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SCHOOL OF BUSINESS, ECONOMICS AND LAW

The Low Volatility Anomaly in Sweden and its Presence During the Covid-19 Pandemic

FEK345

Bachelor's Thesis in Industrial and Financial Management

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Abstract

Investing in the stock market has interested people for a long time as the hope to generate high returns has been an incentive to risk one's money. From this argumentation has a general relationship between risk-and-return been created. The great performance of low risk stocks is an abnormality that has confused economists for a long time as it goes against the fundamental principle of the risk-and-return relationship, where this phenomenon is known as the Low Volatility Anomaly. This thesis aimed to investigate the low volatility anomaly and its presence on the Swedish stock market as well as its presence during the Covid-19 crisis. The analysis was done on historical data from the OMX Stockholm 30 index and the stocks listed on it between 2005-01-03 and 2022-04-29, together with four different market stages during this time period. The result shows no conclusive evidence of the low volatility anomaly on the Swedish market except during the Covid-19 crisis. Future work could include a deeper analysis of the reasons *why* the Covid-19 crisis showed clearer evidence of the low volatility anomaly.

Keywords: Risk, Low volatility anomaly, Covid-19, Capital Asset Pricing Model.

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Glossary

Alpha	A measurement that measures an investment's ability to beat the market.
Bear market	Market stage that shows a generally negative trend of movement.
Beta	A measurement that measures an investment's responsiveness to movements in the market.
Bull market	Market stage that shows a generally positive trend of movement.
CAPM	Capital Asset Pricing Model.
LVA	Low Volatility Anomaly.
Sharpe ratio	A performance measurement that measures an investment's return compared to its level of risk.
Systematic risk	Risk that is affecting a large number of assets.
Unsystematic risk	Risk that is affecting a single or a small number of assets.

1

Introduction

Investing in the stock market may result in both good and bad returns. To be able to consider which investment seems fitting for one's expectation of return there is a risk related to it. One of the most known relationships in finance is between risk and return, where higher risk is rewarded with higher expected return as well as the opposite. One of the most common models used to calculate the expected return is the Capital Asset Pricing Model (CAPM) which calculates the expected return of a security by adding the risk-free return of the market with a risk premium relating to the risk of that security. However, this has not been the case throughout the nearest future. The idea of an efficient market is that an investor can only generate above-average returns by taking above-average risks (Baker et al., 2011). However, this is not the case when one looks at empirical data. This is what is defined as the low volatility anomaly. Through the words of Baker et al. (2011):

"Among the many candidates for the greatest anomaly in finance, a particularly compelling one is the long-term success of low-volatility and low-beta stock portfolios."

1.1 Background

Economists have for a long time presented the idea that there must be a trade-off between risk and return since there must be some form of motivation to purchase and hold a security with high-risk (Hillier et al., 2021). However, studies have shown a connection between low volatility stocks and high future returns in the long term that challenges this idea. To be more precise, low volatility stock returns do not only perform better than predicted but also outperform high-volatility stocks in the long-term (Li et al., 2016). Multiple studies have focused on trying to explain this anomaly where some point to a mispricing of stocks while others point to miscalculation of risk (Li et al., 2016).

However, before diving into this, it is necessary to have a basic understanding of what stocks and portfolios are as well as different types of risk and an understanding of the concept of diversification.

A common stock, also known as ordinary shares, is a type of security that is a part ownership of the company that has issued them. In total, they represent the market's valuation of the company and the owners of stocks are known as *shareholders* or *stockholders* (Hillier et al., 2021). Portfolios are defined by Hillier et al. (2021) as combinations of securities invested in. Each investor investing in multiple different stocks creates individual portfolios representing their specific investment combinations.

One can classify risk into two different types, systematic/market risk and unsystematic/idiosyncratic risk (Hillier et al., 2021). Systematic risk is the risk affecting a large number of assets and is almost impossible to avoid. Unsystematic risk is the risk specifically associated with a particular asset or a small number of assets and can be diversified away by having a large portfolio. Diversification is an effect that is a result when constructing a portfolio. The effect is that some risk (unsystematic risk) can be *diversified away* by investing in multiple securities. This is a result of the correlation between the different investments (Hillier et al., 2021).

1.2 Problem Discussion

Financial markets are, as previously mentioned, uncertain by nature. There are winners and losers every day and there is the potential to generate large profits no matter if the market is growing or failing (Hillier et al., 2021). There are also risks involved in investments due to the uncertainty of markets. However, estimating risk is no easy task. Multiple models have been created to better understand risks, returns, and the general characteristics of markets. Still, it does not exist a single model which has unified the entire scientific field. One of the most well-known and generally acknowledged theories in finance is the Capital Asset Pricing Model (CAPM), which describes that the expected return of a security is linearly related to the security's beta (β), which represents the security's responsiveness to movement in the market (Hillier et al., 2021). Baker et al. (2014) presents that the risk-return relationship assumed to be present in efficient markets is hard to find in data. Furthermore, sorting stocks by either beta or volatility provides evidence of the opposite, with data going back to at least 1972. Data proves that low-volatility stocks do indeed deliver lower risk but also higher average returns than high-risk stocks. Anyhow, as previously mentioned, the Low Volatility Anomaly (LVA) does seem to provide evidence that the CAPM does not represent the real world fittingly.

However, since most research has been focused on either the United States of America or international data, with very few looking at specifically Sweden, there is a gap in knowledge regarding the presence of this anomaly on the Swedish market. Østnes and Hafskjær (2013) found no evidence of the LVA in the similar market that is Norway while Brodén and Fransson (2015) did find evidence on the Swedish market, except during the 2007-2008 financial crisis. Therefore, the need to further investigate if the LVA is present in Sweden is essential to better understand the Swedish financial market and the LVA.

The fact that Brodén and Fransson (2015) did not find evidence of the LVA during the 2007-2008 financial crisis brings forward an interesting question regarding the LVA's presence in different stages of markets. The Covid-19 pandemic led to several changes in society and financial markets. An example is Albulescu (2021) who showed evidence that Covid-19 official announcements during the pandemic phase amplified financial volatility in the U.S market. Sansa (2020) mentions that the general global shock of Covid-19 was severe even compared to the 2007-2008 crisis and that Covid-19 had a significant impact on worldwide markets. Since previous research pointed to no evidence of the LVA during the 2007-2008 financial crisis it is interesting to see what evidence can be found during the Covid-19 pandemic.

1.3 Purpose

The purpose of this study is to explore the presence of the low volatility anomaly on the Swedish stock market and to evaluate if the presence of the low volatility anomaly on the Swedish stock market is affected by the Covid-19 crisis.

1.4 Research Questions

The purpose of this study can be summarized in the two following research questions:

> **R1:** To what extent is the low volatility anomaly present on the Swedish stock market?

Since there have been few studies conducted on the Swedish market and not that recently it is valid to investigate the LVA's presence on the Swedish market. Beyond this, as previous studies did not find evidence of the LVA during the 2007-2008 crisis this study will also have the following research question:

> **R2:** What presence can be found of the low volatility anomaly during the Covid-19 crisis?

1.5 Delimitations

One of the main delimitations is the data representing the Swedish stock market. The stocks included in this thesis are 27 out of the 30 companies listed in the OMX 30 Stockholm Index (OMXS30), which are all large-cap companies. The movement of OMXS30 is generally accepted as representative of the entire market's movement, which was the motivation for choosing these stocks. However, including more stocks, and of other categories e.g. mid- and small-caps, would naturally lead to a more realistic representation of the Swedish stock market as a whole.

Furthermore, there are many different types of risk- as well as performance metrics to determine the level of risk of a stock or portfolio and how well they perform. This thesis will solely use volatility and beta as risk metrics and Sharpe ratio as performance metric. These metrics have frequently been used in previous studies within the same area, and they are suitable for the aim. However, using more metrics would possibly broaden the scope of the thesis.

2

Literature review

The following section will present literature that has done previous research on the low volatility anomaly and some of their conclusions.

2.1 Low Volatility Anomaly

Ang et al. (2009) investigated the tendency that stocks with previous high idiosyncratic volatility had low future average returns on worldwide markets. They found evidence of this effect on the markets of all G7 countries and multiple other markets and that the negative relationship is strongly statistically significant. Ang et al. (2009) concludes that this effect suggests broad factors that are not easily diversified away create this phenomenon.

The finding of the low-risk anomaly was first documented more than forty years ago, and recently Bellone and de Carvalho (2020) found evidence that the anomaly is stronger than ever. The low volatility anomaly refers to the finding that stocks exhibiting lower volatility tend to achieve higher returns than can be explained by the efficient market theory (Capital Asset Pricing Model).

