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LOW-VOLATILITY ANOMALY IN HELSINKI STOCK EXCHANGE

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ABSTRACT

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International research shows that low-volatility stocks have beaten high-volatility stocks in terms of returns for decades on multiple markets. This abbreviation from traditional risk-return framework is known as low-volatility anomaly. This study focuses on explaining the anomaly and finding how strongly it appears in NASDAQ OMX Helsinki stock exchange. Data consists of all listed companies starting from 2001 and ending close to 2015. Methodology follows closely Baker and Haugen (2012) by sorting companies into deciles according to 3-month volatility and then calculating monthly returns for these different volatility groups.

Annualized return for the lowest volatility decile is 8.85 %, while highest volatility decile destroys wealth at rate of -19.96 % per annum. Results are parallel also in quintiles that represent larger amount of companies and thus dilute outliers. Observation period captures financial crisis of 2007-2008 and European debt crisis, which embodies as low main index annual return of 1 %, but at the same time proves the success of low-volatility strategy. Low-volatility anomaly is driven by multiple reasons such as leverage constrained trading and managerial incentives which both prompt to invest in risky assets, but behavioral matters also have major weight in maintaining the anomaly.

TIIVISTELMÄ

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Kansainväliset tutkimukset osoittavat matalan volatiliteetin osakkeiden voittaneen korkean volatiliteetin osakkeiden tuoton jo vuosikymmenten ajan eri markkinoilla. Tämä poikkeama perinteisestä riskin ja tuoton suhteesta tunnetaan matalan volatiliteetin anomaliana. Tämä tutkimus keskittyy selittämään ilmiön syitä ja tutkimaan sen voimakkuutta Helsingin pörssissä. Aineisto koostuu listatuista yhtiöistä ja alkaa vuodesta 2001 ulottuen liki vuoden 2015 loppuun. Tutkimuksessa yhtiöt järjestetään kymmenyksiin perustuen niiden kolmen kuukauden volatiliteettiin, minkä jälkeen lasketaan eri ryhmien kuukausittaiset tuotot. Tämä menetelmä mukailee Bakerin ja Haugenin (2012) työtä.

Matalimman volatiliteetin kymmenyksen annualisoitu tuotto on 8,85 %, kun taas korkeimman volatiliteetin kymmenys tuhoaa vuosittain arvoa -19,96 %. Tulokset ovat samansuuntaisia viidenneksiä vertaillessa, vaikka tämä ryhmittely laimentaa ääituloksia. Tarkastelujaksolle osuu vuosien 2007-2008 finanssikriisi ja euroalueen velkakriisi, mistä johtuen Helsingin pörssin kehitys on heikkoa, vaikka samaan aikaan matalan volatiliteetin sijoitusstrategialla pystytään hyvään tuottoon. Anomalian taustalla on monia syitä, kuten rajoitukset velkavivun käytössä ja vääristyneet kannustimet, jotka molemmat ohjaavat sijoittamaan korkeariskisiin osakkeisiin. Myös käyttäytymistieteellinen rahoitus tarjoaa monia selityksiä ilmiön pysyvyydelle.

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I express my gratitude towards Lappeenranta University of Technology, which has been very convenient place to study. I also thank the academic personnel for cultivating my interest towards the field of finance.

Lastly, I hope that I will be worth the money of which society has invested in me during these 19 years of education, starting from the elementary school and ending here at the university.

On 20th of July 2016 in Heinola,

Juuso Seppälä

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1. INTRODUCTION

1.1 Background

Centuries ago, Italian statesman and political writer Niccolò Machiavelli wrote down the words: “Never was anything great achieved without danger”. He certainly didn’t discuss about finance, but the quotation applies very well to principle finance theory known as risk-return tradeoff.

Main conclusion of risk-return tradeoff theory is that potential returns rise together with increase in risk - huge danger shall lead the adventurer to unbelievable treasures. Theory about tradeoff between risk and return is remarkably fundamental among the finance academics: It is taught in the beginning lectures of every business school around the globe and within the large masses the relation is considered as a fact that requires no further questioning.

The connection between risk and return sounds logical, which might be one reason for theory’s popularity. Risk-return tradeoff has rooted so deeply in our thinking that claiming anything else would sound absurd. However, there is one problem which sets the whole theory under suspicion: Numerous studies show that the relation is not as straightforward as the widely recognized financial theories have stated.

First major research to awake the debate was made by Black, Jensen and Scholes in 1972 when they proved that capital asset pricing model is not working as it should. In this paper we focus on one great aberration, which arises from the fact that some investments bearing low risk have performed better than more risky investments in term of returns during the past decades. This can be well seen by examining the volatility and return correlation in various stock markets around the world.

Volatility is a measure for variation of price of a financial instrument over time – and when variance is high, then the risk of losing capital is also higher. Historical volatility indicates the range where price of an instrument should set among time according to past information, so volatility is widely used to estimate the risk of certain stock. If volatility is high, the price may drift substantially from its current level and vice versa. A simple and easily calculable meter like this is very handy for finance purposes.

Price fluctuation of companies with low volatility is minor, so they are traditionally considered as a good investment choice for more risk-averse investors that do not require high possible return. But because the volatility and expected stock return do not correlate as predicted in traditional finance theories, this effort of seeking high returns by investing in high volatility stocks won't work as intended (Ang et al. 2006). Same abnormality in correlation of risk and return applies to beta (Baker et al. 2011), which is a central variable in capital asset pricing model and thus covered later in this study.

This faulty correlation of risk and return has been baptized as *low-volatility anomaly* by the academics. In finance, the study of anomalies received more publicity around 1970's and extended more during the following decades. Anomaly means systematic deviation from theoretical expectation. These deviations often offer predictable opportunities for earning abnormal returns (Frankfurter and McGoun 2001). Sometimes theoretical expectations can be beaten by using rather simple trading strategies, which is also the case with low-volatility anomaly.

Research of anomalies has received much attention, because they show the flaws of existing theories and may show the path to new viewpoint or even paradigm. However, the existence of these "flaws" in classic theories is understandable. Complex world requires simplifications and conventional theories cannot account for everything that happens in the real world. This has awaked interest of scholars from the field of behavioral finance, and they have

paid some attention to explain low-volatility anomaly and find a reason for its existence.

When behavioral finance is involved, then finding the causation may become hard. Difficulty rises from the question of how to measure and model human behavior. It is easy to obtain data from purely finance-related schemes such as stock or volatility movements, but explaining why humans do something and which are the motives for that is more challenging. Moreover, models are always simplifications of reality. Barbara and Odean (2011) say it simply: “The investors who inhabit the real world and those who populate academic models are distant cousins”.

It is hard to name one single source for the anomaly, but few reasons have been suggested for the anomaly. Some originate from law-related mechanics such as leverage restrictions, but above all, most of the possible reasons are related to human psychology and emotions: Institutional investor’s incentive-linked motives, individual investor’s preference for gambling or too optimistic attitude towards high-volatility stocks (Li 2013). Unfortunately, it seems that the potential impact of psychological factors is not widely acknowledged, and consequently the discussion is fairly scarce.

Anomaly always opens up a possibility for excess profit. If markets are efficient, the anomaly shall have perished years ago via arbitrage process – but still, the low-volatility effect persist almost a half century after it was initially found. This implies that there are mechanisms which prevent the investors from exploiting the anomaly. During the last years the low-volatility investing has raised more attention and new funds have emerged to markets, which is expectable as low-volatility assets have performed especially well in the aftermath of financial crisis 2007-08. These strategies are inspected in the last part of the study.

1.2 Research questions and objectives

What are the reasons for low-volatility anomaly to exist, and why the arbitrage has not yet shrunk those excess returns away? Does behavioral finance play any role in this anomaly? How strong is the correlation between low-volatility stocks and market returns in Finnish stock market? Can investors gain abnormally high returns by using low-volatility trading strategies?

These are the key questions in which we try to answer and find solution in this study. By answering to those research questions we cover the theoretical background of the anomaly, find empirical evidence for it in Finnish stock market and finally make a practical approach when offering ways to put the low-volatility strategy into action.

If we present the previous research questions as objectives, then the aim of the research is describe what is low-volatility anomaly and find possible reasons for its existence. Another main object is to measure if the low-volatility anomaly can be observed also in NASDAQ OMX Helsinki stock market. Finally, the practical objective of the study is to form a trading strategy that takes advantage of this anomaly.

1.4 Delimitations and restrictions

Theme of the study is quite broad, so we will have to insert restrictions - a man’s got to know his limitations. Major delimitation of this study is to focus on Finnish stock market in empirical part, even though most theoretical evidence presented in this paper come from other markets. This delimitation is partly done because of writer’s own interest to learn more about Finnish stock market, but there are also more valid reasons. By choosing this focus we hope to increase the knowledge and possibly even provide new information.

Good motive for market restriction is the lack of low-volatility literature that observes Finnish markets. Local markets have been covered in some thesis

studies, but majority of proper academic research is written with another market locations in sight. This leads to large amount of researches focusing on U.S. markets – of course there is still significant studies from other market regions as the anomaly has been scientifically verified in numerous stock exchanges. In any case for the sake of increasing the amount of comparing research we will focus on OMX Helsinki market.

Another cause for the delimitation arises from characteristics of OMX Helsinki market. A study performed in this market may offer new thoughts, because the natural volatility of this relatively small stock market is somewhat higher when compared to larger exchanges usually covered in international studies. Larger developed markets - such as U.S. stock market – should encounter weaker volatility changes, which by common sense should also have an effect on the studies committed in those environments. Different environment itself works as one touchstone for the anomaly by helping to verify if it appears universally or if the anomaly only works when some specific market conditions are met.

1.5 Structure of thesis

This thesis is divided into two main parts. First part is qualitative overview which is close to literature review in style focusing on presenting prevalent paradigm and low-volatility anomaly. Second part is quantitative empirical study that opens the discussed themes in more practical way. Lastly, from the foundation of these two parts we go through some practical matters and finally summarize the study.

One aim of the first part is to give good presentation of the prevalent paradigm and its theoretical basis. In this first part we discuss about themes such as risk-return tradeoff, market efficiency, ways to measure risk and present central models such as capital asset pricing model. Understanding these concepts is important, since they have more or less influence on nearly every paper in modern finance field and are also tightly linked to low-volatility anomaly.

Another aim of the first part is to open the nature the low-volatility anomaly. There we present evidence of the anomaly, but also go through possible reasons for the anomaly to exist – and think why the anomaly has not faded away. This latter section also challenges some views presented in theoretical framework as the anomaly is in contradiction with the current paradigm. In this latter section we take influence the field of behavioral finance in order to better explain the anomaly.

When the central theories and most significant literature is presented, the study moves to empirical part to see if the anomaly holds in practice. Empirical part concentrates on testing the low-volatility anomaly in the context of Finnish stock markets. Research methodology, data and results are all presented in order.

After empirical part is dealt, then practical matters arising from empirical part and conclusions in overall are presented. This includes discussion when to take advantage of the low-volatility anomaly and how to execute potential low-volatility trading strategies. We also suggest some good themes for deeper research. Lastly, theoretical and empirical parts are summarized.

2. PREVALENT PARADIGM: THE FRAMEWORK

Baker and Haugen (2012) see the rise of low-volatility anomaly as a practical paradigm shift: “In our opinion, we are now in the midst of a second paradigm shift in the field of finance. This time the shift is being driven by the research of practitioners rather than academics, whose self-interest is firmly tied to defending the current paradigm. These practitioners should begin hiring finance graduates who are properly trained in solving problems in real as opposed to imaginary markets.” This quote points well that academic atmosphere changes slowly, but within time all the different anomalies offer too big challenge for the old paradigm to hold. This which paves the way for behavioral finance and other more practically oriented sciences that try to understand the causes behind anomalies.

But to understand which might be changing, we first must recognize the existing structures. Prevalent paradigm of finance consists of theories and models that origin from as far as 1950’s. To mention few, these include modern portfolio theory by Markowitz (1952), efficient markets hypothesis by Fama (1965) and capital asset pricing model by Treynor and number of other researchers in the 1960’s. After 1970’s, those concepts have faced bold criticism, and especially the rise of behavioral finance during the last decades has set many traditional theories on the defensive positions. In the following topics we discuss about the principles of finance in the light of low-volatility anomaly.

2.1 Risk-return tradeoff

Risk is a central theme in this paper, so we will shortly discuss it and present what risk is in financial context. In our context risk can be thought as potential for financial loss, such as possibility that actual return is smaller than the expected one. Potential and possible are the keywords here as they refer to the probability of some event happening. One way to define risk is to formulize it as mathematical probability of some specific event occurring. The concept of risk

arises from uncertainty – we can't predict the future, only present enlightened guesses of how stock prices and other values might develop.

In financial context, the risk can be compartmentalized into multiple categories such as liquidity risk, operational risk, market risk et cetera. As we are studying stock markets, the market risk and its sub-category equity risk is the most pertinent for us. *Equity risk* is the financial risk involved in holding equity, and it occurs when stock prices or implied volatility will change. For example, if stock price falls down, then equity risk realizes as the value of investment drops.

Return is a gain or loss of an investment during particular period. It is normally presented as proportion of the original investment. Return is commonly perceived as positive, but it may also be negative and then considered as loss. Statistics show that company stocks have granted quite high historical average annual return when compared to other financial instruments.

Between years 1928-2013 the S&P 500 index gave an arithmetic average annual return of 11.50 %. During the same time period the 10-year US government treasury bonds gave a return of 5.21 %, and 3-month treasury bills returned 3.57 %. Within the last 10 years previous instruments have performed slightly worse, but have still granted good return. (Damodaran 2016)

As the comparison shows, there is clear hierarchy for different returns depending on the riskiness of financial asset. Short-term money market return is low, long-term money market slightly higher – the longer your investment is bound, the more unwanted events may occur. Government bonds return less than corporate bonds, because returns are less volatile and governments will not go into bankruptcy that easily.

As a side note we have to utter that reality is again more complicated, since the difference between stock and short-term debt returns has puzzled some researchers: Mehra and Prescott (1985) argue that stock returns have been abnormally high when compared to returns of short-term debt instruments, thus

being in conflict with the Arrow-Debreu model, which in turn is crucial part of general equilibrium model. This conflict is known as equity premium puzzle.

Always when humans are involved, the behavioral psychology also plays some part. Many people tend to be risk-averse and thus want to minimize the possibility of loss. They do not want to invest in risky opportunities unless adequately compensated for it. The amount of compensation depends highly on person's own views, prospect of investment outcome and psychological factors such as recent history of successful and failed investments (Shefrin 2002).

For example, investment advisers administer risk tolerance quizzes and use other methods to determine the degree of risk suitable for their clients. This divergence in risk tolerance states the need of variability in investment possibilities, and for one's part it empowers the risk-return thinking. People being less tolerant to risk will surely want to increase the expected payoff by allocating capital also to stock markets if there is provably low-volatile, but well-returning investment opportunities.

Investing in public company shares through stock exchange is considered riskier than any previously mentioned instrument, because in case of company bankruptcy the equity owners are the last group that get anything out of the bankruptcy estate. This hierarchy explains why equity markets are generally considered risky, so the demand for higher returns on stock market can be justified. Derivatives are categorized even more risky, and so is the venture capital investments and other direct investments. Figure below presents the often theoretic relationship between expected return and risk.

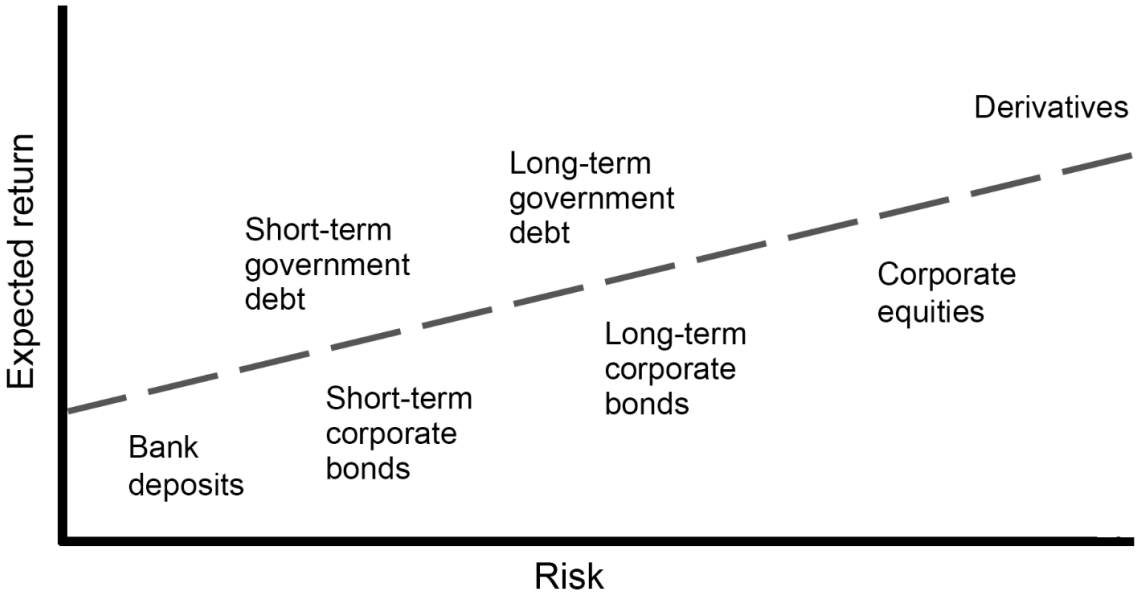

Figure 1: Theoretical relationship between expected return and risk.

