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DOES THE INCREASED TRADING VOLUME CATCH INVESTORS ATTENTION SUPPORTING 52-WEEK HIGH MOMENTUM PROFITS?

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ABSTRACT

The purpose of this study is to find out whether the 52-week high momentum strategy (buying recent winners and selling recent losers) is profitable in the European stock markets. In this particular momentum strategy stocks are ranked to winner and loser portfolios exploiting their 52-week high values. The other focus is to examine how trading volume affects to the strategy profits. In addition, the possible influence of the latest financial crisis has been reviewed. The profitable strategy would impugn the market efficiency.

The daily returns of stocks included to the STOXX Europe Total Market Index as well the index returns are foundation for the data. Daily trading volumes of the same stocks are under examination. The sample period, starting at 2001 and running at the end of the year 2010, provides a unique research frame including the latest financial crisis. The Student's t-test is used to find out the statistical significance of returns.

The main findings are following. Weak, but highly statistically significant profits were found in European stock markets executing the 52-week high momentum strategy. The profits strengthened notably when trading volumes were taken into account. The 52-week high momentum was strongest among low-volume stocks. During the financial crisis the profits increased and when trading volume was observed the profits were considerable. This time the 52-week high momentum was strongest among high volume stocks. Also cyclical patterns of 52-week high momentum profits were found. The result suggests that investors suffer behavioral biases, especially of availability bias more when the uncertainty in markets is pronounced.

KEYWORDS: Momentum, 52-week high-value, behavioral biases

1. INTRODUCTION

One widely discussed but still topical issue of finance is market efficiency. The modern finance theory and its applications are based on the idea of efficient capital markets, where security prices reflects all available information all the time (see Fama 1970). Another school, behavioral finance, has appeared since 1980s to alongside with modern or rational finance theory. Behavioral finance does not focus to prove market inefficiency; more alike market inefficiency is corollary of humanity: because investors are not rational, either market cannot be efficient. Nowadays the question is, more alike, are the markets enough efficient that modern finance theory is still suitable.

Two of the most powerful and widely studied phenomenon or trading strategies, undermining the theory of market efficiency, are anomalies and technical analysis. Momentum can be seen as a simply application of technical analysis. Sometimes it is also situated in anomaly context, because of its anomalous profits. However, it shows that there are predictable patterns in stock returns and markets are not fully efficient.

Momentum strategy, which is based on stocks' past performance, has been profitable as long as the phenomenon has been noted in academic literature. The winner (loser) momentum portfolios consist of stocks which have performed well (poorly) in the time period less than one year. These portfolios seem to generate excess returns for next three to twelve months (see Jegadeesh 1990, Jegadeesh & Titman 1993). Few researchers have argument that trading costs eliminates momentum profits, but also reversed findings have reported (see Lesmond, Schill & Zhou 2004; Korajczyk & Sadka 2004; Xiafei, Brooks & Miffre 2009).

GH (hereafter GH) found that the 52 week high-value of stock largely explain momentum profits. In that strategy, portfolio rankings base to the 52 week high-value of a stock, when price level (instead of price) gets more weighting. GH reported that the 52 week high-value based momentum (hereafter 52WHM) strategy proof more significant profits corresponding to original momentum strategy. They did not found similar phenomenon against the 52-week low-value (52WL). Since GH many studies has supported the significance of 52WHM in different contexts (see for example Liu, Liu & Ma 2009). Regardless, the interaction between volume and 52WHM is unknown area. There are not any studies which have investigated whether trading volume has significant impact particularly to 52WHM. This study will examine the profitably of 52WHM strategy and its connection to trading volume.

Since Fama and French (1996) noticed that their three factor model cannot explain momentum profits, even then it seems to explain many other anomalies, there have been difficulties to find rational and risk-based explanations for momentum. Instead, behavioral finance offers plausible explanations of which both underreaction and overraction are the most salient ones (see Barberis, Shleifer & Vishny 1998, Daniel, Hirshleifer & Subrahmanyam 1998 and Hong & Stein 1999). That is, investors seems to underreact to new information causing return continuation (momentum) and then overcorrection for their previous mispricing leads to long-term reversals (Barberis, Shleifer & Vishny 1998, Hong & Stein 1999). For one's part, Daniel, Hirsleifer & Subrahmanyam (1998) represent that momentum exists as a result of overreaction to prior information and long term reversals as a correction of prior action. In the case of the 52WHM, anchoring bias tend to be more plausible explanation. GH represented that investors use the 52WH-value as their reference and anchoring point. This is contrary to prior studies, which suggested a purchase price as a reference point (see for example Odean 1998).

1.1 Research problem and hypothesis development

As GH pointed out the information and price levels have a significant impact to the 52WHM. GH suggested that investors use the 52WH-value as their reference point against which they evaluate the potential impact of news. When investors receive new information they evaluate and compare them to the reference point. GH also suggested that the stocks which are near their 52WH-value have recently received good information. When stock price goes near to its 52WH or achieves new 52WH-price, it works as a signal for investors that a firm will perform well. Demand of stock increases and stock price rises even more. Climbed demand can also be seen as strengthen trading volume. On the other hand when unfavorable news pushes a stock price far from its 52WH, traders are unwilling to sell the stock in low price and that can be seen as low trading volume. Eventually the information prevails and trading volume increases, when investors begin to sell these stocks. Similar findigs have been reported by Shefrin and Statman 1985, Odean 1998 as well Keloharju 2000. They found that investors sell winners too early (i.e they sell when the prices are getting higher) but they do not sell when price decreases, more alike they hold losers too long (this phenomenon is named as a disposition effect).

Huddart, Lang and Yetman (2009) focused to investigate trading volume around the 52WH-value and found that volume were strikingly higher when stock prices overtake either the upper or lower limit of its past trading range. The longer is the time when stock price last time achieved the price extreme, the more pronounced the volume is. That is, they noticed higher volume when stock price cross its 52WH-value but also when it crosses the 52WL-value. These volume peaks can be seen as positive short term profits. They also pointed out that their result refers that when stock moves outside a prior trading range it is associated not only with predictable volume patterns but also with predictably positive returns in future. According to this, Brown Crocker and Foerster (2009) reported higher trading volume among both loser and winner-stocks.

Besides anchoring there is another essentially bias of the 52WHM, especially when the volume is also in the focus. This availability bias means that investors buy stocks which come easily to their minds, because they have been in view (for example in news) (see Bachmann and Hens 2010: 307). Barber and Odean (2008) found that individual investors display attention-driven buying behavior. They are net buyers of high volume days (following both extremely negative and positive one day returns) and when stocks are in the news. They also noted that an investor is less likely to purchase a stock that is out of the limelight. As Huddart et al. (2009) pointed out, stocks that cross their 52WHs or Ls are widely reported, and business publications such that Wall Street Journal, highlight those stocks and therefore they are likely to attract investor's attention. In addition, the financial press often defaults to a 52-week window for plotting a stock's price path.

The purpose of this study is to find out, whether the 52WHM strategy is profitable in the European stock markets. This study is the first investigating whether trading volume has a significant impact to the 52WHM, as it does have to plain momentum strategy (see Lee & Swaminathan 2000, Brown et al. 2009). This study will also expand the knowledge of availability bias. Because of difficulties to discover the behavioral biases from price data, these irrationalities are slightly researched.

The hypotheses are below:

H_1:

$$H_0 = 52WHM\ portfolios\ do\ not\ outperform\ the\ market$$
$$H_1 = 52WHM\ portfolios\ outperform\ the\ market$$

H_2:

$$H_0$$
$$= Returns\ of trading\ volume\ based\ 52WHM$$
$$- portfolios\ do\ not\ differ\ from\ returns\ of\ pure\ momentum\ portfolios$$

$$H_1$$
$$= Returns\ of\ trading\ volume\ based\ 52WHM$$
$$- portfolios\ differfrom\ returns\ of\ pure\ momentum\ portfolios$$

If the first H_0 can be rejected the 52WHM exists in European stock market. If the second H_0 can be rejected there is interaction between trading volume and 52WHM profits.

1.2 Path of the study

After introducing the subject matter in this chapter, the rest of the study is organized in the following way. It is discussed salient feature of modern finance theory, market efficiency in chapter two. According to market efficiency, behavioral finance is covered in chapter three, focusing to market anomalies, behavioral biases and technical analyses. Chapter four focused to price continuations, including an introduction to both short and long term price reversals. Also explanations for momentum-phenomenon are discussed in that chapter. Chapter five and six contain the empirical part of this thesis in following order: chapter five involves the data and methodology, when empirical findings of this study are reported in chapter six. Finally, chapter seven concludes the thesis.

1.3 Previous studies

Advanced knowledge of momentum has subdivided the phenomenon into several elements. The most essential studies of this thesis are reported next.

Fama and French (1988) confirmed that the variation of 3–5-year stock returns can be predicted by using negative autocorrelation from past returns. The coefficient of determination ranged between 25 (large firms) and 45 percent (small firms). At the same time, Lo and MacKinlay (1988) attested that weekly and monthly returns of extensive stock index are positively autocorrelated. These results are not straight rejection of efficient market hypothesis. Instead, it implies that random walk (i.e. stock prices should follow random motion, see for example Fama 1965) hypothesis is not plausible without adjustments.

Momentum is known as an effect where the stocks which have performed well in their recently past (3-12 months) will also perform well during the next 3-12 months. The exposure of momentum-phenomenom has been made by Jegadeesh (1990) and Jegadeesh and Titman (1993) (hereafter JT). Jegadeesh (1990) presented that stock returns are positively autocorrelated over the periods which are shorter than 3–5 years, actually less than a year. JT showed that superior returns can be gained by buying 10 % of the best performed stocks of the last six month period and selling the bottom 10 % and holding those stocks for the next six month. This simply self-financing strategy will provide monthly 1 % returns. There are no studies which have completely proved that momentum phenomenon does not occur in the market.

Prior to momentum-anomaly has existed, similar manner has been found. Long term reversal from three to five years is documented by De Bondt and Thaler (1985). In this contrarian strategy the portfolio is consisted of stocks which have performed poorly in last 3–5 years. De Bondt and Thaler (1985) reported that when this looser portfolio will be hold next 3–5 years it will perform better than the portfolio which consist of past winners. Therefore contrarian strategy works opposite way.

Moskowitz and Grinblatt (1999) investigated industrial momentum. They observed robust profits when executed industry momentum strategies (i.e. buying stocks from past winning industries and selling stocks from past losing industries), even after controlling for size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns and potential microstructure influences. They pointed out that win-

ner and looser stocks tend to be from the same industry. Moreover, industry based momentum strategies seem to be more profitable and practicable. In addition, industry momentum appeared to remain profitable even with the largest and most liquid stocks. Along with the 52WHM-portfolios GH formed JT and Moskowitz and Griblatt (1999) styled portfolios as a reference portfolios. It was found out that the nearness to the 52-WH is a better predictor of future returns than simply past returns either industry formed returns.