Li et al. (2016) researched whether the performance of low volatility stocks could be explained by market mispricing or if the effect is driven by systematic risks on the U.S market. Market mispricing is defined as the difference between the market's price of a security and its fundamental value. Their result suggested that the low volatility anomaly was best described by market mispricing. Li et al. (2016) concludes therefore that investors appear to prefer high volatility stocks over low volatility stocks.

Baker et al. (2011) researched the low volatility anomaly on the U.S market where they found evidence of it and hypothesized that there were two drivers for it: (1) investor behaviour is not fully rational and (2) there are underappreciated limits on arbitrage, i.e. arbitrage possibilities are not utilized as institutional investors are discouraged to invest in low volatility stocks as they need to outperform benchmarks such as the S&P500 Index. Baker et al. (2011) argues that the combination of these drivers flattens the risk-return relationship, usually measured using the CAPM. They concluded that the two drivers do seem to explain the low volatility anomaly.

Baker et al. (2014) investigated the low volatility anomaly and decomposed it into macro and micro effects. They summarize that the low volatility anomaly is a basic form of market inefficiency that has both macro and micro components. They are however present differently on markets and may therefore affect various markets differently due to the characteristics of the individual markets.

2.2 Low Volatility Anomaly in the Nordics

The presence of the low volatility anomaly on the Swedish stock market, during the years between 2005 and 2014, has been studied by Brodén and Fransson (2015). Their findings were that the low-risk anomaly was found in all market stages, except for 2007-2008. They did not find evidence of the low volatility anomaly these years but do emphasize that further research is needed to generate conclusive evidence. They extended the concept from low volatility anomaly to low-risk anomaly since they used both beta and total volatility as risk measures.

Østnes and Hafskjær (2013) studied the low volatility anomaly in Norway between 1981-2012 and found no evidence of its presence. They studied the Norwegian market and the low volatility anomaly with a focus on idiosyncratic risk. Østnes and Hafskjær (2013) did even find evidence of a monotonically increasing relationship, i.e. a strictly increasing relationship, between the low volatility groups to the high volatility groups of their dataset. They present the theory that the industry composition of the Norwegian market may be a reason for the absence of the low volatility anomaly. However, they do emphasize that this theory does not explain the total lack of the low volatility anomaly on the Norwegian market.

2.3 Low Volatility Anomaly During the Covid-19 Pandemic

It has been observed that low volatility stocks underperformed in 2020 when the Covid-19 crisis entered. Gregory Taïeb (2020) describes that the circumstances during 2020 were challenging conditions for low volatility stocks. The first quarter of the year saw a drawdown in the US S&P 500 index at -33.9% and -38.3% in the EURO STOXX 50 in 23 days, the fastest market corrections in history. During the time period, April to August 2020 a great rebound followed and brought some markets to their highest levels ever. During the first phase, when the drawdowns occurred, the low volatility stocks did quite well, mainly due to their low beta, which is the stock's responsiveness to movements in the market. However, the alpha, which is the stock's ability to beat the market, of low volatility stocks was negative, and they encountered problems from the locking down of economies. Furthermore, during the second phase, when global indices rebounded, both the low beta and negative alpha were disadvantageous for the low volatility stocks and led to lower performance.

What Gregory Taïeb (2020) concludes though, is that the underperformance of the low volatility stocks under the Covid-19 crisis does not give any reason to conclude that the low volatility anomaly is obsolete. Due to recent convincing empirical evidence of the low volatility anomaly, he concluded that the theory works and that prediction of returns from low volatility stocks over short horizons are impossible.

3

Theory

As previously mentioned, the idea that there is a trade-off between risk and return is widespread. The reason for this is that there must be an incentive for individuals to purchase and hold a risky asset. Therefore, there must exist a risk premium that compensates for the risk (Hillier et al., 2021). Thus, the expected return on the market can be represented as

$$E[R_M] = R_F + \text{Risk premium} \tag{3.1}$$

where $E[R_M]$ is the expected return on the market and R_F is the risk-free rate (Hillier et al., 2021).

3.1 Risk

Risk as a concept is therefore crucial to understand since it should be the basis for why some stocks have a higher expected return than others. There are multiple methods to calculate and evaluate risk but the ones that will be used in this thesis are Volatility and Beta.

3.1.1 Volatility

The volatility of a stock can either be defined as the stock's variance or its standard deviation (Hillier et al., 2021). In this thesis, volatility will be defined and calculated as the standard deviation at a specific point in time. This is calculated as

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} R_i - \bar{R}}{N-1}} \tag{3.2}$$

where N is the number of observations, R_i is the return of period i, and $\bar{R}$ is the average return of the stock during the period of observations.

When analysing a portfolio it is necessary to understand that the volatility of the portfolio is measured by both the volatility of its underlying stocks, their weights in the portfolio, and the covariance between the stocks (Hillier et al., 2021). This is mathematically described as

$$\sigma_P = \sqrt{W_A^2\sigma_A^2 + 2W_AW_B\sigma_{AB} + W_B^2\sigma_B^2} \tag{3.3}$$

where W_A is the weight of stock A, σ_A^2 is the variance of stock A, and σ_{AB} is the covariance between stock A and B. The covariance (σ_{AB}) is represented as

$$\sigma_{AB} = \sigma_A \cdot \sigma_B \cdot \rho_{AB} \tag{3.4}$$

where σ_A and σ_B are the standard deviation of stock A and B and ρ_{AB} is the correlation between stock A and B, which spans between -1 and 1. Since the portfolios in this study will consist of more than 2 stocks, the volatility equation can be rewritten as

$$\sigma_P = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} W_i\sigma_i\sigma_j\rho_{ij}W_j} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} W_i\sigma_{ij}W_j} \tag{3.5}$$

where N is the number of stocks. However, this can be translated into matrix calculations which will be used in this study. The calculation will therefore be as

$$\sigma_P^2 = \mathbf{W'} \cdot \mathbf{R} \cdot \mathbf{W} = \begin{bmatrix} W_1 & W_2 & \dots & W_N \end{bmatrix} \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1N} \\ \vdots & \ddots & \vdots \\ \sigma_{N1} & \dots & \sigma_{NN} \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_N \end{bmatrix} \tag{3.6}$$

where $\mathbf{R}$ is the covariance-matrix and $\mathbf{W}$ and $\mathbf{W'}$ are weight matrices. Lastly, one takes the square root of σ_P^2 in Equation 3.6 to get the volatility.

3.1.2 Beta

Hillier et al. (2021) defines beta (β) as the measurement of the responsiveness of a security to movements in the market portfolio, i.e, β measures the security's historic movement in relation to the overall market. The mathematical definition is

$$\beta_i = \frac{\sigma(R_iR_M)}{\sigma^2(R_M)} \tag{3.7}$$

where $\sigma(R_iR_M)$ is the covariance between the return of security i and the return of the market while σ_M^2 is the variance of the market. One crucial part regarding β is that the average β of stocks on the market is equal to 1. This is by definition the case since the market is all securities and must therefore correlate 100% to its own movement (Hillier et al., 2021).

3.2 Sharpe Ratio

Sharpe (1966) presented a measurement, which is now known as the Sharpe Ratio, of an investment's performance by calculating the investment's return minus the risk-free rate of return divided by the investment's risk. When applying this to a portfolio, the equation is written as

$$SR = \frac{R_P - R_F}{\sigma_P} \tag{3.8}$$

where R_P is the return of the portfolio, R_F is the risk-free rate of return, and σ_P is the standard deviation of the portfolio's return. To simply explain it, the measurement explains the investments gain in return for an extra unit of added risk.

3.3 Portfolio Balancing

To begin, the expected return of a portfolio is the weighted average of the expected returns of the securities it contains. For two securities A and B, this can be calculated as

$$E[R_P] = W_A E[R_A] + W_B E[R_B] \tag{3.9}$$

where $E[R_P]$ is the expected return of the portfolio, W_A and W_B are the weights of security A and B, and $E[R_A]$ as well as $E[R_B]$ are the expected returns of security A and B (Hillier et al., 2021).

To continue, an important part of a portfolio is what is known as the diversification effect. The diversification effect implies that in a portfolio containing N securities, the standard deviation of the portfolio will always be less than the weighted average of the individual securities standard deviation if the correlation between the securities is less than 1, i.e., there is no perfect correlation (Hillier et al., 2021). This effect can be derived from Equation 3.5. This further on reveals that the most interesting combination of securities is the one represented by the desired expected return with the lowest risk or the combination with the desired risk and the highest expected return. The diversification effect also brings forward an interesting result when analyzing Equation 3.5 and 3.6. This is that the variance of a portfolio containing many securities is more dependent on the covariances between the securities than the variances of the securities. Therefore, it is possible to diversify away some risk, which is known as the unsystematic risk (Hillier et al., 2021).

