The short and long-term effects of Covid-19 on volatility-sorted portfolios in OMX Helsinki

An event study of beta's impact on portfolio performance during the Covid pandemic

Lappeenranta–Lahti University of Technology LUT

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Viljami Eerola

Examiner: University Lecturer Roman Stepanov

ABSTRACT

Lappeenranta–Lahti University of Technology LUT

LUT School of Business and Management

Business Administration

Viljami Eerola

The short and long-term effects of Covid-19 on volatility-sorted portfolios in OMX Helsinki - An event study of beta's impact on portfolio performance during the Covid pandemic

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Keywords: Return, Risk, Beta, Volatility, Anomaly, Event study, Covid, OMXH, CAPM, Jensen, Sharpe

Low-volatility securities are considered to produce more stable returns than those with higher volatility. The Capital Asset Pricing Model proposes that increased stability is achieved at the expense of the magnitude of returns. The objective of this thesis is to examine in Nasdaq's Helsinki Stock Exchange, the relationship of return and risk in changing market conditions during the Covid-19 pandemic. Throughout the examination, the stocks of OMX Helsinki are divided into deciles which are proxies for volatility portfolios. This thesis' empirical event study aims to measure the difference in volatility portfolios' short and long-term abnormal returns during the analysis window of January 20th, 2020, to December 30th, 2021.

The empirical part studies the overall reaction of the dataset, the short-term reaction of volatility portfolios, and the long-term reaction of volatility portfolios. The COVID-19 decline describes an unforeseeable market shock allowing the measuring of market efficiency and the true effect of volatility on returns. The empirical findings show that the risk-adjusted negative reaction of low-volatility stocks was greater than the stocks with high volatility. The recovery from the decline indicated a significantly greater performance on low-volatility stocks denying the normal risk-return tradeoff of the Capital Asset Pricing Model and supporting the low-volatility anomaly. Linear estimation and the performance indicators of Sharpe ratio, Jensen's Alpha, and abnormal returns of market model estimation indicated low volatility's statistically significant positive effect on stock returns.

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Rahoitusteorian mukaan matalan volatiliteetin arvopaperit tuottavat vakaamman tuoton kuin korkeamman volatiliteetin arvopaperit. Capital Asset Pricing -mallin mukaan lisääntynyt vakaus saavutetaan tuoton suuruuden kustannuksella. Tutkielman tavoitteena on tutkia Nasdaqin Helsingin Pörssin tuotto-riskisuhdetta muuttuvissa markkinaolosuhteissa Covid-19-pandemian aikana. Tarkasteluaika OMX Helsingin osakkeet on jaettu desiileihin, jotka kuvaavat volatiliteettisalkkuja. Tutkielman empiirinen tapahtumatutkimus pyrkii mittaamaan volatiliteettisalkkujen lyhyen ja pitkän aikavälin lisätuottojen eroa aikavälillä 20. tammikuuta 2020-30. joulukuuta 2021.

Empiirinen osa tutkii aineiston kokonaisreaktiota, volatiliteettisalkkujen lyhyen aikavälin reaktiota ja volatiliteettisalkkujen pitkän aikavälin reaktiota. Covid-19 talouskriisi kuvaa ennalta-arvaamatonta markkinashokkia, jonka avulla voidaan mitata markkinoiden tehokkuutta ja volatiliteetin todellista vaikutusta tuottoihin. Empiiriset havainnot osoittavat, että alhaisen volatiliteetin osakkeiden riskikorjattu negatiivinen reaktio oli suurempi kuin korkean volatiliteetin osakkeiden. Markkinashokista toipuminen osoitti, että matalan volatiliteetin osakkeilla oli huomattavasti parempi suorituskyky, mikä on ristiriidassa Capital Asset Pricing -mallin normaalin tuotto-riskisuhteen kanssa ja tukee matalan volatiliteetin anomaliaa. Lineaarinen estimointi ja seuraavat suoritusindikaattorit: Sharpen luku, Jensenin Alfa ja markkinamallin estimoinnin lisätuotot osoittivat alhaisen volatiliteetin tilastollisesti merkitsevän positiivisen vaikutuksen osaketuottoihin.

Table of contents

1 Introduction 7
1.1 Research objectives 8
1.2 Research questions 10
1.3 Structure of the Thesis 10
2 Theoretical background 11
2.1 Risk-return tradeoff 11
2.2 The Efficient Market Hypothesis 13
2.3 The Capital Asset Pricing Model 16
2.4 Low-volatility anomaly 17
2.5 Covid-19 in Finland 19
2.6 Summary of theoretical background 22
3 Methodology & data 24
3.1 Portfolio comparison 24
3.2 Event study 25
3.3 Data 30
4 Empirical Study 32
4.1 Market reaction to the Covid-19 32
4.2 The Covid-19 reactions of volatility portfolios 36
4.3 Long-term performance of volatility portfolios 45
5 Conclusions 52
References 58
Appendices 63

LIST OF APPENDICES

Appendix 1: List of the stocks in volatility portfolios

Appendix 2: New COVID-19 cases daily in Finland and globally 2020-2023

Appendix 3. Proxies for risk-free return

LIST OF FIGURES

Figure 1: Security market line (SML)

Figure 2: Annual changes in gross domestic product, imports, and exports of Finland at current prices 2019-2022*

Figure 3: OMX Helsinki Growth Index and new COVID-19 cases daily in Finland

Figure 4: Event study timeline

Figure 5: The performance of the volatility portfolio average and the market (OMXH GI) from 2.1.2020 to 30.12.2021

Figure 6: Average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) of the dataset during the event window

Figure 7: Abnormal returns (AR) of each volatility portfolio during the event window

Figure 8: Cumulative abnormal returns (CAR) of each volatility portfolio during the event window.

Figure 9: The realized returns of the volatility portfolio during the event window & post-event window

Figure 10: The cumulative abnormal returns (CARS) of the volatility portfolio during the event window & post-event window

Figure 11: The Security Market Line (SML) and the portfolio returns plotted to estimated (Panel A) and realized (Panel B) betas.

LIST OF TABLES

Table 1: Characteristics of earlier studies' regressions

Table 2: Average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) of the volatility portfolios during the event window (EW) (0-59)

Table 3: Summary of the volatility portfolios

Table 4: Mean returns of the volatility portfolios and the market indicator (OMXH GI) during pre-event (panel A), event (panel B), and post-event (panel C) windows.

Table 5: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (0-9 and 10-19).

Table 6: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (20-29 and 30-39).

Table 7: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (40-49 and 50-59).

Table 8: Abnormal returns (AR) and average abnormal returns (AAR) of specific announcement days (t0) and the day after (t1)

Table 9: Summary of short-term panel data

Table 10: OLS panel regression of short-term abnormal returns (AR) with robust standard errors in parentheses

Table 11: Summary of long-term panel data

Table 12: OLS panel regression of long-term abnormal returns (AR) with robust standard errors in parentheses

Table 13: Summary of the performance of volatility portfolios during the event window and post-event window

1 Introduction

The objective of financial theory is to offer answers to complex questions concerning money, currency, and capital assets. Modern financial theory has been sculpted to take on its current form through a variety of research and new inventions. Arguably, the most important cornerstone of basic finance is the management of risk and return to achieve pre-determined goals. Evaluation of this relationship allows investors to calculate and adjust the amounts of capital they are willing to risk to achieve desired returns on the investment. When investors desire more profit, they are required to endure more risk. Harry Markowitz (1952), who created the Modern Portfolio Theory (MPT), describes this as the “expected returns – variance of returns” rule. From Markowitz’s conclusion, financial economists became more interested in the optimization of risk and return in investment portfolios. This thesis evaluates the role of volatility, which is equivalent to risk in financial vocabulary, as a factor in the performance of investment portfolios.

The capital asset pricing model (CAPM), which is a key part of this thesis, was created to rate securities based on the expected return-to-risk -ratio in given markets (Sharpe, 1964). The CAPM disregards idiosyncratic risk with the assumption that the investment portfolio is diversified enough. If the diversification is complete, only systematic risk of the market will play a role in the risk adjustment. Being such a key issue, volatility needs considerable attention from both investors and researchers. As John Campbell’s paper (2006) outlines, private investors face multiple difficulties when performing household investing. The consideration of market risk and the diversification of portfolios are the easiest ways to avoid basic mistakes in finance. (Campbell, 2006, 1590). This paper focuses on volatility defined by the beta of CAPM as it still represents one of the primary instruments used by investors to measure risk. Beta assumes a linear relationship between risk and return. The objective of examining the performance of the whole OMX Helsinki supports the use of CAPM beta as the portfolios are sorted by the market relative volatility.