Statman, Thorley and Vorkink (2006) as well as Griffin, Nardari and Stulz (2007) examined the relation between stocks past returns and trading volume. Statman et al. (2006) found that past returns can predict volume for next few months. Griffin et al. (2007) investigated the influence of past returns to trading activity across 46 countries. They found significant positive correlation between positive returns and volume. However, they suggest that return-volume-relation might be asymmetric, negative returns reduces volume more than positive returns increases it. Volume-return-relation tends to be more pronounced in developing countries than in high income countries. Trading volume related momentum studies are introduced in chapter four.

2. EFFICIENT MARKETS

The principal ideas of stock markets are introduced in this chapter. Investors value stock prices using risk and expected return. The stocks with best risk-return-combination will end up in the rational investors' portfolios. When the stock markets are efficient, stock prices are on their fundamental values and reflect the expected rate of return of the stock. The efficient capital markets are also efficient by allocation viewpoint – the funds find their way where they are most needed.

2.1 The efficient market hypothesis

One of the most important and famous definition of efficient markets is made by Fama (1970): markets are efficient when stock prices reflect all available information all the time. That means quick and right reaction to new information. When stock prices reflect all available information there should not be any free lunches or in other words arbitrage opportunities in the market. If there was arbitrage opportunity, someone would pick it up and it would vanish immediately.

The efficient market hypothesis (EMH) bases on assumption of rational investor. There are three assumptions which lie behind that theory (Shleifer 2000: 2):

1. Investors are assumed to be rational and they value prices rationally.
2. If some investors are not rational their trades are random and therefore they cancelled each other actions.
3. Even if investors are irrational in similar ways, there are rational arbitrageurs who eliminate their influences to prices.

Valuing stock prices correctly means that investors value securities rationally for their fundamental values. That is, the net present values of stock's future cash flows are discounted using their risk characteristics (Shleifer 2000: 2). Following the three assumptions above, investors cannot affect stock prices in the financial markets. Even if investors do not value prices correctly there is always someone who eliminates this irrationality or lack of the information. For example if stocks price have been valued too low investors begin to buy that stock, because of the rise expectations, and the price is settled to its correct value.

Following Shleifer (2000: 5) the empirical predictions of the EMH can be divided into two broad categories.

1. When new information about the value of security hits the market, its price should react and incorporate this news both quickly and correctly.
2. There should be not just quick and accurate reaction to fundamental information but also non-reaction to non-information.

'Quickly' of the first part means that there are not possibilities to get abnormal returns after information issue. Investors should also on average react correctly to information. That means, the prices should not overreact or underreact to news announcement. (Shleifer 2000: 5.) Investors should also react to correct information – in the market should not exists reaction to irrelevant information.

In efficient market, investors who select their portfolios randomly should earn as much as those who try to select undervalued stocks to portfolios, when the risks are assumed to be the same. There is not possibility to get abnormal returns using technical analysis (take a benefit of stocks past performance) neither fundamental analysis (evaluating financial information of firms). (Malkiel 2003.) Everything depends of risk: the higher the risk is, the higher is the expected return and price.

2.2 The three form of efficiency

Market efficiency can be divided into three forms, weak, semi-strong and strong forms (Fama 1970).

The weak- form means that stock prices reflect all information of market trading data, such as the history of past performance, trading volume and short interest. In this context technical analysis is unprofitable. Past stock prices are publicly available and costless to obtain. If past performance included any information about stocks future performance, investors would have already processed and transferred it to prices. (Bodie, Kane, Marcus 2009: 348.)

Semistrong-form means that stock prices reflect all relevant public information of firms. In addition to past prices, fundamental data on the firm product line, quality of management, balance sheet composition, patents held, earnings forecast and accounting

practices are valued in stock prices. (Bodie et al. 2009: 348-349.) Fundamental analysis becomes worthless because all its information has already been preceded.

Finally the *strong-form* states that stock prices reflect all relevant information of firm. In this last and strict form, it is assumed that stock prices reflect also information which is available only for company insiders. Naturally corporate officers have inside information for profitable trading. (Bodie, et al. 2009: 349.) However, for the European stock markets, there are European Union directive, which order all the participant countries of European Union to enforce the abuse of insider information. (Summaries of EU legislation.)

In his later study Fama (1991) categorize the tests by which the fulfillment of forms can measured. The weak form of market efficiency can be tested by focusing on returns predictability. So called event studies can used to test semi-strong form. The strong form can test by focusing on private information and how one can benefit from insiders knowledge. Momentum effect relates to market efficiency through weak form. Momentum strategy basis on past performance and that should not include any information, when at least the weak form of market efficiency holds.

2.3 Random walk

There is another important thing of efficient market theory: a random walk. A random walk relate to weak form of market efficiency. This term means that stock price changes should be random and unpredictable, that is, prices follow random motion. (Bodie, et al. 2009: 345.) In other words, future path of the price levels should not be any more predictable than a path of the series of cumulative random numbers. In statistical terms the same is: successive price changes are independent, identically distributed random variables. Because the price changes have not memory, past prices cannot be used to predict future prices. The independence cannot be perfect; otherwise stock prices would reflect the price mechanism which is totally uncorrelated to real world economic and political events. (Fama 1965.) Anyhow, when stock prices follow random walk, serial correlation should not exist.

It is randomly flowing information which causes a random walk. The flow of information is unpredictable and that information is immediately transferred in stock prices. Tomorrow's price changes will reflect only tomorrow's news and will be independent

of today's price. Because the news is unpredictable and flows randomly, the stock prices change randomly, or in other words, follow random walk. (Malkiel 2003.)

2.4 Are the markets efficient?

Market efficiency is widely studied issue in financial literature and it is still open puzzle. Testing for efficient market began in early 1960s and during the next 20-year period the evidence indicated that the markets fill both weak and semi-strong forms. From the beginning of 1980s there began to appear studies against the market efficiency. That does not mean that market was more efficient in previous 20 years – more alike the evidence against the efficiency were difficult to get published. (Blake 2002: 397-398.) Nowadays the literature for efficient market hypothesis is focused to disprove many irrationalities reported by the theorists of behavioral finance.

One of his studies Fama (1965) focused to random walk and weak form of market efficiency. He examined if portfolio based, easy technical analyses would be profitable. He referred to transaction costs and pointed out, that stock prices are independent at least for all practical purposes. Transaction costs have been powerful argument to this day. Although different regularities are possibly to find, these trading strategies are not profitable when trading costs are taken into account. This is actually one view what theorists often means about market efficiency; prices do not reflect all the information all the time, but limits to arbitrage guarantee that one cannot still cash in on a situation (Fama 1991, Malkiel 2003).

Fama (1998) pointed out that long-term market anomalies (stock price deviations from their fundamental values) are sensitive to used methodology. He argued that anomalies tend to became marginal or disappear totally when different models or statistical approaches are used for measurement. He also noted that market efficiency can only be replaced by a better model of price formation, which has not yet appeared.

Malkiel (2003) represent that it is not possible to earn above-average returns without accepting above-average risks. He argued that market anomalies do not offer extraordinary risk adjusted returns. Firstly investments opportunities which seem to be free lunches actually involve different risks (sometimes it just has been hidden risk). Secondly he pointed out that many of predictable patterns have vanished after they had pub-

lished and analyzed in financial literature. And finally there are always the transaction costs.

3. INEFFICIENT MARKETS – BEHAVIORAL FINANCE

The previous paragraph introduce for what the modern finance is based. It is focused in this paragraph to examined critical holes in market efficiency. The prospect theory (Kahneman ja Tversky 1979) is included in this chapter, being one of the most important theories of behavioral finance. The prospect theory, including the idea of the reference point, is also important especially in 52WH-momentum context. Heuristic driven biases, for one, offer relevant explanations for momentum. Finally typical examples of market inefficiency, anomalies and technical analysis are discussed in this chapter.

Daniel, Hirshleifer and Teoh (2002) propose in their literature review that there are huge amount of empirical evidence which seems to prove that investors make systematic errors as well as psychological biases affect to market prices. They pointed out that stock prices do not follow a random walk more alike they are predictable. They also argued that mispricing causes misallocation of resources and inefficient risk sheering.

3.1 Behavioral finance

Shefrin (2002:4) divided behavioral finance in three themes.

- Heuristic driven bias
- Frame dependence
- Market inefficiency

It is meant by heuristic driven bias that investors are not able to process market data rationally; if anything, psychological biases affect their decision-making process. One example is the scheme of things that “well performed stocks will do that also in future". (Sefrin 2002: 4.) It also seems to be the truth that biases affects to stock prices (see for example Colval and Shumway 2005).

The frame dependence means that practitioners’ perceptions of risk and return are highly influenced by how decision problems are framed (Shefrin 2002:23-34). In the other words, investor’s opinions depends the situation. For example Thaler and Johnson (1991) found that especially investors risk taking-behavior depends of the description or frame of the decision problem. They also found that investors past performance affects their decision making process. Another quite different example is money illusion. Inves-

tors have even problems with discounting cash flows and using real rates instead of nominal rates. (Shefrin 2002:23-34.)

It is assumed that first and second theme causes market inefficiency. That is, the heuristic driven biases and framing effect influence market prices to deviate from fundamental value. (Shefrin 2002: 4.)

There are two types of investors in typical behavioral finance model; arbitrageurs and noise traders. Arbitrageurs are investors who try to work rationally whereas noise traders invest irrationally and behave as there would have been information. Noise traders based their decisions for irrational beliefs or sentiments that are not fully justified by news of fundamental information. But then, arose arbitrage opportunity is risky and limited for arbitrageurs, because investors tend to be risk-averse. For example, the noise traders invest to the stocks with rising price trend, strengthening the trend even more. Arbitrageurs should sell when the price is high, but there is fundamental risk, related unsureness of the highest price and right selling time. Noise traders can became overly optimistic about the rising stocks, when arbitrageurs cannot know how high the price could extend. (Park & Irwin 2007.) It seems to be the truth that rational investors cannot cancel all actions made by irrational traders when prices do not execute market efficiency. (Shleifer 2000:12).

3.2 Prospect theory

The Prospect theory is created by Kahneman and Tversky (1979). It is a theory about how humans work in situations where they have to decide between risk and return. It is one of the most important theories of behavioral finance and many later studies based on their findings. Kahneman and Tversky (1979) found that people underweight outcomes that are merely probable and they prefer outcomes which are obtain certainty (certainty effect). This causes risk aversion (in later literature often loss aversion). Risk aversion means that people do not value wins and losses equally. People are actually more sensitive for losses than for gains. Kahneman and Tversky (1979) found that the hurt after loss is actually twice as strong as the happiness after gain. Later on Thaler and Johnson (1991) pointed out that the degree of loss aversion depends of prior gains and losses.

