market efficiency. (DeBondt and Thaler 1985)

Also, Lakonishok et al. (1994) state, that past losers (or value stocks) are not riskier than past winners (glamour stock) when risk is measured with conventional methods like beta or standard deviation. They claim, that profitability of contrarian strategies can be explained by the tendency of investors to make judgmental errors, and perhaps also by a tendency of institutional investors to actively prefer past winner (or glamour) stocks. Thus, previous loser stocks become underpriced relative to their risk and return characteristics. One explanation is also that market participants have consistently overestimated future growth rates of winner stocks relative to loser stocks. Because markets overreact to past growth, they are surprised when it mean reverts. As a result, past poor performers gain higher future returns than past strong stocks. Also, the short-term contrarian profits were initially regarded as evidence that market prices overreact to new information. (Lakonishok et. al. 1994)

However, Lo and MacKinlay (1990), who investigate short-term contrarian profits by decomposing the cross-section of stock returns, suggests that abnormal profits of contrarian strategies are not entirely due to stock price overreaction to information. The method they use and results they get are very different from those presented in the literature earlier. They decompose the contrarian profits using the model in equation (10) in a way that directly relates the different parts of contrarian profits to their sources, identified based on how stock prices respond to information. They show, that also *underreaction* of some stocks to new information, or equivalently when returns of some stock lead the returns of others (first term in equation 10), can cause the contrarian strategy to work. They argue it is impossible to draw definitive inferences about how stock prices react to information based on the observed profitability of contrarian strategies. Thus, in theory both overreaction and underreaction (or equivalently delayed reaction) of prices to new information can lead to contrarian profits. (Lo and McKinlay 1990)

Jegadeesh and Titman (1995) show further evidence consistent with the overreaction and underreaction hypotheses. In order to decompose the returns they develop a method slightly different from that of Lo and McKinlay (1990), because, as they criticize, it biases the importance of delayed reaction upwards. They decompose the contrarian returns into components attributable to stock price reactions to firm-specific information and common factor realizations. They find that stock prices react with a delay to common factors but overreact to firm-specific factors. When investigated separately, the primary source of observed contrarian profits is, however, the tendency of stock prices to overreact to firm-specific information. This overreaction leads to reversal of the firm-specific component of returns. (Jegadeesh and Titman 1995) Antoniou et al. (2006) present similar results when investigating short-term contrarian strategy in London Stock Exchange. They state that most of the contrarian profits are related to firm-specific overreaction, while common factors contribute little or even negatively.

However, Baytas and Cakici (1999) show results challenging the overreaction hypotheses. They show, when investigating the contrarian profits with international data, that long-term investment strategies based on size and especially price produce returns higher than those based on past performance. Since losers tend to be low price and low market value firms, price and size effect might explain some of the long-term price reversals observed in winner and loser stocks. Thus, that casts a doubt on overreaction hypothesis. Also the relations of contrarian profits with January effect can be seen as a challenge to overreaction hypotheses.[4] (Baytas and Cakici 1999) These short-term strategies are also transaction intensive and based on short-term price movements, thus their profitability may reflect the presence of short-term price pressure or a lack of liquidity in the market rather than overreaction (Jegadeesh and Titman 1993).

As can be seen, the results are very controversial when regarding the behavioural models. The methods used to investigate different sources of returns are in a major role, and results vary accordingly. All in all, there is no clear consensus among behavioralists about the sources of contrarian profits, and test methodologies can be really complicated which makes the results even more fragile and controversial.