This thesis aims to inspect portfolio management during a market decline. The market decline chosen is the recent COVID-19 pandemic from the year 2020 to 2022. Our dataset has a timespan of four years, to offer the information to study all significant factors. Long-term effects after the phenomenon's actual appearance must be taken into consideration for the investigation of COVID-19 effectively. (Long et al., 2022). The timespan is restricted to December 30, 2021, to portray the long-term performance without including the market decline caused by the Russo-Ukrainian War in early 2022. The two-year data before the year 2020 allows an accurate estimation period for the normal returns. The impact of COVID-19 on financial markets is examined with a broad event study approach of both short and long-term effects.

From the start of 2020, the pandemic disrupted the economy deeply and was compared to the economic effect of the world wars. The rapid scaling of the pandemic disrupted simultaneously supply, demand, and logistics, and had long-term effects on each one. (Ivanov, 2020, 9) Concerning this thesis, the effects of the decline in the Finnish economy were massive. The Official Statistics of Finland (OSF) (2023a) indicates that turnovers in the year 2020 in different sectors fell dramatically. A few examples include industry (-29,0%), transportation and storage (-58,4%), and accommodation and food service activities (-9,1%). Profitability was also deeply affected as the net profits in different industries showed negative figures (Official Statistics of Finland, 2023a). The decline was followed by significant economic growth which was a result of central banks and governments reviving the economy in unparalleled scales with purchase programs and other supportive actions to keep the economy from crashing. (Nicola et al., 2020, 187) The uncertainty that COVID-19 inflicted on stock markets offers this thesis an opportunity to measure beta's effect on stock performance when market conditions and investor sentiments change.

COVID-19 illustrates an unpredicted event that leads to the economy being unstable. The news of media and official announcements dictate investor sentiment as well as short-term reactions. (Liu et al., 2020, 2) An event study enables the close examination of changes in abnormal returns during the decline. We measure the importance of the volatility analysis of an investment portfolio during a market decline. Our objective is to test the effect of portfolio beta's when the Covid-19 pandemic disrupted the Helsinki Stock Exchange. The empirical study will address the question of whether a low-volatility portfolio served as a safer investment option during COVID-19 or not.

1.1 Research objectives

According to Markowitz (1952) and Sharpe (1964), more volatile investment requires more expected return for investors to bear the risk of losing capital. Considering that, how is it possible historical data points out opposite behavior in financial markets and in many cases, low-volatility portfolios deliver more profits than portfolios with high volatility (Baker, Malcolm, Bradley and Taliaferro, 2014, 43) Academia has explained the low-volatility anomaly with many different perspectives starting from the early 1970s (Fama, E. F. and MacBeth, 1973). The explanations vary greatly. If other factors, such as size and valuation are added, as in the Fama-French 5F model, the low-volatility anomaly vanishes (Kohls and Mager, 2022, 12). The papers of Kohls and Mager (2022); and Baker, Bradley, and Taliaferro (2014) indicate that after reexamining the anomaly, it can be explained and considered with many factors, but they don't entirely remove the existence of it. This low-volatility anomaly during a relatively short window is acknowledged in our empirical study of OMX Helsinki.

To understand the financial phenomena of risk-return tradeoffs and low-volatility anomaly, a continuous examination of different markets and fields is necessary. This thesis aims to express the significance of risk assessment and the effect it has on realized returns. The timespan allows the phased analysis of the effects that COVID-19 had on investments with different volatility levels. The study is implemented in Nasdaq's Helsinki Stock Exchange (OMXH) as it offers a broad enough stock selection, and it is restricted enough to establish an understanding of possible low-volatility anomaly. The amount of Finland's international trade and the global dependence on OMXH offers suitable data to study the effects of the global pandemic on advanced markets. During the pandemic, Finland's policy markers reacted strongly with both, restrictions, and revitalization of the economy. This allows the all-around examination of the pandemic's effects on different beta levels.

The restriction of including only one market enables the utilization of only one benchmark index, the OMXH GI when comparing stocks. The empirical part of this thesis has been carried out by gathering daily and monthly data of all OMXH stocks and OMXH index from the estimation period as well as the analysis period. The dataset was beta-sorted and divided into deciles that illustrate volatility portfolios. The volatility portfolios were analyzed with quantitative research methods, such as the event study approach and linear ordinary least squares regression.

The investment strategy used in this thesis was selected as buy and hold. The main reason for that strategy was the aspiration to concentrate solely on volatility. According to Barber and Odean (2000), an active strategy to rebalance beta-sorted portfolios would not be profitable. Their study indicates that a high level of household trading leads to poor performance on average. As an application of the paper from Lyon, Barber, and Tsai (1999), this strategy allows us to ignore transactional costs by weighing the selected stocks in their portfolios by the transaction volume to shares outstanding ratio (*turnover ratio*) during the four-year timespan. The turnover ratio also helps to address illiquidity as it is proven to have a positive correlation with expected returns (Amihud, 2002, 52). Therefore, the portfolios were diversified and balanced correctly. These decisions allow us the robust examination and modeling of financial phenomena surrounding our research questions.

1.2 Research questions

Main research question:

1. How did the performance of low-volatility stock portfolios differ from high-volatility portfolios in OMX Helsinki during and after Covid-19 (2020-2022)?

Secondary research questions:

2. How does beta affect the short-term returns of a portfolio during a market decline?

3. Does a low-volatility anomaly occur in OMX Helsinki?

1.3 Structure of the Thesis

The structure of this thesis closely follows the guidelines of LUT University. It is divided into seven sections which all contribute to the entirety. The second section contains a versatile literature review to pave the way for empirical research. With a vast analysis of financial literature, the reader understands the underlying factors behind the phenomena comprehensively and can internalize the results of the research. The third section of this thesis addresses the necessary methodology and variables as well as acquired stock data. The fourth section covers the empirical study of OMX Helsinki. To understand the results of this section, it is quite necessary to get familiar with the earlier sections. The fifth and last section is the conclusion of this thesis. The conclusions answer the research questions by analyzing the empirical results.

2 Theoretical background

This section describes the theoretical background surrounding the risk-return tradeoff. Having gotten acquainted with this section, the reader is aware of underlying factors significantly influencing financial topics covered later in the empirical study. A detailed literature review is necessary when studying complex quantitative issues. This theoretical basis enables the interpretation of methodology and empirical results as precisely and flawlessly as possible.

2.1 Risk-return tradeoff

The return on investment refers to the amount of financial benefit an investor produces due to investing. These returns are the basic description of investor's motive to invest their money from the surplus sector to the deficit sector. Therefore, returns on investments are the heart of the financial markets. In this thesis, the financial instruments include only stocks which means the returns consist of the capital gain and dividend payouts.

The risk-return tradeoff represents a deep-rooted line of reasoning concerning basic financial decisions. In finance, the generalization is that to receive a larger return on investment, one must expose oneself to additional risk (French, Schwert, and Stambaugh, 1987; Sharpe, 1964). William Sharpe (1964) framed this as a choice between the *price of time*, meaning the pure risk-free interest rate, or the *price of risk*, meaning the additional expected return due to a risk premium. This thesis' major topic is risk (volatility) therefore, we'll discuss the basis of the issue next.

Risk is a financial phenomenon caused by uncertainty and it is significantly tied to the performance and riskiness of other securities in the same market (Markowitz, 1952, 4). The correlation between securities' returns varies greatly but normally it is greater among the same industry and market. To take risk into account, investors diversify their investments. Diversification is a tool that offers investors a way to reduce the overall risk of their investments by creating a portfolio of multiple securities. Correlation plays a key role in portfolio management as it dictates the benefit of diversification. At best, diversification can theoretically lead to a zero-risk portfolio if securities are either not correlated or negatively correlated. (Markowitz, 1952, 5)

Risk can be defined in various ways but most often in finance, it is divided into two levels: the market risk (*systematic risk*) and the specific risk (*idiosyncratic risk*). Market risk is a category that can't be eliminated by diversification. However, it can be reduced with global diversification. It contains for example risk-free interest rates, the political state, and the economic state of the market. The other level of risk is the specific risk which is the diversifiable part. It is bound to certain security characteristics such as the company's economic state, legal issues, et cetera. One of the main goals of investing is to adjust the riskiness to match the willingness of investors.