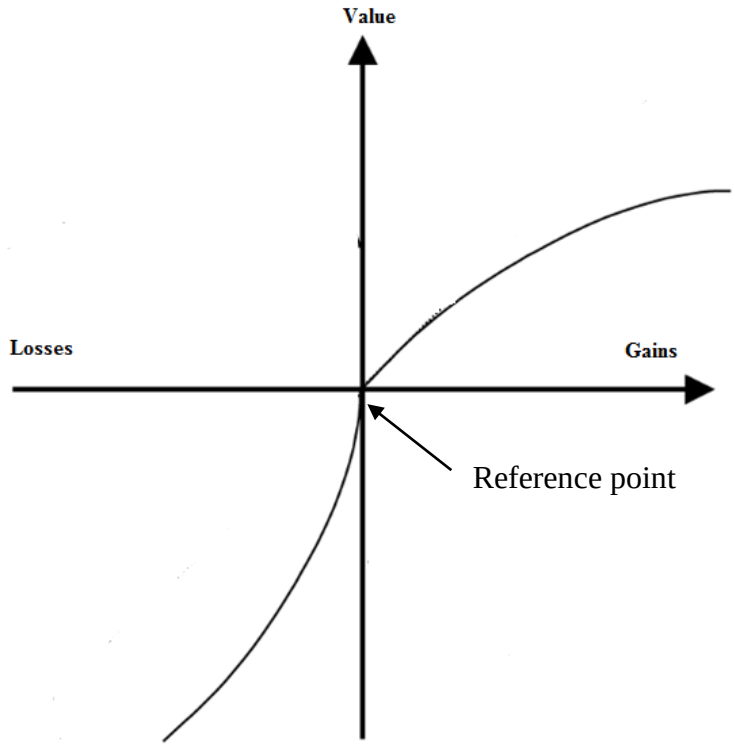

Figure 1. Value function (Kahneman & Tversky 1979).

Kahneman and Tversky (1979) represent S-shape value function to illustrate how people work under uncertainty. The function is value function instead of utility function (see Markowitz 1952) because people get utility of gains and losses in wealth, rather

than in absolute levels (Barberis & Huang 2001). There are several important things of Value function. The function is normally concave for gains and convex for losses. The function is generally steeper for losses than for gains. These two things illustrate that investors experience gains and losses differently and that they are normally risk averse.

Critical to this value function is the reference point. The reference point is the place where function is converted from negative to positive or in other words where losses changes to gains. If the reference point is purchase price, the gains and losses are determined by purchase price. That is, investors refer the current price to purchase price. When the current price is above the purchase price investor is in winning position. But then, when the current price decline below purchase price he is in losing position. In other words, the current price has to be above the reference point before investor feels to win. The price which becomes to be the reference point is individually (if often the purchase price) and it can also change during the investment period. (Kahneman & Tversky 1979.) The alternative reference point candidates are average purchase price, the last purchase price and the highest purchase price of the stock, documented by Odean (1998). This study follows GH and suggests the 52WH-price as investors' reference point.

3.3 Behavioral biases

It has been found that investors suffer several behavioral biases. This biased behavior is not inconsequential, because it affects to market prices. The common biases are discussed next.

Investors do not react to new information enough, more alike they anchor in old information. This is known as *anchoring and adjustment bias* as well *conservatism*. The good example is financial analyst's earnings forecasts. When the new information arrives, analysts do not revise their earnings estimates enough to reflect the new information – they underreact and anchor to old estimates. The scheme of things "that the positive earnings surprises tend to be followed by more positive earnings surprises" (and other way around in case of negative surprises) is typical even for financial analysts. Also investors tend to regard too conservatively to new information and do not update their knowledge. (Shefrin 2002:19-20.) This comes into conflict with the Fama's (1970) EMH definition, that stock markets reflect all available information all

the time. GH suggested that investors anchor tightly to stocks' 52WHs causing momentum profits.

Belief perseverance relates to conservatism and anchoring, meaning that people cling to their opinions too tightly and for too long. Thaler (2005: 15) mentioned two effects of belief perseverance. First people are reluctant to search for evidence that disclaim their beliefs. Even if they find such evidence they attach it unreasonable skepticism. Good example is Efficient Market Hypothesis. When people start out to believing it, they may continue to believe in it long after compelling evidence to the contrary has emerged.

Availability bias means that investors cannot base their decision for the most pertinent information (Thaler 2005: 15). When investors estimates probabilities and judge the attractiveness of alternatives, they favor the alternative that comes easily to their minds because they either have experienced it or it is easy to imagine (Bachmann and Hens 2010: 307). Barber and Odean (2008) found that individual investors display attention-driven buying behavior. They are net buyers of high volume days (following both extremely negative and positive one day returns) and when stocks are in the news. They also noted that whether the investors were a contrarian or trend follower, he is less likely to purchase a stock out of the limelight.

Representativeness means judgments based on stereotypes. Investors do not always think separately and critically different things – more alike their conclusions based on stereotypes. Following scheme of things is typical for humans: if all turn out to be heads, after five tosses of a fair coin, the next should be tail. Some humans even think that the probability has changed; now it is more probable to get tail than head. This is also known as a phenomenon named *gambler's fallacy*. (Shefrin 2002:14-18.) In financial markets investors use past prices for future predictor; for example they prefer stocks which have performed well recently (Chen, Kim, Nofsinger & Rui 2007) or execute momentum strategies.

When investors are *Overconfident* they naturally think to be better than others. Thaler (2005:12) have two points here. If investor have to set range for example some index (during the one year, say) they fail. Investors set systematically their highest guess too low and their lowest guess too high. Another point is that humans are poorly calibrated when estimating probabilities: events they consider to be certain occur only 80 percent of the time and events they think to be impossible occur approximately 20 percent of the time. Overconfidence can also be seen as reduced returns, increased risks and inefficient

portfolio selections (Gort & Wang 2010: 244). One consequence of overconfidence is too voluminous trading (Barber & Odean 2000). There is evidence that investors trading widely get lower returns corresponding to investors who follow buy and hold-strategy (see Barber & Odean 2000).

There is another bias which relates to overconfidence. Most of the humans display unrealistic rosy views of their abilities and prospects, in other words they are *optimism* and *think wishful*. Often mentioned example in this context is driving abilities. 90 percent of people think to be better car driver than average. (Thaler 2005: 13.) Then there is also *self-attribution bias* in which investors see successful outcomes as their own skills and unsuccessful outcomes as bad luck (Shefrin 2002: 101).

Regret is not only the pain of loss, it is also the pain associated with feeling responsible for the loss. That is, after loss you are angry for yourself of buying the particular stock. Regret affects to human's decision making: the person who suffer the regret strongly try to naturally avoid it. *Regret avoidance* can lead to stronger risk aversion and investor might start to work always the same approved way. (Shefrin 2002: 30-31.)

Self-control means naturally controlling emotions. Investors have problems to working rationally; they do not critically evaluate their preferences. One example is dividends. Dividends seem to label as income not capital. Investors choose to portfolio stocks that feature high dividend payouts and they feel quite comfort spending dividends. (Shefrin 2002: 30-31.)

One more item, more alike phenomenon than bias, is still discussed. Shefrin & Statman (1985) found that investors tend to sell winners too early and ride losers too long. In financial literature, this phenomenon, caused by investor's loss-aversion is known as *disposition effect.* Shefrin and Statman (1985) pointed out that tax consideration cannot alone explain the phenomenon. That is, investors sell stocks in the end of the year for tax benefit purposes. Thereafter for example Odean (1998) and Griblatt and Keloharju (2001) reported similar findings. The phenomenon occurs, because investors do not want to realize transaction before the share price has climbed above reference point. Therefore and because of difficulty of timing, they hold losing stocks in hope of future rise, but sell winning stocks.

In addition to empirical evidence discussed above, there are many other studies related to behavioral biases. Hirshleifer (2001) as well Daniel et al. (2002) proved in their liter-

ature review the salience of behavioral biases. In addition, for example Chen, Kim, Nofsinger and Rui (2007) found that investors of their sample made trading mistakes, because the stocks they sold would have outperformed the stocks they bought and they also held losers too long. Consequently, they suffer from a disposition effect and regret aversion. Their investors tend to be overconfident, that is, they trade too much and they are underdiversified. As mention above, their investors also suffer of representativeness bias. They also pointed out that more experienced investors, who tend to be more sophisticated, are as prone to behavioral biases as are inexperienced ones.

3.4 Anomalies

Anomalies are by definition, deviations from market efficiency and especially from information efficiency. In other words, stock prices deviate from their fundamental values in a degree that it can be find out empirically. In the efficient markets, anomalies should not exist, but regardless, there is huge amount of literature and empirical evidence proving price deviations. It has been reported abnormal risk-adjusted returns using several easy statistical tools (Bodie et al. 2009: 361). It can be argued that there are not different anomalies more alike one phenomenon. As later is discussed, size has a quite strong influence to many anomalies. However, different anomalies have own characteristics and it is logical present them as own groups. All market anomalies are not discussed, only the ones which are salient in the momentum context.

Contrast to, for example Malkiel's (2003) argument, there are anomalies which still exist in the market. Schwert (2002) pointed out that anomalies have vanished or at least attenuated after they have published and analyzed in financial literature, but this not seem to be the truth. In the efficient market viewpoint, it is even more serious, if those price deviations have not totally vanished after all this attention. One reason that anomalies still existence is the problems related to transactions and liquidity as well transaction costs. Other reason is information. Many of anomalies are based on easy measures and they are not dependent upon tricky information. But as mentioned earlier, investors have difficulties to process information. There is continuously lot of financial literature explaining anomalies by different risks. Unless CAPM beta or Fama and French's three factor model could not explain the underlying risk (see Fama & French 1996), there could always be some other risk factors which can explain the abnormalities.

Size and January

Banz (1981) found that during the long time period (1926-1975) smaller firms have earned higher risk adjusted returns than larger firms. The portfolio which contains the very least stocks, returned in average 8.86 % (annual returns) more than the largest stocks. The smaller-firm portfolio should be riskier, but Banz pointed out that risk cannot describe the difference.

There are several explanations for size effect. Roll (1981) pointed out that the lower liquidity of small firms causes their higher returns. Barry and Brown (1984) made another explanation and argue that this anomaly occurs because the available information of firm depends of size. Small firms received less attention from analysts and in financial papers. This lack of information is displayed as higher risk and higher returns.

Higher stock returns in January have also been reported. Gultekin and Gultekin (1983) reported high January returns in 17 different countries. Keim (1983) pointed out that more than 50 percent of January premium comes during the first trading week of the year, actually during the first trading days. The evidence both for and against to this anomaly occurs (see Sullivan, Timmermann & White 2001). Bodla and Jindal (2006) do not found high January returns neither in United States nor in India. Tonchev and Kim (2004) reported that occurrence of this anomaly is contingent on the country.

However, small firms-effect and January-effect relates strongly to each other. It actually can be seen as a one effect: small firms' stock performance during January. Most of the abnormal returns of small firms cumulate during January, but at the same time January-effect is the most powerful among small stocks. Keim (1983) found that abnormal returns during January explain about half of the size-effect. More recently Haug and Hirchey (2006) as well as Moller and Zilca (2008) focused to small-firms and reported two times higher profits in January than during the other months.

The most used explanation for January effect is tax loss selling hypothesis (Branch 1977). As it was mentioned with disposition effect investors sell losing stocks in the end of the year for tax benefit purposes. In the beginning of the next year they invest received funds back in the stock markets and prices tend to rise. (Kim 2006.)

Value and growth

Value measures are P/E-ratio, book-to-market ratio, sales, cash flows and dividends. The relationship between market value of share to measures above, specify the value or growth stock. Value stocks have low price relative to these measures, whereas growth stocks have higher relation. When preferring growth stocks, investors believe that a firm will experience expeditious growth to justify market prices. (Bodie et al. 2009:107). Expectations of growth stocks are not always realistic, more alike, they are overoptimistic. Value stocks have more moderate buyers in the market. In general, growth stocks are overvalued and value stocks are undervalued.