3.3.1.2 Momentum strategy

Besides the complete theoretical models of behavioralists' which are developed to explain the momentum effect, there are several behavioral-oriented studies that try to explain the momentum effect as a result of some stock-specific characteristics. The arguments of these behavioral studies commands support of empirical evidences that momentum profits are related to several stock characteristics not typically

[4] January effect refers to anomaly of stocks earning abnormal profits in Januaries. Explanations for this are numerous; see for example Jaffe et al. (1989), and Bhardjaw and Brooks (1992).

associated with the priced risk in standard asset pricing models. These characteristics are, among other things, earnings momentum (Chan et al. 1996 and 1999), industry factor (Moskowitz and Grinblatt 1999), and analyst coverage (Hong, Lim and Stein 2000). These methods may provide some insights into the driving force behind the momentum effect, but they do not explain why it exists in the first place. (Swinkels 2004)

Earnings momentum

Chan, Jegadeesh and Lakonishok (1996 and 1999) show that underreaction to earnings news can partly explain momentum profits. Also, Jegadeesh and Titman (1993) investigate the relation of earnings announcements to momentum profits with an event study method, and find evidence in favor of that. Chan et al. (1996) examine the ability of both past returns and public earnings surprises to predict subsequent returns at horizon of six months and one year using a multiple regression. They relate the evidence on momentum in stock prices to the evidence on the market's underreaction to earnings-related information. They examine earnings momentum by using three measures of earnings news: standardized unexpected earnings (SUE) (defined as the scaled earnings change relative to the same quarter in the previous year), the abnormal return around earnings announcement and the change in analysts' forecasts of earnings. As a measure of price momentum they use a stock's past compound return, extending back six months prior to portfolio formation.

They found that both of these strategies, based either on past returns or earnings, yield significant profits, and there is only marginal difference between returns of these strategies. They also found that each of the momentum variables studied here exploit underreaction to different pieces of information and accordingly, do not subsume any of others. (Chan et al. 1996) These findings are based on sample from years 1973–1993, but when the study was repeated with shorter sample, containing years 1994–1998, the results were approximately the same. (Chan et al. 1999) These findings are consistent with the idea that the market does not promptly incorporate the news in past prices or earnings. The adjustment is gradual meaning that prices exhibit predictable drifts and these drifts last for up to a year.

Since earnings provide an ongoing source of information about a firm's prospects, the study examines market's reaction when earnings are released. Results show that substantial portion of the momentum effect is concentrated around subsequent earnings announcements. For example, about 41% of the superior performance in the first six months of the price momentum strategy occurs around the announcements dates of earnings. These findings are consistent with Jegadeesh and Titman (1993). More generally, if the market is surprised by good or bad news, then on average the market continues to be surprised in the same direction at least over the next two subsequent announcements. (Chan et al. 1999)

Industry effects

In general the literature relates momentum profits to firm-specific returns[5]. However, results of Moskowitz and Grinblatt (1999) challenge that when industry portfolios are used to investigate momentum. They examine the returns to a strategy that buys firms that were winners over a past ranking period and shorting an equal dollar amount of firms in the loser industries. Their sample consists of NYSE, AMEX and Nasdaq stocks from 1963 to 1995. The study shows that even after controlling for size, book-to-market equity (BM/ME), individual stock momentum, the cross-sectional dispersion in mean returns, and potential mictrostructure influences (liquidity, trading costs and so on), the industry portfolios exhibit significant momentum, about 0.43 percent per month when six-months/six-months strategy is used. They also argue that industry momentum strategies are more profitable than individual stock momentum strategies and that once returns are adjusted for industry effects, momentum profits from individual equities are significantly weaker and, for the most part, are statistically insignificant.

However, several studies show, that Moskowitz and Grinblatt's (1999) results are most pronounced when the formation period is contiguous with the investment period because much of the observed profitability of an industry momentum strategy comes in the month immediately after the formation period (Jegadeesn and Titman 2001, Grundy and Martin 2001).

[5] See for example Jegadeesh and Titman (1993), Grundy and Martin (2001), Kang and Li (2004)

Lewellen (2002) claims also that momentum effect cannot be attributed solely to momentum in industry-specific returns, even though he finds that industry portfolios do have momentum. However, he also shows further evidence that momentum is not entirely driven by firm-specific factors either. He investigates momentum in size and B/M portfolios which can be seen well diversified because they all contain stocks more than 200. Results show that momentum in these portfolios is strong, in some cases stronger than in individual stocks or industries. Thus, there has to be some non-idiosyncratic, maybe macroeconomic factors driving the momentum effect. The specifications of those possible factors are however far from being solved. (Lewellen 2002)