The two risk levels dictate the overall risk of one's investments. According to Harry Markowitz's pioneering "Portfolio selection: efficient diversification of investments" (1952), portfolio management allows investors to capitalize on securities covariance (*correlation*) and thus reduce their investment overall risk to only contain market risk. By diversifying the investment portfolio, investors can dispose of all securities with individual-specific risks. This leads to a situation where the combination of securities can result in yielding more return with less risk than any of the securities individually. This method is called the modern portfolio theory (MPT). MPT's objective is to select high and low-volatility securities for a portfolio to maximize expected returns to the level of risk an investor is willing to endure. (Markowitz, 1952)

Our empirical study applies the MPT to include enough diversification when building portfolios. Its one objective is to include both low and high-volatility securities in the portfolio to adjust risk and return to the wanted level (Markowitz, 1952). As an exception to the MPT, the portfolio selection of our study will be done so that the same volatility-level stocks are assigned to the same portfolios.

The concepts of financial volatility and portfolio management have been empirically studied intensively after Markowitz's (1952) and Sharpe's (1964) findings. Ang, Hodrick, Xing, and Zhang (2009) measured the effect of idiosyncratic risk on returns in 23 developed countries including Finland. Their findings indicate that there is global evidence that high idiosyncratic volatility stocks yield lower future returns than low idiosyncratic volatility stocks. Their dataset suggests that the highest volatility quintile has statistically significantly 1.31% lower average monthly returns than the lowest volatility quintile. Cognate results of risk-return tradeoff are found in the papers of Baker, Bradley, and Taliaferro (2014) as well as Kohls and Mager (2022). The phenomenon referred to is called the low-volatility anomaly. Its proven existence creates a need for studies, such as this thesis, to reexamine the subject and evaluate its role in investing.

The research methods for measuring risk and expected returns include financial models, such as the capital asset pricing model, measuring the effect of risk variables on logarithmic returns. These economic models rely on assumptions that exclude some factors to measure the effects of predetermined variables. The economic modeling requires high accuracy and for example, data frequency, liquidity, company size, and stock price contribute to the significance of the results. In this thesis, we take the findings of Bali and Cakici (2008) into consideration and compare both daily and monthly results, and set limitations to stock liquidity to make results more accurate.

The Modern Portfolio Theory (MPT) suggests that by including negatively correlated stocks in an investment portfolio, investors can diversify the unsystematic risk in the best way. This leads to systematic risk being the only significant factor in the portfolio’s risk. By only accounting for systematic risk, the Capital Asset Pricing Model relies on the assumption of the Modern Portfolio Theory. If investors were able to predict future correlations perfectly, the zero-risk portfolio would be utilized in investment strategies. To study the effect of beta on portfolio performance, diversification is applied without utilizing negatively correlated stocks in portfolios. The portfolios constructed in our empirical study are diversified across industries, and they include at least 11 different-sized companies, making the unsystematic risk minimal. Therefore, the utilization of the beta of the Capital Asset Pricing Model which accounts for only the systematic risk is supported by the Modern Portfolio Theory.

2.2 The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is an assumption in economics that claims markets are efficient. This efficiency means that the prices of assets are accurate and represent all information available. This assumption leads to a situation in which investors can gain greater returns only by greater exposure to risk (Baker, Malcolm, Bradley, and Taliaferro, 2014, 43). The EMH provides a basis for economists to study financial markets and investors to develop investment strategies that capitalize on different efficiency levels. The type of information that affects the price formation of a certain market dictates the efficiency level. Market efficiency does not imply a complete availability and equal possibilities to reach information for all investors, as transaction costs, taxes, and cost of information disrupt these assumptions (Knüpfer and Puttonen, 2018, 170). Eugene Fama (1970) introduced the formula of investors’ price expectations:

$$\mathrm{E}(\widetilde{p_{j,t+1}} \mid \Phi_t) = [1 + \mathrm{E}(\widetilde{r_{j,t+1}} \mid \Phi_t)]p_{jt}, \tag{1}$$

in which E is the expected value; p_{jt} is security j's price at time t; $p_{j,t+1}$ is the same security's price at time t+1; $r_{j,t+1}$ is the percentage return of one period; ϕ_t is a symbol for any information that is "fully reflected" to the price at t. The tildes indicate random variables at t. The EMH formula assumes that the expected value is a valid indicator for measuring market efficiency. It categorizes efficiency into three different levels concerning the information prices are reflecting. The common factor in all three levels is the assumption that they are reflecting the real value of the securities, thus investors cannot outperform the market in the long run.

The lowest stage is the weak level of efficiency. It reflects only the past prices. This means that the stock prices reflect the historical stock information accurately and correctly. Weak-level market inefficiency allows the usage of technical analysis whose objective is to forecast future returns of past price data. Technical analysis strives to identify trends from stock data in an early stage and benefit from future returns (Park and Irwin, 2007, 786). If investors can generate abnormal returns consistently with technical analysis, it indicates the inefficiency of the market. The weak level of efficiency is at the essence of this thesis as we utilize technical analysis when constructing the volatility portfolios.

The semi-strong level takes account of past prices and all public information. The public information includes for example quarterly reports, news, and economic forecasts. At this level the price changes instantly due to new related information emerging. If investors can benefit from fundamental analysis, it indicates that the market is inefficient at the semi-strong level. Fundamental analysis aims to forecast the true price and possible mispricing of a security at a given moment, based on the two information sources mentioned above. This inefficiency emerges from the possibility of consistently beating the market in the speed of decisions and transactions.

The strong level efficiency considers all the above-mentioned information while also reflecting private information. Private information includes all the decisions of the board of directors as well as up-to-date forecasts and reports concerning cash flows. This information has a somewhat peculiar character as it is private yet rapidly passed on to the prices. The prices are therefore formatted when the decisions are made not when they become public through announcements. In a strong-level efficiency market, no investor or investment strategy can gain higher than market returns over a long period. (Knüpfer and Puttonen, 2018, 171-172)

Eugene Fama's "Efficient Capital Markets" (1970) reveal that in the late 20th century economist widely accepted that markets were strong level efficient, and the prices reflected information immediately and correctly (*random walk*) (Malkiel, 2003, 59). The efficiency levels of actual markets are often disputed topics as they are complex and difficult to measure objectively. Eugene Fama's (1970) paper suggests that all of the efficiency levels are found in the security markets. The existence of anomalies disrupts the strong level efficiency of markets as they produce arbitrary possibilities for investors. Typically, these anomalies are short-period but for example, low-volatility anomaly is argued to be a long-period phenomenon. According to the paper of Malcolm Baker et al. (2014, 56), the low-volatility anomaly is a very basic form of market inefficiency. More theoretical discussion about low-volatility anomaly will occur later in the thesis (section 2.4).

The critique concerning the efficient market hypothesis states that the security price behavior is inconsistent with the EMH (Basu, 1977, 680), and the EMH framework is based on a flawed method (Shostak, 1997, 45). According to Suddhasatwa Basu (1977,), the proof for the refutation of the efficiency of markets is seen in his empirical study which states that the P/E ratio is not fully reflected in the market prices of securities. This creates arbitrary possibilities for investors. The same phenomenon is also acknowledged with different factors such as low volatility (Baker, N. and Haugen, 2012), small market value (Banz, 1981), high book-to-market value (Rosenberg, Reid and Lanstein, 1985), high profitability (Cohen, Gompers and Vuolteenaho, 2002), low investment rate (Fairfield, Whisenant and Yohn, 2003), high accruals (Sloan, 1996) and high momentum (Jegadeesh and Titman, 1993).

As we cover the efficiency of markets, it is crucial to highlight the impact of liquidity. Liquidity is an indicator of a security's trading volume and therefore expresses how many securities are traded in a given time. Greater liquidity illustrates a more accurate price in the market. This thesis accounts for liquidity by a ratio of transaction volume and shares outstanding. Literature indicates that low trading volume offers the possibility of a greater illiquidity premium (Lee and Swaminathan, 2000, 2027). Our thesis acknowledges this factor by weighting the stocks of constructed portfolios based on an application of Sarr's and Lybek's (2002,13) turnover ratio:

$$Tn = \frac{Vi}{S} \qquad V_i = \sum Q_i \tag{2}$$

Where monthly trading volume V_{it} is a sum of trading volume Q_{it} in month t. Tn indicates the turnover ratio which is the quotient of monthly trading volume Vi and shares outstanding S.