There is much evidence that value stocks generate excess returns over time, whereas growth stocks underperform them (see Fama and French 1992, Lakonishok, Shleifer and Vishny 1994). Many researchers have addressed to explain this asymmetry. Lakonishok et al. (1994) argued that these returns are not compensate for risk but occur of over- and underpricing of various stocks. Furthermore, La Porta, Lakonishok, Shleifer and Vishny (1997) attested that the earnings announcements of value stocks present mostly positive surprises. This indicates that market participants have systematically too pessimistic expectations for value stocks compared to growth stocks.

Dougas, Kim and Pantzalis (2002) proposed that stocks with high book-to-market ratios are exposed to high forecast errors and downward recommendations. This indicates that the expectations of growth stocks are not overoptimistic. Conrad, Cooper and Kaul (2003) presented that a large portion of measured abnormal returns of value and growth stocks are due to data snooping, which can occurs when given set of data is used more than once during the research process.

Post announcement drift

Ball and Brown (1968) were the first ones to detect an anomalous behavior after earnings announcement and reported that stock markets do not react immediately to new information. The phenomenon is known as a post -announcement drift (PAD) or PEAD when the focusing information is earnings. It has been found that after earnings announcement, the unexpected returns are higher with firms reporting positive earnings surprises corresponding to firms reporting negative surprises. Ryan and Taffler (2004) pointed out, that earnings announcements are the most important information for stock

markets. Therefore PEAD is one of the strongest arguments against the EMH: if investors do not react probably to the most relevant information, how the information efficiency could hold?

It has been paid a lot of attention to PEAD in finance and accounting literature. Bhushan (1994) found strong relation between firm size and PEAD returns. Small firms earned higher PEAD returns, because they are less liquid. It is more difficult to take advantage of mispricing when lower share price and volumes indicates also higher trading costs. Bernand and Thomas (1990) as well as Battalio and Mendenhall (2005) found different investors as an explanation for PEAD. The information process is linked to trade size. In other words, those initiating small investors appear to base their decisions to less advanced information, than those who initiate large investors. They found that smaller traders ignore earnings signals based on analysts' forecasts and instead they anchor in the old information and time series. Larger traders notices and processes analyst earnings forecasts along with other information. Some investors ignore or at least significantly underweight the implications of current earnings innovations for future earnings levels and they heighten PEAD.

Booth, Kallunki and Martikainen (1996) studied whether PEAD is different with non-smoothing and smoothing firms. They suggested that PAD is caused by firms with non-smooth income stream because their earnings are more surprising. More recently Mendhal (2004) as well as Garfinkel and Sokobin (2005) findings support the existence of PEAD. Mendhal (2004) pointed out that arbitrageurs do not eliminate the drift, because the required trades contain idiosyncratic risk. Garfinkel and Sokobin (2006) suggested that higher opinion divergence at the earnings date might follow higher positive returns during the post announcement period. Studies related to momentum and earnings announcement are gone through in the next chapter jointly with other momentum studies.

3.5 Technical analysis

It is exploiting the past price data in technical analyses, trying to find trends and predictable patterns. In the efficient markets, where stock prices follow random walk, technical analyses should not give remarkable value for investors. Despite its criticism, there are many studies proving the profitableness of technical analyses. Momentum strategy exploits the past performance of stocks as a future predictor and momentum profits evidences that the idea of technical analysis is practical.

Generally the goal of technical analysis is identify regularities in time series by detected nonlinear patterns from noisy data. Important for this goal is the recognition of the significance of various price movements. Some movements are valid containing significant information and others are merely random fluctuation to be ignored. (Lo, Mamaysky & Wang 2000).

Trends are also an essential part of technical analysis. The very first theory of technical analyses and for which today's more sophisticated methods base is a Dow Theory. Following that theory, there are three different trends for which price movements follows. These are (1.) primary trends, (2.) secondary or intermediate trends and finally (3.) tertiary or minor trends. The primary trend is the actual long run trend. In the secondary trend there is only short-term deviation of prices from the underlying trend line. These movements correct when prices get back to trend line. The last trend, tertiary or minor trend is only daily fluctuation without significant information. (Bodie et al. 2009:397).

Resistance and support levels likewise are important components of technical analysis. The trading technique based on these levels is price channel. The logic behind it is linked to demand and supply process. That is, buyers increase market price by investing and sellers decrease by selling. Support level is referred as demand and a resistance level as supply. The important concept is that when the resistance level is successfully penetrated, that level usually becomes new support level, and similarly if the support level changes it usually becomes as new resistance level. (Achelis 2001: 14-25). These levels tend to be price levels where stock prices seem to remain. It is difficult for stock prices to rise (fall) above (below) its resistance level. (Bodie et al. 2009:350). Logically when stock price breaks these levels it can be seen as buy or sell signals.

One well known and widely used tool of technical analyses is moving average. This method shows the real trend of stock price movements, smoothing the daily fluctuation (i.e. last trend) away. A simple moving average is calculated by adding the most recent time period (n) to the security price and then dividing this by n. When price rises above its moving average it indicates that investors are going to invest and logically it is good time to buy. Other way around, when price fall below its moving average, it is selling signal. (Achelis 2001: 25-29).

Brock, Lakonishok and LeBaron (1992) tested two of the simplest and most popular trading rules of technical analysis, moving average oscillator and trading-rage break,

which refers to resistance and support levels. In the first method, buy and sell signals are generated by long and short period moving averages. In the second part, signals are generated as stock prices hit new highs and lows. They found that these simple tools can be used to predict future stock prices. They also reported that market increased more after buy signal than decrease after sell signal. At the same time the returns following buy signals are less volatile than the returns after sell signals. More recently Martin (2001) and Skouras (2001) reported positive returns using moving averages. Martin (2001) focused on currencies in 12 developing countries when Skouras (2001) used Dow Jones industrial stocks. Martin (2001) reported positive returns even after transaction costs.

Lo et al. (2000) constructed a functional algorithm for automating the detection of technical patterns. They found that certain technical patterns, when applied to many stocks over many time periods, do provide incremental information. They note that although this not directly means profitable trading strategies, it does raise the possibility that technical analysis can add value to the investment purposes and one can improve that value using automated algorithms.

Park and Irwin (2007) review the studies and evidence of technical analyses. They summarize that in general studies of early (1960-1987) stock markets show limited evidence of the profitable of technical trading rules, while studies in foreign exchange markets and future markets find frequently substantial net profits. Modern studies (1984-2004) indicate that technical trading rules yielded economical profits in US stock market until the late 1980s but not thereafter. In future markets, strategies were profitable until the mid- 1980s and in foreign exchange market at least until the early 1990s. Park and Irwin (2007) remind that despite the evidence of profitable technical trading rules, many studies have various problems in their testing procedures, for instance data snooping, selection of trading rules or search technologies and difficulties in estimation of risk and transaction costs.

4. MOMENTUM STRATEGIES

Price reversals and continuations refers the phenomenon that past prices has predictable power of future returns or in other words, stock returns are autocorrelated during the different time periods. Short run reversals (i.e. momentum) are positively autocorrelated in less than one year time period. Long term reversals (i.e. contrarian-strategy) are negatively autocorrelated from three to five year time period. Because of availability of past price information, price reversals provide notable possibility to study market efficiency.

In this chapter it is focused first to introduce different reversals strategies and thereafter both rational and behavioral explanations are represented. Because of the extensive amount of momentum literature, only studies motivating these theses are discussed. The contrarian part is intended to be superficial introduction. The 52WHM-chapter is the most extensive; all noteworthy studies have been gone through.

4.1 Momentum

JT found, analyzing NYSE and AMEX stocks, significant momentum profits over the 24-year long time period (1965-1989). The momentum strategy was executed by buying winner stocks and short selling looser stocks. JT reported significantly larger returns of winner than looser portfolios. The 6-6 strategy (which selects stocks based on their past 6-month returns and holds them for 6 months) realizes a compounded excess return of 12,01 percent per year on average. They prohibit that the profitability of different winner portfolios would be due to their systematic risk.

International momentum

It has been shown that momentum profits occur on an international scale. Rouwenhorst (1998, 1999) reported significant momentum returns in emerging markets as well as in different European countries. Chan, Hameed and Tong (2000) used international indices and found predictable time series of stock indices but only weak predictability in currency market. Also Griffin, Ji and Martin (2003) found significant profits in 40 different countries around the world. Chui, Titman and Wei (2000) studied momentum strategies in Asian countries and their findings supported momentum effect, except in Japan.

Momentum and business cycles

Chordia and Shivakumar (2002) argued that the momentum profits can be explained by common macroeconomic variables that are related to business cycles. They found that the returns of momentum strategies were positive only during expansionary periods. During recessions, returns were negative and statistically insignificant. Different findings have been found. For example Griffin, Ji and Martin (2003) found that neither business cycle risk either country specific risks can explain momentum profits. Nor Muga and Santamaria (2009) found significant relation between momentum and market states. Avramov, Chordia, Joustova and Philipov (2007) focused to momentum and credit rating. They found that momentum portfolios (both loser and winner) consist of low-grade stocks (rated by S&P). Moreover they found higher momentum profits during recessionary periods and suggest that the reason were higher credit risk.

News related momentum studies

As it has been discussed in first chapter, GH considered information as a salient parameter of momentum profits. They suggested that the winner stock would be the stock received recently positive information. This positive information has pushed the stock near to its 52WH-value and would also relate to good future performance. There are other studies focused to relationship between information and momentum. Dische (2002) focused to German stock market executing following earnings forecast momentum strategy: stocks with strong upward revision in analyst earnings forecasts were bought and stocks with strong downward revision were sold short. It is noteworthy that the lower the dispersion in analyst earnings forecasts was, the more forceful the abnormal momentum returns were. Chan (2003) reported that momentum profits are dependent of public news: stocks with some public news exhibit momentum profits while stocks without news did not. He showed that stocks with negative news display a negative drift up to 12 months, when less drift were reported for stocks with good news. In addition, Zhang (2006) reported higher momentum profits when the information uncertainty was greater, but this is more detailed later alongside the momentum explanations.

Hong, Lim and Stein (2001) situate hypothesis that momentum profits should be higher for firms with weaker rate of information flow. This necessitated testing whether small firms have larger momentum profits (because the less amount of information available from small firms). They observed that moving past the very smallest capitalization stocks the profitability of momentum decreases. On the other hand, momentum profits

were higher among stocks with low analyst coverage. Also Chan's (2003) found the most pronounced profits with small, illiquid stocks. Also Jegadeesh and Titman (2001) found that momentum profits of large firms were somewhat weak but at the same time there was strong momentum effect for small firms.