Altogether, risk-return tradeoff sounds logical concept. It is clear that interest return on bank deposit is mild and capital is protected, so the expected return must be low. In stock investments the value may change rapidly and the base capital is not protected, because the price moves freely according to the markets and whole investment may be lost in case of bankruptcy. Level of risk tolerance guides the investor to choose the correct instrument.

In 1972 Haugen and Heins published a working paper, which clearly proved that risk and return in stock markets is higher than in bond markets – but within both asset classes, the relationship was actually negative! The problem is that this intuitively very smart framework of risk-and-return won't apply inside an asset class. Silva (2012) also confirms that risk-return –tradeoff is not generally observed in stocks. When inspecting stock assets alone, the low-risk stocks tend to beat their more risky counterparts. This can be proved by examining return and risk relation on asset level. We dig deeper into this problem in later chapters which challenge the prevalent paradigm.

2.2 Market efficiency

Since 1960's there has been continuous debate whether the financial markets are efficient or not, and to what extent the efficiency holds. The question is relevant also for this study, since existence of low-volatility anomaly would harm the market efficiency.

As most financial models, also the efficient markets framework requires bunch of assumptions to function properly. Most importantly, efficient markets hypothesis calls for investors to not only maximize utility, but also have rational expectations about the future stock prices. Investors should in average be correct in their estimates and make only random errors.

When utility is maximized, expectations are rational and errors are random, then expected prices do not systematically differ from equilibrium prices. When new information arrives it should be incorporated immediately into previous estimates, which in turn guides the investors and makes the prices to match new equilibrium. This way the price is constantly updated, and as all available information shall be included, then the market price is the most precise estimate of asset's true value.

All investors are not required to be completely rational in the decisions, but their reactions should be random enough, which leads to normal distribution pattern and in that way makes the net effect of actions balanced. When stock prices reflect the investors continuously updated forecast, which takes all available information into account, then all changes in the price should be result of random events that cannot be predicted. Hence, stock prices should move randomly and rise or fall in an unexpected manner. When stock prices exhibit signs of random walk, then one cannot consistently outperform market averages – which would also ruin the exploitation of market anomalies.

If markets are highly efficient and stock prices remain unpredictable, then it is utterly difficult to gain excess returns via arbitrage process. Professional investors spend already considerable amount of time scouting for stock mispricing. Number

of market participants is enormous and competition among investors is fierce. New information is digested immediately and transferred into prices quickly. Computer algorithms search for mispriced assets just to execute the transactions within milliseconds. It really looks like there is only slight room for arbitrage process, but is the market perfect enough?

Real-world evidence raises serious suspicions of whether the markets truly are as efficient as the theories state. Actually all earlier presented pro-efficiency arguments can be set under suspicion and the justifications can be found quite easily from live market occurrences. There is overwhelming evidence that market prices differ occasionally from fundamentals, stock prices do not drift randomly, arbitrage won't effectively fix the errant prices and markets are misguided by the constant presence of noise traders.

Various examples could be used, but classical one is the adaptation of stock prices to surprising fundament changes. Numerous cases show how stock prices won't adjust immediately after unexpected earning announcements, but continue to move as long as months after the announcements. This post-earnings announcement drift happens possibly because of investor's habit to response conservatively to new information, i.e. investors underreact to news that differ from the expected (Shefrin 2002).

Even when stock prices have all the time to adapt, still there is examples of inefficiencies where stock prices won't derive straight from market fundamentals such as upcoming cash-flows. Dual-listed companies offer interesting view to this logic, since for these companies the underlying fundamentals – most importantly cash-flows - are similar, which should naturally lead to similar valuation.

Classical and widely used real-world example is the price discrepancy between Royal Dutch and Shell Transport. Two companies have merged their interests on a 60:40 basis – whereupon Royal Dutch equity should trade at 1.5 times higher than Shell Transport. However, markets have continuously violated this parity heavily, i.e. prices do not reflect the fundamental value. Factors such as

exchange rate, government structures, taxes, etc. cannot explain the magnitude of violation (Dabora and Froot 1999).

Series of other well-known finance anomalies also work against the market efficiency. Calendar phenomenon such as January effect, overly good performance of small capitalization stocks, momentum effect and overperformance of low price-to-earnings –ratio stocks are few cases worth to mention. They simply do not fit into the traditional finance theory paradigm.

Our main interest, low-volatility anomaly, actually appears just to be another thorn in the already ripped flesh of traditional finance theory. Nowadays long list of different anomalies go against the efficient markets thinking. If efficient market hypothesis would hold even in weakest form, then anomalies should not offer excess returns in the long run like they have offered. This long-lasting, continuous overperformance of certain stocks and strategies is severe violation against efficient market hypothesis.

Another violation against efficient markets is the clear presence of noise traders, whose decisions are uninformed and erratic. When the number of noise traders is sufficient enough, their actions will cause prices to drift away from expected market equilibrium. When prices start moving, then rational traders must evaluate what is the basis for the price change – have the fundamentals changed or do the prices move because of pointless trading executed by less-informed market participants. Speculative and enterprise trading causes harm in different ways. Unnecessary buying and selling increases the market volatility, and this high level of volatility is not justified on the basis of news about underlying fundamentals.

Stock market bubbles present the most conspicuous problem for efficient market hypothesis, because exceptional chain of events and irrational trading behavior are often linked to those crashes. Black Monday in 1987 is perhaps the utmost example, and it is still unclear which precisely triggered the loss of one-fifth in value of Dow Jones Industrial Average. The financial crisis of 2007-08 has particularly increased the debate of irrationality of market forces, but as always,

the wisdom to explain those crashes appears only after the events. From efficient market hypothesis viewpoint the unpredictability of crashes is actually in line with the theory: If investors would have knew in advance what is upcoming, then they prices would have sank before the crisis actually started.

2.3 Measuring the risk and return

In this study we focus on measuring equity risk with volatility, but as beta is central factor in capital asset pricing model - which in turn is important part of this study's theoretical framework - we pay some attention also to it. Two common return measurements, Sharpe ratio and Jensen Alpha, are also presented as they are used in this study to compare different volatility groups.

2.2.1 Volatility

Equity risk can be evaluated by examining the volatility of the prices of particular stock. Volatility is widely used risk measurement, and it is incorporated in numerous financial models such as Black-Scholes-Merton option pricing model. By definition, volatility is a measure for variation of price of a financial instrument over time. In other words, it tells how far from the expected value the actual outcome might be.

Standard deviation is well-fitted statistical measurement for estimating volatility, and actually in financial context the standard deviation is quite commonly known as volatility - but it must be noted, that volatility can be measured also by other means than standard deviation and hence no equal sign shall be drawn between these two. However, in this work we use volatility as a synonym for standard deviation as we actually use this method to measure the price fluctuations.

Volatility can be calculated from daily returns by using the closing prices as a standpoint. More complex method is high-low volatility estimator, which adds the intraday data to calculation by taking the highest and lowest value during the day into account. Even more developed method is high-low-open-close volatility

estimator that also incorporates the opening and closing prices (Dobrev 2007). In this study we satisfy with the close-close prices as they provide enough information for our purpose.

Volatility is usually presented as a percentage change during one year. Other practical and often used time intervals are one and three month volatility – common for all is that last observation is the most recent price. Another adaption is solving out the expected volatility by estimating return probabilities, but in our work the historical volatility based on realized prices is more relevant. In order to calculate the historical volatility, we need to first find out the natural logarithm of closing price returns for particular stock:

$$r_t = \ln \frac{P_t}{P_{t-1}} \tag{1}$$

Where r is the return over period t, Pt is closing price and Pt-1 is previous day closing price. Next thing is to take the average of historical returns and calculate deviations from mean for each return observation. All deviations are squared in order to make them positive numbers so they count and do not cancel each other. Lastly, the average of squared deviations is calculated. If we estimate sample variance, then the outcome is divided by n-1, and variance of returns is solved.

$$\sigma^2 = \frac{\sum_{t=1}^{n}(r_t - \bar{r})^2}{n-1} \tag{2}$$

Standard deviation is the square root of variance, therefore:

$$\sigma = \sqrt{\sigma^2} \tag{3}$$

As earlier said, volatility is often presented as a percentage change during one year. To annualize the volatility the standard deviation must be multiplied with the square root of 252, which is widely used number of trading days in a common year. In fact, actually number 251 is used in this study as it is calculated to be the

closest to reality in Finnish market. To get monthly volatility, then monthly trading days – usually 21 - shall be used and so on. When T stands for time horizon, the generalized volatility is:

$$\sigma_T = \sigma\sqrt{T} \tag{4}$$

The direction of actual price movement is indifferent, since calculating standard deviation requires squaring all deviations from the mean so they can be summed up and observations do not cancel each other. Any upward or downward change in price will have an effect as it alters the standard deviation. This may be somewhat problematic, since for the most investors only the downside risk matters – but when keeping this restriction in mind, the volatility is useful risk meter.

Another feature worth to remark is the proportionality of volatility to the square root of time. Theoretical assumption is that stock prices follow the Wiener process. This assumption rises from the efficient-market thinking and more precisely stems from the random walk hypothesis, which states that stock prices evolve according to random movement and thus cannot be predicted. This sounds quite logical, since as the time increases larger changes can happen.

Overall market volatility is meaningful information on macroeconomic level, and it tells about the characteristics of different marketplaces. Different markets face varying level of volatility – for example, the Finnish stock exchange is more close to emerging markets than U.S. markets in terms of overall volatility. Only the Oslo stock exchange is more volatile among Scandinavian countries, which is consequence of country's high dependency on energy sector.

Chicago Board Option Exchange upholds a popular volatility index, shortly known as CBOE VIX. It estimates the implied volatility of S&P 500 index options over the next 30-days. It is quoted as percentage points, which predicts the expected movement with an approximate likelihood of 68 % (one standard deviation) during the following year. VIX was originally created in 1993 and the values were derived

from eight at-the-money S&P 100 options, but the index was completely revamped 10 years later in 2003 to cover more numerous amount of options from S&P 500.

If S&P 500 index moves largely, then VIX often makes a clear move to opposite direction – this is why the index has gained nickname “fear gauge”. The index works as a good measure for investor sentiment as it estimates the future volatility, although the reliability of estimation power has been criticized from time to time. Below is the VIX index plotted for the last quarter century.

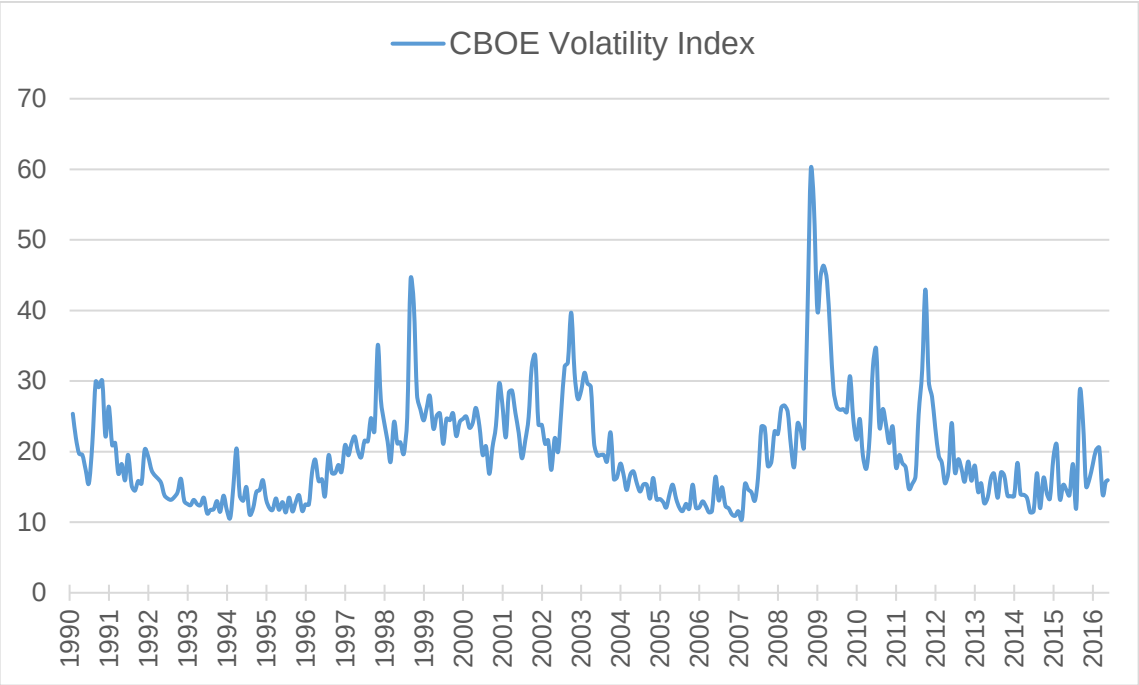

Figure 2: Chicago Board Option Exchange Volatility Index during years 1990-2016.

The period of last 25 years covers few persistent periods of low and high volatility. Years around the millennium were exceedingly volatile, and so were the years after last financial crisis. Clear peaks are caused by financial and euro-zone crisis, and the index stays constantly rather high also during those times. Generally speaking, if index receives a value less than 20, then the times are quite stable.

When index is over 30, then times are very volatile as investors are frightened of potential financial distress. It must be underlined that CBOE VIX registers the implied volatility, which is different than historical actualized volatility. The upper index still gives good information of events that have caused volatility spikes in past 20 years, which is useful information for any volatility-related study.

2.2.2 Beta coefficient

Beta is not used as risk measure in this study, but it is significant factor in capital asset pricing model, which in turn is highly in contradiction with the low-volatility phenomenon. The model is broadly discussed later, but before proceeding to it we must unmask the beta. Beta is a measure of asset's risk in relation to the market, and it is compared in respect to some benchmark index such as S&P 500 or OMXH. Therefore nature of volatility and beta differs significantly as beta is benchmark-relative measure and volatility is not.

Beta of 1 means that price of security moves along the market. A beta larger than 1 indicates that price moves generally in the same direction as market, but with greater leaps. Beta less than 1 indicates that movement is still parallel, but changes are slower than in benchmark. Beta of 0 states no correlation and value less than zero indicates that prices move to opposite direction than comparative index. Beta is mathematically expressed as follows:

$$\beta = \frac{Cov(r_{stock}, r_{market})}{Var(r_{market})} \tag{5}$$

Where β is beta, numerator is covariance of stock return and market index return. Denominator is variance of market index return. As the formula shows, only stock and comparative index return data is needed to calculate beta and rest is linear regression done in spreadsheet program.

Generally speaking, high beta stands for high risk as market movements are magnified. High beta is typical for companies in growth or turbulent business environment, while utility stocks typically have low beta. However, beta has number of setbacks which needs to be taken into account when using it. For example, zero beta doesn't mean riskless investment if there is no correlation between the asset's return and return of comparative market index because they represent different asset classes.

Another mistake is to compare betas that are calculated by using different benchmark index – this might come into questions when comparing two companies located in separate markets. Numerous finance databases provide data of company betas, but the information is somewhat worthless without knowing the comparative index or timespan of data. All in all, beta should be used with judgement.

Beta and volatility correlate strongly together even though the basics behind them differ fundamentally. Long-term global beta of 0.7-0.8 is typical for low-beta investing strategies, but low-volatility approaches as well have same sort of beta levels very often. One key difference between these approaches is that low-beta strategies allow more leeway for volatility movements, while low-volatility strategies often strictly restrict the allocation only to stocks below certain pre-determined volatility levels (Fallon and Davis 2015).

2.2.3 Sharpe ratio

William F. Sharpe (1966) developed the reward-to-variability ratio to enhance the calculation of risk-adjusted return. Originally used for comparison of mutual fund performance, the ratio has become possibly the most popular risk-adjusted return measurement in whole finance industry.

Ratio has its own drawbacks, such inaccuracy when the observed statistical distribution differs from normal distribution. Another weakness of Sharpe ratio is

that it penalizes from upside volatility – however, the issue is the same with all measuring that doesn't differentiate positive price fluctuations from negative.