2.3 The Capital Asset Pricing Model

The Nobel Prize-winning Capital Asset Pricing Model is one of the main instruments to measure an investment's risk-return tradeoff relative to a certain market. CAPM accounts for security's contribution to systematic risk to compare portfolio returns to market returns. The model suggests that if diversification at the necessary level is employed, investors can pick any point on the security market line (SML) (Figure 1) which then dictates expected returns and the risk of the investment. (Sharpe, 1964)

As demonstrated in Figure 1, the security market line draws from risk-free return R_f linearly to the market's expected returns $E(R_m)$. All points in the SML are considered efficient as they correspond to market's risk-return ratio. Investors calculate their risk tolerance and decide if they want to enter "bullish" high-volatility or "bearish" low-volatility markets. The extreme ends are the risk-free investment and more than double the volatility of the market. The paper from William Sharpe (1964) suggests that investors must choose efficient investment plans. This efficiency means that there is no alternative with either larger expected returns or smaller volatility. The efficient choices are in the efficient frontier of the investment opportunity curve. The investment opportunity curve indicates all possible efficient portfolios concerning assets.

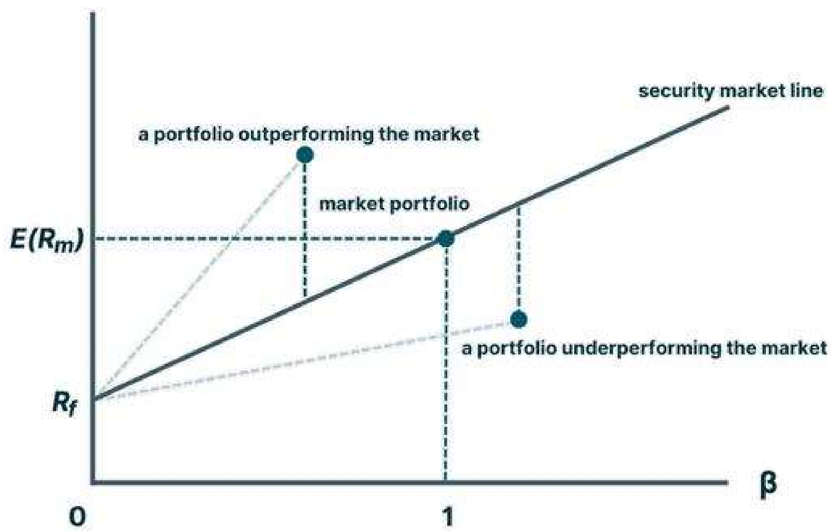

Figure 1: Security market line (SML) (Finance Strategist, 2023)

Figure 1 indicates the effects of under- and outperformance in relation to the market which are caused by abnormal performance of certain assets. In an outperforming situation, security has a larger return than the volatility equilibrium model expects, and in case of underperformance vice versa. The formula of CAPM can be derived from the security market line (Figure 1).

$$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big) \tag{3}$$

$$\beta_i = \frac{cov(R_i R_m)}{var(R_m)}$$

In the formula $E(R_i)$, $(E(R_m)$ and R_f indicates the expected return of investment, expected return of the market and risk-free return. β_i is the main instrument that describes the relationship between the volatilities of investment and the market.

Literature indicates that various other factors affect expected stock returns. Studies show that for example company's small market value (Banz, 1981), a high book-to-market value (Rosenberg, Reid and Lanstein, 1985), high profitability (Cohen, Gompers and Vuolteenaho, 2002), low investment rate (Fairfield, Whisenant and Yohn, 2003), high accruals (Sloan, 1996) and high momentum (Jegadeesh and Titman, 1993) all yield higher expected stock returns. These factors are included in multiple different models attempting to explain a company's expected returns as statistically significantly and as accurately as possible. Arguably, the most famous ones are the Fama-French three-factor (1993) and the Fama-French five-factor (2015) models which take previously mentioned factors into account with the CAPM beta, the latter explaining 71-94% of security's expected returns. (Fama, E. F. and French, 2015, 17)

As previously revealed, there are multiple ways to calculate the expected returns of securities. In our paper, the volatility of stocks is the most important measurement as we attempt to measure volatility's importance in investment portfolios on the Helsinki Stock Exchange. The empirical study implements CAPM's beta as a key figure in portfolio selection. This limitation means that a proportion of expected returns is deliberately not explained as we aim to concentrate on the volatility perspective.

2.4 Low-volatility anomaly

This section reviews the phenomenon of low-volatility anomaly which is very much linked to the three earlier topics: the risk-return tradeoff (section 2.1), the Efficient Market Hypothesis (section 2.2), and the Capital Asset Pricing Model (section 2.3). The low-volatility anomaly refers to the abnormally good performance of stocks with low volatility relative to the market (*beta*). It is argued to be a typical case of exception from the efficient market hypothesis, as it has proven to be a long-time and widely conscious phenomenon (Malkiel, 2003).

The famous Capital Asset Pricing Model was introduced in 1964 by William Sharpe as a model for measuring the effect of volatility on the expected returns of stocks. In under a decade, Robert Haugen and James Heins (1972) published a paper suggesting that the risk premium does not lead to more expected returns. They also added that over the long term, the stocks with more volatility (*variance*) will experience less expected returns. The same conclusions are reached in more recent studies by Nardin Baker and Rober Haugen (2012). Their comprehensive evidence indicates that the negative relationship between volatility and expected returns is found in all developed and emerging markets. Malcolm Baker et al. (2014) calculated the abnormal risk-adjusted returns of five risk-level quintiles in the United States and found empirical evidence that low-volatility stocks outperformed high-volatility stocks economically largely and statistically significantly. Frazzini and Pedersen's (2014) conclusions in global equity markets found a relationship between high-beta stocks and significantly lower Sharpe ratios and Jensen's alphas. These before-mentioned studies empirically recognized the low-volatility anomaly.

There are multiple explanations offered for the existence of low-volatility anomaly but here are a few: Baker et al. (2012) point to investors' behavioral explanations such as lottery preferences, representativeness, and overconfidence; Black et al. (Black, 1972) indicated the role of leverage; and Karceski emphasized the effects of intermediation. Karceski (2002, 585) suggests that the aggressive behavior of mutual fund investors drives fund managers to overweigh their portfolios with high-beta stocks. These reasons are all related to the overpricing of high-volatility stocks and the underpricing of low-volatility stocks. An important issue concerning volatility is how much of the variation in expected returns is caused by risk and how much by mispricing (Fama, E. and French, 2008). This thesis considers the mispricing caused by illiquidity premium by weighting the portfolios with the turnover ratio previously presented (section 2.2) (Lee and Swaminathan, 2000, 2027).

The Capital Asset Pricing Model's beta is utilized to illustrate the linear dependence of the return on a particular security and its market. When constructing a financial model from a certain timeframe's dataset, the beta is calculated and retained as such for the whole forecasting period. This imposes a possible shortcoming for these models and thus produces more insignificant results (Baker, Malcolm, Bradley, and Taliaferro, 2014, 45). Market relatively measured volatility can change greatly, especially in the long term. Changes in volatility are caused by changes in portfolio variance and market covariance. According to Bakaert and Wu (2000, 2), a simultaneous positive market shock and negative portfolio shock will lead to portfolio beta decreasing because of the decreasing covariance and increasing market variance. In a low-leverage portfolio, negative market shocks result in a lower beta than with high leverage which is partly explained by the lack of a strong volatility feedback mechanism (Bekaert and Wu, 2000, 28). Although some literature acknowledges that past volatility has predicted future volatility which means that the beta of the estimation period should indicate the beta forecast period relatively accurately (Baker, N. and Haugen, 2012, 5). In our empirical study, we estimate the daily beta pre-event to examine the buy-and-hold strategy during the timeframe of the thesis. We aim to study the relationship between beta and standard deviation in the Covid-19 market decline and draw conclusions about beta's effect on short and long-term returns.