Analysts' coverage

Hong, Lim and Stein (2000) test whether momentum effect is caused by gradual diffusion of firm-specific information, like proposed by the study of Hong and Stein (1999) and the study of Chan et al. (1996 and 1999). Their sample consists of all stocks traded on NYSE/AMEX and sample period is 1976–1996. They consider the analyst coverage as a proxy for the rate of information flow, and stocks with low analyst coverage should, all else equal, be ones where firm-specific information diffuses more slowly across investors. They find, when the size is hold fixed, the momentum strategies are more profitable when the analyst coverage is lower. Size and analyst coverage interact in a plausible fashion: among the smallest stocks, the marginal importance of analyst coverage is the biggest. Additionally, the effect of analyst coverage is much stronger for past losers than past winners. Accordingly, low-coverage firms seem to react more slowly to bad than good news. This is consistent with the theory based on the flow of firm-specific information. (Hong, Lim and Stein 2000)

Size

When investigating the size of the firms on momentum portfolios, Jegadeesh and Titman (1993) show that even though momentum profits follow an inverted U-shape with respect to size, the differences across subsamples are very small. This may be due to that they use only three size classes and exclude all Nasdaq firms. Hong, Lim and Stein (2000) also report, using ten subsamples break-points determined by NYSE/AMEX deciles, that there is an inverted U-shape when momentum profits are plotted against size deciles. When the mean market capitalization is $7 million (tiny stocks) the momentum is negative, by the second decile they are positive and reach a peak in the third decile, where average market capitalization is about $45 million with momentum profits of 1.43% per month (t-value: 6.66). After the third decile the profits decline monotonically and for the largest stocks they are zero. Several other studies also show that continuation effect is not restricted to some specific size decile even though it seems to be stronger for smaller stocks.[6] This confirms that size as a risk factor cannot explain the continuation effect.

There is no clear consensus that could be made from results above but they clearly show that factors causing momentum effect are various. It still remains unresolved whether momentum effect can be regard as a firm-specific phenomenon or are there some common factors that could explain it. In general, the behavioralists tend to believe more on those firm-specific components, whereas risk-based models support the common factor explanations.

3.3.2 Risk-based explanations

Criticism the behavioral models face is increasing as the lacks of behavioral models have become better known, and the development of asset pricing models has gone further. These risk-based explanations defend the market efficiency and suggest that abnormal profits of trading strategies can be captured by asset pricing models or model misspecification, and that they are not at least completely result of investors' irrational behavior. The results gained when the CAPM-model is used are naturally challenged after the notification of all the lacks the model has. Thus, the results gained by using the FF three-factor model should be considered as more significant.

[6] See for example Rouwenhorst (1999), who reports that based on international data past winners outperform past losers in every size decile.

3.3.2.1 Contrarian strategy

Chan (1988) was one of the firsts suggesting that the abnormal returns earned with the contrarian strategy are just a normal compensation for the risk related to the strategy. He states, that the abnormal returns to contrarian strategy are very sensitive to the model and estimation methods used. When using CAPM-model, and an empirical method that is free of the problems caused by risk changes, they find that the abnormal returns to contrarian strategy become very small, and are probably economically insignificant. Further, they show that because losers' betas increase after a period of abnormal loss, and the winners' betas decrease after a period of abnormal gains, the betas estimated from the past should not be used. Also DeBondt and Thaler (1987) find that abnormal returns associated with contrarian strategies disappear once betas are allowed to vary over time. Because the risk of the strategy is not consequently constant over time, the estimation of abnormal returns to contrarian strategy can therefore be sensitive to how risks are estimated.