Sharpe ratio formula is the following:

$$S_i = \frac{E(R_i - R_b)}{\sigma_i} \tag{6}$$

Numerator of the formula consists of asset return R_i minus the benchmark asset R_b. In this study the risk-free rate is used as a benchmark, but it could as well be a stock market index. Numerator forms the expected excess return over the benchmark return, which is then divided by standard deviation of an asset σ_i.

2.2.4 Jensen's alpha

Jensen's alpha measures excess return of an asset over the theoretical return. Meter can be used to evaluate if asset is generating proper return for its risk level. Jensen's alpha relies heavily on basics of capital asset pricing model, which is used to derive the theoretical return. Thus, meter suffers from the weaknesses of CAPM that are discussed later in chapter 2.4.

The meter is presented by Michael Jensen (1967) in a study evaluating fund manager's forecasting ability of future returns by using data of over hundred mutual funds in 1945-1964. Jensen finds that on average managers could not beat the buy-and-hold strategy and in many cases could not even cover the brokerage expenses.

$$\alpha_J = R_i - [R_f + \beta_i * (R_m - R_f)] \tag{7}$$

Jensen Alpha requires following inputs: R_i as portfolio return, risk free rate R_f, portfolio beta β_i and market return R_m. If outcome is positive, then the asset or

portfolio generates excess returns and if negative, then the investment underachieves.

2.4 CAPM and its critique

Capital asset pricing model (later: CAPM) is used to determine the expected return on capital asset, and it is widely used in valuation calculations and other financial computations. According to one of the model's creator William Sharpe (1964), an investor must choose between price of time and price of risk, first one being the pure risk-free interest rate and latter one being additional expected return per unit of risk borne. These allocations can be done along capital market line, which shows the risk and return relationship for all efficient portfolios.

All investors should invest in the portfolio with the maximum compensation for risk taken - or maximum Sharpe ratio - and alter the leverage of portfolio to suit their risk tolerance level (Northern Trust 2014). So the central underlying assumption is that security returns should be a positive linear function of risk. As we know, this statement is in contradiction with the low-volatility anomaly experienced on real markets. To better evaluate the divergence between CAPM and some deviant research results, we shortly present the model:

$$E(R_i) = R_f + \beta_i(R_m - R_f) \tag{8}$$

Where $E(R_i)$ is expected return of an capital asset, R_f is risk-free rate, β_i is beta on an asset and R_m is the expected market return. Proxy for risk-free rate is usually the rate on short-term treasury bill, since those are considered as safe investments. Beta measures the exposure to market movements and it is calculated as presented in preceding chapter. Market risk is obtained by subtracting the risk-free rate from expected market return, and thus it is also called as market premium. Consequently, individual risk premium is beta multiplied by market premium. Needless to say that model requires bunch of assumptions to be made before it can be used.

An important concept related to this is the security market line, which can be though as graphical presentation of CAPM. It displays the risk of an individual security as a function of systematic risk. As CAPM predicts the relationship between expected return and risk to be straightforward, also the security market starting from risk-free rate is presumed to be linear and positive. Hence, y-intercept is the risk-free rate R_f, while beta marks the exposure to market changes and slope is the market premium $R_m – R_f$. Following igure visualizes this:

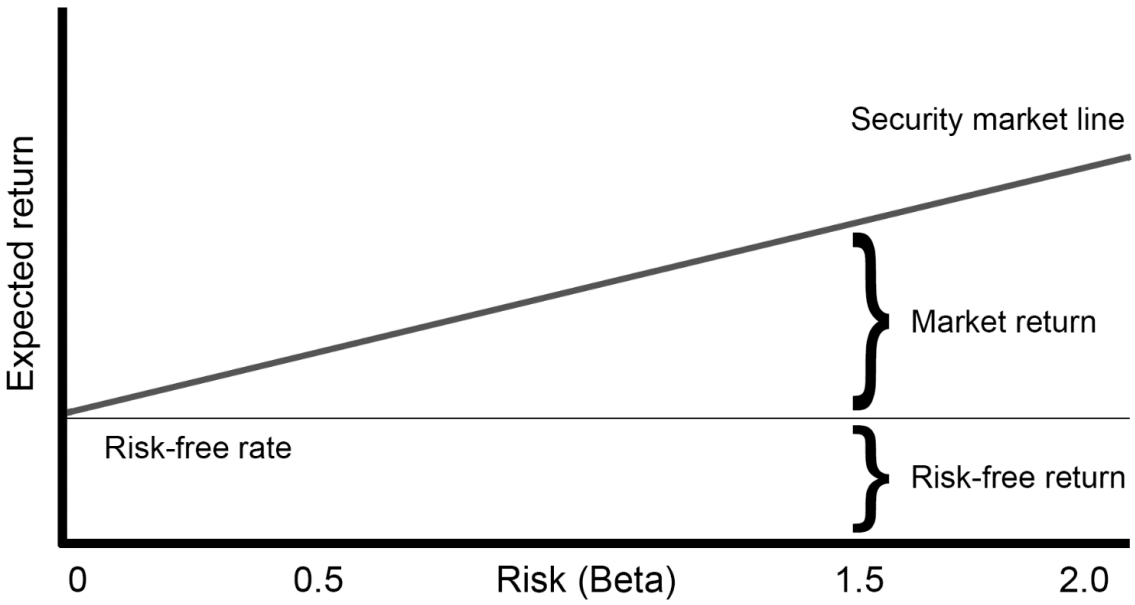

Figure 3: Security market line.

CAPM and related theories have been criticized since the 1970's. Black, Jensen and Merton (1972) summarize the result of their broadly-cited study: "Intercepts are consistently negative for the high-risk portfolios (B > 1) and consistently positive for the low-risk portfolios (B < 1). Thus the high-risk securities earned less on average over this 35-year period than the amount predicted by the traditional form of the asset pricing model. At the same time, the low risk securities earned more than the amount predicted by the model." Alphas for low-risk securities were too high in light of theory, and correspondingly the alphas for high-risk securities were too low.

Threesome claim that high-beta securities had significantly negative intercepts and low-beta securities had significantly positive intercepts, which denotes that low-risk portfolios performed consistently better than predicted by CAPM. They still confirm that the relation between return and risk is linear, but the slope of security market line differs from theory. The slope was steeper during the pre-war period of 1931-1939, but then it turned gentle and even negative in last period 1957-1965 – so the stocks with low beta performed better than the CAPM predicted. This finding is steeply against the traditional risk-return relationship.

Fama and MacBeth (1973) ended up with the same kind of results: “On average there seems to be a positive tradeoff between return and risk”. In general, studies of that time accepted the linearity of return and beta, but criticized the intercepts or slope of the security market line. Capital asset pricing model actually faced lot of criticism already in the yearly years, but that apparently that has not had much effect on subduing its popularity.

As the time went on, Fama and French (1992) conducted cross-sectional research two decades later, and they found that the relation between average return and beta disappears during the more recent 1963-1990 period. Therefore, central prediction of CAPM – linearity of return and beta – was not consistent with the new data ranging from 1963 to 1990. This finding also reduced the credibility of beta as risk measurement.

Last phrase that summarizes the results is crystal clear: “We are forced to conclude that the Sharpe-Lintner-Black model does not describe the last 50 years of average stock returns”. Fama and French questioned the whole CAPM model instead of just criticizing the slope or other minor glitches. Interesting sidenote is that Fama and French found the size and the market-to-book –ratio to explain the cross-section of returns better than beta. Since then these observations have gained more interest among the academia, and many studies have focused on those factors.

After all, the most constitutive critique again CAPM is made by Roll (1977): “The theory is not testable unless the exact composition of the true market portfolio is known and used in the tests. This implies that the theory is not testable unless all individual assets are included in the sample.” Market portfolio should contain every asset in the world, but forming a true market portfolio like that is practically impossible, so shortly said the market portfolio is unobservable.

Usual manner is to use some index as a proxy for market portfolio, but Roll also points out that CAPM can be very sensitive to choice of market proxy, so the choice of index proxy has strong influence on results. From theoretical perspective, CAPM is suffering from numerous problems and is not valid enough, which has led many researchers to attempt in creating better model. However, many of these extensions come with the cost of giving up the mean-variance efficiency (Ross 1978) or are constrained in other ways.

3. LOW-VOLATILITY ANOMALY

Now when we have understanding of prevalent paradigm, it is eligible to continue forward. This part focuses on explaining the low-volatility anomaly, provide evidence of its existence, present possible explanations for the anomaly and finally analyze the phenomenon from the perspective of behavioral finance.

3.1 What it is?

The punchline of low-volatility anomaly (also called volatility anomaly or low-beta anomaly) can be summarized in the following: Stock portfolios consisting of low-volatility or low-beta stocks will perform better on average than the high-volatility or high-beta portfolios.

Low-volatility anomaly challenges the equilibrium asset pricing theory, which says that an asset's expected return is directly proportional to its beta or systematic risk. This traditional view emphasizes that higher-risk securities should be rewarded with higher returns while lower-risk assets receive lower returns, just like the CAPM predicts (Soe 2012). This may intuitively sound reasonable theory, but the empirical evidence brings strong support for the contrary view.

We have already provided evidence that the trade-off between risk and return works between different asset classes such as corporate bonds and stocks, but not within asset classes such inside stock markets. The digression from expectations of risk-return trade-off theory is large, and some studies have found the same deviation inside bond markets, but this study focuses on the equity side.

Low-risk stock portfolios have performed better than their high-risk counterparts for decades not only in US, but also in numerous other economies around the world. Leading study that proves this is the one committed by Baker and Haugen in 2012. This study is described and partly replicated in empirical section of this paper.

The anomaly has been under evaluating since the 70's and discovery of empirical flaws in capital asset pricing model (Cowell 2013). The research around the anomaly has intensified during the last decades and because the rise of behavioral finance. Financial crisis of 2007-2008 also substantially increased the consciousness of this anomaly. The evidence concerning the low-volatility anomaly is comprehensively delved through later in own chapter.

The whole phenomenon could be impugned by questioning is low-volatility anomaly really an anomaly, or simply a mere indication that stock returns are poorly explained by capital asset pricing model or its extensions. Earlier we have presented plentiful of evidence which could terminate the whole CAPM – and not only it, as even the more sophisticated extensions of the model suffer from various problems.

Anyhow, the framework of risk and return has existed longer than many finance models like CAPM, but regardless of that, if we still intuitively agree that risk and return should correlate positively inside equity markets, then there certainly is anomalous effect that causes disturb to theories and thus needs to be solved.

If and when the low-volatility anomaly exists, it will offer a way to gain abnormal returns. Since low-risk stocks seems to be mispriced, then one could simply build a low-risk portfolio that has better risk-return characteristics than the market portfolio or contrary to this, short-sell high-risk stocks (Silva 2012).

For a portfolio like that returns are not only higher, but at the same time risk is lesser. One major question is why this phenomenon has not yet been arbitraged away, even though awareness of the anomaly has increased rapidly after financial crisis and the anomaly has been commercialized in form of just few years old low-volatility funds and other investment methods.

3.2 Evidence of anomaly

Next we focus on providing evidence of low-volatility anomaly. Most evidence come from recently performed time-series studies in order to show that low-volatility anomaly is still “alive and doing well”. Actually the last decades show that general interest - and consequently the research - around this phenomenon has increased, which means that up-to-date research results are quite easy to find. Evidence presented now is just a scratch from the total literature that supports the low-volatility anomaly - but even part of it is worth to present for the sake of understanding the magnitude of anomaly. Most of the articles now presented are highly cited.

Haugen and Heins (1972) were among the first to document the lack of positive relationship between risk and return in stock markets: “The results of our empirical efforts do not support the conventional hypothesis that risk – systematic or otherwise – generates a special reward. Indeed, our results indicate that, over the long run stock portfolios with lesser variance in monthly returns have experienced greater average returns than their ‘riskier’ counterparts.” Interestingly, they also found similar results from bond markets. Risk-return tradeoff clearly works between asset classes, but the findings by Haugen and Heins prove that the case is different inside single asset classes.

Another early groundbreaking study advocating the high return of low-volatility stocks was the paper by Black et al. in 1972. The study is already presented in section “CAPM and its critique” along the other critical views focusing on debating against capital asset pricing model. It is worth to mention that numerous studies since 1970’s that criticize the CAPM directly or indirectly do simultaneously advocate the low-volatility anomaly. Most of those studies would also fit well into this section, but they are dealt separately as they are more associated with general critique of CAPM. It is good to comprehend that modern research doesn’t really bring that much new information – it just fortifies the existence of anomaly that was initially found decades ago. Resilience of the anomaly is a mystery as such.

There are few typical ways to do research on the low-volatility anomaly. One way to find proof for the anomaly is to compare the performance of low-volatility indices to other market indices. Generally speaking, snapshot of most widely noted low-volatility funds shows that low-volatility indices have performed well when compared to general main indices.

Popularity of low-volatility funds and indices have expanded fast in last couple years, but finding real data for index comparison with a longer time perspective is unfortunately hard. Various brokerage companies show figures in their brochures that are actually formed by backtesting, which indeed is good way to demonstrate the past performance when in lack of real historical actualized data. As backtested results are often used in marketing funds, they also contain some risk – for example, fund manager might want to tune the strategy to capture the past market successes at the cost of losing long-term strategic choices. Despite these thoughts, next we present partially back-tested low-volatility index.

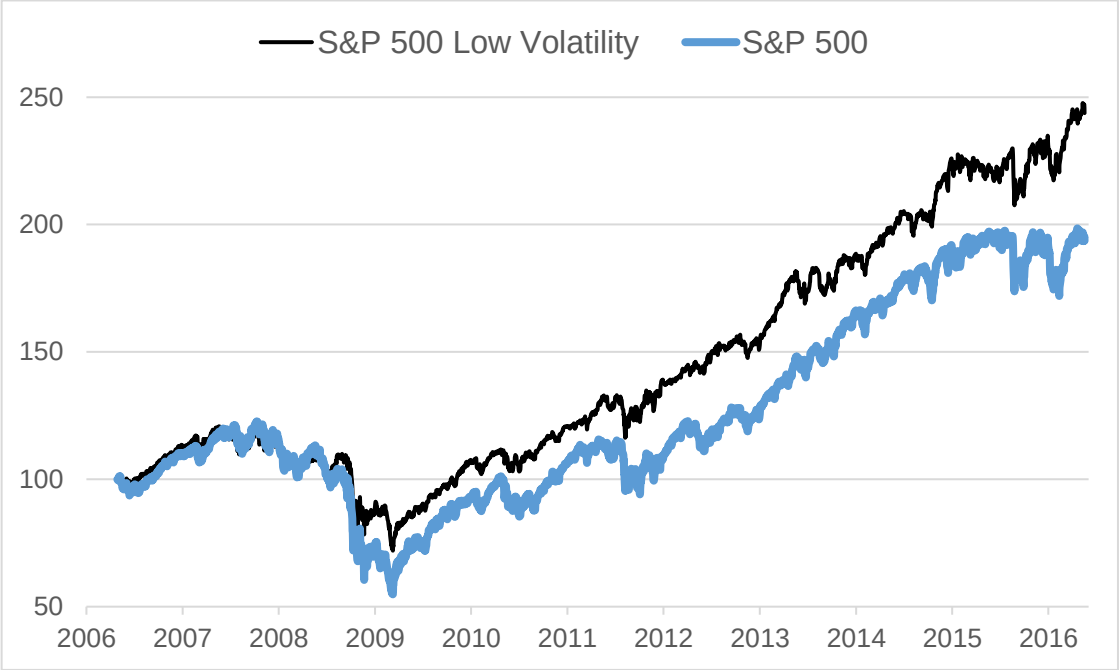

Figure 4: S&P 500 Low Volatility performance compared to S&P 500.

During the last 10 years the S&P 500 Low Volatility Index – which consists of 100 least-volatile stocks of S&P 500 from U.S. markets - has generated higher annual medium returns than main S&P 500 Index (S&P Dow Jones Indices 2016). Figure below shows total return development of S&P 500 Low Volatility and S&P 500 indices. In our Figure the indices start in June 2006 at 100 points, but actually the low volatility index started in 2011, so earlier data is formed by other ways. The most obvious remark is the good performance of low-volatility stocks during the financially harsh times.