Low-volatility anomaly is both a microeconomic and macroeconomic phenomenon. Malcolm Baker et al. (2014, 56-57) emphasize that the anomaly affects varyingly in each industry and country. Their findings also indicate that the macro-economic effects are more drastic than the micro-economic effects. In our empirical study, the capital asset pricing model is used for the calculation of risk-adjusted returns to examine the possible low-volatility anomaly. The objective of the thesis is to compare the abnormal returns and the overall performance of each of the portfolios. The macro-effects are limited in this study as we concentrate solely on the Finnish stock exchange and ignore international diversification.

2.5 Covid-19 in Finland

This thesis' event of interest is the COVID-19 pandemic which is a serious illness that has over 750 million confirmed cases and almost 7 million confirmed deaths (updated 1.6.2023) (The World Health Organization, 2023). According to the Centers for Disease Control and Prevention (CDC) (2023) Covid-19 (SARS-CoV-2) emerged in the Chinese city of Wuhan in December 2019. It spread rapidly and by the end of January 2020, it had already arrived in Europe. In February 2020 the whole world began to be seriously affected by the epidemic and on March 11th, 2020 World Health Organization (WHO) declared COVID-19 a pandemic. (Centers for Disease Control and Prevention, (CDC), 2023) As a global pandemic Covid-19 represents a macro-economic phenomenon.

The COVID-19 outbreak had global effects as no country was left unaffected by it (Donthu and Gustafsson, 2020, 284). While being a developed and service-oriented country, Finland is a relatively small and open economy. This leads to Finland's financial market being highly dependent on the global economy and its trading partners as the exports covered 39,9% of gross domestic product pre-Covid (2019) and 35.8% in the year it emerged (2020) (Official Statistics of Finland, 2023b). The economic effects of declines are strengthened by stock markets being interlinked and interdependent (Liu et al., 2020, 4). The examination of global COVID-19 status is justified as the pandemic status of Finland followed the trends of the global status (see Appendix 2) and because of scale, the Finnish economy is exposed to the disruption in the world economy.

The scale of stock market decline is unmatched in history as COVID-19 has just a fraction of the Spanish Flu's mortality rate but a much greater recession (Baker, S. R. et al., 2020, 749-751). According to Baker et al. (2020), the reasons for the economic decline are the globalization of trade, the flow of information in the digitalized modern world, and the extent of government restrictive actions. The extent of impact leads to the realization that global changes in investors' sentiment, decisions of policymakers, and pandemic status define our event's period of interest, although this paper concentrates on studying impacts limited to the Finnish economy. In their paper, Baker et al. (2020) state that in the US market, the early market decline is due to news about the pandemic course, and later jumps are influenced by policy responses and prospective finance and monetary policy. The later jumps in late March and April are boosting the stock markets due to changes in investor sentiment caused by the acts of policymakers.

Figure 2 indicates the changes in the annual gross domestic product, exports, and imports of Finland. COVID-19 affected a -10.9% decrease in exports, -10.8% in imports, and -0.8% in gross domestic product. The year 2020 illustrates an essential part of the reason global declines such as COVID-19 affect the Finnish economy deeply. The substantially lower exports and imports, seen in the graph, relates to lower demand and supply. The trade-exposed regions are also vulnerable to global supply chain disruptions which were a serious threat for Finnish companies (Ivanov, 2020; OECD, 2020a). The crisis and uncertainty in the real economy transfer instantly to the financial markets according to the efficient market hypothesis (Section 2.2).

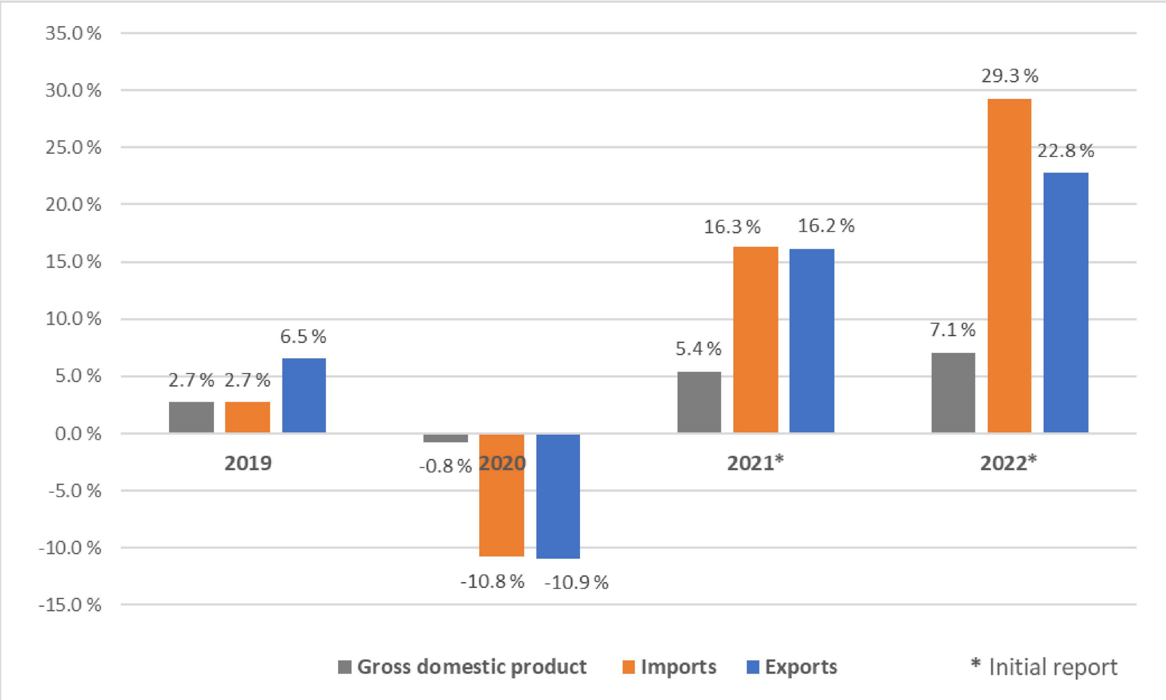

Figure 2: Annual changes in gross domestic product, imports, and exports of Finland at current prices 2019-2022 (Official Statistics of Finland, 2023c)*

Figure 2 indicates a clear negative effect of the pandemic but also the astonishing growth that followed it. The year after the start of the pandemic, 2021, shows an abnormally great increase in GDP (5.4%), imports (16.3%), and exports (16.2%) while 2022 improved even more as GDP grew 7.1%, imports 29.3% and export 22.8%. The notes of the OECD (2020b) predicted that the pandemic to disrupt the global economy tremendously. According to the note, every month of strict containment measures equals a 2 percent decrease in annual GDP. Their output approach evaluates the effect of widespread shutdowns in the most affected sectors (30-40% of economies), stating they are possibly decreasing the GDP by 20-25% in advanced economies. These economy-wide projections seem extreme and inaccurate as for the Finnish economy the decrease in 2020 was only -0.8%.

Financial markets estimate future prices which in the case of stocks means that news concerning future cash flows of companies changes the prices of stocks rapidly. Figure 3 indicates the strong reaction of OMX Helsinki to early Covid announcements in the first quarter of 2020. After the initial negative reaction, the prices began to increase despite the remarkable growth of Covid-19 cases. The short-period event studies of Ji et al (2022), (Liu et al., 2020), and Singh (2020) found a negative correlation between Covid-19 cases and abnormal returns of national indexes when the longer period estimation in the paper of Scherf, Matschke, and Rieger (2022) claims national covid cases did not affect the stock market significantly. Their results indicate that the stock market reactions show a delayed response to news concerning COVID-19. The stock market seemed to overreact to information and correct it after three days which revealed abnormal positive results. This discovery demonstrates the inefficiency of financial markets. These earlier results will be tested in our dataset in the empirical study.