Fama and French (1996) use their three-factor model (equation 4) in order to explain the results of DeBondt and Thaler (1985). They find that the long-term return reversals can be captured by the model. When portfolios are formed using returns from 60 to 13 months prior to portfolio formation, the reversal of long-term returns for the period 1939–1993 can be explained by the three-factor model. The model works, because stocks with low long-term past returns (losers) tend to have positive *SMB* and *HML* slopes. That means loser stocks are behaving like small distressed stocks and the model predicts that the long-term past losers will have higher average returns. So, this evidence claims that contrarian strategy (based on long term past returns) is not a proof of market inefficiency, and accordingly not a means to earn some excess returns without taking some extra risk. (Fama & French 1996) However, Antoniou et al. (2006) use the three-factor model to explain short-term contrarian profits in London Exchange, and find that it can explain abnormal profits only partly.

Microstructure biases

Although contrarian strategies are, according to Conrad and Kaul (1998) among many others, profitable at the weekly horizon in the period of 1962–1989, recent research shows that the profitability of short-term strategies may be spurious because it is generated by market microstructure biases, for example, bid-ask bounce and inventory effects. The transactions on stock exchanges occur at bid or ask prices, thus the recorded prices contain a measurement error to the extent of the bid-ask spread. Since the prices fluctuate between bid and ask prices, the security returns measured over adjacent intervals will exhibit negative serial correlation. (Conrad, Gultekin, and Kaul 1997)

Conrad, Gultekin, and Kaul (1997) show, using bid returns (which do not contain bid-ask bounce) for NASDAQ stocks, that a major part of short-term price reversals can be explained by bid-ask errors in transaction prices which lead to negative serial covariance in individual security returns. Though, only half of the return reversals in NYSE/AMEX stocks can be explained by bid-ask bounce. (Conrad, Gultekin and Kaul 1997) Fama (1991) point out also, that the short-term return reversal evidence of Jegadeesh (1990), Lehman (1990), and Lo and McKinlay (1990) may be due to CRSP data errors, at least to some extent.

Loughran and Ritter (1996) point out that it should be remembered that when portfolios are formed on a single variable such as past performance, price or size, the combined effects of other correlated variables that are present, overstate the effect of single variable. So, it is very difficult to say how big a part of the contrarian profits are due to risk-bearing and how much to overreaction. (Loughran and Ritter 1996) Also Dissanaike (1994) points out, that estimates of portfolio performance are highly sensitive to the methods used to compute both the formation period and test period returns.

However, it can be concluded that the results of risk-based explanations for contrarian abnormal profits should not be so controversial because of the ability of FF three-factor model to explain them. Of course, the doubts whether three-factor model is sufficient descriptor of reality can cause some arguments about the origins of contrarian strategy. However, the relation of contrarian profits to size and January anomaly additional to evidence from the FF three-factor model can be interpreted as a strong evidence in favor of market efficiency and dooming evidence against the overreaction hypotheses and other market inefficiency-based explanations.

3.3.2.2 Momentum strategy

The FF 3-factor model has been used in order to explain also the abnormal returns generated by momentum strategy. However, unlike with contrarian profits, the momentum effect cannot be explained by the model. Fama and French (1996) find that the exposure patterns of losers versus winners are the same whether past performance is defined as short- or long-term. That means, relative to short-term winners short-term losers load on average more on *SMB* as well as on *HML*, and the same pattern is observed for long-term losers relative to long-term winners. The three-factor model predicts reversal for the post-formation returns of short-term losers and winners, and thus misses the observed continuation. In fact, Fama and French (1996) report that the abnormal momentum returns increase marginally after adjusting for risk under the CAPM-model and the FF three-factor model. Similar findings about increasing risk-adjusted returns show Jegadeesh and Titman (1993 and 2002). Jegadeesh and Titman (1993) show, that beta of the portfolio of past losers is higher than that of past winners. Thus, as the CAPM- or three-factor model is used there seems to be no reward for risk related to momentum profits.