Momentum and trading volume

Several papers have focused to study whether there is correlation between trading volume and momentum. Lee and Swaminathan (2000) found out, using U.S. data that past trading volume predicts both the magnitude and the persistence of price momentum. That is, stocks with high past turnover ratios earn lower future returns and other way around. However, they reported stronger price momentum among high volume stocks. Chan, Hameed and Tong (2000) supported the evidence of Lee and Swaminathan (2000) with international data. Scott, Stump and Xu (2003) argued that this momentum-volume-phenomenon occurs, because investors underreact to earnings news and they showed that after earnings-related news, when a stock's growth rate has been controlled, the correlation between momentum and volume largely disappears. Brown et al. (2009) hypothesized that the relationship between low trading volume and high returns among small stocks can be explained by lower liquidity. Therefore, they separate small and large stocks and focused especially to large stocks (of S&P500 index). They found using two measures for volume (share and turnover), that large and most heavily traded stocks seemed to have higher subsequent returns. That is, high trading volume indicates positive momentum returns. They also found that for illiquid (often small) stocks the correlation between trading volume and returns were negative, but with liquid (often large) stocks it was positive. In addition, they discovered U-shape relationship for momentum strategies – that is, winners and losers both tend to experience high trading volume and turnover, whereas the middle stocks do not.

4.2 52-week high momentum strategies

GH found using US data, that momentum profits can be significantly explained by stock's nearness to its 52WH-value. Winner stocks seemed to be near to their 52-WHs whereas looser stocks far from that value. GH created momentum portfolios as JT did, but instead of simply past performance they use the 52WH-value as a ranking criterion. GH observed that 52-WHM profits are more notable corresponding to the JT's momentum strategy as well as Moskowitz and Grinblatt's (1999) industry-momentum strategy.

However, the profits of 52WHM-portfolios were rather low, because of well performance of loser stocks. That is, the return of winner portfolio were 1,51 percent per month, whereas corresponding return of loser portfolio were 1,06 percent when the difference between winner and loser is only 0,45 percent. At the same time, their findings of JT-styled original momentum strategy were similar. One reason can be the data set and other that markets are becoming more efficient. George and Hwang used similar data with JT, but much longer sample period, covering the years from 1963 to 2001. Anyway, the higher significance of 52WHM does not lie in higher returns, more alike in the fact that the 52WH-value explains significantly momentum-profits. Next the different approaches and findings of 52-WHM-strategy are discussed.

Liu et al. (2009) tested whether the 52-WHM-strategy is profitable in international context focusing to European and Asian markets. They found statistically significant 52-WHM in nine out of thirteen European stock markets. Those average returns were even two times larger than in the study of GH. Further, the traditional momentum strategy was significant in all European stock markets. They did not found significant 52-WHM strategy either traditional momentum strategy in two of three Asian countries, Japan and Taiwan. In Hong Gong both 52-WHM strategy and traditional momentum strategy were significant. Li et al. (2009) showed that those two different momentum strategies tend to co-exist in stock markets and that is why they suggested they are not separate phenomenon. Marshall and Cahan (2005) tested the 52-WHM strategy by Australian stock data and included only stocks available for short-sale to sample. 52-WHM profits from Australia outperform corresponding returns from the US as well as the profits of other momentum-strategies.

52-WHM in index levels is also examined. Data including gross price indices of 18 developed stock markets uncovers significant profitable momentum and the 52-WHM strategy (Du 2008). By including emerging markets and by extending time period, the index level based 52-WH ratio is not relevant any more. In the developed markets results were significant but weak and in the emerging markets returns were negative. In addition, contrary to evidence from company level examination, indices far from the 52WH produced the highest significant profits. According to Pan and Hsueh (2007), the 52WH trading strategy is significantly profitable at index level when overlapping data is used. This mode of data used explains similar results in previous studies. Otherwise, phenomenon seems to be non-existent. In addition, they pointed out that index momentum is might consequence of their own autocorrelations.

Li and Yu (2009) tested whether there is difference between the returns of the 52-WHM strategy and historical high strategy. They found that the 52-WH positively predicts future returns of stocks and the historical high negatively predicts future market returns. They also noticed that momentum is two or three times stronger for stocks that are more likely to experienced underreaction in past.

Siganos (2007) argued that the profitability of (52WH)momentum strategy depends on portfolio´s size-sorting. By including only 40 extreme winner and loser stocks to the portfolios, the returns are nearly doubled compared to conventional portfolio. The strategy is considered to be profitable even when short-selling is not conceivable.

Sturm (2008) focused to 52-WHM with large firm stocks and found that stocks which make currently new high or alternatively hit long term high are more important for momentum payoffs than stocks making an intermediate-term new high. That is, the 52-WHM profits grow when looking back period, or in other words the data for which the 52-WH-value basis increases. From elsewhere Huddart et al. (2009) noticed that the increase in volume (when stock reach its 52WH) is more pronounced the longer the time since the previous high or low were established.

4.3. Contrarian strategies

According to momentum phenomenon, there is longer term reversal named contrarian-strategy, documented first by De Bondt and Thaler (1985). The strategy works opposite way corresponding to momentum strategy; stocks which have performed poorly in last 3 to 5 years will be hold next 3–5 years. De Bondt and Thaler (1985) reported that loser stocks outperformed winner stocks by 25 percent. They also noted, calculating risk adjusted returns with Capital asset pricing model (CAPM), that loser stocks tend be less risky than winner stocks. Chan (1988) found only small profits executing contrarian strategy and argued that contrarian returns are sensitive to changes in return calculations and especially in risk adjustments. He found large variation in betas from the ranking period to the test period and pointed out that losers are riskier than winners after portfolio formation.

GH studied also whether long term reversals occurs when the portfolio formations is based to 52WH-value. They did not found positive returns anymore and therefore they

conclude that according to previous literature, momentum and contrarian strategies seems to be different phenomenon.

Conrad, Hameed and Niden (1994) investigated the relationship between volume and autocovariances with contrarian time scale and represent that the information of trading activity appeared to be important predictor of future stock returns. They found negative autocorrelation (i.e. contrarian phenomenon) between the most heavily traded stocks and returns whereas the autocorrelation were positive between low-transaction securities and returns. They pointed out that in low-transaction stocks, trading activity can reliably predict the returns of next period and these relations are more remarkable with smaller stocks. More recently Avramov, Chordia and Goyal (2006) got higher contrarian profits with low-liquidity stocks than high-liquidity ones with both weekly and monthly frequencies. However, these profits were smaller than likely transaction costs, referencing that the contrarian strategy were only statistically, not economically significant.

4.4 Explanations for reversals

There are two kinds of explanations for momentum profits, rational and irrational. The first one supports the market efficiency whereas the second one relates to behavioral finance. Next both type explanations are gone through.

4.4.1 Risk related explanations

JT showed that the profitability of their momentum trading strategy were not due to the systematic risk. Later on Fama and French (1996) discovered that their three-factor model, which factors related to market risk, size and book-to-market-ratio, cannot explain momentum effect. After them, different risk based or limits to arbitrage related explanations have appeared.

Conrad and Kaul (1998) argued that the cross-sectional variation in mean returns is an important determinant of profitable momentum strategies. They pointed out that momentum strategies contain cross-sectional component that would arise even if stock prices are unpredictable and follow random walk. They also noted that momentum strategy could be executed as buying high-mean securities and selling low-mean securi-

ties. As long as there is some cross-sectional dispersion in stock returns, there will be profitable momentum strategy.

There are also limits to arbitrage related explanations for momentum profits. In other words, momentum anomaly occurs, because there are essential limits to realize these profits. McInish, Ding, Pyun and Wongchoti (2008) attempted to find abnormal returns by using shorter than one month investment period and found that losers followed momentum. They pointed out that short period momentum strategy requires short selling permission. In addition, few researchers have shown that momentum is an illusion, because trading costs eliminate excess momentum profits (Lesmond et al. 2004). This explanation is might not sustainable because reversed findings have been achieved (Korajczyk & Sadka 2004; Xiafei et al. 2009). Those empirical results authenticate certain momentum strategies to be profitable even when trading costs have been taken into account.

Furthermore Pastor and Stambaugh (2003) as well Sadka (2006) found that liquidity risk can substantially explain momentum profits. Pastor and Stambaugh (2006) found that stocks which were more sensitive to fluctuations in liquidity generated higher future returns. They also pointed out that the momentum strategy becomes less attractive when portfolio spreads (the difference between the top and bottom liquidity portfolios) based on liquidity risk are available to investment. Sadka (2006) showed that momentum portfolios generally outperform when there are positive liquidity shocks but then underperform when there are negative shocks in liquidity. He suggest that part of momentum returns can be viewed as a compensation for unexpected variations in the aggregate ratio of informed traders to noise traders and the quality of information possessed by the informed traders.

Johnson (2002) pointed out that performance of winner and loser stocks are related to their natural growth rate. He found that when holding other things equal, past performance is correlated with levels of expected growth rate, which is related to risk. Generally, the higher is the expected growth rate or future cash flows the higher is the risk. He noted that the potential differences in expected cash flows between winner and loser portfolios could provide one rational and remarkable explanation for momentum.

4.4.2 Behavioral explanations

There are three major behavioral explanations reported by Daniel, Hirsleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) as well Hong and Stein (1999). Some behavioral biases offer also explications for momentum profits. Furthermore GH provided 52WHM-related explanations.

Daniel, Hirsleifer and Subrahmanyam (1998) considered overconfidence and self-attribution bias as an explanation for momentum. That is, investors overestimate own abilities and therefore they underreact to public information and instead overreact to private information. Overreaction can be seen as momentum profits and when prices gradually draw to fundamental value the contrarian profits occurs.

Barberis, Shleifer and Vishny (1998) represent that positive short run price drift and autocorrelation occur because news is incorporated only slowly into prices. Nonetheless, these stocks tend to became overvalued and returns decreases in longer run, which can be seen as contrarian profits. The biases which they represent as explanations are conservatism and representative heuristics – the reaction to new information depends on the stream of past news. When investor observes surprise, he raises the likelihood that the returns are in bullish trend, whereas when a positive surprise is followed by a negative surprise, the investors raises the probability that the returns are in mean-reverting regime. When investors periodically update theirs investment situation and performance they have the idea above in their minds.

For one's part Hong and Stein (1999) present a model, not based psychological bias, but to two classes of traders. News-watchers behave as Daniel, Hirsleifer and Subrahmanyam (1998) suggest, emphasizing private information instead of public, causing short run drift. Momentum-traders are simply price followers who try to exploit the drift caused by news-watchers. Therefore momentum-traders do not necessarily suffer of behavioral biases more alike they are rational arbitrageurs.

Zhang (2006) investigated the underreaction hypothesis in different way. He hypothesized that if investors really underreact to information, this reaction should be even more strengthening when the information is somewhat unclear. The information uncertainty was modeled as a volatility of a firm's underlying fundamentals and poor information. He found that investors underreact to unclear information with higher degree, returning higher momentum profits and this supports the underreaction-hypothesis.

GH represent that stock nearness to its 52WH-value remarkably explain momentum profits. That is because JT's momentum profits reduced significantly, when the stock's 52WH-value was controlled. Therefore GH suggested that explanation for momentum really lies in anchoring and adjustment bias – as earlier mentioned, investors use the 52WH-value as their reference point and do not want to sell below it. According to others above, also George and Hwang noted that investors do not seemed to process relevant information, more alike they used price patterns and base their investment decisions for simply and easily available value. They also pointed out, that the explanation for long term reversals lies elsewhere, because 52WH-strategy did not success in the long run.