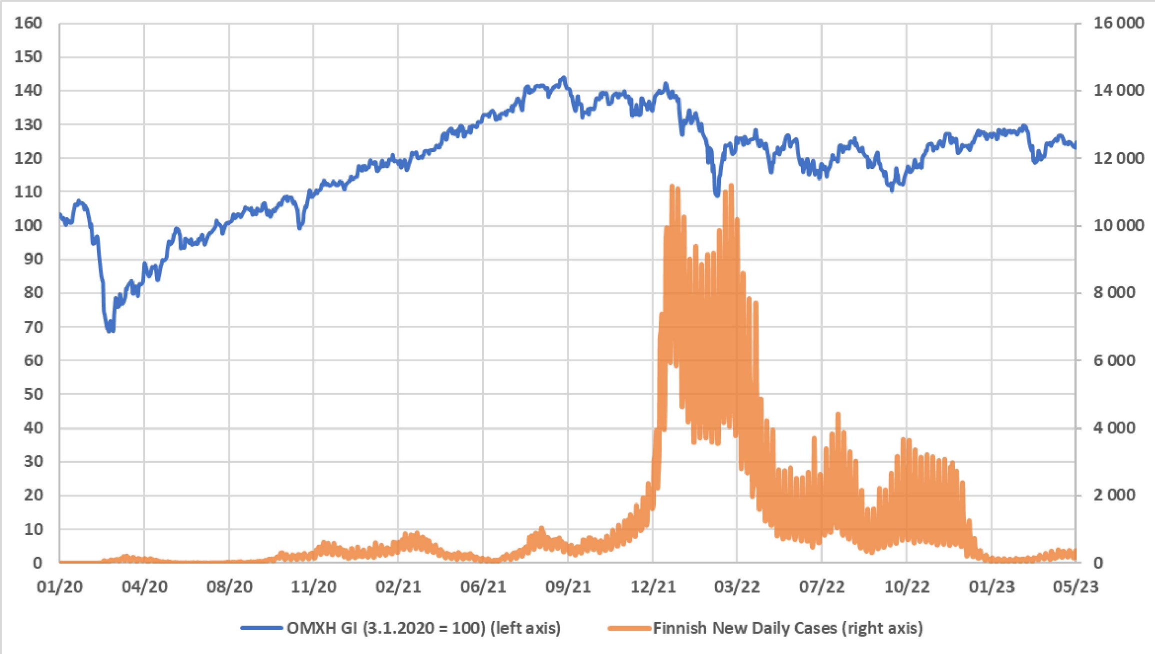

Figure 3: OMX Helsinki Growth Index and new COVID-19 cases daily in Finland (World Health Organization, 2023)

2.6 Summary of theoretical background

The theoretical background enables an academically correct examination of the research questions in the empirical study. Literature highlights and explains various necessary theories and empirical evidence that are utilized in our quantitative research on the Helsinki stock exchange. The essence of this thesis is the thorough examination of the risk-return tradeoff.

The Efficient Market Hypothesis is highly tied to the research of risk-return tradeoff as we determine the efficiency of OMX Helsinki during the pandemic. The three efficiency levels of EMH are divided by the type of information the prices reflect. Literature suggests the market is inefficient if investors can gain significantly larger abnormal returns by capitalizing on historical volatility with technical analysis (Baker, Malcolm, Bradley, and Taliaferro, 2014, 56). Thus, one of the research objectives is to examine the low-volatility anomaly and the inefficiency it causes.

We aim to investigate the effect of OMX Helsinki stock's volatility on their returns. To examine the relationship between volatility and stock returns we use the beta of the Capital Asset Pricing Model which illustrates the correlation between a certain security's returns and the returns of the market. Our empirical study uses the stock betas to divide OMX Helsinki into volatility portfolios. The portfolios are diversified from the EMH point of view as they contain securities from multiple sectors (Appendix 1). To further accuracy and reliability this thesis takes liquidity into account by weighting the stocks in portfolios by their turnover ratio. These portfolios are observed during the COVID-19 decline for their responses to uncertainty and negative news. The market efficiency and role of volatility are tested with the event study approach. Due to the COVID-19 decline's nature, we also measure the long-term returns of the volatility portfolios during 2020-2022.

In the empirical study our objective is to utilize the theoretical background to answer the research questions (1) How did the performance of low-volatility stock portfolio differ from high-volatility portfolios in OMX Helsinki during and after Covid-19 (2020-2022), (2) How does beta affect short-term returns of a portfolio during a market decline, and (3) Does low-volatility anomaly occur in OMX Helsinki. The similarities and contradictions between the empirical findings and earlier studies are accounted for and explained.

3 Methodology & data

The methodology in this thesis contains a relatively regular event study approach. We aim to quantify the possible differences in abnormal returns across different volatility-level stocks. This paper follows closely the methodologies of Craig MacKinlay's paper "Event Studies in Economics and Finance" (1997) as well as S.P. Kothari's and Jerold Warner's paper "Econometrics of Event Studies" (2007). Utilization of the previously discussed Market Model is conducted with consistent ordinary least squares (OLS) estimation.

3.1 Portfolio comparison

The objective of this thesis is to measure the effect of the covid-19 on different volatility-based portfolios and the overall performance of these portfolios during the four-year timeframe. The overall performance concentrates on long-term returns during and after the event study. The measuring is done with annualized realized returns, Sharpe ratio which measures risk-adjusted return in relation to the equity market, and Jensen's Alpha. Sharpe ratio is suitable for comparing portfolios with incomplete diversification or relatively small capitalization which are both possible factors in our volatility portfolios. The ratio is calculated with the following formula:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

where the remainder of portfolio returns R_p and risk-free returns R_f is divided by the standard deviation of portfolio σ_p. Jensen's Alpha is an indicator of the difference in the portfolio's realized return and its CAPM predicted returns. Its calculation is conducted with the next formula:

$$Jensen's\ Alpha = R_i - (R_f + \beta_i(R_m - R_f)) \tag{5}$$

which is an application of the CAPM (Equation 3) formula. R_i, R_f and R_m are the portfolio return, risk-free return, and market return. The β_i describes the relationship between the volatility of the portfolio and the market.

3.2 Event study

The methodology employed in this thesis for studying the effect of volatility in portfolio selection builds around the event study approach. Event study enables the utilization of a big dataset from where we may measure the economic impact of certain predefined events (MacKinlay, 1997, 13). This way changes in daily data over a long period, such as ours, can be tested reliably. The event study methodology fits both micro- and macroeconomic observation. In this paper, it will be applied to measure abnormal returns in case of a market decline caused by a global pandemic. Stock market reactions to Covid-19 news are longer than corporate news which emphasizes the importance of valid methods of measurement. The event study approach in this thesis considers both cross-sectional and time-series aggregation of abnormal returns (Kothari and Warner, 2007, 9-10). Event study methodology is connected to the Efficient Market Hypothesis as it measures the market's reaction time and the correctness of the reaction to the selected event.

The event study approach insists on correctly and accurately chosen event windows. In this thesis, the macroeconomic nature of the event requires both a global and a national examination of information to define the event windows. In a long horizon event study, a correct risk adjustment and modeling of expected returns are in essence. The measuring of post-event abnormal performance should ignore historical risk estimate biases. (Kothari and Warner, 2007, 22). This thesis manages the modeling of expected returns with the Market Model approach.

To model the normal state of the economy we calculated a 417-day pre-event (*estimation*) window which is quite extensive for modeling the expected returns. The length of the estimation window ensures realistic estimates for long-term returns. As the paper of Craig MacKinlay (1997) suggests the estimation period and event window should not overleap as it exposes the estimation to the actual event distorting the results. Therefore, our estimation period ends twelve trading days before the event. As the length of the estimation window becomes large the sampling error of variance approaches zero, making the estimation accurate. (MacKinlay, 1997, 21)

The event window for this study is formed to start at the date of the first global announcement of possible worldwide threats. That date is January 20, 2020, when in an interview Zhong Nanshan, a high-level expert of the National Health and Fitness Commission of the People's Republic of China, suggested that the disease could be transmitted from human to human. This event illustrates the start of global attention to the virus in China. (Liu et al., 2020) To measure the immediate effect of the Covid-19 pandemic, we use an event window of 60 days. This event window ignores the anticipation which is often included as a period before the event announcement. This is justified as the phenomenon of a pandemic symbolizes an unpredictable event. A relatively long event window ensures that the event, which is difficult to identify, is included with certainty (MacKinlay, 1997, 35).

COVID-19 studies by Singh et al. (2020) and Liu et al. (2020) employ January 20th, 2020, as the event date for the measuring of stock market reaction to COVID-19. The validation of this event date is the following related events: the first official suggestion of human-to-human transmission on January 20th, 2020, lockdowns of Wuhan on January 23rd, 2020; Italy on January 30th, 2020; United Kingdom on February 10th, 2020; and WHO's announcement of Covid-19 being a Public Health Emergency of International Concern on January 30th, 2020. On February 21st, 2020, a dramatic decrease in European indices was caused by a significantly worsened infection status in Europe, especially in Northern Italy (Council of the European Union, 2023). As seen from the dates they are relatively close to each other and as such overlapping events. This means that the individual studying the announcements would be biased by clustering. For that reason, we concentrate on the overall effect on the portfolios.