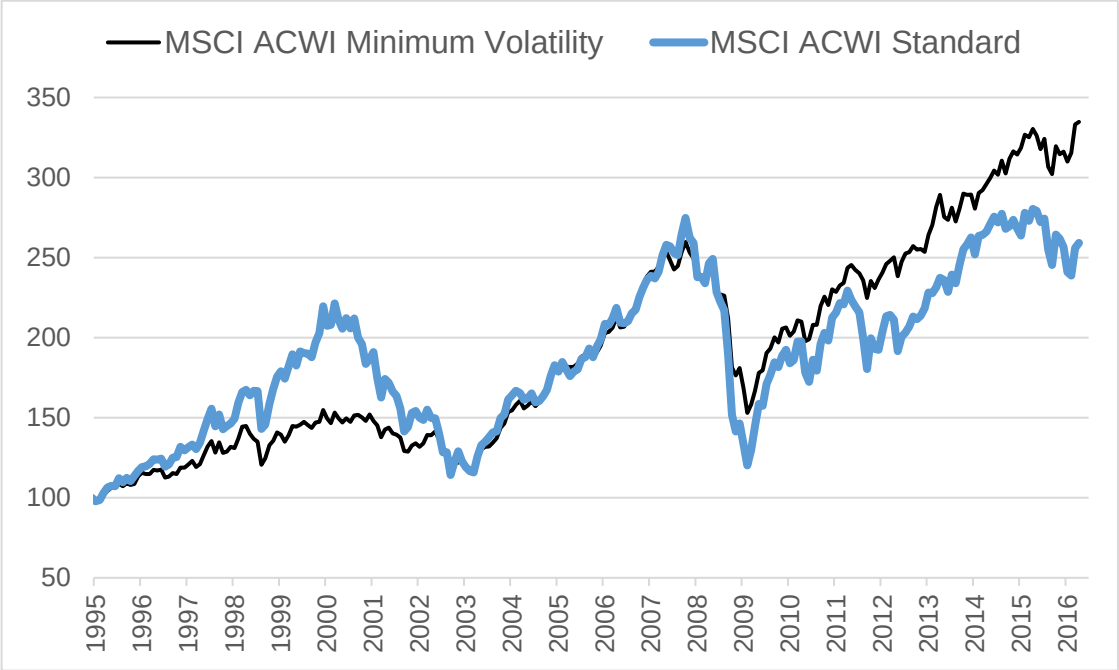

Figure 5: MSCI ACWI Minimum Volatility performance compared to MSCI ACWI Standard.

Worldwide MSCI ACWI and MSCI ACWI Minimum Volatility indices give us broader look with a longer perspective of 20 years, but the results are parallel to U.S. markets. Main index covers 23 developed and emerging markets, but quite familiar development can be seen when compared to S&P 500 index: Total returns for lower volatility index are notably higher during the last decade (MSCI 2014). An interesting point is the supreme performance and fall of standard index around the millennium. One explanation for this is the technology bubble,

because technology stocks tend to have high volatility and are weakly in presence in the minimum volatility index.

Both graphs show that low-volatility investments have performed well after the financial crisis of 2007-08. Many investors prefer less volatile investment opportunities during the bad times, but hard times relatively favor companies with more stable business environment. Typical example is utilities sector, which has low volatility by its nature – those goods are bought despite of economic condition.

Current comparisons show the differences between low-volatility index and standard index, but the deviations would be overwhelming if low-volatility index is compared to high-volatility index. A trick like this is actually done another method. Popular research method for evaluating volatility-related performance is to form portfolios of individual stocks, and divide them into quintiles according to expected risk. Normally beta or pure volatility is used as a proxy for the risk. Then top and bottom quintiles are compared to see whether their returns differ. Usually they do significantly differ for the benefit of low-volatility stocks. Next we present few salient studies done in this way.

Blitz and van Vliet (2007) find undisputable evidence of low-volatility performance in terms of in terms of Sharpe ratios and CAPM alphas. They use data of global large-cap stocks over the 1986-2006 period located in US, Europe and Japan. Globally, risk-adjusted low-risk portfolio combines a beta of 0.56 with positive alpha of 4.0 %, while the most risky portfolio has beta of 1.58 and a negative alpha of 8.0 % per year – so the alpha spread of the top versus bottom decile portfolio amounts to 12 %. Beta-sorted portfolios have 3-7 % lower alpha spread among different regions, so they conclude that volatility effect is stronger than beta effect. They also find that low-volatility anomaly is distinct effect and cannot be entirely explained by size, value or momentum phenomenon.

Baker et al. (2011) call long-term outperformance of low-risk portfolios “perhaps the greatest anomaly in finance”. They divided U.S. stocks into five groups based

on their five-year trailing values of volatility or beta. Data used ranged from 1968 to 2008 covering 40 years. Bottom quintile beta and bottom quintile volatility portfolios both outperformed the most risky portfolio. They also show in graphic that low-risk portfolios' paths from historical values to the present value are a lot smoother when compared to paths of high-risk portfolios.

Despite beta and volatility are highly correlated measures of risk, the writers still found slight differences between those two: Beta drives the anomaly in large stocks, but in small stocks both the beta and volatility provide equal results. Portfolios with low beta performed better than volatility portfolios during bull market, so they conclude that "low beta is high alpha is a robust historical pattern." Interestingly, they also point out that return gap has widened slightly since 1983. Explanation for this might be the increase of institutional managers, who are better capitalized and more quantitatively sophisticated.

Baker and Haugen (2012) covers the time period of 1990 to 2011. Data includes stocks from 21 developed countries and 12 emerging markets. They find the relationship of risk and return inverted for both, the developed and emerging countries. Baker and Haugen summarizes the obvious results with the statement: "As a result of the mounting body of straightforward evidence produced by us and many serious practitioners, the basic pillar of finance, that greater risk can be expected to produce a greater reward, has fallen." They also propose the manager compensation and agency issues as an explanation for the low-volatility phenomenon. These arguments are evaluated later.

Hsu et al. (2013) use global equity dataset including the emerging markets. Sample period for developed countries run from 1987 to 2011 and for emerging countries from 1994 to 2011. Their empirical results corroborate to the previous results in other studies. They contribute to existing research by extending the research on emerging markets. Low-volatility anomaly exists in both, developed and emerging markets. Researchers also find interesting information about the sell-side analyst behavior, which is reported in the following chapter.

Frazzini and Pedersen (2014) use wide dataset of U.S. and international stocks, but also treasury markets, corporate bonds and futures. They confirm the findings of Black et al. (1972) for U.S. stocks as they find security market line being flatter than predicted by CAPM. They find the same flatness in 18 of 19 international equity markets, but also in treasury, corporate bonds and futures markets. In general, they have strong proof that portfolios of high-beta assets have lower alphas and Sharpe ratios than portfolios of low-beta asset. They suggest that investor's should bet against beta, i.e. invest in low-beta assets.

3.3 Explanations for the anomaly

There are few main types of explanations for low-volatility anomaly. First ones are attempts to explain the puzzle by finding economic reasons for weird relationship of risk and return. Another common explanations rises from the psychological viewpoint, which treats the investors as puppets whose actions are led by incentives and other somewhat primitive behavioral influences. Lastly, of course there are number of attempts to explain the whole anomaly away by arguing that empirical findings are not robust and may disappear when slightly different methodological choices are made.

Black (1972) presented one of the earliest explanations for underperformance of high-volatility stocks. Investors seek for higher returns by leveraging up their portfolio – but often leverage is costly or unavailable, so investors drift to buy high-risk stocks so to achieve better returns. This over-allocation of risky stocks leads to underpricing of low-volatile stocks as they attain less savor from investors. Explanation is convincing, since scarcity is the natural state of economy, and investors – individual or institutional - are always more or less leverage constrained.

Avoiding leverage may rise from two causes: Conservative investment habit or restricted mandate. First one might be more pertinent for individual investors, as they usually are particularly shy to leverage their investments. Many ordinary people see it as a good habit to only invest with own capital instead of using debt

money. Undoubtedly, investing with debt increases the overall financial risk, but the other side of the coin is that restricting leverage actually leads the investors to choose more risky assets as earlier presented. When tendency for individual investor's overconfidence and preference for gambling are taken into consideration, the argument is even more reasonable.

Leverage restriction is relevant explanation when it comes to professionals, since institutional investors usually have strict mandate to operate and are leverage constrained in many countries also by law. For example, in U.S. the Investment Company Act severely restricts the maintainers of mutual fund to use leverage or borrow against the value of securities in its portfolio, so mutual fund's maximum allowed debt leverage is only 33 %. Shorting is also monitored, and allocation of assets is regulated. These leverage restrictions effects are stronger for mutual funds, since for hedge funds the constraints are not as tight and more freely use of leverage is allowed.

In some cases the fund manager's actions are not be restricted by law, but by the trading strategic of fund. It certainly is important to communicate openly to clients which is the chosen trading strategy, but at the same time these petrifying choices restrain the fund manager from doing major maneuvers. If the fund doesn't particularly happen to be specialized in low-volatility assets, then the strategic choices also leave open the possibility to invest in high-volatility stocks in order to seek better returns.

Consider a situation where half of the capital is allocated to bonds and the other half to stocks. If interest rates are low – just like now in many European countries – the one half of the investment is performing poorly. At this point it is tempting for the manager to change allocation within the stock capital towards higher risk, so the underperformance of bond-side would be balanced. Baker and Haugen (2012) actually prove that also institutional investors hold more volatile stocks, but the reasons are not only related to mandate, but also to manager compensation incentives.

Baker et al. (2011) as well present that agency issues create redundant demand for volatile stocks, which results in their overpricing and their production of inferior returns in the future. Institutions often set certain performance-based incentives for their professional traders to enhance the results. If the incentives are placed in a negligent way, they may actually work against the client's interest. These agency issues are mostly linked to manager compensation bonuses, and according to Baker and Haugen it is one of the main reasons behind low-volatility anomaly.

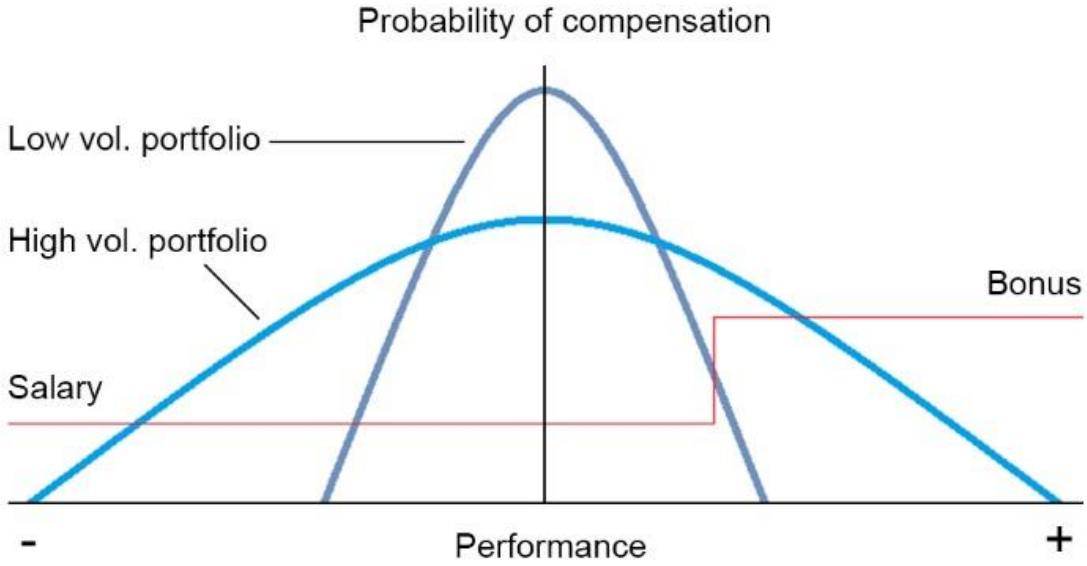

Figure 7: Manager compensation and incentives.

Professional traders usually have performance bonus which realizes after certain goal is fulfilled, like is shown in the upper picture presented originally by Baker and Haugen (2012). If trader upholds a portfolio of low-volatility stocks, he is not that likely to reach the performance bonus, even though client might be satisfied with the smooth returns.

By changing the allocation more towards high-volatility portfolio, the trader will more probably reach the performance bonus, but respectively the risk for client increases as returns become more unstable. Hence, sloppily set performance

bonuses will encourage the trader to take excessive risk, which works against the benefit of client.

Portfolio performance can be compared with different meters. One very popular meter is called tracking error, which is the measure of portfolio's performance in terms of closely it follows the selected benchmark index. Some index funds' objective is to strictly replicate the underlying index, but for actively managed funds the differing from comparison benchmark index is required for the purpose of making excess returns over passive investment strategies, i.e. generating alpha. Therefore, the tracking error can be considered as active risk taken by the manager.

Tracking error is by definition the standard deviation of active returns, and active return in turn is simply benchmark return subtracted by portfolio return. Scheme for calculating tracking error is presented below.

$$TE = \sqrt{Var(r_p - r_b)} \tag{9}$$

Where TE is tracking error, r_p is return of portfolio and r_b is return of benchmark index. Portfolio manager's skills are commonly evaluated by looking at information ratio, which is risk-adjusted performance measure. Information ratio can be defined as expected active return divided by tracking error as the following presents.

$$IR = \frac{\bar{r}_p - \bar{r}_b}{TE} \tag{10}$$

Where IR stands for information ratio, Avg(r_p) is average expected return of portfolio and Avg(r_b) is the average expected return of benchmark index and TE is tracking error.

Baker et al. (2011) point out that institutional equity managers often have an implicit or explicit mandate to maximize the information ratio. Unfortunately, this might cause an agency problem, since there is a certain incentive for institutional investors to overweight stocks with high beta. In information ratio the fund manager's return is compared to a benchmark index, both in the numerator and in the denominator, first being the return difference and last being the standard deviation of the return difference. Mathematically, this leads to favoring of low-beta and high-alpha stocks in order to maximize the information ratio. Iwasawa and Uchiyama (2013) have opened this incentive structure broadly in their paper. Ideally, buying undervalued stocks with beta close to 1.0 would minimize the tracking error, while still offering excess gains.

Hsu et al. (2013) reminds that analysts tend to issue upward-biased earnings forecasts. They analyze this behavior more closely and find that the optimism might not be caused by the lack of skill, but rather by tendentious optimism rising from few matters. Especially analysts who are in close terms with the underwriter of initial public offering process are doomed to have over-optimistic view about the firm, supposedly because of the biased thoughts promoted by the underwriter, who in turn has incentive to give positive image of the firm – and usually also does it, which causes large errors in recommendations (Michaely and Womack 1999).

There certainly is strong agency problem between the investors and the underwriter, as the latter one has incentive to promote overly optimistic view. In theory, analysts from underwriting company should have superiorly accurate information when compared to non-affiliated analysts, but their tendency to give overly positive recommendations will make the statements untrustworthy.

Interesting point for us is that Hsu et al. noticed analysts to be more likely to inflate earnings growth forecasts for more volatile stocks. This might be because clients can't detect inflation in growth forecasts if stocks are more volatile by nature. When expectations for volatile stocks are high, then the investors also advocate those stocks and buy them – until the earnings materialize and high expectations

fade, revealing the worse performance than expected. As forecasts are upward-biased, the finding by Baker and Haugen (2012) just amplifies the issue: Volatile stocks are better covered by financial analysts!

Baker et al. (2014) inspected if size, value or momentum anomalies could interfere the low-volatility anomaly, but they find no evidence that any of previously mentioned aspects would alone explain wholly the performance of low risk strategies, even though they slightly reduce the statistical significance of low-volatility anomaly. Same variables have been used as a control measure in various other studies.

3.4 Behavioral finance perspective

Behavioral finance has interesting viewpoints to low-volatility anomaly as well as in many other problems which can't be explained by traditional finance approaches. Behavioral finance has flourished within the last decades, but in economics the psychological aspect has been present for longer. For example, Adam Smith discussed about individual choices, fairness and justice as early as 1759 in his classic work The Theory of Moral Sentiments.

Decades later Jeremy Bentham wrote much about psychological side of utility, and John Stuart Mill elaborated these thoughts to develop utilitarianism in 19th century. Classical era economists tried to shape the economics towards natural sciences, which led the economic agents in models to be highly rational and wealth-maximizing. Later scientist have argued that modeling human action is more complicated than modeling natural sciences, so some simplifications are intelligibly needed. Still, it is unfortunate how much the finance world relies on models and schemes that can describe only the shades of real world.

Behavioral aspects didn't fit very well into the "rational wealth-maximizers" standpoint, so psychological viewpoint was more or less forget for over a century. Behavioral thoughts began receiving attention again in 1970's as many academics pointed out the flaws in traditional models by means of drew influence from psychology. For example, the creators of prospect theory, Kahneman and Tversky, both had their academic background in psychology and successfully merged studies from completely different field to finance. Nowadays the modern behavioral finance paradigm states that our rationality is bounded, actions are highly biased, simple heuristics are used to make complex decisions and we do not always act in a way which would maximize our wealth.

Quotation from Barber and Odean (2011) concretizes the previously written: "In theory, investors hold well diversified portfolios and trade infrequently so as to minimize taxes and other investment costs. In practice, investors behave differently. They trade frequently and have perverse stock selection ability,

incurring unnecessary investment costs and return losses. They tend to sell their winners and hold their losers, generating unnecessary tax liabilities. Many hold poorly diversified portfolios, resulting in unnecessarily high levels of diversifiable risk, and many are unduly influenced by media and past experience." When forgetting the old "rational wealth-maximizers" thinking, taking more pragmatic view and leaning to new assumptions, we will get a totally different look to low-volatility anomaly.