Even though the empirical evidence stating that abnormal momentum profits cannot be explained by existing pricing models and are not a compensation for bigger risk, the recent literature has concentrated more and more on examining risk-based explanations. One of the first and most important studies stating that momentum really can be an independent risk factor, and thus the profits can be a compensation for bigger risk, is presented by Carhart (1997). He uses the momentum as a factor in order to investigate performance of mutual funds.[7] He examines the affect of momentum anomaly as an explainer of returns and equilibrium by constructing a 4-factor model using Fama and French's (1993) three-factor model plus an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly. This 4-factor model is consistent with a model of market equilibrium with four risk factors.
When this four-factor model is used to evaluate abnormal returns, it can be written as

[7] For further studies about relations between momentum strategies and mutual fund performance, see: Grinblatt, Titman and Wermers (1995).

$$r_{it} = \alpha_{iT} + b_{iT} RMRF + s_{iT} SMB_i + h_{iT} HML + p_{iT} PR1YR_t + e_{it} \qquad (11)$$

where r_{it} is the return on portfolio in excess of the one-month T-bill return; *RMRF* is the excess return on a value-weighted aggregate market proxy; and *SMB, HML*, and *PR1YR* are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. The intercept e_{it} equals the error term. The study shows that the 4-factor model can explain considerable variation in returns. The factors' correlations with each other and market proxy are very low which means that the 4-factor model can explain sizeable time-series variation. The high mean returns on *SMB, HML* and *PRI1YR* can mean that these three factors could account for much cross-sectional variation in the mean return on stock portfolios. Carhart's results show that 4-factor model remarkably improves on the average pricing errors of the CAPM- and the 3-factor model. The errors of the FF 3-factor model are strongly negative for last year's loser stock portfolio and strongly positive for last year's winner stock portfolios, and so adding a momentum factor this error gets noticeably lower. So, this study strongly states that momentum factor really is a measure of risk because adding it to the FF three-factor model substantially lowers the pricing errors, but it still remains unsolved what is the interpretation of this risk factor. (Carhart 1997)

The main concern is, what could be the risk related to momentum effect, if it really is a risk factor like Carhart (1997) evidence shows. When *SML* and *HML* factors are concerned the risk interpretations are clearer. Like Vishny and Schleifer (1997) state, if data regularity, momentum, does not have a sufficient risk component then it is too early to assume that anomaly is maturing to a factor. As Grundy and Martin (2001) report, the risk-adjusted returns associated with momentum investing do not imply an arbitrage opportunity, because the hedged total return momentum strategy lost money in 261 of 828 months. Even though the transactions costs may explain the persistence of a 1.3% per month anomaly, they do not explain the equilibrium underlying that anomaly. Assuming that the anomaly endures, then, it will enter the lexicon of finance as a 'factor', whose economics are as well understood as the *SMB* and *HML* factors: if it remains a fact, it becomes a factor.

Cross-sectional variations

Conrad and Kaul (1998) examine the causes of momentum profits by decomposing them according to the model of Lo and McKinlay (1990), equation (10). Their results show that actual trading strategies implemented based on past performance contain a cross-sectional component that would arise even if stock prices are completely unpredictable and follow random walk. They suggest that higher returns of winners in the holding period represent their unconditional expected rates of return, and thus predict that the returns of the momentum portfolio will be positive on average in any postranking period. They find that the cross-sectional variation across stocks' expected returns is the main source of momentum (last term in equation 10) relative to time-series properties of stock returns. This is contrary to both market efficiency and behavioral explanations which both presume that momentum profits derive from the time-series predictability of stock returns. According to Conrad and Kaul the momentum profits can be entirely seen as pure compensation for risk.

It is important to note, however, that their decomposition of trading profits is based on the assumption of mean stationary of the returns of individual securities during the period in which the strategies are implemented. Also, the mean returns are estimated for a wide cross-section of firms with a finite set of time series observations. This will result in an exaggeration of the importance of the cross-sectional variation in mean returns. (Conrad and Kaul 1998)

However, when examining the postholding returns, Jegadeesh and Titman (2001) find that portfolio performance in the 13 to 60 months following the portfolio formation is negative and this evidence clearly rejects the hypotheses of Conrad and Kaul (1998). Moreover, Jegadeesh and Titman (2002) show that the main results in Conrad and Kaul's study (1998) are largely driven by small sample biases in their experiments and estimation errors in the estimation of expected return variables. Their bootstrap experiment is a subject to the identical measurement error problem as their original results. Even though the cross-sectional variation in returns can, in theory, account for momentum profits, Jegadeesh and Titman (2002) conclude that its contribution is likely to be very small in practice. They show, that the cross-sectional variation in unconditional expected returns is small relative to the variation in realized returns and a stock's realized return over any six-months period provides very little information about the stock's unconditional expected return. (Jegadeesh and Titman 2002) Also, Grundy and Martin (2001) find strong evidence against findings of Conrad and Kaul (1998).