5. DATA SETTING AND TESTING METHODOLOGY

This section begins the empirical part of the study. First it is looked the data used and its special characteristics. Then it is focused to portfolio formation, first to momentum portfolios and then to trading volume portfolios. The return calculation and statistical testing methodology is introduced at the end of the chapter.

5.1 Data sample

The data used in this study is consisted of daily stock returns from the STOXX Europe Total Market Index (TMI). Sample period is 1.1.2001-31.12.2010. This period provide a unique possibility to investigate the 52WHM also during the financial crisis. The data is from the department of Accounting and Finance of University of Vaasa.

TMI-index covers approximately 95 percent of the free float capitalization across 18 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. The index consists of large, mid and small indices of STOXX EUROPE. The stocks with more than 10 non-trading days during the past three months have not been included in the index. (STOXX Europe TMI Index Methodology.)

This data set is reasonable to find out whether there exists irrational behavior relate to 52WH-value in Europe. It is also interesting to find out whether there are references of availability bias in European stock market, where are less trading and attention than in the U.S. markets. From the capital market perspective, the data contain the major European countries and it provides good sample of European stocks. The Eastern Europe has been leaving out from the sample because of different capital market structure and the possibility of lower amount of trading volume. Because the stocks used are most liquid and most followed stocks of Europe, they should realize market efficiency. At the same time, because these stocks are in view, they might suffer more about the availability bias.

All the stocks that has been listed since the analyzing period have already started have been cut of the sample. Also 25 % of the stocks with the lowest trading volume are ig-

nored to be avoiding the liquidity problem. Furthermore, all the stocks with no trading in any sample day have been removed. After these cuttings there are totally 594 stocks of which the winner and loser portfolios are formed. At each time *t*, there are 178 stocks in both winner and loser portfolios. In addition, after sorting winner and loser portfolios with trading volume, there are 54 stocks in each separate portfolio.

5.2 Portfolio formations

This study is executed using JT's portfolio approach and George and Hwang's application for that. In the JT's approach three momentum portfolios are formed:

Winner portfolio	30 % of the best performed stocks
Loser portfolio	30 % of the worst performed stocks
Middle portfolio	the rest 40 % of stocks, which did not end up either winner or loser portfolios

The portfolio approach above is used in this study, but the difference comes from how the past performance is measured. Following GH stocks will select to portfolios using the following ratio

(1) $$\frac{P_{i,t-1}}{High_{i,t-1}}$$

Where $P_{i,t-1}$ is the price of stock *i* at end of month *t-1* and $high_{i,t-1}$ is the highest price of stock *i* during the 12-month time period (that ends of the last day of the month *t-1)*.

The portfolios used in this study are following:

Winner portfolio	30 % of stocks which are the nearest to their 52WH-value
Loser portfolio	30 % of stocks which are the furthest from their 52WH-value
Middle portfolio	the rest 40 % of stocks, which did not end up either winner or loser portfolios

In the earlier studies (see for example JT and Moskowitz and Grinblatt (1999)) the six, six (6, 6) strategy has been in focus, but also different time scales had been studied. The (6, 6) strategy refers to six month looking back period and six month holding period. Specifically, it is investigated which stocks have performed best (worst) during the last six month to find out which stocks belong to winner (loser) portfolios. Then the monthly returns are cumulated during the next six months. Following GH, in this study two holding periods, with fixed looking back period, are used. Because of the 52WH-approach, the looking back period has to be twelve months. Then there are two holding periods, six and twelve months. The two strategies used in this study can be written to the following form: (12, 6) and (12, 12) strategies. The strategies are realized by shorting the losers and longing the winners.

It is calculated daily based monthly returns for all winner and loser portfolios. The difference between winner and loser portfolios gives the profitability of momentum strategy and therefore it is called momentum portfolio. All returns are logarithmic.

Following De Bondt and Thaler (1984), returns are adjusted by market model (equation 2.)

(2) $$MAR_{pfit} = R_{pfit} - R_{mt}$$

Where MAR_{pfit} is market adjusted return of portfolio i in time t, R_{pfit} is logarithmic return of portfolio i in time t and R_{mt} is logarithmic return of STOXX Europe total market index in time t. This adjustment has been done to know whether 52WHM strategy outperform the index.

Huddart et al (2009) found that there is higher trading volume when the stock price crosses its 52WH- or 52WL-value and suggested that this might continue providing positive returns and predictable volume patterns in future. The volume related to 52WHM is examined in following way. First, after the stocks are ranked to momentum portfolios, the trading volume of these stocks is controlled. Following Lee and Swaminathan (2000) three trading volume-portfolios are formed for both winner and loser portfolios. The looking back-period for volume-portfolios is the same as it were for pure momentum-portfolios, 52 week or one year. The same as the pure momentum, there are three volume portfolios, high, middle and low volume-portfolio. High-volume-portfolio includes 30 percent of stocks with the highest (lowest) trading volume whereas

the rest 40 percent of stocks belongs to the middle volume-portfolio. Finally there are three volume-winner portfolios as well as three volume-loser portfolios, totally six composite-portfolios for both strategies (12, 6) and (12, 12).

Most previous studies, like Lee and Swaminathan (2000), used the share turnover (shares traded/outstanding shares) as a measure of trading volume. Since the both variables, number of shares outstanding and the number of shares traded, have both grown steadily over time, the use of turnover helps to reduce the low-frequency variation in the series (Campbell, Grossman & Wang 1993). Turnover as a measure of trading volume is used also in this study.

The trading volume of momentum portfolios during the holding periods, are also studied. It is looked the possible volume-difference between 52WH-winner and –loser portfolios. The trading volume of momentum portfolios are also compared to average trading volume in market. Market volume relates to average trading volume of stocks including to TMI-index. The actual volumes are used at this time.

As mentioned above, success of the both 52WHM and volume-momentum strategies during the financial crisis have been studied. Zhang (2006) found higher momentum profits as the uncertainty increased. Zhang's (2006) uncertainty relates to information, but in any case it can hold true with overall uncertainty. Because of uncertainty about the beginning and especially ending of the crisis, years 2007 and 2008 are used as crisis period in this thesis.

For investigate the risk of momentum strategy the betas are calculated for both winner and loser portfolios and also it is revised the betas of momentum portfolios during the financial crises. Grundy and Martin (2001) suggested that in order for momentum strategy to be profitable, winners should be stocks with betas greater than one. Furthermore, they noted that during up markets momentum-betas should be positive. That is, the strategy will go long in stocks with betas greater than one and short in stocks with betas less than one. From elsewhere, following bearish markets, momentum strategy have to involve a negative beta to beat the market.

5.3 Testing

It is tested two main things in this thesis. First it is focused to the profitableness of 52WHM. After calculated the returns of momentum portfolios, it is investigated if these returns are statistically significant.

The second issue is the volume in portfolios. It is focused to two different things in this part. The first question is related to the interaction between volume and 52WHM profits and therefore also volume based momentum profits are studied. Secondly, do momentum-stocks (stocks included in some of the momentum portfolios) in general exhibit higher trading volume that exists in average in the market? This is executed by comparing the volume in momentum portfolios to average volume in the market.

The statistical significance of this study is sorted out using daily returns and Student's t-test as a test-statistic. Three significance levels are used: *, **, *** referring respectively as ten, five and one percent risk level.

6. RESULTS

The overall results of this study are reported in this chapter. First it is looked the profits and risks of pure 52WHM strategy as well as 52WHM volume strategies during the whole sample period. Second section consists of the same items but the sample period includes only financial crisis time period. The last part investigates whether the 52WHM-portfolios exhibit higher trading volume that exists on average in the market.

6.1 Success of 52WHM and volume strategies during the years 2002–2010

The profits of pure 52WHM-portfolios are reported first and thereafter the profits of 52WHM volume portfolios. The return of momentum-portfolio corresponds to the return difference between winner- and loser portfolios, describing the eventual success of 52WHM strategy.

6.1.1 52WHM

Table 1 provides average market adjusted monthly returns of 52WHM strategy during the sample period. There are returns for winner- and loser- as well for momentum-portfolios. Returns for two holding periods (6, 12 months) are reported separately. The t-statistics for momentum portfolios are in parenthesis.

Table 1. Returns of 52WHM.

holding period (months)	**winner**	**loser**	**winner-loser**
6	0,48 %	0,11 %	0,37 % (-2,55)***
12	0,45 %	-0,14 %	0,59 % (-5,66)***

The difference between winner and loser portfolios has been positive during the two holding periods and both are highly statistically significant. Both winner portfolios outperform the index more than 0,40 percent, when loser portfolios are slightly above (6-month portfolio) or below (12-month portfolio) the index. Contrary to GH, 12-month holding period outperforms 6-month holding period with 0,22 percent (GH did not found large difference in returns between these two holding periods). Both winner and loser portfolios underperform corresponding portfolios of GH, but the return of 12-month momentum-portfolio is slightly greater than their momentum portfolio (GH's six month winner portfolio returned 1,51 percent when corresponding loser portfolio returned 1,06 percent). Anyhow profits of pure 52WHM-strategies are quite low, regardless of the fact they are monthly returns. Therefore the economic significance of the strategy is doubtful. On the other hand, the data set involves the financial crises period, when returns were generally low.

Figure 2 provides better outlook to 52WHM profits, showing high variation in profits during the sample period. Because the graphs for two different holding periods are nearly identical, only the graph of 12-month strategy, which has been found to be more profitable in this thesis, is reported. It shows that most of the returns of winner portfolios have been generated before the financial crisis. Since the year 2007 until the year 2010 the return of winner portfolios has been negative. It is not clear if markets are becoming more efficient and momentum profits thinner, because of rising of winner portfolio profits in the end of sample period. Figure 2 also suggests that 52WHM seems to be most profitable during the recession periods. Profits of 52WHM-portfolio were notable at the beginning of sample period (year 2002) and during the years 2007 and 2008. The first profit peak is related to repercussion of technology bubble and the second positive peak to financial crisis. Avramov et al. (2007) got the most congruent findings with this thesis. They found higher momentum profits during recessionary periods. They suggested that return premium would be consequence of higher credit risk. This can be the truth; the credit risk was substantial especially during the last crisis. Two negative profit peaks (of momentum portfolios) have occurred immediately after positive peaks or in other words after crisis time. These negative peaks are caused by positive returns of loser portfolios.