Baker et al. (2011) argue that preference for trading high-volatility stocks derives from the biases that afflict the individual investor. They especially mention three types of biases: Preference for lotteries, representativeness and overconfidence. Closely-related phenomenon is also the availability heuristic. These as well as numerous other biases which influence human actions are widely studied in the field of behavioral finance. Next we shortly go through each of the most significant phenomenon, and present how the human psychology drives the low-volatility anomaly in stock markets.

Preference for lotteries (or gambling) is common behavior among less-enlightened people. Even when expected payoff is known to be negative, people are willing to set wager for the chance of success. This behavior also applies to many individual investors in stock markets: They are often willing to take high risks even if the investment has lottery-like payoff. Kumar (2009) finds that individuals invest disproportionately more in stocks with higher idiosyncratic volatility, higher skewness and lower prices, irrespective of the fact that these stocks have lower mean returns. This behavior is linked to low-volatility anomaly, because noise trading increases the volatility and makes already risky investments even more unpredictable.

Kahneman and Tversky (1979) created the prospect theory, which illustrates how people choose between risky alternatives when probabilities of outcomes are known. They find that losses hurt more than gains feel good, which makes investors loss averse. If there is an equal 50 percent chance of winning 110 euros or losing 100 euros, most people do not attend the gamble. However, when

probabilities come more complicated, the animal spirits kick in and people lose their touch on risk.

For example, national lottery is held weekly in Finland, and the return rate is commonly known to be around 40 percent. Truly rational individual would not attend to lottery at all, because the expected return is clearly negative – but still people go to kiosks time after time to fill the coupon and test their luck. So buying a low-priced, but highly volatile stock is like attending in a lottery: Small chance for win, but with good luck the stock may multiple its value.

Good real-life example of this behavior was the case of Talvivaara Mining Company in Finland. Price of one stock in OMX Helsinki was over 7 euros in 2011, but the decreasing price of nickel, difficulties in industry processes and negative publicity caused by environmental problems started to press down the price. Financers lost their trust in 2013, and the company was set in company reorganization process. At this point the price of stock was 0.058 euros. A year later the company was declared bankrupt, and last quotation was 0.030 euros – this stock certainly was not the ace of spades.

During the last struggle, many small investors still found Talvivaara an alluring company to invest, which changed the ownership structure largely as institutional investors pulled their money off at the same time. As a footnote, interesting question is did the cheap-looking stock price attract the interest of small investors, in other words, do less rational investors think something is worth acquiring just because the price is low in absolute terms? This thought that stock being cheap in absolute numbers are cheap also in real terms, even being enormously erroneous fallacy, is surprisingly strong among the casual investors.

Representativeness is another phenomenon worth to mention. Shefrin (2002) writes: “People tend to base their predictions and probability judgments on how representative an event is. Alas, predictions based on representativeness exhibit too much volatility.” For example, some investors seeks high returns by investing in growth companies, so they can later sell the stocks with high price. These

companies tend to have high volatility, and thus are more risky than more mature companies with stable businesses.

Many would consider newly established high-technology company as a typical growth company, especially when newspapers are full of hype promoting the technology startups like Rovio and Supercell. Purpose of these state-of-the-art technology companies indeed is to seek quick growth, but unfortunately large number of these attempts fail. Here is the linkage to base rate fallacy, which tells that people easily ignore the base rate information and rely on specific information. Therefore a layman easily ignores the huge rate of failure of early stage innovative companies and usually ends up losing the capital.

On the other hand, many non-technology companies are seen as boring enterprises – especially the utility sector has wide variety of examples. However, when enough people avoid investing in casual and stable-performing enterprises, they will eventually come undervalued. Some investors see potential in this. For example, Carnegie Investment Councel (2014) writes in their webpage that "Every investor likes to believe they can find and invest in the next Google or Facebook", but quickly abandon that illusion and market their low-volatility products by telling that "Boring means little volatility and constant, predictable gains year after year which is a critical component of our client investment strategy."

Availability heuristic only accelerates the effects of representativeness and base rate fallacy. Stocks receiving great media attention tend to have higher than average volatility, because the intense new information flow builds up the trading volume and causes prices to move (Baker and Haugen 2012). The duo declares that most professional money managers are not very quantitative in their stock picks, so newsworthy stocks are easier to recommend to the clients. When money manager does changes in client's portfolio, those alternations can be more easily explained to the clients if the company is famous – especially if there is no proper quantitative analysis done. Falkenstein (1996) also finds that mutual funds tend to hold firms-in-news more.

Archetype of well-known companies are new technology stocks, because new innovations and the image of growth-seeking startup company usually attracts excessive interest from media. In overall, this also leads to preferring high-volatility stocks over less-fashionable ordinary companies. As a side note, if efficient market hypothesis does hold even in weakest form, then actually the stocks that are often in news should contain less potential for excess returns, because the information about stock is better among market participants.

Some say all publicity is good. If a company receives huge media visibility, even though the publicity would be bad, it will rise attention among crowds. Mining company Talvivaara works again as a good example. Before bankruptcy the company was constantly on news and received massive amount of publicity, even though most of it was very negative. Still it attracted the interest of individual investors – one reason might be that it simply felt familiar stock, and as the Finnish state-owned investment company Solidium had also invested in it, the stock must have felt even more acquainted. All individuals who were even slightly interested of finance news knew the background of company and understood the very basics of its business. So, if investor wanted to pick a lottery stock from Helsinki stock exchange, then Talvivaara would have been easy choice. In overall, this case resembles very well that investors are everything but rational.

Overconfidence is astonishing phenomenon – it is coded deep in human nature to believe that I and only I, over the others, know the truth, make the right decisions and have the best guesses. Overconfidence has gained much interest from researchers of behavioral finance, since it is considered as very notable and fundamental bias. Different researchers have done experiments to measure the overconfidence, such as presenting a numerical question and asking participants to provide 90 percent confidence interval around their answer.

Most confidence intervals appear to be too narrow, which means that people are overconfident in their estimates. When this investor overconfidence is applied to stock markets, it leads the people to think they can predict the future stock quotes and pick the winners. Unfortunately, in reality they are likely to become surprised

by outcomes. Cornell (2009) argues that overconfident investors tend to favor highly skewed and volatile stocks, which actually makes the stocks overpriced – and thus enhances the low-volatility anomaly even more.

As an interesting side note one study must be discussed. Psychological research has showed that men are more eager to take risks than women. Barber and Odean (2001) published a study with a topic “Boys will be Boys” – the heading says it all. They find support for the hypothesis that men execute more risky trades: They tend to hold stocks of small-size and high beta firms. However, men won’t acquire worse returns because of their stocks choices, but because they trade too often and make the profits disappear in transaction costs.

As finance realm is dominated by males, then also the base of traders is gender-biased and thus there occurs more unnecessary and pointless trading activity – this increases the volume, but jointly with overconfident views, also makes the prices spread more wider. Interestingly, Barber and Odean also find that differences are most pronounced among single men and single women. This leads to conclusion that married individuals do influence or make the trading decisions on behalf of spouse, and thereby flatten the effect of gender differences in overconfidence. In light of this evidence, we shall remind of the advice given in numerous interviews by Warren Buffet: Get married. It will not only make you happier, but provably improves the trading performance.

3.5 Limits to arbitrage

In general, with a good conscience we can rely on earlier studies and suppose that investors can benefit from arbitrage activity. Now to the interesting question: Why the low-volatility anomaly has not been arbitraged away? Even though the anomaly has awaken discussion since 1970’s, the increased knowledge has not lead the anomaly to fade away. And why even the sophisticated, well-informed institutional investors haven’t tried to benefit of this anomaly in a scale which would have vanished the anomaly? Most evidence alludes the low-volatility

anomaly being rooted deep in finance world or having some protective mechanisms.

In a perfect finance world, rational agents will quickly overtake the less rational investors from influencing security prices by trading mispriced securities through the arbitrage process. In the real world they try to do the same, but as arbitrage is often costly, risky or agents are restricted in various ways, the arbitrage process simply won't work as smoothly as in theory. Market psychology and human factors also play their own role in limiting the arbitrage. In literature, these handicaps are commonly referred as limits to arbitrage.

First of all, potential arbitrageurs may not know that the opportunity for arbitrage exists (Hans and Ramos 2013). One reason deteriorating the arbitrage might be simple intuition, which keeps masses of investors believing in the concept of risk-return tradeoff. The concept sounds intuitively so fundamental that a layman can't be doubtful of it.

As the tradeoff theory is taught practically in every business school when going through the basics of finance, it will be hard also for professionals to start suspecting the relation of risk and return. People tend easily to stick to the same old paths instead of venturing into new ones and changing old habits.

Some propagandists have taught that "the bigger the lie, the more it will be believed". Certainly, no-one is stating that risk-return tradeoff within stock markets would literally be a lie, but when one view is continuously repeated from decade to another by credible academics, then crowds of people start believing it as a "given fact" which requires no questioning. This public illusion may not be the primary explanation for the anomaly, but it may be somewhat noteworthy in explaining why the anomaly persists.

There are also more sophisticated guesses. Usually when persisting anomaly is found, it is good to examine how it relates to institutions. Baker et al. (2011) suggest that institutional investor's mandate to beat a fixed benchmark

discourages arbitrage activity in both, high-alpha and low-beta as well as in low-alpha and high-beta stocks. Institutional investor's implicit or explicit goal to beat the benchmark index leads to overweighting the high-volatility stocks. Therefore the "smart money" does not offset the price impact of any irrational demand.

For short-selling high-volatility stocks the incentive are as well too weak. Risky stocks usually tend to be small firms which are costly to trade in large quantities, since the borrowable volumes are small and costs are often high. Baker et al. also mention that institutional investment managers became progressively more numerous. As proportion of institutional investors has increased greatly since the 70's, the time must have amplified the effects related to institutional investors. Because of the same reason, studies concluded decades ago won't probably reflect the real state of today's finance world.

Often arbitrage is costly, which prevents the arbitrageurs from fully exploiting all the available opportunities. When opportunity cost rises up too high, then the attainable benefits decrease and it is no more reasonable to participate in arbitrage activity. Market is saturated by other investors searching for the same mispriced assets, so discovering those before else will require demanding research and good resources, which is expensive. Another expense comes from executing the arbitrage deal. If transaction costs are higher than the profit gained from arbitrage, then it is better to cancel the trade and withdraw.

For individual investors the price of arbitrage partly shows in form of fund's fees. Fund manager has to do constant research in order to pick the stocks that suite well to the active strategy. This research work requires human resources and other investments, which are in the end paid by the client in form of trading fees. Costs arise also from the transactions. From time to time, the fund manager has to update the portfolio to meet the low-volatility criterion, which requires selling old stocks and buying new ones. Update rate is relevant factor, since frequent checkup of chosen stocks increases the management costs.

Always when active trading strategy is executed, the trading costs climb up – and set on higher level than by following a passive strategy. Some research have been critical towards low-volatility investing and claimed that potential benefits are shrink when trading costs are included into calculations. This may be relevant point for the most often updated low-volatility funds, and it is worthy for investors to include this in their calculations. Same tenet applies to any actively managed fund.

4. EMPIRICAL ANALYSIS IN OMX HELSINKI

4.1 Methodology

Methodology used in this study is an adaptation of low-volatility study committed by Baker and Haugen (2012). Studies with closely similar methodology have been executed also by other researchers, but in this particularly comprehensive study Baker and Haugen use 22-year period dataset starting from 1990 for 21 developed countries (including Finland) and 11-year dataset starting from 2001 for 12 emerging countries.

Their study uses the last 24 months of returns to calculate average standard deviation for every stock and then sort the results into 10 deciles according to volatility. Same sorting is done for every month in dataset. Next, the average returns for monthly-sorted volatility decile are calculated so that the relation of return and volatility can be examined. The whole process is repeated by sorting the stocks also into quintiles and halves.

In this work the methodology is closely the same, but standard deviation is calculated using the last 3 months of returns. This way the changes in volatility have more immediate effect to the analysis outcome. The availability of daily data also encourages to use 3-month time frame - there is no need to cover the lack of data points by extending the horizon and at the same time taking more irrelevant older data into account.

Downside of short time frame is the exposure to non-stationary fluctuations of price. Several large low-volatility funds have come to use 12-month data, even though the portfolios are usually reorganized within 3 month intervals. However, the choice of time frame in volatility calculations seems to be an eternal questions as all options have their own pros and cons. Methodology of the study is illustrated in the following.

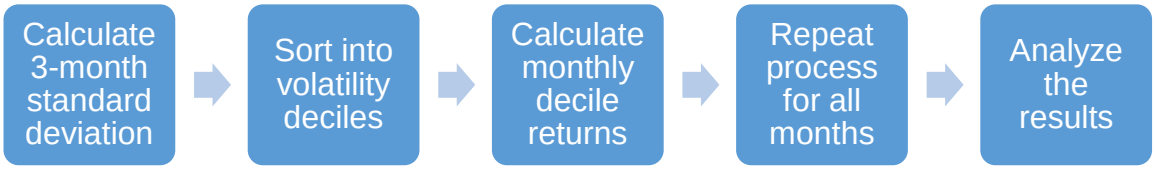

Figure 8: Principles of methodology.

The real number of trading days is taken into account for every month. Monthly volatility results are annualized by 251 trading days – average for Finland - so the results are comparable to other studies. Study covers the time period from the beginning of 2001 until the October of 2015, because this avoids the abnormal 2000's dot-com bubble peak prices from being taken into the study and thus provides more regular results. As OMX Helsinki is used as a comparative index, the key macroeconomic factors and development of OMX Helsinki main index during the study period are described in 4.3 Results chapter.

4.2 Data

Raw share price data was retrieved from Datastream and it covers the time period of 2001-2015. Data contains closing prices of all public companies listed in NASDAQ OMX Helsinki during almost the 15-year period of 1.1.2001 – 30.10.2015, hence providing close to 4000 observation points if the company has existed in exchange for the whole time period. Average number of observations is 2646, which is equivalent to circa 10 years.

Price data for shares was quite easily achievable, but refining raw data into usable form required significant amount of handmade work. Raw data was refined so that only one active share reflected a single company at time, which meant deleting some share series granting special voting rights or other functions. In addition to individual share data, supporting data concerning the OMX Helsinki main indexes was retrieved from NASDAQ OMX Nordic.

Number of companies is highest in year 2001 being at 152 and then steadily falls to around 123 companies in 2015 – the average being at total of 135, e.g. 13-14 companies in each decile. Larger company count is a substantial difference to Baker and Haugen (2012) as their data from OMX Helsinki includes only an average of 69 companies.

Data includes extinct companies to avoid the survivorship bias, but also for the sake of more data points. Otherwise the data would have been pretty thin as OMX Helsinki currently holds approximately 130 companies and only a portion of these have consistently existed for the 15 years. Data lacks few very new companies, since companies are not taken into observation before they have been listed for 4 months as the first batch of volatility information comes available for 3 month old companies and the return information requires one additional month to complete the cycle.

Some challenges arise with highly illiquid penny stock companies, which may appear as low-volatile companies because of minor exchange volume. Same companies still occasionally undergo significant price changes when large trades take place and shake the decimals of market price. These companies could have been secluded from the study for control purposes, but that would have distorted the study other ways and make the data more thin - so all OMX Helsinki listed companies remain in study.

4.3 Results

Please take note that even study of different volatility levels is committed mostly on decile level, still many results are graphically presented in quintiles or halves for the sake of clarity. If all ten deciles would be plotted, then many of the figures would come quite unreadable. Exact numerical information behind the figures is located in Excel file, which is available from the author.

Following figures shows the development of OMX Helsinki main index within past 15 years. OMXH PI is a price index, while OMXH GI index as a return index takes

also the dividend income into account. Attention must be paid for the matter that OMX Helsinki index return figures differs slightly from return figures calculated out of company level return data, because companies sorted by volatility into different decile classes contribute equally to decile's total return. 3-month rolling historical volatility between 1.1.2001 and 30.10.2015 is also plotted in the graph.

It is clearly visible that volatility has been comparably high for the whole period and has varied mostly within 20 and 30 percent – the all-time average being at 26 percent. Returns have also varied highly through the years, but for the years 2001-2015 dividend-including growth index finished positive with 16.22 % return or 1 percent sharp as annualized return. This underlines the significance of dividend paying stocks, since PI index went down -35.63 % during the same time period. Good dividend payers tend to be mature and stable companies, which fits well to low-volatility investing.