As Figure 4 indicates another important date is the end of the event window. The end of a pandemic is vague and thus difficult to define but starting from March 2020 the global financial market indices began to rise and by the end of the year 2020 they had reached the pre-event level. The short-term event window is therefore adjusted to April 14, 2020, as it captures the first adjustments to the COVID-19 decline. The long-term returns of the volatility portfolios are studied in the post-event window. The performance of financial markets in the worst recession since world wars is made possible with the extensive help of central banks. This help was implemented by accommodative monetary policy which in return added inflation pressure. Although this policy added inflation, it did reduce unemployment and keep the economy relatively stable. (Long et al., 2022, 2666)

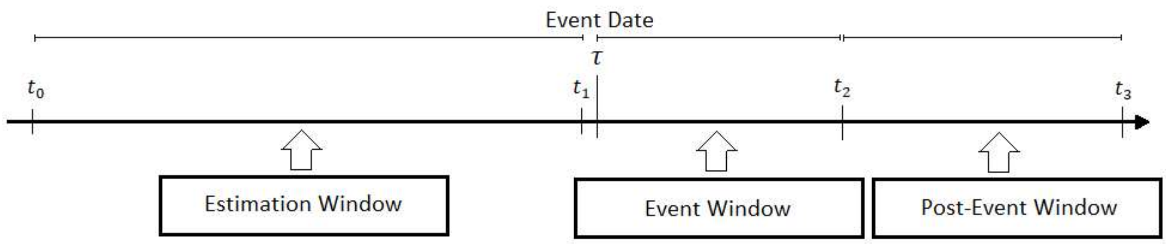

Figure 4: Event study timeline

$$R_t = \ln\frac{P_t}{P_{t-1}} \tag{6}$$

The actual (*realized*) returns of a particular security are measured with the formula above. R_t stands for return in period t and $\ln\frac{P_t}{P_{t-1}}$ indicates the logarithmic return between consecutive period t's. The main objective of the event study approach is to measure how realized returns differ from normal (*expected*) returns. The remainder of the expected and actual returns result in abnormal returns that are calculated with the following formula:

$$AR_{it} = R_{it} - E(R_{it}|X_t) \tag{7}$$

Where AR_{it}, R_{it} and $E(R_{it}|X_t)$ indicates the abnormal, actual, and normal returns in period t. The calculation of security's normal performance is completed with time prior to the given event. This paper utilizes the market model when modeling the normal return X_t as it assumes a linear relation between the market return and the return of security (MacKinlay, 1997, 15). This guarantees an estimation of normal performance which is undisturbed by the event of interest.

This thesis utilizes the assumption of jointly multivariate identically distributed returns when measuring the normal performance of securities. This assumption allows the utilization of the market model which measures the returns of security i in relation to market return. The long estimation window and the relatively large number of samples assure precise estimation with the market-adjusted model.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{8}$$

$$E(\varepsilon_{it} = 0) \qquad\qquad var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

Where R_{it} and R_{mt} are the returns of a given security and market in period t. α_i, β_i and $\sigma^2_{\varepsilon_i}$ indicate the necessary parameters for the market model whereas ε_{it} is zero mean disturbance term. The market model allows a more precise examination of event effects as it uses the beta indicator to remove the part of the return that is related to the market variation. (MacKinlay, 1997, 17-18)

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{9}$$

As we begin to examine the differences in the performance of securities, the abnormal returns are calculated with the formula above which measures the returns that have differed from the expected ones.

$$AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau} \tag{10}$$

The average abnormal return is calculated as a sum of abnormal returns at time t. The formula of AAR is calculated with the number of observations N and the sum of those observation's abnormal returns $AR_{i\tau}$ at time t.

$$CAR_i(\tau_1\tau_2) = \frac{1}{\tau_2-\tau_1+1}\sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \quad (11)$$

The formula above indicates the calculation of the cumulative abnormal returns. CARs are calculated as a sum of abnormal returns from the start of the analysis period to the end of it (τ_1-τ_2). In our study, the event window is divided into smaller analysis periods for a closer investigation of event effects.

$$CAAR_i(\tau_1\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1\tau_2) \quad (12)$$

The statistical significance of the empirical results is determined with a parametric t-test. The null hypothesis in all event study results is that the event has no impact on the returns of the portfolios which means that mean abnormal performance is zero. The statistical significance of average abnormal returns is calculated with t-statistic as follows:

$$t - Test_{AAR} = \frac{AAR_t}{\sigma^2(AAR_t)} \sim N(0,1) \quad (13)$$

where test statistic θ_1 is calculated with average abnormal returns AAR_t at period t and the variance of those returns $\sigma^2(AAR_t)$ which is calculated with the following equation:

$$\sigma(AAR_t) = \sqrt{\sum_{-417}^{59}(\overline{AR_t} - \overline{\overline{AR}})^2/(417+59)} \quad (14)$$

where $\overline{\overline{AR}}$ is calculated of the sum of average abnormal returns $\overline{AR}$ during the estimation period and the event window. The variance estimations in our study consider the observations of both the estimation period (417) and the event window (59) to account for possible unusual prior performance, extreme characteristics of stocks, and defining of the event window (Kothari and Warner, 2007, 22)

$$(\overline{\overline{AR}}) = \frac{1}{417+59}\sum_{-416}^{59} \overline{AR_t} \quad (15)$$

The average abnormal returns $\overline{AR}$ are the average of abnormal returns $\overline{AR}$ of observations N in time t.

$$\overline{AR_t} = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \quad (16)$$

The statistical significance of cumulative average abnormal returns is measured with t-statistics as follows:

$$t - Test_{CAAR} = \sqrt{\frac{CAAR(t_1 - t_2 + 1)}{\sigma^2(AAR_t)}} \sim N(0,1) \tag{17}$$

The calculation of statistical significance insists on preciseness as the variability of the event window is supposedly higher than the variability of the estimation window (Kothari and Warner, 2007, 12). The variances of AARs, CARs, and CAARs are calculated considering the possible increase of variance due to the macroeconomic event.

The characteristics of earlier empirical studies of Covid-19 market reactions are listed in Table 1. The studies of Liu et al. (2020), Singh et al. (2020), Scherf et al. (2022), and Ji et al. (2022) implemented event studies with different datasets and variables, as well as deviating methodologies. These studies used comprehensive global datasets of 13-42 indices. Liu et al. (2020), Singh et al. (2020), and Ji et al. (2022) found a statistically significant ($p<0.10$) negative relationship between abnormal returns and Covid-19 cases. The findings of Scherf et al. (2022) show the opposite result as the global cases have a positive statistically insignificant ($p=0.26$) relationship and national cases have a negative statistically insignificant ($p=0.12$) relationship.

The contradiction of these findings is a sum of many factors. One key element is the fact that the estimation of normal returns varied between the studies which affected the abnormal returns and therefore the results. The data on COVID-19 cases and the selection of market indicators have a significant effect on the results. The R-squared of studies varies greatly which is caused by the estimation method, selection of independent variables, and the type of regression method. The largest R-squared values were 0.824 for Liu et al. and 0.801 for Ji et al. Both studies used the Ordinary Least Squares (OLS) regression method to examine the initial COVID reactions of global stock markets. The largest contributors to R-squared were the independent variables return of index and return of the market.

The objective of this thesis is to examine the effect of beta on short and long-term performance during the Covid-19 pandemic. The time dimensions and the estimation periods of Table 1's studies were relatively short. Therefore, we use an application of those research methods to include the long-term examination in this thesis. The empirical part is divided into two stages: the event window, which is short-term; and the post-event window, which is long-term. For a more reliable post-event examination the estimation period is significantly longer, and the t-tests are adjusted to consider the increased variance of the event window and the post-event window.