3.4 CAPM

The CAPM is one of the most well-known models used to estimate the expected return of an asset (Hillier et al., 2021). The CAPM calculates the expected return of a security by calculating the expected return of the market in relation to the securities' responsiveness to movement in the market (β) (Hillier et al., 2021). The CAPM equation is given by

$$E[R_i] = R_F + \beta \cdot (E[R_M] - R_F) \tag{3.10}$$

where $E[R_i]$ is the expected return of a security, R_F is the risk-free rate, β is the beta of the security, and $E[R_M]$ is the expected return on market.

Furthermore, the CAPM has three points that must be mentioned (Hillier et al., 2021). Firstly, the model assumes linearity. This means that not only is the relationship between the expected return of a security and its beta to be positive, the relationship is continuously the same no matter the level of risk. Secondly, the model and the relationship also hold for portfolios. This can be derived from Equation 3.9 and calculating the beta of the portfolio as a weighted average of the betas of the portfolio's securities. Lastly, the CAPM is not to be confused with the expected return of an *efficient* portfolio in relation to the standard deviation of the portfolio's return, which is known as the capital market line. The CAPM holds for all securities and portfolios and represents the expected return in relation to the security's or portfolio's beta.

4
Method

To begin with, the method of this thesis was of quantitative nature due to the analysis of financial numerical data. Bell et al. (2022) mentions that the use of a quantitative research strategy is preferable when wanting to measure relationships between different phenomena. Since the aim of this thesis is to test whether or not the LVA is present on the Swedish market and if it was present during the Covid-19 pandemic as well as to what extent, the choice of a quantitative research strategy seems fitting. The research process will be described as deductive since the aim is to analyse data to prove or disprove hypotheses which help to revise developed theories (Bell et al., 2022).

Firstly, the data was processed using the programming language Python. From the analysis of the characteristic of the data, time intervals for different market stages were chosen. Thereafter, five portfolios ranging from low volatility to high volatility were created based on the risk metrics beta and volatility. The portfolios were then simulated over both the entire time period of the data, as well as for the chosen market segments. During the simulations, the portfolios were re-balanced at different time steps, depending on the length of the time interval for the simulation, with moving values of beta and volatility. For each simulation, the portfolios' performances were calculated by the Sharpe ratio.

4.1 Data Collection and Manipulation

The sample data was collected from Nasdaq Nordic (2022), which offers daily information on historical opening, closing, high, low, and average prices as well as the total volume and turnover for stocks. We used data from stocks listed on the OMX 30 Stockholm Index (OMXS30), which are the 30 stocks with the largest trading volumes on the Swedish market. The data collected was over the period from 2005-01-03 to 2022-04-29, and was chosen to include both much historical data for calculations and comparisons, as well as it includes the Covid-19 crisis which mainly happened from 2020 to 2021. The analysis was done using the daily closing price of each stock. However, data for the entire time period was not available for Essity B, Sinch, and Evolution so the analysis was based on the remaining 27. These stocks and their stock symbol (ticker), can be seen in the following table, Table 4.1.

Table 4.1: The 27 stocks, and their tickers, used during the analysis.

Stock	Ticker
Skanska B	SKA-B
Getinge B	GETI-B
Boliden	BOL
Kinnevik B	KINV-B
Swedish Match	SWMA
Atlas Copco B	ATCO-B
Investor B	INVE-B
SEB A	SEB-A
ABB	ABB
SCA B	SCA-B
Astra Zeneca	AZN
Autoliv	ALIV-SDB
Svenska Handlesbanken A	SHB-A
Atlas Copco A	ATCO-A
Telia Company	TELIA
Hexagon B	HEXA-B
Hennes & Mauritz B	HM-B
Ericsson B	ERIC-B
Tele 2 B	TEL2-B
Sandvik	SAND
Assa Abloy B	ASSA-B
SKF B	SKF-B
Nordea	NDA-SE
Alfa Laval	ALFA
Electrolux B	ELUX-B
Swedbank A	SWED-A
Volvo B	VOLV-B

Beyond this, the analysis was also done on four segments of the market, containing different categories of market stages, *bear market*, *bull market*, *mixed market* and *Covid-19 (crisis) market*. Bear and bull markets are widely used terms in the context of market stages. A bear market is when the market shows, over a time period, negative movement while a bull market is the opposite (Sri Taylor, 2020). The mixed market was defined specifically for this thesis to broaden the number of different markets analyzed. The aim was to capture a market stage that contains both milder bull and bear markets and is over a larger time span than the other market stages. The Covid-19 crisis market can be defined in many ways, especially its' end date. In this thesis it is defined as when the market showed a trend of fast and large negative movement, with a positive bounce back over a time period. The reason for extracting segments containing these stages from the market was to gain insights into if the LVA shows various presence during them. The different market stages start and end dates were chosen by plotting the market's behaviour over the entire time period and detecting fragments containing the desired looks of the wanted market stages.

4.2 Portfolio re-balancing and Calculating Sharpe ratios

The calculations were based on an algorithm that began with calculating the beta values and volatility for all different stocks at a specific date. In order to do this, a parameter deciding how much historical data of the stocks' and market's return should be included. This parameter was set to 252, which corresponds to approximately one year's trading days. When the beta and volatility for all the stocks were calculated, they were assigned to 5 different portfolios based on beta value and 5 different portfolios based on volatility in parallel, an approach similar to the one Brodén and Fransson (2015) had in their methodology. Since the total amount of stocks used in this thesis was 27, the portfolios were assigned with 5, 5, 7, 5, 5 stocks each. In both the beta and the volatility case, the stocks were assigned to the portfolios in an ascending level of risk, i.e. portfolio 1 containing the least risky stocks and portfolio 5 containing the riskiest ones. All the portfolios were equally-weighted. When the portfolios were created, their Sharpe ratios could be calculated.

The next step in the algorithm was to re-balance the portfolios after a given time step. The time step decides after how long time the risk of the stocks should be re-calculated. The shorter the time step is, the more reactive the calculations are to changes on the market. On the other hand, a really small time step in relation to the length of the whole time frame penalizes the time complexity of the algorithm, i.e. it makes the algorithm very slow, and doesn't necessarily improve the results much. The choice of the time step is therefore a trade-off between these factors. So, after one time step from the previous date, all the stocks' volatility and beta values are re-calculated based on one year's history from the new date (previous date + time step = new date). Then the portfolios are assigned with stocks in the same way as previously described, but based on the new beta and volatility values. In other words, the portfolios are re-balanced. Lastly, the Sharpe ratio for each re-balanced portfolio is calculated.

The algorithm continues to re-balance the portfolios and calculate their Sharpe ratios after every time step until the end date is reached. This procedure is applied on both the entire time frame of the data as well as on every selected market stage previously mentioned.

4.3 Risk-free Rate

The risk-free rate used in the calculations was the interest rate benchmark ”3-month STIBOR rate”, which is commonly used in contexts like this. Historical data of the rate was collected from the Swedish Riksbank (Sveriges Riksbank, 2022). However, rates after 2020-07-03 were not available since the responsibility for calculating and publishing it was redirected to The Swedish Financial Benchmark Facility (SFBF)

(Swedish Financial Benchmark Facility, 2022). Thus, rates after 2020-07-03 are published on their website, but complete data files with them, which are needed for the calculations for this thesis, are not available. The incompleteness of data was handled by setting the risk-free rate between 2020-07-03 and 2022-04-29 to 0. This simplification is often used in similar calculations since the rate during this time period has been very close to zero.

4.4 Critical Analysis of Method

There are some shortcomings in this thesis due to the methods used and the most important ones will be presented and addressed below.

One of the shortcomings of the methods used in this thesis is the use of a small sample with the goal to represent an entire market. By doing this mass generalisation, it might occur a sampling error, i.e. the sample does not represent the population, and therefore the representation may be twisted. However, the choice to use the 30 most traded stocks was deliberately done to minimize this particular shortcoming. By analyzing stocks that were heavily traded, the goal was to create a generalized picture of the market by having a representative sample.

Furthermore, when analyzing the market stages bear, bull, mixed, and Covid-19, the time frames were chosen, to some degree, arbitrary. The time frames were chosen according to the definitions of the stages, but not in greater detail due to the time limits of this thesis. The time frame of the Covid-19 crisis market was also chosen according to what is, at this point in time, classified as the Covid-19 crisis. Therefore, this time frame can be seen as ”blindly” analyzed since the definition might change in the future due to the advantage of looking back on an event. This might have reduced the generalisability of the results since it may have created a bias.