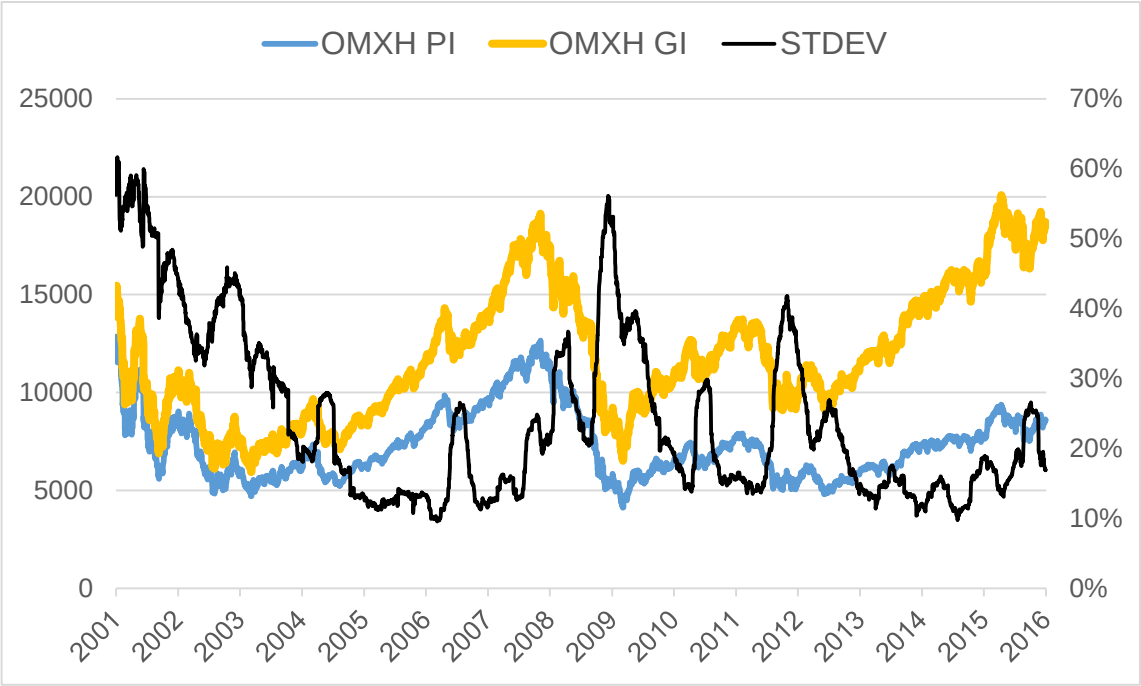

Figure 9: OMX Helsinki PI and GI indexes and annualized volatility of PI index during years 2001-2015.

Outside the graph it is worth to mention that Finland was in major economic depression in the early 1990s. In 1992 the OMX Helsinki main index lost nearly half of its value when compared to preceding year. These recession years were followed by times of high volatility, but at the same time economic recovery took place and especially the technology cluster drew Finland back among to the flourishing economies.

OMX Helsinki price index was peaking at over 18000 points in spring 2000, but sank to under 6000 points in autumn 2001. Figure captures part of this downward swing, but it also shows that volatility was running high after the technology bubble exploded around the millennium. Volatility was actually on peak level in 2000 and stood at high level for the consecutive year.

It is essential to mention that OMX Helsinki index was heavily influenced by changes in stock of world-leading communication devices company Nokia, which was and is still widely owned by numerous private and institutional investors. The exploding technology bubble harmed badly this stock, which clearly affected the index movements. State of the company had major impact on country's economy also because of its national subcontractor network.

Years 2004 – 2007 were quite steady from volatility perspective. Average volatility was around 16 % during these years with one notable volatility spike appearing around the summer of 2006. These years were very not favorable only for the Finnish stock market, but also for the national economy which was leaping forward and thus supporting the investor's optimism.

Another periods of peaky high volatility have occurred around financial crisis of 2007-08 and few years later during the European debt crisis. Greek government debt-crisis increased the market volatility during 2010 and the risk of debt crisis contagion to other Euro countries kept the volatility on high level until the end of 2012.

The next figure presents the returns of different volatility quintiles during 2001-2015 in OMX Helsinki. The graph is especially important since it captures the development in retuns of volatility deciles throughout the studied years. Quintile 1 (abbreviated as Q1 in all figures) is lowest volatility quintile, while Q5 is most volatile quintile. The lowest volatility quintile has outperformed the most volatile quintile for 14 years out of 15, which is very impressive result.

Figure 10: Returns of volatility quintiles during 2001-2015 in OMX Helsinki.

Only exception is the year 2003, when Q5 outperformed Q1 returns by 13 percent. The year 2003 was as well the only year when traditional risk-reward – relationship held just like the traditional financial theory suggests. Deeper study would be required to reveal why the year was so special that all equities performed well regardless of their volatility.

Worst year for nearly every quintile was year 2008, even though the most volatile quintile had enormous drawbacks also during the years following the technology bubble. Even being the worst quintile overall, still the most volatile quintile

produced positive returns during six years of 15-year period. However, the least volatile quintile managed to produce positive returns 11 times within same time.

Cumulative accrual of returns is another interesting point as it shows what would have been the investing outcome if low-volatility investing strategy would have been executed for the entire period of 15 years. The results reveals overwhelmingly positive cumulative return of 257.66 % for D1, while D10 receives negative return of -96.46 %. Least volatile decile has more than doubled the investment, while most volatile decile vanishes the original invested amount.

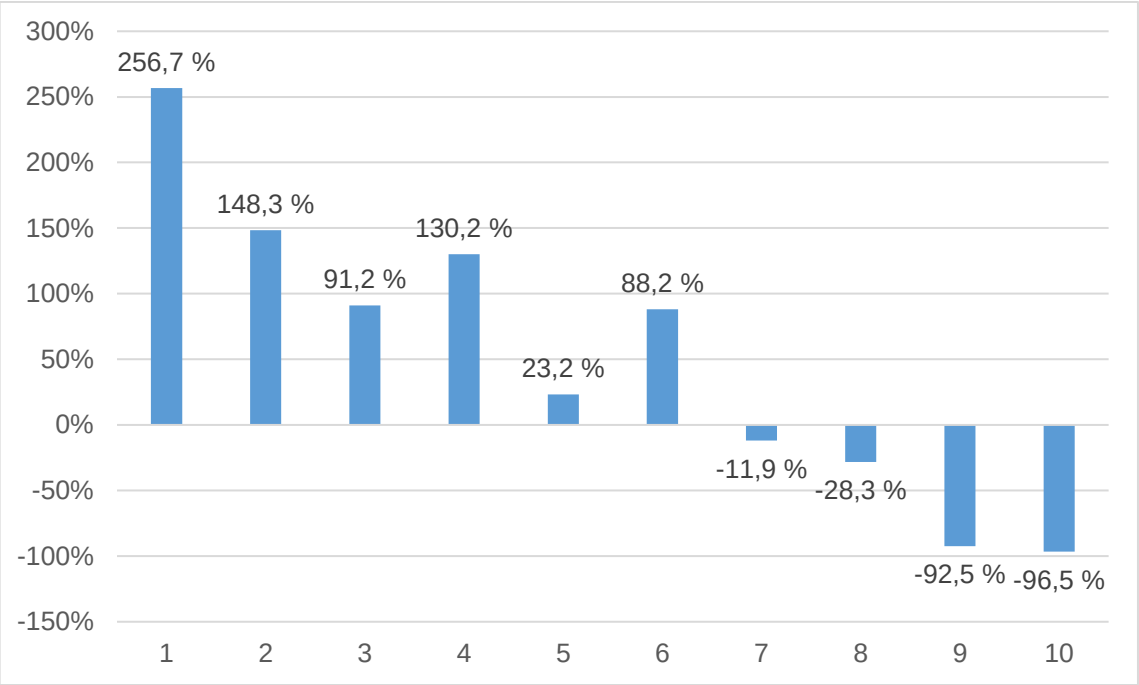

Figure 11: Cumulative returns of volatility deciles for the years 2001-2015 in OMX Helsinki.

Cumulative returns are positive for deciles from 1 to 6, but deciles 7, 8, 9 and 10 are all negative. It is noteworthy to see that cumulative returns are lined according to volatility decile with the exception of deciles 4 and 6. Regression model for variables “volatility decile” and “cumulative return” gives R-squared of 0.90. This denotes that low volatility is clearly associated with high returns.

Following figure captures the same cumulative returns, but in this case those are plotted against actual volatility levels rather than volatility quintiles. Results are obviously parallel to previous graph. Still this graph reveals the very important message of the negative correlation among risk and return, which is completely against the theoretical expectation from capital asset pricing model.

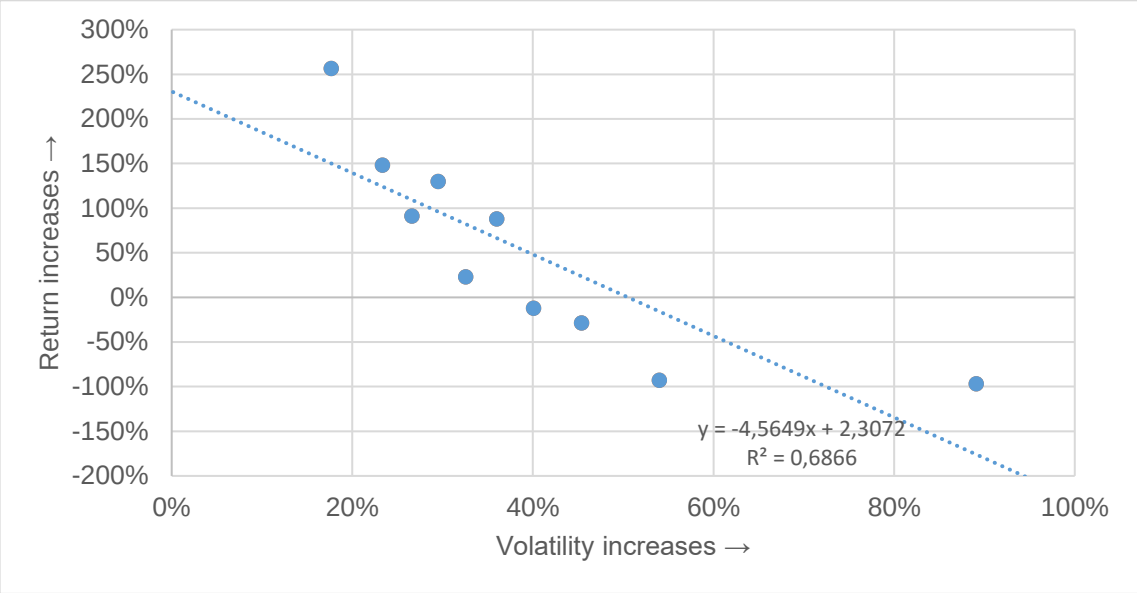

Figure 12: Correlation between volatility deciles and return during 2011-2015 in OMX Helsinki.

If the CAPM would work according to theory, then the trendline should have positive slope stating that returns are rising according to volatility. In reality the trendline goes downward, which mutilates the expectations of traditional financial theory. Digressions from the line are rather small, which hardens the evidence. Logarithmic trendline would have slightly better fit, but as the comparison is done CAPM in mind, then the linear trendline is most relevant.

Next figure presents the same information and main conclusions as earlier figure, but now annualized returns of volatility deciles throughout years 2001-2015 are under observation. Annualized returns for extreme deciles are 8.85 % for D1 and -19.96 % for D10. Therefore the total difference of extreme deciles in annualized returns is 28.81 %, which tells that there is significant difference in performance of these volatility groups.

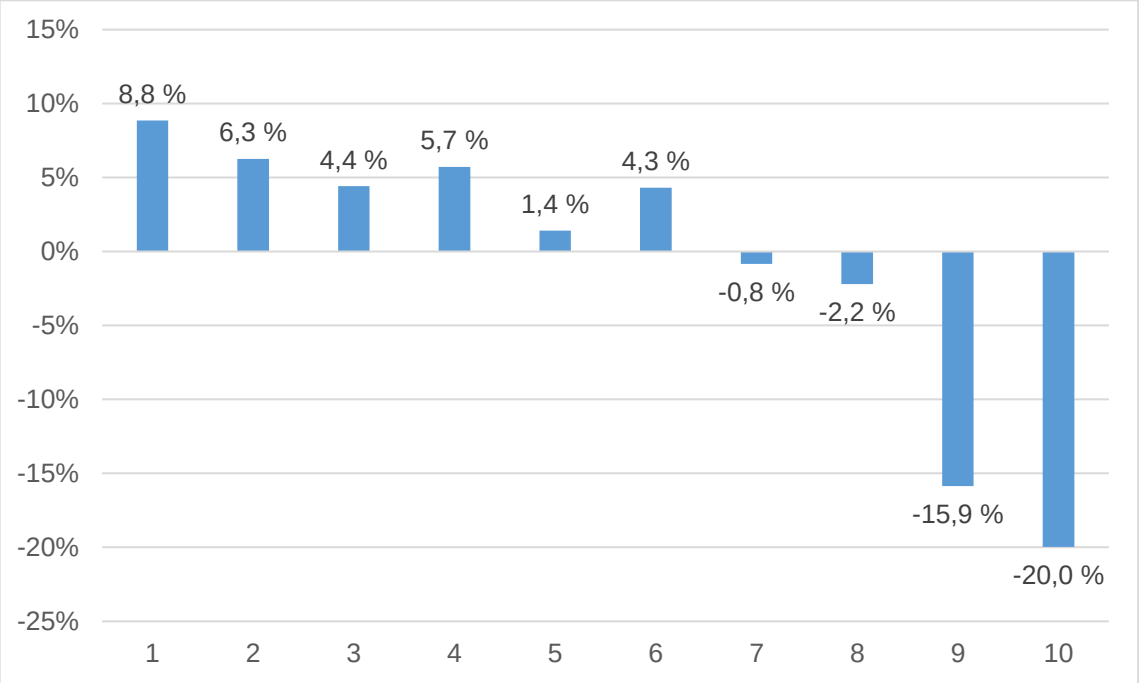

Figure 13: Annualized return of volatility deciles for the years 2001-2015 in OMX Helsinki.

It is notable that D9 - which is second-highest volatility decile – also faces destroying annualized return of -15.86 %, which turns into -92.50 % in cumulative returns. While D10 contains the most volatile companies in whole dataset, such as penny stock companies with very low volume, the D9 represents a bit more normal sample of naturally volatile stocks and it shouldn't be vulnerable to ultimate events that often occur among the most volatile tenth of the stocks. Another point to mention is behavior of second-least volatile decile D2, which is far away from performance of D1. However, D2 still performs well as it manages to bring annualized return of 6.25 % and cumulative return of 148.32 %. It seems

that top tenth of least volatile companies are extraordinary in their performance, while D9 and D10 groups behave quite the same way in terms of returns.

Below is a figure of volatility quintiles on monthly level through 2001-2015 as measured by 3-month standard deviation. The movement of different volatility groups is closely similar to main index changes as plotted in figure 9. However, this graph plots the movement of five quintiles and thus provides information about the mutual behavior of different volatility groups. General knowledge of volatility movement is indifferent if the volatility deciles behavior very differently.

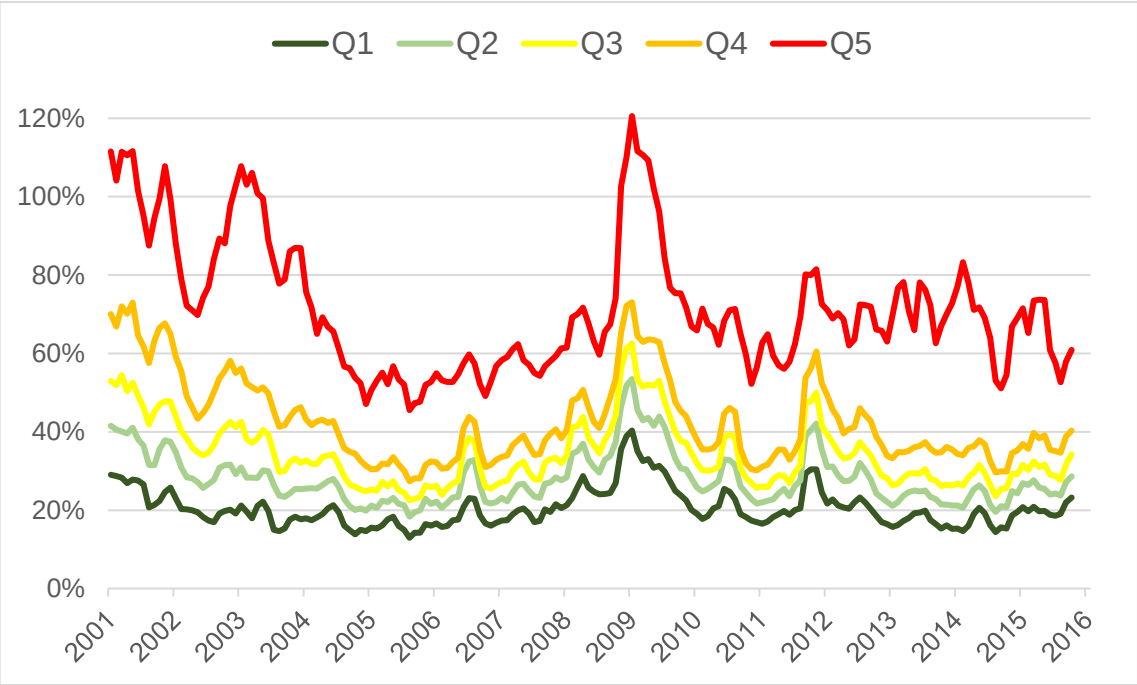

Figure 14: Volatility quintiles on monthly level during 2001-2005 in OMX Helsinki.