Moreover, Jegadeesh and Titman (2002) point out, that given the difficulties associated with obtaining an accurate estimate of the cross-sectional variance of expected returns it is probably impossible to directly measure the different components of momentum profits based on the widely used decomposition of profits given by equation (10). Thus, it could be better to directly investigate how big a part of momentum returns is due to cross-sectional differences in expected returns. That is done by using different kind of asset pricing models, though thus far results are not very striking. (Jegadeesh and Titman 2002)

Conditional asset pricing framework

The FF three-factor model cannot capture the momentum effect, because it predicts that short-term winners and long-term winners have the same exposure to risk factors, as well as short-term losers and long-term losers have similar exposures among themselves. The results mentioned above are strongly changed when the assumption that prices of risks and degrees of risks *do not* stay constant through time, is made. Wu (2002) claim that one potential reason that the FF tests fail to accommodate short-term momentum may be that assets' exposures to the *SMB* and *HML* factors are indeed time-varying and that time-variation characteristics of different assets may play a major role in asset pricing. He uses the conditional version of the FF three-factor asset pricing model, which can be written as:

$$r_t^{wml} = \alpha + M_{t-1}\gamma_m + M_{t-1}\gamma_s r_t^{smb} + M_{t-1}\gamma_h r_t^{hml}, \qquad (12)$$

where r_t^{wml} is the return for winner minus loser portfolio, *M* is a vector of macroeconomic variables, and γ_m, γ_s and γ_k capture the linear dependency of the macroeconomic variables to the risk exposures. According to the study the parameters γ for the macroeconomic sensitivities are statistically significant, and thus there is evidence supporting the conditional exposure approach.

The evidence that risk patterns between return momentum and reversal are not similar in a conditional framework is strong. Tests of cross-correlation of risks between portfolios show evidence of that. Exposures to the two mimicking portfolio factors for short- and long-term pairs exhibit a clear asymmetry: For the short-term winners and losers, the *SMB* risks as well as the *HML* are significantly negatively cross-correlated (correlation = -0.22 and –0.47, respectively). For long-term winners and losers these risks are significantly positively cross-correlated (correlation = 0.30 and 0.46 respectively). Thus, the results show that the different time-variations in the *SMB* and *HML* risks are empirical fact which clearly distinguishes the short-term winners/loser from the long-term winners/losers. But still, the conditional regression model fails to price assets correctly. Wu uses two other test methods, which can be seen as alternative conditional analogues to the static GRS multivariate test, and results indicate that conditioning information does help the FF model to capture the cross-sectional patterns of return continuation as well as return reversal. (Wu 2002)

Macroeconomic risk and business cycle variation

Fama (1991) suggests that search for links between time-varying expected returns and business conditions should be deepened in order to get more information about unsolved events in the asset markets. The research in that area is increasing, also when momentum effect is concerned. However, results are still very controversial.

Conditional forecasting model is used by Chordia and Shivakumar (2002) to investigate the time variation in risk premium on momentum profits. In the model historical momentum profits are projected onto lagged values of the following macroeconomic instruments; value-weighted market dividend yield, default spread, term spread, and yield on three-month T-bills. After estimating the regression over the prior 60 months, the projection gives rise to a one-period out-of sample forecast, which is used to explain momentum in current month. They find that these predicted profits are positive and can explain the momentum profits. Thus, momentum profits can be explained by macroeconomic variables that are related to business cycle. The evidence is consistent with time-varying expected returns being plausible explanation for momentum effect. Accordingly, profitability of momentum strategies represents compensation for bearing time-varying risk and, hence, is not inconsistent with rational pricing theories. The predictability could be traced to either time-varying risk premia, or time-varying asset pricing misspecification, or both. (Chordia and Shivakumar 2002)

However, these results have faced a lot of critics. Among others, Cooper et al. (2004), Kang and Li (2004), and Griffin et al. (2003) show that key results of Chordia and Shivakumar (2002) are not robust to the skipping of one-month between portfolio formation and investing period, and to removing highly illiquid and high-trading-cost stocks.