Lastly, the missing values of the risk-free rate will affect the results for the time frame when the values are missing and therefore decrease the quality of the results. However, the simplification to set the rate to 0 is commonly used and it doesn't differ much from the real values. Thus, the impact of the shortcoming can be assumed to be small.

5

Results

The following section will present the results obtained during the development of the thesis. The section will be heavily represented by graphs to visualize the results in a comprehensive and distinct way.

5.1 Market Performance

Figure 5.1 shows the market's (OMXS30) performance between 2005-01-03 and 2022-04-29. The different stages of the market were chosen based on the shape of the graph, and are visualised with vertical lines.

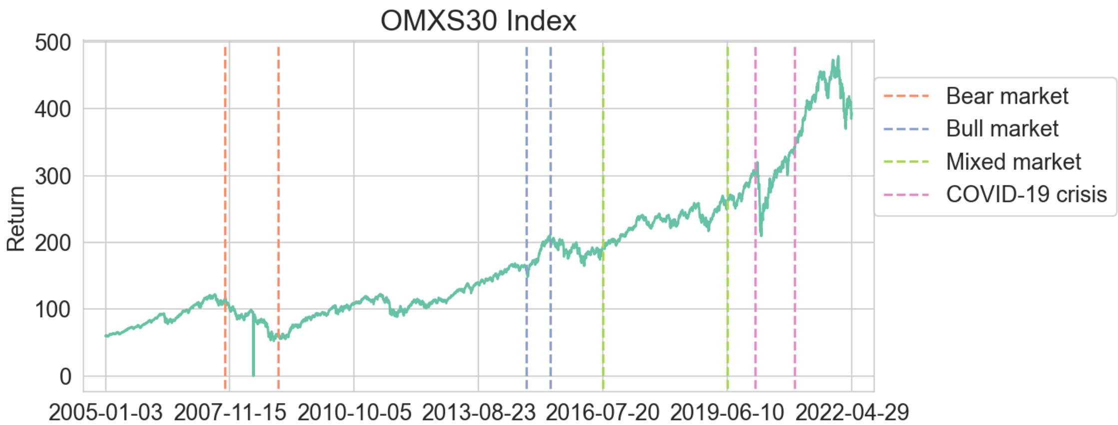

Figure 5.1: OMXS30 performance 2005-01-03 → 2022-04-29.
Bear market 2007-10-03 → 2008-12-29, bull market 2014-10-01 → 2015-04-27, mixed market 2016-07-20 → 2019-06-07, and Covid-19 market 2020-02-03 → 2020-12-30.

The different market stages and their designated time periods can be seen in the following table, Table 5.1.

Table 5.1: Market stages and their designated time periods.

Market stage	Time frame
Bear market	2007-10-03 → 2008-12-29
Bull market	2014-10-01 → 2015-04-27
Mixed market	2016-07-20 → 2019-06-07
Covid-19 market	2020-02-03 → 2020-12-30

In Figure 5.2 the different market stages are extracted from the total time frame and plotted separately. This was done to show them in greater detail and to make it easier to interpret them properly.

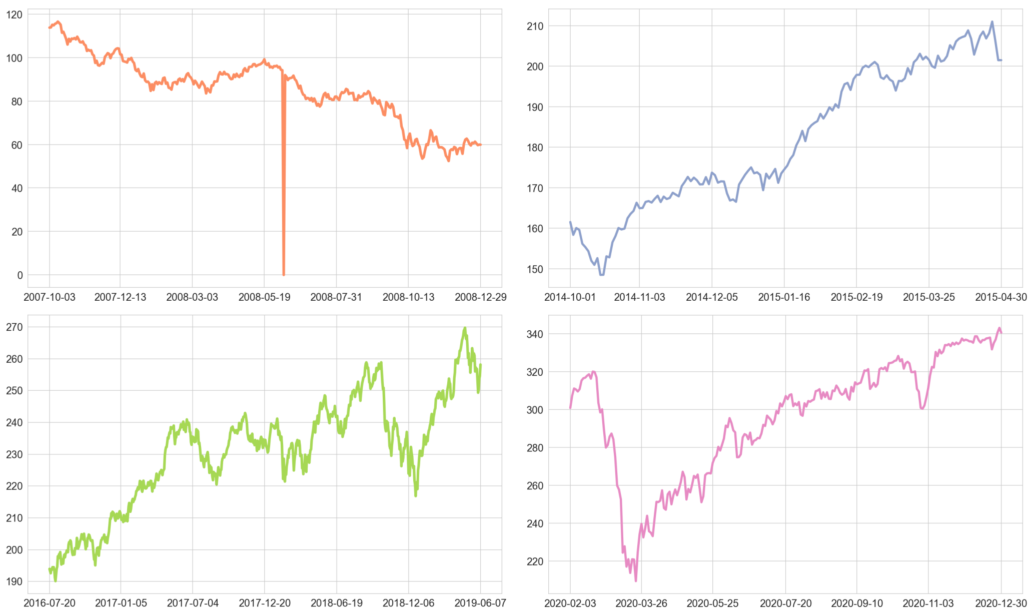

Figure 5.2: Market stages zoomed in.
Bear (up-left), bull (up-right), mixed (bottom-left), and Covid-19 (bottom-right) market performance.

One important thing to consider when comparing the different market stages in Figure 5.2 is that they are over different time-lapses, which can be seen in Figure 5.1. Since their time periods do not have the same lengths, comparison of movement in Figure 5.2 may be difficult.

The curve of the bear market presented in Figure 5.2 has an extreme dip, which is caused by the financial crisis during 2007-2008. Due to the extreme behaviour of this, the bear market was analysed in two ways, with the crash included and also with the crash excluded. Figure 5.3 shows the looks of the market in the different cases. By doing this, potential differences caused by the crash could be discovered.

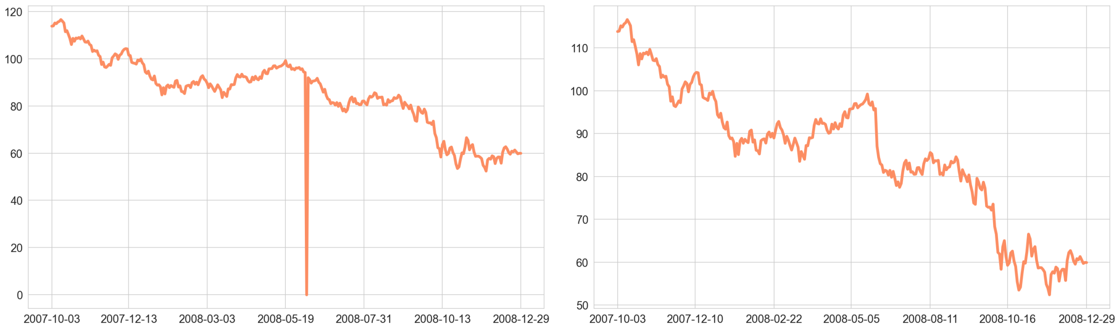

Figure 5.3: Bear market with crisis included (left) and excluded (right).

5.2 Portfolio Performance

Figure 5.4 shows the performance, measured by the Sharpe ratio, over the total time frame. Note that the start date in the plot is 2006-01-02, and not 2005-01-03, because the first year's data had to be used as historical data for calculating the risk at 2006-01-02. The portfolios were re-balanced based on two different risk metrics, beta and volatility, every 30$^{\text{th}}$ workday based on data from the previous year from that date.