Average volatility for Q1 is 20.49 %, while following quintiles from Q2 to Q5 correspondingly receive volatilities of 28.05 %, 34.30 %, 42.76 and 71.61 %. Extreme deciles are D1 with volatility of 17.65 % and D10 with volatility of 89.07 %, median numbers being 16,79 % and 83.99 % correspondingly. Combined average volatility of all deciles has moved somewhat around the years. Year 2005 was the least volatile with average volatility of 29 %, while year 2001 was the most volatile with volatility of 56 %. Year 2009 was also very volatile with average

53 % average volatility. The average has been quite steadily around 35-40 % through the last five years, but there are some peaks as early already described.

The strong correlation among different volatility quintiles is easily recognizable, but the magnitude of changes among volatility quintiles is somewhat surprising. For example, during financial crisis of 2007-08 the volatility of Q1 sprung from 25 % to 40 % just in four months. This underlines that defensive stocks are not safe from strong price fluctuation if conditions get extreme. Another remark is that highly volatility stocks really have earned their reputation. During the same four months in end of 2008 the volatility of Q5 rocketed from 60 % to record-breaking level of 120 % - so the already high volatility level actually doubled just in few months.Return and volatility decile averages on yearly level are composed in two tables below. This gives a better view of intra-class return and volatility changes during the study timeline.

RETURN	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	18	14	30	20	32	20	7	-39	24	13	-22	3	13	11	15
2	14	5	27	26	26	17	-4	-46	40	11	-23	-13	21	10	21
3	12	0	29	13	26	15	2	-47	40	19	-30	2	19	-6	11
4	10	-1	31	19	18	16	8	-48	31	18	-21	10	3	9	16
5	1	1	12	11	25	20	-3	-54	35	3	-28	-2	12	5	24
6	11	-8	49	14	11	17	-5	-50	43	6	-16	-2	10	4	24
7	-18	-19	25	10	24	15	-6	-50	17	7	-26	9	28	0	10
8	-15	-40	48	10	29	15	-1	-51	36	18	-30	-1	2	-3	6
9	-60	-50	48	2	19	8	-9	-58	7	2	-22	-15	-13	-18	-4
10	-56	-60	35	-20	-3	8	-28	-52	26	9	-34	-8	-28	-33	26

Table 1: Returns of all deciles during 2001-2015 in OMX Helsinki. Values are in percents.

Returns vary a lot even in least volatile decile, which reminds that there are no certain safe havens even among the low-volatility equities if the bad times really erupt as happened in crisis years of 2008 or 2011.

VOLATILITY	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	22	16	15	15	13	15	17	24	25	17	19	18	15	15	18
2	30	23	22	20	18	21	21	30	33	23	25	23	19	19	23
3	35	27	25	23	20	24	24	34	37	26	28	26	22	22	25
4	40	31	29	25	22	26	27	38	41	28	31	29	24	24	27
5	46	36	33	28	24	28	29	41	45	31	33	32	27	26	30
6	52	41	38	32	26	30	32	44	49	33	36	36	29	29	32
7	62	48	44	36	29	33	35	48	54	36	39	39	32	32	35
8	71	55	52	42	32	37	39	52	59	39	44	44	38	36	39
9	85	64	63	50	38	43	45	59	68	46	52	53	51	45	47
10	121	101	121	73	65	66	72	88	115	84	82	83	93	90	82

Table 2: Volatilities of all deciles during 2001-2015 in OMX Helsinki. Values are in percents.

Most volatile decile really differs from the other groups. Even the 9. volatile decile has notably lower volatility levels. This indicates that most volatile decile is subject to extreme price fluctuations, which is also the reason why quintiles are used in parts of this study to flatten these extremes.

Next figure shows the Sharpe ratio of different volatility quintiles on each year. Monthly results are annualized for each year, so the return and standard deviation factors are achieved, while Republic of Finland 5-year obligation is used as a proxy for risk-free term. Average interest for the obligation is 2.59 % and the interest rate steadily falls through the entire 15-year period, starting from rate of 4.70 % at 2001 and ending at zero in 2015. This annual change in risk-free rate is included in calculation.

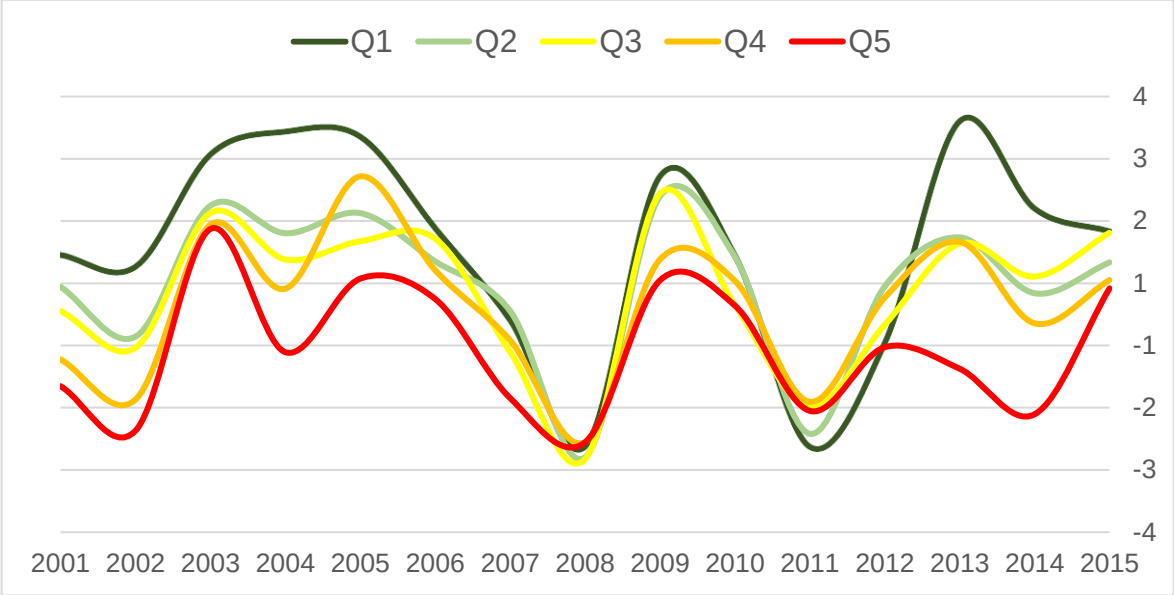

Figure 15: Sharpe ratios of volatility quintiles during 2001-2015 in OMX Helsinki.

Sharpe ratio of Q1 is 1.06 and the following quintiles from Q2 to Q5 correspondingly receive ratios of 0.48, 0.33, 0.14, and -0.55 for Q5. Ratios for extreme deciles are 1.12 for D1 and -0.68 for D10. Ratios differ the most in years 2004, 2013 and 2014. Financial crisis of 2008 squeezes the ratios close to each other. Year 2008 is relatively the best for Q5 as it reaches the same level as Q1.

Regression run for volatility deciles and Sharpe ratios show their linear alignment. Low volatility results in high Sharpe ratio with R-Square of 0.91. This is expected result after seeing in figure 12 that low-volatility deciles perform much better than higher volatility ones. Results underline that investing in low-volatility assets provide the best risk-adjusted returns.

Beta is calculated for every month based on progress during last 12 months, i.e. yearly beta is used in this study. Average of all deciles works as a comparative index. Start of time series requires some alternations to this as the needed data is not in place. Therefore the beta for first six months represent the average of July – December, which in turn are calculated based on the returns during first six months from January to June. First properly calculated year is thus the year 2002.

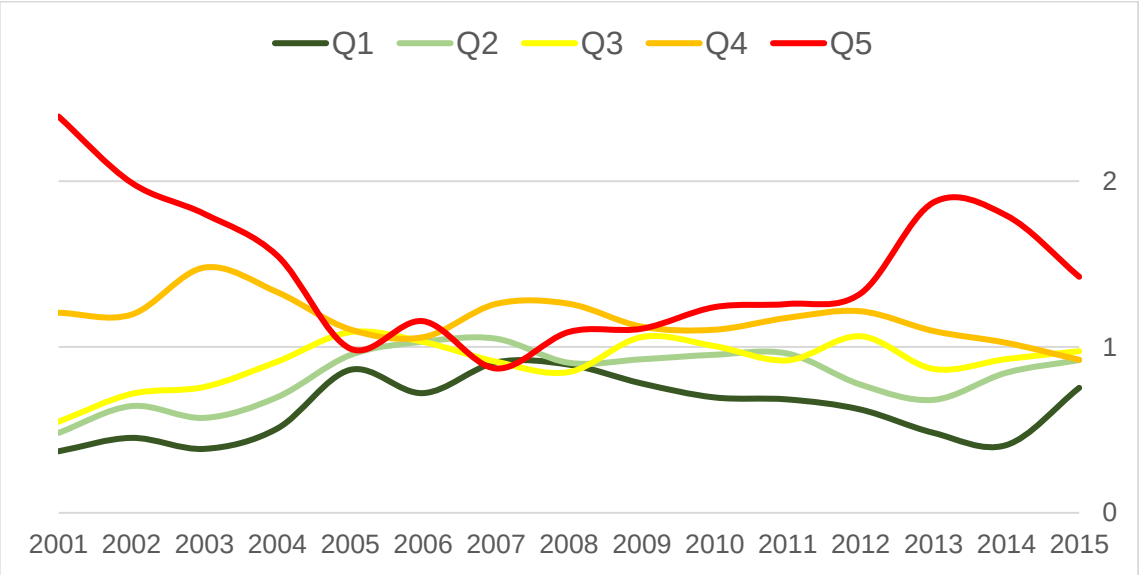

Figure 16: Beta of volatility quintiles during 2001-2015 in OMX Helsinki.

Beta levels vary largely in the first years of millennium and also during the last few years. Gap is widest in year 2001 with a difference of two units. During years 2005 – 2012 the beta levels are near to each other and average difference is 0.36 units, so for these years the changes in volatility are very coherent with beta. In general the beta values tell that price fluctuations of low-volatility stocks are rather solid.

In theory volatility and beta have strong mutual correlation - this is actually also seen in results as quantiles are in expected sequence. Beta level for lowest volatility quintile stays under 1, while beta level for highest volatility is almost constantly higher than 1. This outcome strengthens the use of volatility as a proxy

for risk in the entire study – after all, beta is also widely used risk meter and its clear correlation with volatility is convincing.

Next figure plots the development of Jensen Alpha for volatility quintiles. Ratio shows that first quintile has varied slightly, while having average of 0.73 % of abnormal return over theoretical expectation. This statistic has received negative values only in 2011 and 2012. Since average alpha for the most volatile quintile is -1.36 %, the volatile stocks have not performed nearly as well as the less volatile ones. Range for Q5 has been wide as in year 2001 the statistic was at lowest point of -3.73, but then managed to get mildly positive value of 0.24 % in 2011, only to fall again negative for the years to come.

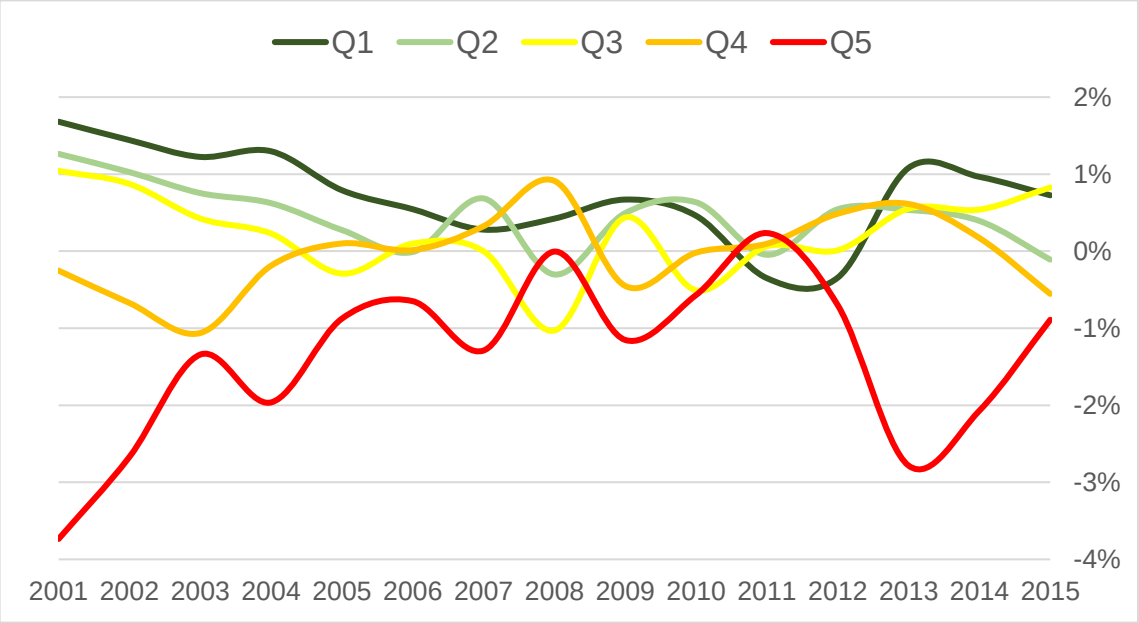

Figure 17: Jensen's Alpha of volatility quintiles during 2001-2015 in OMX Helsinki.

From theoretical standpoint the Jensen Alpha is linked to capital asset pricing model. According to CAPM the risk and return are positively correlated, so in our study the highest volatility quintile should generate largest profits than lowest volatility quintile. However, as can be seen the results are completely contrarious to the theoretical expectation. This fortifies the evidence that CAPM is not working

in practice – at least not in OMX Helsinki, but actually not also in many other developed and developing markets as Baker and Haugen (2012) have proved. The critique of CAPM has already been expressed in Chapter 2.4.

Highlights of the previous figures are summarized numerically in the below table that takes the whole timeline of 2001-2015 into account. Decile, quintile and halves are expressed individually. Calculations behind the numbers and more complete results are provided in .xlsl spreadsheet file available from the author.

	Volatility	Total return	Annual return	Sharpe	Beta	J. Alpha
1	17,65 %	256,66 %	8,85 %	1,12	0,56	0,78 %
2	23,32 %	148,32 %	6,25 %	1,00	0,71	0,67 %
3	26,57 %	91,17 %	4,41 %	0,45	0,82	0,39 %
4	29,48 %	130,18 %	5,72 %	0,50	0,83	0,51 %
5	32,54 %	23,22 %	1,40 %	0,32	0,85	0,11 %
6	35,99 %	88,19 %	4,31 %	0,34	0,97	0,32 %
7	40,04 %	-11,88 %	-0,84 %	0,16	1,05	-0,03 %
8	45,36 %	-28,35 %	-2,20 %	0,12	1,29	-0,03 %
9	53,99 %	-92,50 %	-15,86 %	-0,43	1,47	-1,15 %
10	89,07 %	-96,46 %	-19,96 %	-0,68	1,45	-1,57 %
1	20,48 %	201,22 %	7,63 %	1,06	0,64	0,73 %
2	28,03 %	111,96 %	5,14 %	0,48	0,83	0,45 %
3	34,27 %	55,09 %	2,97 %	0,33	0,91	0,22 %
4	42,70 %	-18,32 %	-1,34 %	0,14	1,17	-0,03 %
5	71,53 %	-94,55 %	-17,63 %	-0,55	1,46	-1,36 %
1	25,91 %	121,74 %	5,45 %	0,68	0,76	0,49 %
2	52,89 %	-61,55 %	-6,17 %	-0,10	1,24	-0,49 %
Total	39,40 %	-1,49 %	-0,10 %	0,29	1,00	0,00 %

Table 3: Numerical summary of results by deciles, quintiles and halves.

Empirical study offers straightforward conclusions: Low-volatility stock provide better returns than high-volatility stocks in OMX Helsinki throughout the years 2001-2015. The results are in line with earlier studies concluded for this market but also for numerous other developed and still emerging markets (Baker and Haugen 2012). Shortly said, phenomenon known as low-volatility anomaly is well alive in NASDAQ OMX Helsinki stock exchange.