Support for risk-based models being able to explain momentum and relation of momentum profits to business cycles is presented further by Avramov and Chordia (2006). The results show that when model mispricing (alpha) is allowed to vary with business-cycle variables in the first-pass regression, then this variation captures the impact of momentum on returns. This in itself does not suggest that momentum is explained within a rational asset pricing model or that momentum represents reward for risk. However, the study further suggests that there may exist an undiscovered risk factor related to the business cycles that may capture the impact of momentum on the cross-section of individual stock returns. (Avramov and Chordia 2006)

The evidence that momentum profits also in Europe can be explained by business cycle patterns is showed by Antoniou et al. (2007) who use the predictive regression framework of Chordia and Shivakumar (2002) and the conditional asset pricing model of Avramov and Chordia (2006) to investigate that. The results when using the predictive regression framework of Chordia and Shivakumar (2002) show that momentum profits can be explained by the business cycle for the UK, but not for Germany or France. The conditional asset pricing model of Avramov and Chordia (2006) allows, on the other hand, for both risk and expected return to vary with conditioning information. The results indicate that the momentum profits in Europe are largely attributable to asset misspricing that systematically varies with global business conditions. That is consistent with findings of Avramov and Chordia (2006) and suggests that there might be an unidentified risk factor related to business cycles that captures the momentum in stock prices. (Antoniou et al. 2007)

Griffin et al. (2003) test a widely used unconditional method introduced by Chen et al. (1986) to investigate whether momentum profits around the world can be explained by macroeconomic factors of the model. They construct four of the factors introduced by Chen et al. (1986) for each country, namely, unexpected inflation (UI), changes in expected inflation (DEI), term spread (UTS) and changes in industrial production (MT). If momentum profits are driven by macroeconomic risk, profits should exhibit significant sensitivity to these factors. In order to examine the sensitivity they fit the regression where they use these factors for each country. Estimated profits are gained by similar equation.

If Chen et al. (1986) factors suffice to explain the momentum profits, the difference between actual momentum profits and those estimated by the model should equal to zero. Results of Griffin et al. (2003) show, however, that the difference between actual and estimated returns is significant in six countries, and that the factors are not able to explain momentum profits. Model is not able to capture the time-series variation in momentum profits. 8 out of 51 factor sensitivity estimates are statistically significant at the 5% confidence level. The average adjusted R^2 over all countries is however only 0.012%. That is very weak, also compared to Fama and French (1996) results, which state that when their three factor model is used to explain the variation in winner and loser portfolios, the R^2 values are 0.75 and 0.86, respectively. (Griffin et al. 2003)

The ability of macroeconomic risk to explain momentum profits can optionally be analyzed by investigating the profits of momentum portfolios during different economic states. If strategy is risky, it should underperform at least in some states of the world (states, where investors' marginal utility is high). If momentum strategies do poorly during bad economic states (for example during low GDP growth), and vice versa, there is evidence in favour of the ability of macroeconomic risk to explain momentum profits. Griffin et al. (2003) use seasonally adjusted real GDP as an indicator of economic state. Their results show that in 17 of the 22 markets momentum profits are positive during negative periods of GDP growth. For developed countries (excluding the US) the momentum profits are statistically significant 0.59% during negative growth GDP months as compared to 0.74% during positive growth months. This does not confirm the existence of macroeconomic risk.

The results of Chordia and Shivakumar (2002) however, show totally opposite, suggesting momentum profits of 0.53% during expansion and –0.72 during recession in the United States. This difference compared to results of Griffin et al. (2003) might be a result of a fact that Chordia and Shivakumar (2002) do not include the month between portfolio formation and holding periods.