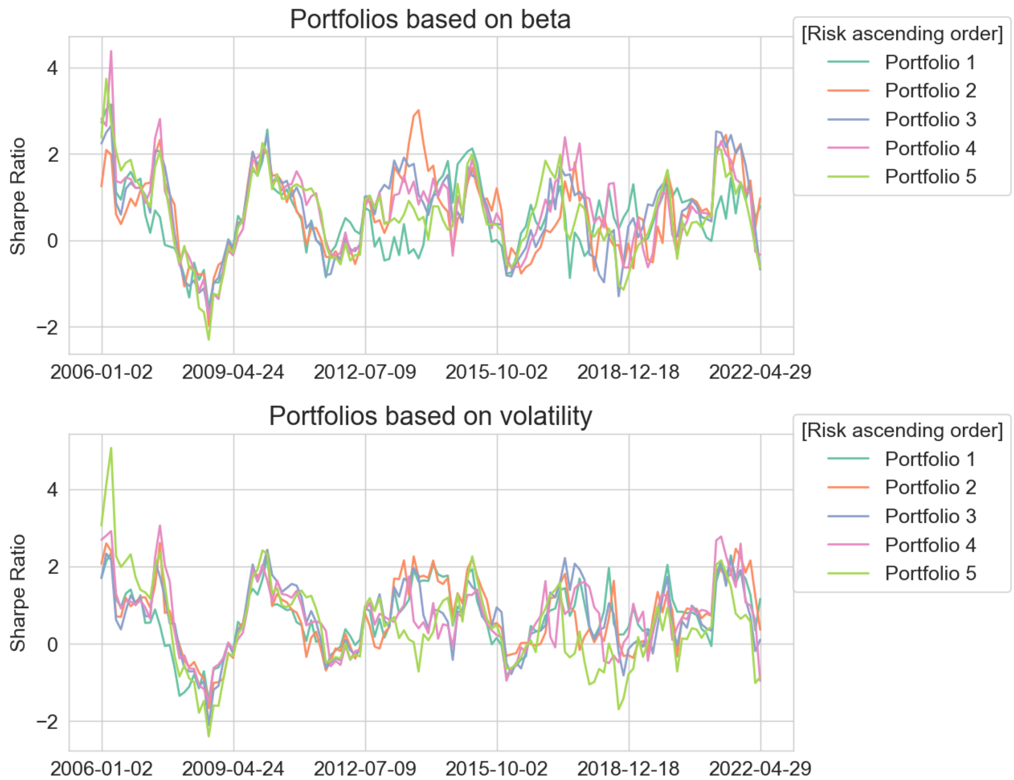

Figure 5.4: The different portfolios' performance 2006-01-02 → 2022-04-29. Portfolios re-balanced based on beta in the top graph, and based on volatility in the bottom graph.

The graphs in Figure 5.4 do not give clear information about exact performance but do show the difference in calculated performance depending on the chosen risk metric. One example of different performance depending on the risk metric is portfolio 2 between 2012 and 2015, where it shows a much higher spike when calculated using beta than volatility. To more easily compare the performances though, the following figure, Figure 5.5, shows the mean Sharpe ratio of the portfolios over the time period for both the volatility and beta as risk metrics when re-balancing the portfolios. By seeing the mean Sharpe ratio, the performance will become more evident since it will show the mean performance of all portfolios.

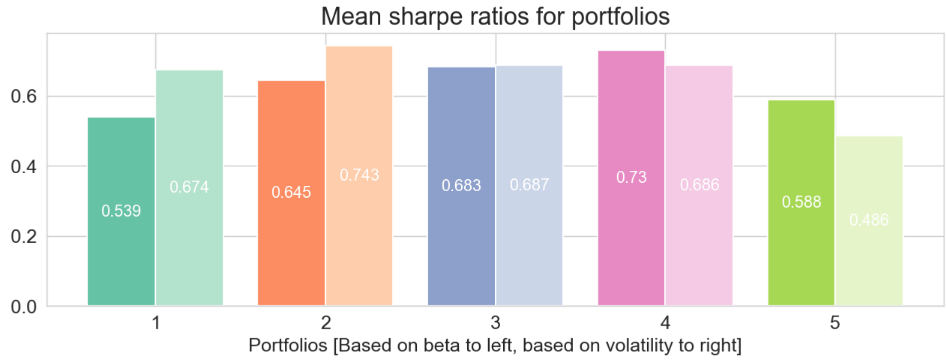

Figure 5.5: The different portfolios' mean Sharpe ratio 2006-01-02 → 2022-04-29. Portfolios re-balanced based on beta on the left and based on volatility on the right bar of every pair.

The mean Sharpe ratios in Figure 5.5 are rather similar. The clearest result is that portfolio 5 seems to perform worst though if volatility is chosen as the risk metric. One interesting thing is that portfolios 1 and 5, which are the most polarized ones based on level of risk, seem to perform almost as good if beta is the risk metric used when re-balancing. However, if volatility is used as the risk metric instead, the difference is quite big. Furthermore, the portfolios with the medium levels show continuously better performance than portfolios 1 and 5 with portfolio 3 showing even performance regardless of the risk measure.

5.2.1 Bear Market

The first part of the analysis of the bear market *excluded* the financial crash. Figure 5.6 shows the performance, measured by the Sharpe ratio, of the five portfolios between 2007-10-03 and 2008-12-29. The portfolios were re-balanced based on two different risk metrics, beta and volatility. The portfolios were re-balanced every 5$^{\text{th}}$ workday based on data from the previous year from that date.

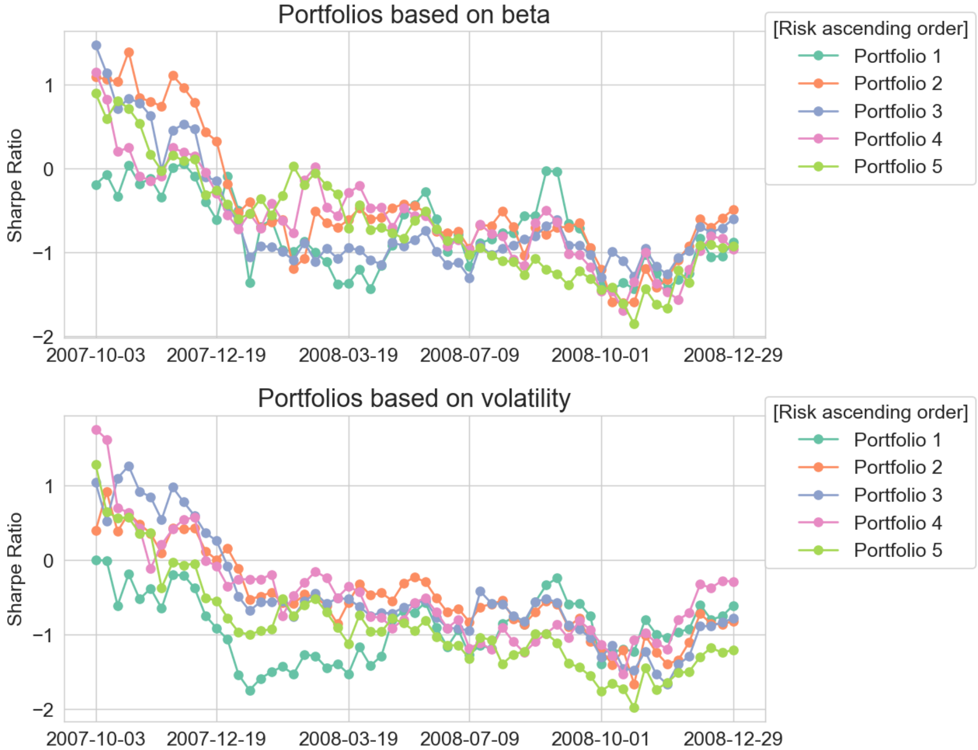

Figure 5.6: The different portfolios' performance 2007-10-03 → 2008-12-29, financial crash *excluded*.

Portfolios re-balanced based on beta in the top graph, and based on volatility in the bottom graph.

The portfolios, regardless of the risk metrics, show similar performance over the time period, but are not identical. For example, portfolio 1's performance between 2007 and 2008 differs depending on the risk metric used, and around 2008-09 portfolio 1's performance differs quite much from the other portfolios' with beta as risk metric, but is almost the same if volatility is used.

To get a clearer view of the performances shown in the graphs in Figure 5.6, their means were calculated. The results are shown in Figure 5.7.

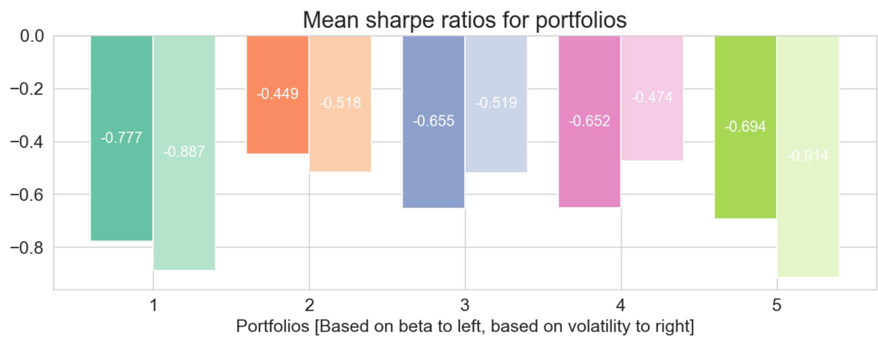

Figure 5.7: The different portfolios' mean Sharpe ratio 2007-10-03 → 2008-12-29, financial crash *excluded*.

Portfolios re-balanced based on beta in the left and based on volatility in the right bar of every pair.