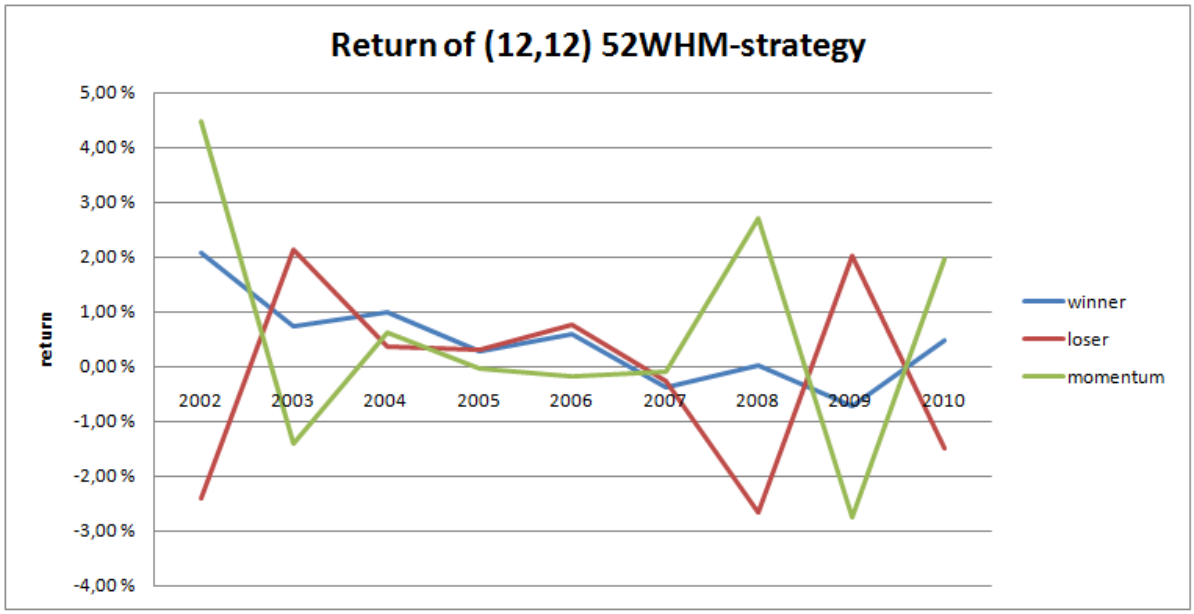

Figure 2. Variation in 52WHM profits.

The betas of 52WHM portfolios are reported in table 2. On the contrary to Grundy and Martin (2001) all the betas are positive and loser portfolio betas are greater than winner betas. Grundy and Martin (2001) suggest that betas of winner stocks should be greater than one, whereas loser betas less than one. The Betas propose that loser portfolios will be more sensitive to market movements (and naturally more risky) whereas winner portfolios follows market index quite straightforward. The betas of winner portfolios are naturally related to the returns of winner portfolios. As it can be seen from figure 2, winner returns on average deviate only slightly from the market returns. The betas of loser portfolios support the efficient market hypothesis, the higher unexpected profits are compensation for risk, but the betas of winner portfolios are against it.

Table 2. Betas of 52WHM strategy.

holding period (months)	**winner**	**loser**
6	0,92	1,52
12	0,94	1,53

6.1.2 Volume strategy

Table 3 reports average market-adjusted monthly profits after sorting momentum portfolios by trading volume. Returns of high and low volume portfolios as well as return difference between high and low volume portfolios are reported for both winner and loser portfolios. The correlative t-statistics are in parentheses.

Table 3. Returns of 52WHM-volume strategy.

	volume	**high**	**low**	**high-low**
portfolio	**holding period (months)**			
winner	6	-0,09 % (-0,77)	0,80 % (5,53)***	-0,89 % (-4,77)***
	12	-0,08 % (-0,87)	0,31 % (2,96)***	-0,39 % (-2,83)***
loser	6	-0,33 % (-1,37)	0,28 % (1,30)	-0,61 % (-1,89)*
	12	-0,73 % (-4,35)***	-0,31 % (-1,95)**	-0,42 % (-1,81)*
winner-loser	6	0,24 %	0,51 %	
	12	0,66 %	0,62 %	

The main findings related to volume-part are congruent with Lee and Swaminathan (2000). The momentum effect is the most pronounced among low volume winners and high volume losers. But then, it can be seen that on average low volume stocks outperform high volume stocks. Low-volume return premium is even more remarkable when the significance of the profits is observed. Most of low volume portfolios are significant, while only one high-volume portfolio is significant. The difference between the best and worst succeed portfolios is remarkable. Six month low volume winner portfolio succeeds the best, providing 0,80 percent profits per month. The weakest successed portfolio is 12-month high volume portfolio returning –0,73 percent. It seems that incresed trading volume of declining stocks is more important signal for investors than increased trading volume of rising stocks. This links to the loss aversion, losses hurts

more than gains and therefore investors pay more attention for increased selling actions than for incresed bying actions.

When 52WHM profits are calculated using only high volume portfolios (i.e high winner - high loser) or alternatively corresponding low volume portfolios the findings are contrary to Lee and Swaminathan (2000) as well as Hameed and Tong (2000). The 52WHM is, on average, more profitable among low volume stocks than among high volume stocks. To be exact, the difference between high volume winners and losers is higher than the difference between low volume winners and losers. From elsewhere, the most successful momentum-portfolio is high volume 12 month momentum-portfolio, but because of low returns of corresponding six month portfolio, the low-volume portfolios dominate. This evidence support the underreaction-hypotheses: more profits can be found with stocks with less activity. In other words, when there is less trading, reaction to public news can be lower and higher momentum profits occur. However, the average returns of all volume-momentum portfolios are between 0,24 - 0,65 percent. The profits of high volume six month momentum portfolio is the lowest (0,24 percent) when the profits of all other momentum portfolios are above 0,5 percent.

The low volume return premium evidenced in this study supports also the liquidity risk hypotheses, reported for example by Pastor and Stambaugh (2003) as well as by Sadka (2006). Momentum-volume profits tend to be compensation of lower liquidity. All the low volume returns outperform the high volume returns and three out four of these are also statistically significant. However, better returns of low volume stocks do not support the attention-driving buying-behavior of Barber and Odean (2008).

Figure 3 shows the return variation of volume-portfolios. It can be seen that from 2003 to 2007 the returns have moved to same direction. Like the returns of pure 52WHM, the variations between volume-portfolios have been highest during and afterwards the recession or crisis periods. It seems that high volume winner portfolios have succeeded the best during the deepest crisis time, when high volume loser portfolios have performed the worst. But then, at the year 2009 the situation is opposite, high volume loser portfolio won whereas high volume winner portfolio lost. However the return-variation during the sample period has been pronounced.

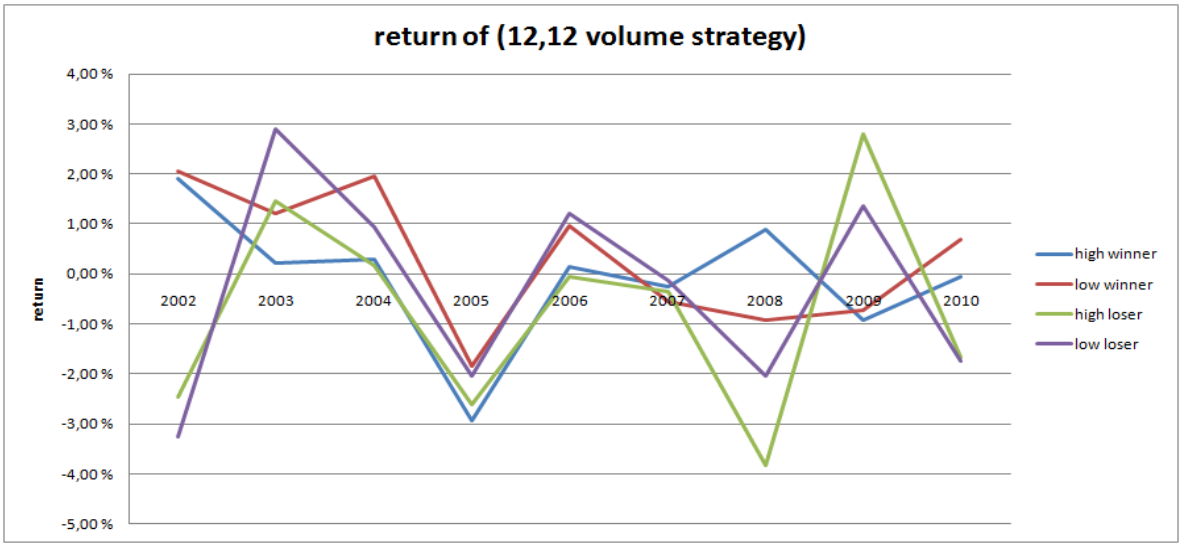

Figure 3. Variation in 52WHM-volume profits.

Table 4 on the next page involves the betas of volume-portfolios. The same phenomenon as with pure 52WHM-betas can be seen. All the winner betas, betas of both high- and low-portfolios are below, but quite near to one. Other way around, the loser betas are above one (except the low volume six-month portfolio.) The twelve-month loser portfolio seems to involve risk the most, but contrary to the pure strategy, all other betas deviate from one at the same degree. High and low loser portfolios seem to be more sensitive to market movements than correlative winner portfolios.

Table 4. Betas of volume portfolios.

	volume	**high**	**low**
portfolio	**holding period (months)**		
winner	6	0,77	0,88
	12	0,83	0,84
loser	6	1,25	0,92
	12	1,47	1,32

6.2 Financial crisis

This part includes the same items above, but with financial crisis time scale. Firstly the pure 52WHM profits are examined and thereafter the volume-based profits.

6.2.1 52WHM

52WHM strategy succeeded well during the financial crisis. As it can be seen from table 5, both momentum-portfolios are highly statistically significant providing remarkable returns. Positive returns are even higher corresponding to whole sample returns. Returns of momentum-portfolios during the crisis time are more than two times higher corresponding to GH's returns. Again, twelve-month holding period outperformed six-month holding period. It should also be noted, that the profitably of 52WHM during the crisis time is consequence of higher negative returns of loser stocks.

Table 5. 52WHM profits during the financial crisis.

holding period (months)	**winner**	**loser**	**winner-loser**
6	0,36 %	-0,63 %	0,99 % (3,82)***
12	-0,17 %	-1,48 %	1,30 % (5,73)***

Results suggest that investors overreacted to negative news during the crisis time. Also Chan (2003) found stronger drift after bad news. Stocks in loser portfolios, which had already yielded poorly and are farthest away from 52WH-value, seem to react more to negative news. It can be the situation, that 52WHM profits are higher when overall market inefficiency is higher. Irrational behavior in market, especially overreaction can strengthen during the crisis time, because of unsureness occurs in large-scale in markets. This might arouse arbitrage opportunities.

It seems that stocks performed poorly year before the crisis and those which have dropped far away theirs 52WH-values suffer the most of financial crisis. Other way around, stocks with better performance in past, manage to avoid strong decline. But

then, as it was mentioned earlier, before the financial crisis totally ends, loser portfolios won.

The evidence above suggests that anchoring to the reference point has even more plausible role during the crisis time. Stock prices have probably been far away from their 52WH-values and investors tend to use the 52WH-value as their reference point. This can be seen as negative returns of loser portfolios. When the stock prices have gone far away their 52WH-values, investors (on average) tend to sell them and do not want to buy them, causing even higher negative returns. At the same time stocks near to their 52WHs are those performed positively even crisis time and therefore they are attractive investment opportunities.

Below are the betas of 52WHM-portfolios of financial crisis. Winner betas, when they are compared to whole sample period, have grown slightly, but at the same time loser betas have decreased. It appears that higher risk cannot explain higher profits during the financial crisis, more alike another way around.

Table 6. Betas of 52WHM during the crisis period.

holding period (months)	**winner**	**loser**
6	1,07	1,39
12	1,19	0,94

6.2.2 Volume strategy

The profits of 52WHM-volume strategy are representing in table 7. Market adjusted monthly returns as well their t-statistics (in parentheses) are reported.