Highest volatility quintile outperforms lowest volatility quintile only in year 2003 – but most often the first or in some years the second low volatility quintile is always the best performing group. Time turns this difference in returns into magnificent difference in total returns as Q1 reaches return of 256 %, while Q5 provides negative return of -97 % within the fifteen years of data.

Interesting theoretical conclusions is the fact that some established and widely recognized traditional financial theories such as capital asset pricing model are not properly functioning inside Finland's equity markets – and this state has continued over decades. Empirical evidence against CAPM is robust, since observations from international equity markets support these findings.

As a consequence of this empiricism the CAPM shows more like an echo from the past than a modern financial theory that should necessarily be taught as a truth to every business school student. University academics hopefully approve this conclusion and act according to it when planning the future courses and sessions.

Main conclusion from the investor point of view is the potential to achieve excess returns by investing in low-volatility stocks in OMX Helsinki. This possibility is put into practice and further investigated in chapter 5.2, where also trading costs and other factual matters are judged.

5. PRACTICAL MATTERS AND CONCLUSIONS

5.1 Appliance of low-volatility strategy

A certain wise man said that it is not the big earnings that matters, but the small expenses. This ideology fits well to one prime motive for low-volatility investing, which is the minimization of downside risk. Investors often pay too much attention for potential gains, but forgot that volatility is also accrued from downside movements.

Minimization of downside risk also means protecting against mechanic known as volatility drag. If one invests 100 000 euros into equity market, which then drops by 10 %, the remaining capital is 90 000 euros. If markets now rise by the same 10 %, the investor still remains one thousand euros short of 100 000 euros. As behavioral economics is closely related to the theme, it is nice to be aware that many non-professional investors might forget these basic mechanics in their calculations and thus pay less attention to downside risk control.

Strategy aiming at minimizing the downside risk has worked well in past years. The performance of global low-volatility stocks MSCI ACWI Minimum Volatility versus global stock index MSCI ACWI Standard as described in chapter 3.2 shows that minimizing the downside risk has worked especially well through the financial crisis. Some investors particularly consider low-volatility strategy as a hedge for bad times, but this is actually in contradiction with the development of markets, since the MSCI ACWI Minimum Volatility has remained performing better than the standard index also during the bull market that followed financial crisis. The gap between indexes actually just widens around 2011-2012 when the uncertain future of European economies shake the markets.

On the other hand, the low-volatility strategies might not capture the upside movement. Dot-com bubble is great example of an event where the low-volatility stocks did not have much capture, which of course also means that the valuations

did not crash very badly after the bubble had burst. If investor would like to bet more on upside movements, then the selection of low-volatility stocks might have to be done by paying some attention also to the fundamentals and not only looking at the pure heuristics such as allocating only the decile of lowest standard deviation stocks into portfolio. Some professional investors underline this need to also take fundaments into calculations rather than allocating the stocks purely on heuristical basis *(*Santicchia 2015).

5.2 Transaction costs and other practical restrictions

All investment strategies requiring dense reallocation of funds do encounter significant barriers caused by transaction costs. Li et al. (2013) state that excess returns of low-risk portfolios reverse rather quickly, thereby requiring traders to rebalance the portfolios in order to stay committed to the low-risk strategy. Even though transaction costs are key determinants of net returns, still too often they are not incorporated into calculations. Hence, a practical review of transaction costs within low-volatility trading is presented.

Let’s assume that portfolio is owned by private Finnish individual, who uses the services of popular internet broker Nordnet. Investor would form and update the portfolio as presented in the empirical part of this study, so approximately 13 stocks out of around 133 stocks in OMX Helsinki would have to be reallocated once every month so that lowest volatility decile is properly formed. Some companies stay longer in the same volatility group, so the amount of companies needing reallocation is smaller, which decreases the number of trades to be done every month.

Selected broker prices the transaction costs according to trading activity – the most relevant category for this test would be the second highest trading level of 11-50 trades a month, which means that individual would have to pay 5 euros commission per trade executed, or alternatively 0.10 % of the trade value. If half of the portfolio would have to be sold every month and same amount of stocks to bought back, then 13 trades in total would have to be executed. This would cause

total trading costs of 65 euros per month if values of single trades do not exceed 5000 euros.

If individual would have invested 50 000 euros in OMX Helsinki lowest volatility decile in start of 2001 and reallocated it every month according to the presented strategy, then the capital would have increased to 178330 euros by the end of October 2015. When monthly trading costs of 65 euros are included, then the investment would have increased to only 160231 euros. Same investment in lowest volatility decile with 10 000 euros base capital would result in 35666 euros, but significantly lower outcome of 17677 euros when trading costs are included.

It must also be kept in mind that continuous sales do trigger capital gain tax consequences and active managing causes all sort of administrative work for the individual. However, if investor would have invested the 50000 euros capital passively and free of transaction costs in OMX Helsinki main index and forgotten everything, then the investment would have developed to 58111 euros when trading costs are not calculated. Therefore investing only 10000 as base capital in actively managed low-volatility strategy would have led to almost even result than investing the whole 50000 passively in main index.

This practical example shows that investor would have gained a lot more profit by following active low-volatility strategy rather than investing passively in index, which is quite fascinating result. It seems that transaction costs – at least with the selected broker and level – are not effectively diminishing the returns, just when the investable amount is larger enough. Comparison of the investments is presented below.

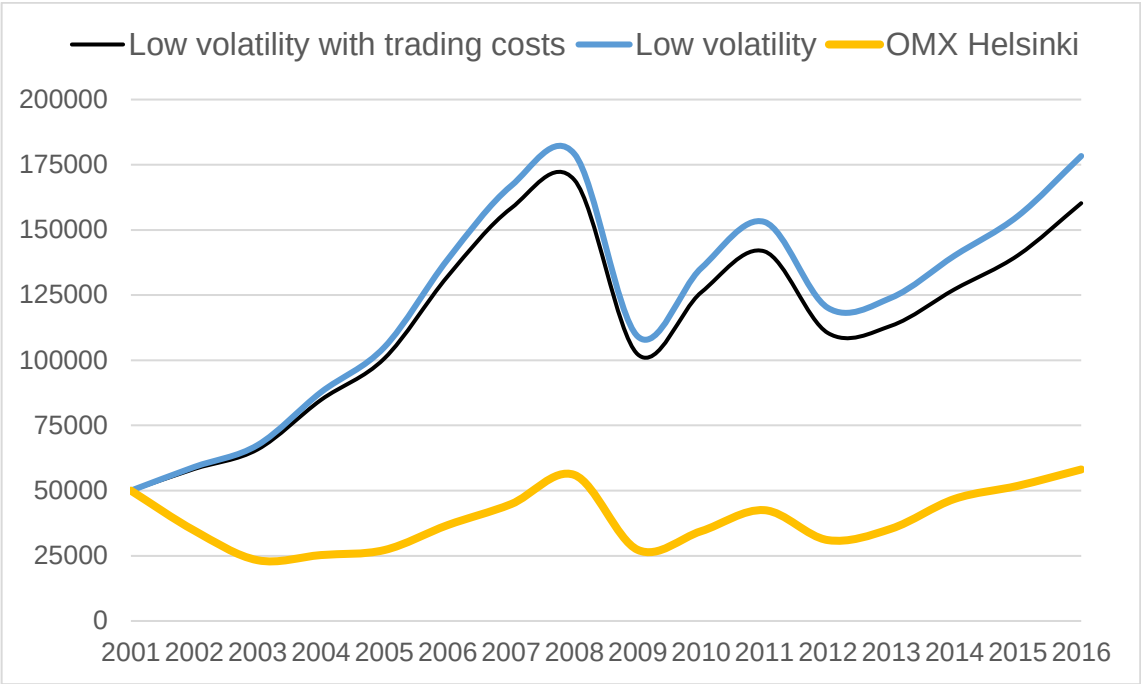

Figure 18: Investment outcome for low-volatility portfolio and main index.

Investable amount has somewhat notable effect on the strategy choice. Investor would have to invest in large enough batches to tackle the transaction costs. Small size of investable amount would effectively fade away possible gains, since the impact of trading costs would grow significant and start to dominate. The case is of course the same for all strategies requiring dense allocation.

Dense allocation is certainly not a problem for fund managers, but private investors often forget the magnitude of transaction costs, which easily decapitates otherwise smart investing strategies. If private investors would want to allocate only few thousand euros into low-volatility equities, then it would be better to stick to either low-volatility funds or passive choices style instead of performing active strategy by self.

If portfolio is managed by institutional investor, then the examination of different costs comes a bit more complex. Costs of service should of course be known by the investor who decides to give his capital in the hands of low-volatility fund manager, but in reality there is different cost factors that are not usually included

into expense ratio or stated directly elsewhere. These tend not to be problem for index funds or otherwise passively managed funds, but as low-volatility strategy may be committed at least partly with active management style, then it is worth to scope through few cost factors that might terminate otherwise successful strategy.

One cost factor arises from the same transaction costs such as brokerage fees that also individuals have to pay. Bogle (2014) states that these brokerage commissions are typical cost factor that are not included in the expense ratio and thus reported to investors. A good proxy for the transaction costs of funds is the annual turnover ratio. If stocks in the lowest volatility group change a lot, then turnover increases as stocks have to be changed to commit the investing strategy properly.

High turnover also leads to increased trading costs and capital gain tax consequences caused by sales. As portfolio must anyway be updated on pre-decided time intervals for the sake of keeping volatility on controlled level, then extending the selection interval to 3 months or even longer would lead to lesser trading costs. Negative effect would of course be the decreased the agility and allowance of more volatile stocks to remain in portfolio for some time.

Bogle also mentions the cash drag as a factor that lowers returns of many funds. Funds often have some percent of their capital in cash positions, which lowers the effective amount of capital and thus creates drag on potential returns compared to situation where whole capital would be in work. If strategy is to allocated capital monthly according to simple heuristic such the one presented in this study, then capital should be more easily continuously in effective state and not lying on the money account. Clarity of strategy and thus quick execution of decisions is certainly a big advantage for strategies that follow simple heuristics.

Investors also have to pay for the research done by fund managers of whom face research costs that are usually not measured by private investor whose only resource is the spare time he gives to trading. When decisions are based on

simple heuristics such like in this study, then the research doesn't require much effort and costs are minimal – however, if any more active selection is included, then the original investor has more management fees to pay. Good thing is that these management fees are normally well reported.

Will low-volatility strategy fit better for individual's trading style or shall institutional traders such funds be used? Examination reveals that both individuals as well as funds can execute low-volatility strategy quite cost-efficiently, when stock selection is based on simple heuristic and reallocation of assets is kept minor. If these principles are not met, then the costs start playing bigger role regardless of who is in control of them.

If investor would like to passively invest in low-volatility stocks and not to bother investigate volatility groups now and again, then having long positions in so-called stable sectors would be cost-efficient and easy way to have shelter against radical movements. Goods and services from these sectors tend to have demand even when the times get rough. For example, utilities, staples and healthcare are generally considered as solid sectors that won't be so heavily influenced by market turmoil (Santicchia 2015).

Lastly, if simple heuristics or buy-and-forgot style is not the thing, then it is up to investor's own view whether he personally wants to include fundamentals and other factors into game or pay to the fund manager to do the same sorting of stocks into low-volatility portfolio. In any case, certain benefit on low-volatility investing is the fact that it can be done via multiple ways, actively, passively, basing on fundamentals, relying on heuristics and so on.

5.3 Suggestions for further research

The low-volatility anomaly has gained more publicity among last years, which has increased the amount of research done. Therefore low-volatility studies have seen good variation in terms of market regions, time frames and methods. Still, there are many interesting alternations to studies that may verify or repeal the current conclusions. For example, it is astonishing that tremendous majority of studies measuring risk do it by using standard deviation of returns or company beta as a proxy for risk.

Most common risk measurements know nothing about company fundamentals nor behavioral aspects that guide stock markets, so they mostly just reflect what has happened – like in volatility's case, the measurements says that instrument's price has changed by this much within this time frame. This certainly does not describe such an important matter as risk in a very accurate form! If factually nearly every study and financial model uses these measurements for evaluating risk, then almost all results from these sources are prone to the same shortcomings.

Could the risk be measured more truthfully by other ratios or even by qualitative approach instead of number crunching? If new methodologies would alter the results, then not only the low-volatility studies would gain new perspectives, but also every other study that measures risk somehow by the known traditional methods. Risk modeling has developed through time, so it is very possible that volatility or beta will lose their gleam and new methods arise, which possibly take advantage of big data or other sources that have yet been unable to fully deploy.

Interesting attempt would be to estimate risk by evaluating company fundamentals or other factors such as business events that have power to move the stock price. After all, price fluctuations are more like a reflection of the events occurred, so focusing the scope directly on the fundamentals and events instead of price reflections might provide more exact information about the course of where stock is heading. By looking only at the volatility levels one can indeed tell

if the stock seems risky or not, but still be totally without knowledge why the risk is on the certain level.

Totally different, but exceedingly interesting, theme would be to examine how strongly volatility is driven by investor's behavioral influences on different markets. As earlier discussed in this paper, the psychology plays important role in market movements. Human behavior and its consequences are hard to model and measure, so analyzing the impact of behavioral aspects on markets would be very challenging task. However, if financial modeling is ever to be developed to reflect more the real living world, then the animal spirits must be somehow incorporated into the models.

6. SUMMARY

International research starting from 1970's reveals that low-volatility stocks have beaten high-volatility stocks in terms of returns for decades. Traditional risk-return framework seems to work only between asset classes, but not inside equity markets. This is steeply in contradiction with fundamental financial theories such as capital asset pricing model.

Research questions were the following: *What are the reasons for low-volatility anomaly to exist, and why the arbitrage has not yet shrunk those excess returns away? Does behavioral finance play any role in this anomaly? How strong is the correlation between low-volatility stocks and market returns in Finnish stock market? Can investors gain abnormally high returns by using low-volatility trading strategies?*

Different explanations have been offered for the anomaly. Leverage-constrained investors favor high-volatility stocks as they offer larger potential, which makes low-volatility ones underpriced. Fund managers often have performance bonuses, so it is also smart for them to build riskier portfolio that has potential to launch the incentives. Behavioral aspect such as investor's overconfidence in their actions, gambling habits and tendency to pick shiny news-covered stocks are likely accelerators of the low-volatility anomaly.

Arbitrage has not shrunk the anomaly away, even though it has gained more attention after financial crisis, which has led to surge in low-volatility funds and strategies. Still, the large audience trusts to traditional risk-return framework, which has not been wiped out neither by 'smart money' managers having their own incentives. Executing low-volatility strategies also requires some research and constant refreshing of portfolio, which increases costs and adds friction to arbitrage process.

Empirical part of study examines the presence of anomaly in OMX Helsinki stock exchange between years 2001 and 2016. All functioning companies are included, thus making the count to vary from 152 to 123. Companies are sorted according

to standard deviation of returns on a monthly basis, so the returns of different volatility groups can be compared to find out if low-volatility ones perform better. Methodology is closely the same to study by Baker and Haugen (2012).

Study reveals that low-volatility stocks provide better returns than high-volatility stocks in OMX Helsinki throughout the years 2001-2016. This outcome is expected, since international studies also point to parallel results. Interesting point is the powerful magnitude of differences among the volatility groups.

Annualized returns are 8.85 % for the lowest volatility decile and -19.96 % for highest volatility decile, while annualized return of OMX Helsinki main index is 1 percent sharp. Total return is 256.66 % for lowest volatility decile and -96.46 % for the highest volatility decile, while OMX Helsinki has returned 16.22 % during the same 15 years. Possible transaction costs are not calculated into these numbers.

Large differences are observed also in other measures. Lowest volatility decile has significantly better Sharpe ratio of 1.12 when compared to highest volatility decile ratio of -0.68. Jensen Alpha is 0.78 % for least risky decile, but -1.57 % for the most risky decile. Ratios are parallel when first and last quintiles are compared, so results are equivalent even when the weight of extreme stocks is lightened.

Practical results of this study, but also other recent low-volatility studies, do really encourage investors to execute low-volatility strategies in search of higher returns. Brokers offer managed funds with couple years of track record, but selection of stocks can be done easily by one’s own initiative when relying on simple heuristic like selecting only the lowest volatile tenth of stocks in certain market. Low-volatility strategy could be executed also passively by holding stocks from defensive sectors.

Perhaps the most important secondary product of all low-volatility studies is the evidence showing how traditional finance theories are vulnerable. For example,

badly broken capital asset pricing model certainly requires re-evaluation before it can be used as accurate tool. Shortcomings of popular theories should also be made clear to finance students in business schools around the world. All in all, low-volatility anomaly is just another phenomenon proving how something though to be elementary is actually quite complicated.

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