Due to the characteristic of a bear market, the means of the Sharpe ratios over time are exclusively negative. The lowest mean value is found in portfolio 5 based on volatility, the riskiest one, and the two least negative means are found in portfolio 2 based on volatility and beta. Overall, the means are quite varying over the different portfolios and risk metrics.

In the second part of the analysis of the bear market, the financial crash was *included*. The graph plots of the portfolios' performance, done in the same way as in Figure 5.6, did not show any clear difference from when the financial crash was excluded. To be able to compare the two cases in a more comparable way, the means of the Sharpe ratios were calculated, which are shown in Figure 5.8.

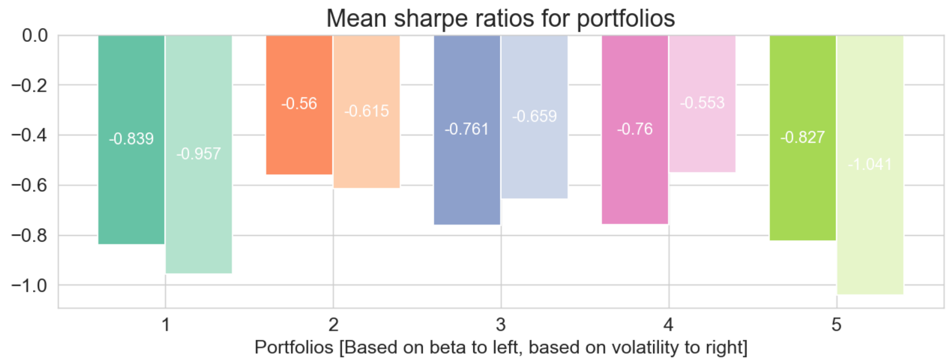

Figure 5.8: The different portfolios' mean Sharpe ratio 2007-10-03 → 2008-12-29, financial crash *included*.

Portfolios re-balanced based on beta in the left and based on volatility in the right bar of every pair.

The means in Figure 5.8 do not differ very much from the ones in Figure 5.7. Overall, the means got more negative for all the portfolios, which is derived directly from including the financial crash. One noticeable thing regarding the performance, for both when the financial crisis was included or not, is that portfolios 1 and 5 performed worse than the others regardless of the risk metric used.

5.2.2 Bull Market

Figure 5.9 shows the performance, measured by the Sharpe ratio, of the five portfolios between 2014-10-01 and 2015-04-27. The portfolios were re-balanced based on two different risk metrics, beta and volatility. The portfolios were re-balanced every 5^{th} workday based on data from the previous year from that date.

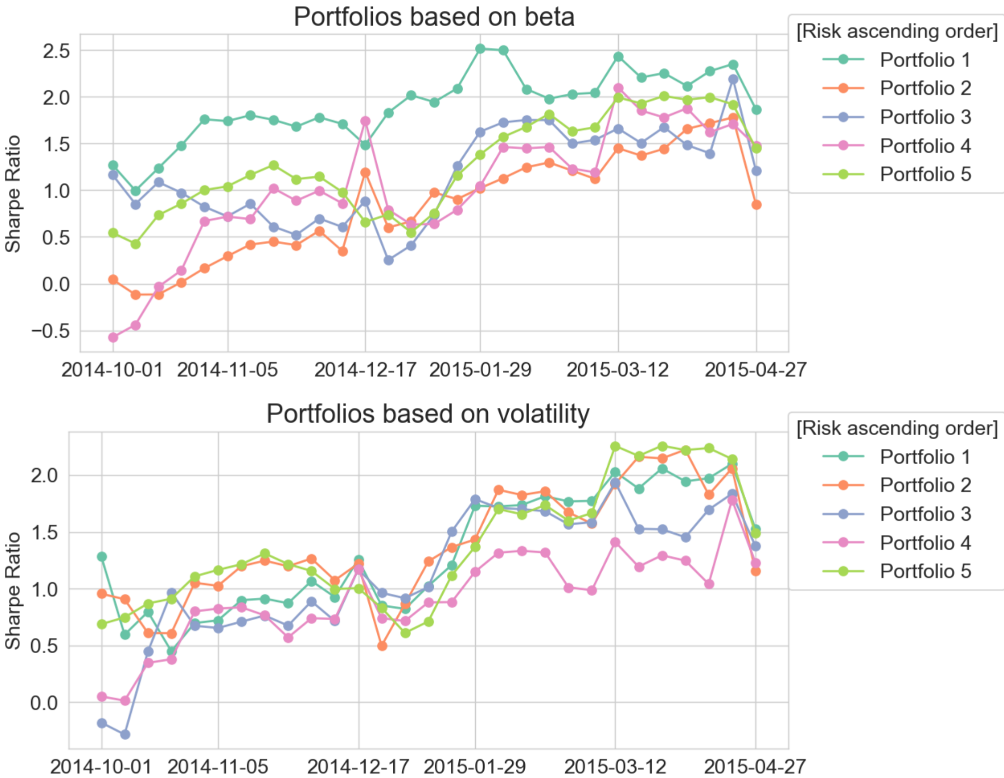

Figure 5.9: The different portfolios' performance 2014-10-01 → 2015-04-27.
Portfolios re-balanced based on beta in the top graph, and based on volatility in the bottom graph.

Once again is the performance of the portfolios similar regardless of the risk metric, however, portfolio 1's performance differs more than previously. The performance for portfolio 1 when using beta as the risk metric can actually be seen to be rather different than when volatility is used.

The means of the performances shown in the graphs in Figure 5.9 were then calculated, and the results are shown in Figure 5.10.

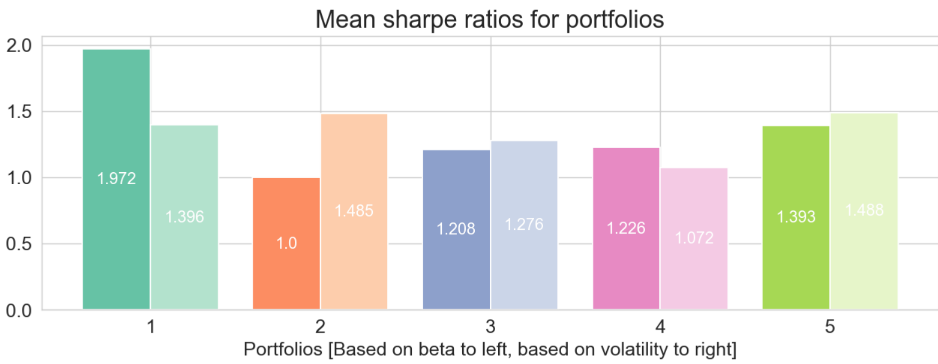

Figure 5.10: The different portfolios' mean Sharpe ratio 2014-10-01 → 2015-04-27.
Portfolios re-balanced based on beta in the left and based on volatility in the right bar of every pair.

The mean Sharpe ratio of portfolio 1 based on beta is the largest one by far. All the other ones are quite alike. Something that differentiates portfolios 1 and 2 from the others is that the difference between the mean Sharpe ratio depending on which risk metric is used, beta or volatility, is much larger than for the others. This pattern was pointed out to be visible in the graphs in Figure 5.9 as well. The Sharpe ratios over time for these two portfolios have very different looks in the different graphs, whilst the other portfolios are more or less the same in both graphs.

5.2.3 Mixed Market

Figure 5.11 shows the performance, measured by the Sharpe ratio, of the five portfolios between 2016-07-20 and 2019-06-07. The portfolios were re-balanced based on the different risk metrics and every 5$^{\text{th}}$ workday based on moving values determined by data from the previous year from that date.