Table 7. Profits of volume portfolios during the crisis period.

	volume	high	low	high-low
portfolio	**holding period (months)**			
winner	6	0,23 % (0,95)	0,43 % (1,51)	-0,20 % (-0,51)
	12	0,32 % (1,48)	-0,73 % (-2,82)***	1,06 % (3,12)***
loser	6	-1,48 % (-3,22)***	0,12 % (0,31)	-1,60 % (-3,02)***
	12	-2,10 % (-5,6)***	-1,09 % (-3,51)***	-1,01 % (-2,16)**
winner-loser	6 12	1,71 % 2,42 %	0,31 % 0,35 %	

Low volume six month winner portfolios have been the most profitable also during the financial crises. But then twelve month low volume winner portfolio has yielded negatively as well as congruent loser portfolio. Negative profits of the high volume loser portfolios are substantially higher than whole sample period. It seems that during the financial crisis, higher trading volume had provided higher 52WHM returns.

Results of crisis period supported the findings of Barber and Odean (2008) and Huddart et al. (2009). Barber and Odean (2008) found attention driving buying-behavior whereas Huddart et al. higher profits as well higher volume around 52WHs and –Ls. It might be the situation that "herd behavior" strengthens during the unstable time; investors follow others in their buying and selling decisions. During the crisis investors sell the stocks in a fear of large losses and trading volume increased. The increased trading volume and conceivable reported losses may catch investors' attention, causing even higher negative profits. At the same time less declined stocks were likely to work similar, but positive way: they became respectable investment opportunities.

During the crisis time, the momentum phenomenon is stronger among high-volume stocks, providing superior returns, 2,42 percent in a month (twelve-month portfolio). Twelve-month momentum-profits of high-volume stocks are nearly four times larger than twelve month 52WHM profits of whole sample. Also Hirshleifer (2001) as well

Daniel et al. (2002) pointed out that the irrational behavior, caused by behavioral biases, increased when the overall uncertainty is greater. In addition Zhang (2006) found higher momentum profits with greater information uncertainty.

There are not many surprises in the betas of volume portfolios. As table 8 shows, nearly all betas are above or exactly one. Only beta of high-volume 6-month loser portfolio is below one. This time, loser portfolio with twelve month holding-period seems to be riskier than others. But then also betas of low-volume winner portfolios are higher than one.

Table 8. Betas of volume portfolios during the crisis period.

	volume	**high**	**low**
portfolio	**holding period (months)**		
winner	6	1,09	1,19
	12	1,03	1,32
loser	6	0,84	1,00
	12	1,39	1,38

6.3 Trading volume of momentum portfolios

Figure 4 shows average trading volume of 52WH-winner- and loser-portfolios as well average (absolute) trading volume of market (TMI-index). Volume of loser portfolios has been slightly higher compared to winner portfolio. There seems to be some negative correlation between winner and loser portfolios, when market volume seems to go between these portfolios. The correlation coefficient between volume of winner and loser portfolios of whole sample is low, only -0,08 but during the years 2003 to 2010 it is -0,68. Since the financial crisis started, the volume of winner and looser portfolios has moved inverse direction. The correlation coefficient of this period (2007-2010) is -0, 9.

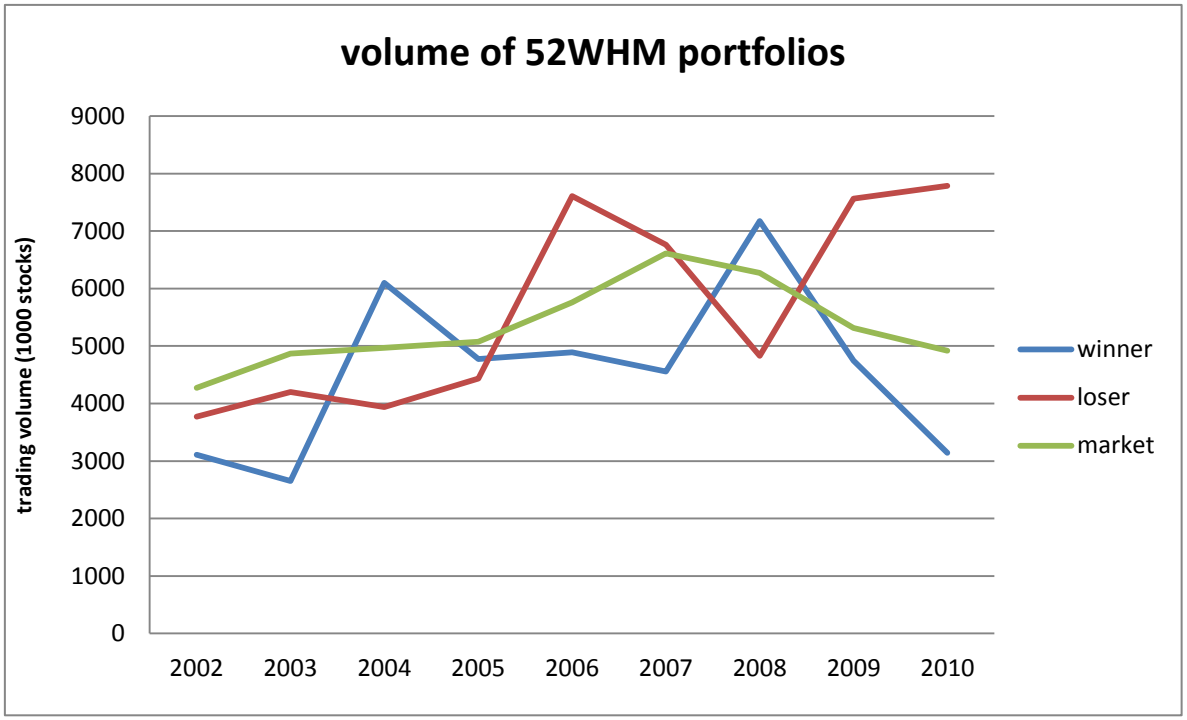

Figure 4. The average trading volume of 52WHM-portfolios and index.

Huddart et al. (2009) found higher trading volume in event time when the stock price reacts either its 52WH- or 52WL-value. They also suggest that it is possibly that there are predictable return- and volume-patterns in longer run. Findings of this thesis do not support that. Firstly the approach of this study differs from the approach of Huddart et al. (2009). The stocks in winner portfolios correspond to the stocks reaching 52WHs (but some stocks are only near to that value, because of 30 percent limits). But then, stocks in loser do not completely correspond to the stocks reaching 52WLs, because by definition, they are only the 30 percent furthest stocks from 52WH-value. In other words they do not necessarily have to be near their 52WL-value, they have to be only enough far from the 52WH-value to be ranked to the loser portfolio. Anyhow, volume of winner and loser stocks outperform the market volume by turns, but they are not systematically above (or below) the index. The winner and loser portfolios seem to be strongly correlated with each other, but not with market.

7. CONCLUSION

Since Jegadeesh and Titman (1993) reported profitable of momentum strategy in U.S stock market, the phenomenon has achieved lot of attention. Quite recently GH extend the knowledge of the strategy, reporting that stock's 52WH-value can significantly explain momentum profits. That is, the winner stocks tend to be stocks near to their 52WH-value whereas loser stocks tend to be furthest away that value.

The focus of this thesis is to study the 52WHM-anomaly in European stock market. It is also investigated whether trading volume have significant impact to strategy profits. The sample period, extending from year 2001 to 2010, offered a unique possibility to examine the 52WHM strategy during the last financial crisis.

The empirical findings of this study support the existence of 52WHM-phenomenon in European stock market. This, for one, supports the George and Hwang hypothesis, that investors use 52WH-value as their anchoring and reference point. However and instead of highly statistical significance, the returns of 52WHM were low, outperforming the index at best by 0,6 percent per month. Therefore, and because trading costs were not took into account, the economic significance of the 52WHM in European stock market is doubtful.

When the 52WHM-portfolios were sorted again, based on their past trading volume, the profits strengthened. The best succeeded portfolios were low-volume winner portfolios and the momentum-phenomenon was more pronounced among low-volume stocks, which is reversed with earlier findings (see for example Lee & Swaminathan 2000). Evidence of this study supports the underreaction-hypothesis. That is one of the most used explanations for momentum, representing that the momentum profits is consequence of investors' underreaction to new information.

During the financial crisis the momentum profits rise remarkably. The pure 52WHM strategy, with twelve month-holding period, outperformed the market on average by 1,3 percent per month. During the crisis time the momentum phenomenon were the most powerful among high-volume stocks, monthly returns being even 2,4 percent. The thing which boosted the returns during the crisis time was the poor success of loser stocks. Possible explanation is the investors pessimism and overreaction during the crisis time; stocks which have already performed poorly, suffer the most of the overall price decline. Anchoring and the 52WH-value as a reference point, offer also a plausible

explanation. Probably many stocks fell far away from their 52WHs because of large-scale selling actions causing higher negative returns. Higher trading volume in recently past might also catch investors' attention especially during the crisis time causing higher 52WHM profits. The high trading volume – high negative returns combination also supports the ideas above. From elsewhere, the stocks which contrived to remain near their 52WHs did not suffer of the crisis that much, providing even positive returns. These can be the stocks which investors buy during the crisis time and for which they might invest when realizing their losses. Return charts can also boost the momentum during the crisis time, stocks near their 52WHs seem to perform well or at least they do not decline much, whereas investors saw declining graphs of loser stocks, because they are far away their 52WHs.

Hirshleifer (2001) and Daniel et al. (2002) noted that biased behavior increases when the uncertainty in market increases. The evidence of this study supports strongly their findings. Especially availability bias becomes more powerful during the financial crisis, when the common uncertainty was enormous. Also the reference point, as indicator of losses have more plausible role during the financial crisis.

Although business cycles were not in focus in this study, there are straight references that the 52WHM profits would be susceptible to economic fluctuation. The strategy seems to success best during the crisis time. Also Avramov et al. (2007) found higher momentum profits during recessionary periods and suggest that this occurs because of pronounced credit risk. The credit risk can explain higher profits of 52WHM especially during the latest financial crisis time, but also other factors and explanations can lies behind the profit variation.

The evidence of this study do not support the suggestion made by Huddart et al. (2009) that the higher volume around stocks 52WHs or Ls would continue in longer run. However the approach of this study cannot completely control their effect. Although high negative correlation occurs between trading volume of winner and loser portfolios, these portfolios do not seem to suffer higher volume than market. The negative correlation between winner and loser portfolios strengthened during the crisis time. Anyhow, it seems that the volume is high just around the 52WHs and –Ls, but there are not any continual volume patterns.

The main conclusion is that 52WHM is existing phenomenon in European stock market impugning the market efficiency. Returns during the sample period were quite low, but

highly statistically significant. Because of low returns the market efficiency can hold throughout the transaction costs. But then, during the financial crisis, the 52WHM strategy strengthened and the volume based 52WHM strategy offers even superior returns, especially when the prevailing downtrend is observed. It was also found references that biased behavior, especially related to availability bias increased notable during the financial crisis. In other words, during the whole sample period increased trading volume did not catch investors' attention supporting 52WHM profits, but during the crisis time it did.

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