However, as can be seen, the empirical results of risk-based explanations are very controversial and mixed, and there is no straight conclusion that could be drawn from results presented here, or those proposed in the literature in general. It is clear however, that traditional unconditional asset pricing models are not able to explain momentum profits, and the conclusion they suggest is that there is no extra risk related to momentum strategy. Empirical results show, that conditional pricing models with time-varying risk premium could be able to give some kind of risk-based explanation for the existence of momentum effect. However, conditional models require more parameters which make their explanations less reliable and more controversial. Yet there does not exist a conditional asset pricing model that is proved to be valid and able to correct the lacks of traditional unconditional pricing models. Whether the causes of momentum should still be searched from macroeconomic factors and states of the economy, is also controversial. Thus far, however, results of macroeconomic factors are very mixed.

4 CONCLUSIONS

The aim of this paper is to investigate whether two opposite trading strategies, namely momentum and contrarian strategies, are able to produce excess returns, and to examine the different explanations given for their profitability. Momentum investment strategy implies buying stocks that have gained bigger returns in the past and selling those that have performed worse. Contrarian strategy, contrary, implies buying past losers and selling stocks that have performed better in the past. In this study different models explaining the profitability of momentum and contrarian strategies are divided to those of behaviorals, and to those that are risk-based and defending market efficiency.

The evidence shown in literature and in this paper is clear, momentum and contrarian strategies are able to beat the market. For momentum strategy the evidence seems to be stronger and less controversial. Whereas, the results of profitability of contrarian strategy are more sensitive to different methods and sample periods used in investigations. However, both of these strategies are profitable around the world, so at least data snooping biases are out of question. These findings of profitability of momentum and contrarian strategies are closely related to weak-form market efficiency, because they could mean that future stock prices may be predicted from past return data. Thus, research in order to explain real causes behind the profits is vigorous, and very controversial.

Basically there can be seen two different scholars that try to explain these results, namely behavioralists and those, who defend the market efficiency and rational pricing. Among both of these the number of models and theories in order to explain abnormal momentum and contrarian profits is huge. When contrarian strategy is concerned, the market-efficiency seems to be less challenged than with the momentum effect. Namely, the three-factor asset pricing model of Fama and French (1993) is able to capture the contrarian effect, and thus, abnormal profits generated by the contrarian strategy can be seen as a compensation for a bigger risk.

However, when momentum effect is concerned, there is no asset pricing model that could capture it. Given the joint hypotheses problem, it is impossible to tell whether this anomaly is a result of miss-specified asset pricing models or market inefficiency. (Fama 1991) Macroeconomic factors and conditional asset pricing models have been actively tested in order to capture the momentum effect. There are promising results, but still they all are very controversial. The conditional approach especially could be seen as worth of further studies. It is notable, however, that more complex the models get, more controversial and vulnerable their results will be. Moreover, the role of analysts and institutional traders should be taken into account more carefully. It is also remarkable, that even though evidence of profitability of medium-term momentum strategies is well-known and actively used, for example by institutional traders, it still seems to be able to generate excess returns. Returns from momentum strategies rather seem to be increasing instead of decreasing. That makes the puzzle even stronger.

Behavioralists strongly believe there is a connection between momentum and contrarian returns, underreaction and overreaction, which can be explained by market inefficiencies and investors' behavior. The need for more specific and predictive models, testable hypotheses, and out-of sample tests are required before their theories can replace the efficient market hypotheses, and they can be considered as tenable explanations for existing anomalies, among those momentum and return reversal. Even if momentum was a result of irrational behavior of investors, that is very difficult to prove adequately enough.

The evidence of momentum effect as an independent risk factor shown by Carhart (1997) is also remarkable. The main issue there is, however, how the risk related to momentum could be explained. It remains to be seen, whether momentum becomes an independent risk factor, in addition to those of Fama and French three-factor model. Thus far, however, the puzzle remains unresolved.

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