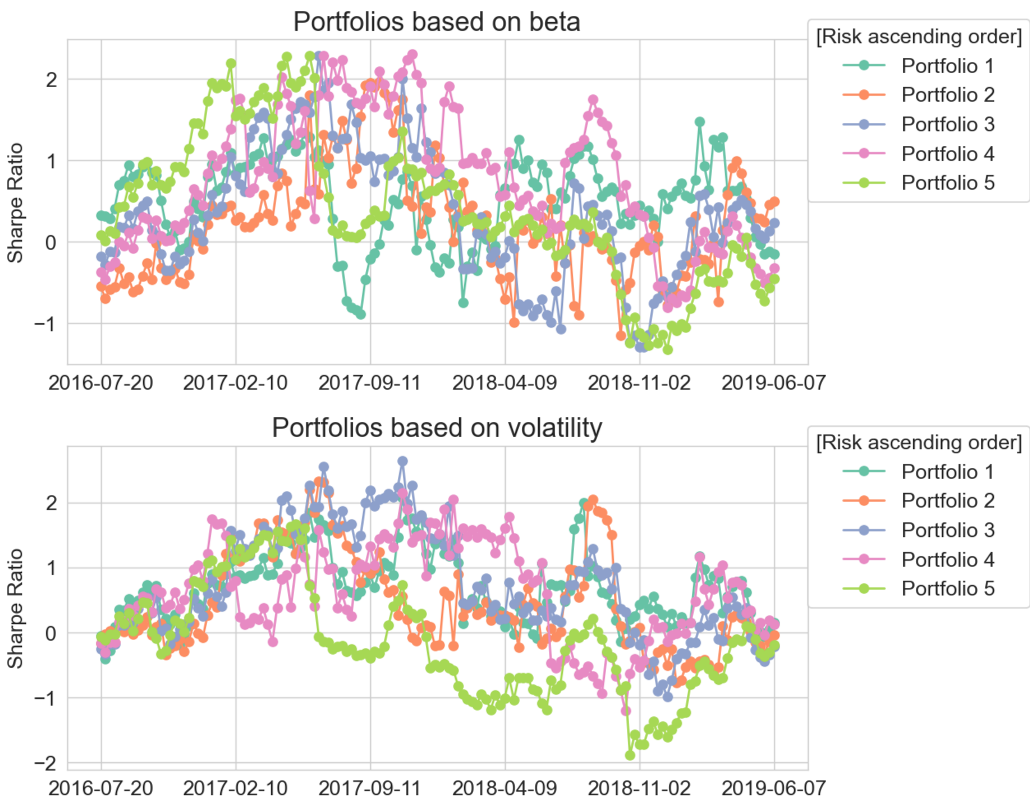

Figure 5.11: The different portfolios' performance 2016-07-20 → 2019-06-07. Portfolios re-balanced based on beta in the top graph, and based on volatility in the bottom graph.

One important factor to notice is that the mixed market is over a longer time period than the other stages. The reason for this is to see if the length of the time period might have an impact on the results. One interesting detail is that portfolio 5 has a much lower minimum value when it was re-balanced based on volatility. This can be seen when comparing the graphs around November 2018. The mean Sharpe ratio over this stage can be seen in the following figure, Figure 5.12.

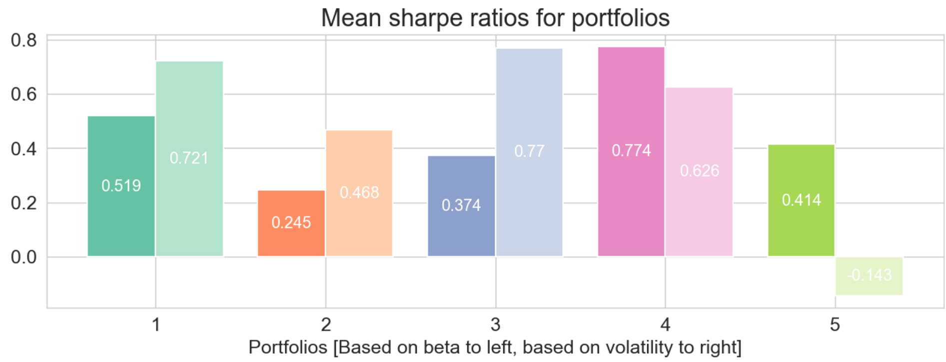

Figure 5.12: The different portfolios' mean Sharpe ratio 2016-07-20 → 2019-06-07.

Portfolios re-balanced based on beta in the left and based on volatility in the right bar of every pair.

The mixed market shows a larger average Sharpe ratio when the first three portfolios were re-balanced based on their volatility rather than their beta. Interestingly, the two portfolios with higher risk show the opposite result. Furthermore, the best performance is by portfolio 3 re-balanced depending on volatility and portfolio 4 re-balanced on beta. Lastly, the Sharpe ratio for portfolio 5 is interesting as it is positive when it was re-balanced based on beta but negative for volatility. Overall, the performance differs significantly for all portfolios depending if beta or volatility was used as the risk metric.

5.2.4 Covid-19 Market

Figure 5.13 shows the performance, measured by the Sharpe ratio, of the five portfolios between 2020-02-03 and 2020-12-30. The portfolios were re-balanced based on the different risk metrics and every 5$^{\text{th}}$ workday based on moving values determined by data from the previous year from that date.

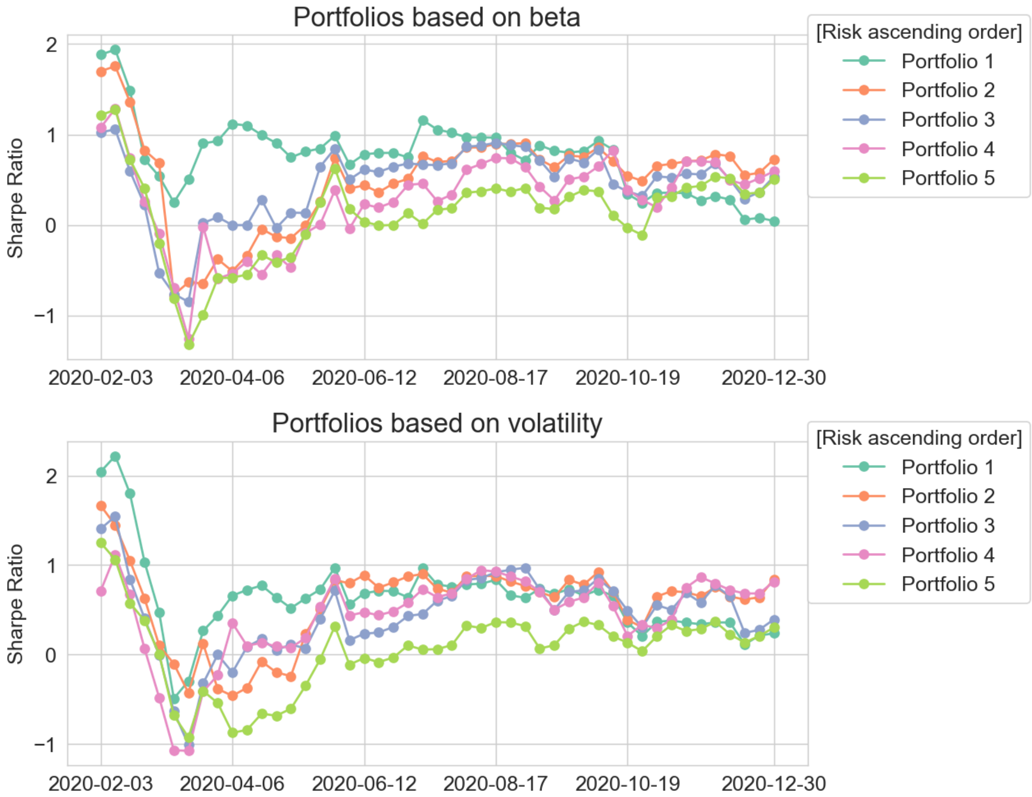

Figure 5.13: The different portfolio's performance 2020-02-03 → 2020-12-30.
Portfolios re-balanced based on beta in the top graph, and based on volatility in the bottom graph.

There is a somewhat clear difference between the graphs in Figure 5.13 where the graph where the portfolios are re-balanced based on beta shows a clear difference in portfolio 1's drop around March of 2020. Therefore, to better understand the performance, the mean Sharpe ratio over the time period of the crisis market is shown in Figure 5.14.

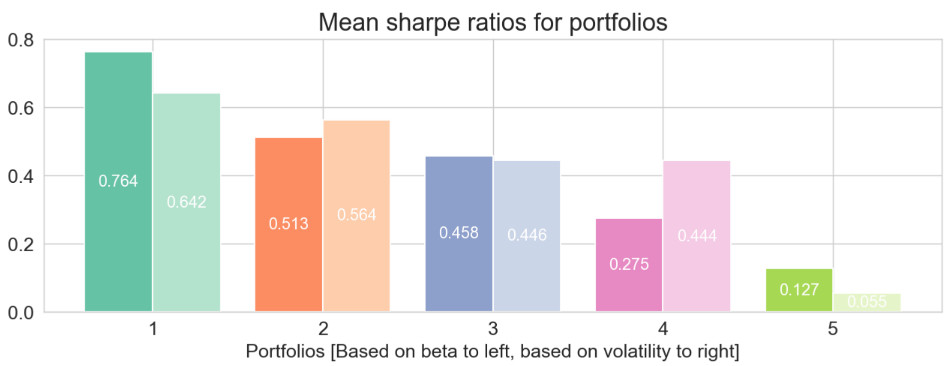

Figure 5.14: The different portfolios' mean Sharpe ratio 2020-02-03 → 2020-12-30.
Portfolios re-balanced based on beta in the left and based on volatility in the right bar of every pair.

The performances in Figure 5.14 show that the lower the risk, the better the performance. The relation between the risk of the portfolios and their performance shows a clear negative relation. This is only not the case between portfolios 3 and 4 when they were re-balanced based on volatility.

6

Analysis & Discussion

This thesis aims to investigate the presence of the LVA on the Swedish market and especially during the Covid-19 pandemic. This was done by analyzing 27 stocks, divided into five portfolios with different levels of risk, which were simulated over the time period between 2005-01-03 and 2022-04-29.

6.1 Result Assessment

The result presented in Figure 5.5 shows very little difference in portfolios' performance depending on their risk level. Portfolio 3 shows the evenest performance over the entire time span while portfolio 2 has the highest Sharpe ratio when the portfolio was re-balanced based on volatility. However, since portfolio 3 includes 7 stocks while the rest of the portfolios have 5, the performance may be based on the portfolio having a lower level of unsystematic risk that has been diversified away.

During the bear market, it is rather difficult to draw any clear conclusion about how risk affects the performance since it varies a lot. Something that can be seen in Figure 5.7 is that the portfolio with the worst performance is number 5, the riskiest one, when volatility is used as risk metric and both when the financial crash is included or excluded. Considering this, there is a slight tendency for LVA. However, the fact that the clearest result is that portfolio 1, together with portfolio 5, has the most negative performance, regardless of risk metric and if the financial crash is excluded or not, speaks against it.

During the bull market, the relationship is to some degree present when beta was the used risk metric. Figure 5.10 presents this, where the performance of portfolio 1 is the highest by far. However, performance is not decreasing as risk increases, but instead, the second-best performance is found in portfolio 5. Furthermore, when volatility was used as the risk metric, there was no clear indication of a relationship between risk and performance at all.

The mixed market shows results of big diversity. No clear relationship between increased risk and performance is present and the difference in performance between using beta or volatility as the risk metric is large for all portfolios. The most interesting result, in this case, is that the mean Sharpe ratio for portfolio 5, with volatility as the risk metric, was the only one that got a negative Sharpe ratio, which is shown in Figure 5.12. This could be a slight indicator of the presence of the LVA on this market. However, the means of Sharpe ratio for portfolios 2-5 speaks against this, since the performance does not decrease with increased risk.

Lastly, the Covid-19 crisis market shows interesting results. Figure 5.14 shows a clear relationship between high performance and low risk. During this period, the performance of the low risk portfolios generally outperformed those with higher risk, which corresponds with the LVA.

Overall, there are no clear conclusions to draw. The LVA does not seem to be obviously present on the Swedish market but does, to some degree, seem to be present in different stages. The bull market and the Covid-19 crisis market show a larger presence of the LVA than the total and the other stages. However, one important piece of information that has been presented during all stages is the difference in performance depending on if one uses beta or volatility to re-balance the portfolios. This demonstrates that the definition of risk has a big impact on the calculated performance of stocks and portfolios. Furthermore, the use of five portfolios gave better insights into the presence of the LVA rather if the study only would have used, e.g. using only the least and most risky ones, since the performance of portfolio 1 almost always outperformed portfolio 5. By including the other portfolios as well, it is clear that there is not a constant relationship between risk and performance. Hence, the presence of the LVA is not clear when looking at all portfolios but one could draw the conclusion if only looking at portfolios 1 and 5.

6.2 Result Validity

The result presented does not show a clear presence of the low-risk anomaly on the Swedish market, which contradicts the findings of Brodén and Fransson (2015). The result shows some signs of a presence but not conclusive evidence. The data of this study is of a later date than that of Brodén and Fransson (2015) which might be a reason for the contradicting results. Additionally, the lack of presence in this analysis is not conclusive evidence that the low-risk anomaly is not present on the Swedish market. The low-risk anomaly might be present on the Swedish market considering the small sample of data analyzed in this study and this specific time frame.

Furthermore, the result of this study does seem to initially contradict the findings of Gregory Taïeb (2020). However, this study looks at a longer rebound after the crash than that of Gregory Taïeb (2020). As Gregory Taïeb (2020) concludes that predicting results of low risk stocks over short time frames is impossible and that the idea of the LVA is not obsolete, the result of this thesis seems to prove the statement correct. During the Covid-19 crisis, the LVA seems to be more present than at any other stage. The extended time frame of the crisis may be the reason for the different results. The fact that similar studies with contradicting results predicted the results of this study, due to the extended time frame, strengthens the validity of the results.

6.3 Improvement Areas

Something that was simplified in this thesis was to set the risk free rate between 2020-07-03 and 2022-04-29 to 0, due to lack of good data. Even though this seems like a fair simplification, it would make the analysis more robust to find good data for this time period and see if it has any, and in that case how big, impact on the results.

The stocks included in this thesis were 27 out of the 30 listed on the OMXS30, which are all large-cap companies. To improve the analysis done in this thesis, more stocks of the same character could be used to get a more robust result. Furthermore, including different types of stocks, e.g. from mid- and small-cap companies, would improve the results regarding the existence of LVA on the entire stock market in Sweden.

The portfolios in the simulations were always equally weighted. A possible improvement could be to tune the weights, e.g. based on market capitalization. In this thesis, this would probably not have a very big impact on the results, since all the stocks were of the same type, large-cap companies. However, if stocks of different types would be included, as previously proposed, this would probably be of greater importance.

The simulations that were done in this thesis required many settings of parameters. One example of parameter settings is the time steps between re-balancing the portfolios, in other words how often the portfolios are re-balanced. The smaller the time steps are, the bigger the time complexity of the simulations. E.g. re-balancing the portfolio every day over the entire time period included in this thesis would be extremely time demanding. To handle this, the time steps were adjusted depending on the time period in the simulations, as the time step for the extracted market stages was 5 workdays and 30 workdays for the entire time period. The drawback of this is that the fine-tuning of the results is reduced. However, systems that are more fluctuating are more sensitive to longer time steps. Since the system in this thesis, or in other words the market, isn't very fluctuated, the chosen time steps seem reasonable.

Another parameter setting that has an impact on the results is the time span for historical data that is used for calculating values of beta and volatility. Variables as e.g. beta and volatility depend on, among other things, means of historical data, so calculating the means over a time period of for example one year or three years will naturally generate different values. In this case, there is no right or wrong way to choose the settings. However, it is of great importance to be aware of the settings' potentially big impact on the results. One possible improvement is therefore to try different settings of parameters and compare the results from this.

6.4 Future Work

The presented improvement areas can all be a foundation for future work. However, below are specific ideas for future work that can develop the future understanding of the LVA, the Swedish market, and the impact of Covid-19.

Future work could investigate the reason why the LVA shows to be more present during the Covid-19 crisis. The reasons presented by Baker et al. (2011) and Li et al. (2016), which are investor behaviour and underappreciated limits on arbitrage, could be interesting to investigate if they can explain the LVA during the Covid-19 crisis in Sweden. Change in investor behaviour after the crash to prefer high volatility stocks, as Li et al. (2016) concluded to be a reason could be a possible explanation but further investigation is needed, as previously stated. A further reason for future work to investigate the reason why the LVA shows to be more present during the Covid-19 crisis is the seeming lack of presence during the 2007-2008 financial crisis. Future research can therefore examine the specific reasons for the LVA during the Covid-19 crisis and how they may differ from those of the financial crisis of 2007-2008.

Furthermore, future work could analyze if the same result would be presented if one constructed the portfolios using different stocks, for example, combinations of large-, mid-, and low-cap stocks and portfolios containing more stocks. By investigating this, the understanding of the LVA in Sweden would be developed and future work would have more data to analyze the possible reasons for why the LVA shows to be more present during the Covid-19 crisis.

Lastly, future work could specifically investigate what macro and micro components of the LVA were present during the Covid-19 crisis and how they affected the Swedish market. This research could develop upon the work of Baker et al. (2014), presented in the literature review, which presented the idea that the LVA is a basic form of market inefficiency that has both macro and micro components, which affect different markets differently due to the market's characteristics.

7

Conclusions

The aim of this thesis was to investigate the presence of the low volatility anomaly on the Swedish market and what its presence was during the Covid-19 crisis. The results show no clear evidence of the low volatility anomaly on the Swedish market but do show its presence during the Covid-19 crisis. Furthermore, the study investigated to what extent the low volatility anomaly was present at different stages of the market with the aim of better understanding its presence. The result shows that the only clear evidence of it was during the Covid-19 crisis stage. The result is however unclear and further research is needed on the Swedish market to better understand the low volatility anomaly and the reasons why it appears to be the most present during the Covid-19 crisis.

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