Table 1: Characteristics of earlier studies' regressions

Author	Estimation method	Estimation period	Time dimension	Indices	Independent variables	R-squared	Relationship between AR and Covid-cases
Liu et al.	OLS	180-234	35-43	21	Log cases, Return of index, Return of market, Asia dummy	0.824	Negative (p<0.05)
Singh et al.	Random effects	150	58	19	Log cases, Return of index, Return of market, Abnormal trading volume, Developing economy dummy	0.441	Negative (p<0.10)
Ji et al.	OLS	196	62	13	Log cases, Return of index, Return of market, Asia dummy	0.801	Negative (p<0.05)
Scherf et al.	-	119	83	42	Cases in country, global cases, strict measures dummies, changes in government interventions, lagged interventions	0.06	Not significant (p>0.10)

3.3 Data

Correct and accurate data is a cornerstone to achieving a significant quantitative study. The suitable historical stock data for this thesis was collected from Yahoo!Finance (2023a) website mainly for its easy accessibility with a Python program. This empirical study is limited to include 140 stocks of Nasdaq's Helsinki stock exchange (Nasdaq OMX Nordic, 2023a). Of these stocks, 24 were deleted from the dataset because of their short timeframe or because the company had multiple series of stocks listed. The deleted duplicate was selected by the lower liquidity ratio. In addition, one stock was deleted because its price data was corrupted. Therefore, the dataset includes 115 stocks of OMX Helsinki (Appendix 1). The data from each stock contains adjusted closing prices, dividend payments, stock splits, and transaction volumes. The data was acquired with both daily and monthly frequencies to be able to calculate beta with both frequencies. The closing prices of each stock have been adjusted so that they reflect the full returns on investments. Adjustment is done by accounting stock splits and dividend payments to stock price. As we examine financial subjects through the investor's eyes, the changes in price data inform us of the changes in actual returns which we are most interested in. In addition, the shares outstanding data of each stock were acquired from Yahoo!Finance to calculate the stock liquidity (*turnover ratio*).

The acquired data was carefully examined, and every "null" or other error in returns was amended into zero so that it wouldn't affect the analysis. For sufficient analysis, the logarithmic returns of adjusted closing prices from both the stocks and the index (OMXH GI) were calculated. Three stocks required dividend currency and split adjustments which were performed manually.

As a market return indicator, we decided to use OMXH GI (growth index) which is an unrestrictedly value-weighted index including all shares listed on Helsinki Stock Exchange (Nasdaq OMX Nordic, 2023b; Yahoo!Finance, 2023b). The OMXH GI represents a value-weight (*VW*) market portfolio, making it a valid market indicator for our dataset (Fama and French, 2015, 3). All together the daily frequency panel data has 921 observations in each category from every valid stock and the market index. The volatility portfolios are constructed by the calculated stock betas of pre-event data. As a proxy for risk-free returns examined Bank of Finland's (2023) Finnish benchmark long-term government bonds as well as short-term Euribor (see Appendix 3). They all have negative averages during the timespan which led to the use of a fixed 1 percent risk-free rate for comparability to normal risk-free rates.

The data of this study includes all suitable stocks of the Helsinki Stock Exchange which means it contains rather "abnormal stocks" meaning for example penny stocks or relatively illiquid stocks which can affect the results. We chose to include them in the research as it suits the nature of this market-wide study. In principle, for investors, the "abnormal stocks" are as noteworthy as "normal stocks". The objective of this thesis concentrates on the whole Helsinki Stock Exchange and thus both high and low volatility are desired to reach extensive empirical results. The large number of observations offers our research vast and reliable data. Thus, the significance of certain abnormal companies or outliers will have a minimum effect on the reliability of the results.

4 Empirical Study

The empirical study consists of three different sections which measure the performance of the volatility portfolios. The first part of our empirical study concentrates on the overall COVID-19 reactions of the Finnish stock market. The second section examines the short-term performance of the portfolios. This section utilizes the event study to discover the reactions of each portfolio to different stages of the decline. The last section aims to measure more long-term performance within the two-year timeframe. It includes the examination of low-volatility anomaly in OMX Helsinki.

4.1 Market reaction to the Covid-19

The empirical study started with the measurement of the overall effects of Covid-19 on the dataset. The emphasis of the study is the market relative performance of the volatility portfolios. The average performance of the constructed liquidity-weighted volatility portfolios and the market indicator OMXH GI are shown in Figure 5. The average of portfolios reacted similarly to OMXH GI to the start of the decline from January 2, 2020, to March 23, 2020, which is the lowest point for both indicators. After the initial collapse of the indicators, OMXH GI outperformed our dataset until December 2020, when the average of portfolios exceeded it staying above for the rest of the timespan. The maximum value of our dataset was on July 10, 2021, when it reached a 43.41% increase.

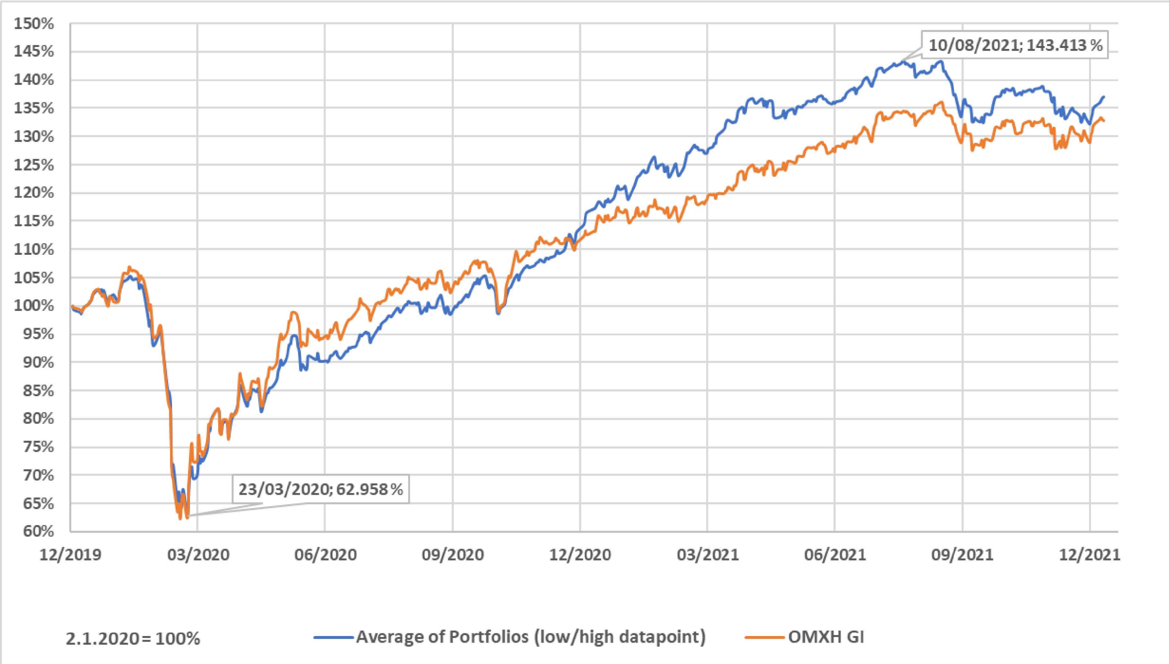

Figure 5: The performance of the volatility portfolio average and the market (OMXH GI) from 2.1.2020 to 30.12.2021

The risk-adjusted overall reaction is illustrated with abnormal average returns (*AAR*) and cumulative abnormal returns (*CAAR*) in Table 2. The event window (EW) starts relatively early as described in methodology (section 3.2) which leads to the first event days showing weak or no effect. The event day (τ) indicates a statistically insignificant 0.362% increase in AAR. The first statistically significant AAR happened on day five of the event when it decreased by -1.063% with a p-value of 0,0562. The largest change in AAR happened on day 38 when it decreased by -4.878% (p-value 0,0000). Table 2 indicates the most critical points of the event window which are days 25, 35, 38, 40, 44, 45. The nature of the event window is portrayed with the CAAR of the event window. The cumulation of AARs shows moderate growth from the start of the event to day 34. Day 35's 5.833% is the first statistically significant value (p-value 0.0806) which is followed by the largest Covid-19 effects of days 37-45 with the lowest CAAR value being -15.538% on day 43.

*Table 2: Average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) of the volatility portfolios during the event window (EW) (0-59) (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

EW	AAR		t-stat	p-value	CAAR		t-stat	p-value
0	0.362 %		0.6523	0.5145	0.362 %		0.6523	0.5145
1	0.061 %		0.1104	0.9122	0.423 %		0.5393	0.5899
2	0.539 %		0.9702	0.3325	0.962 %		1.0005	0.3176
3	-0.249 %		-0.4478	0.6545	0.713 %		0.6425	0.5208
4	0.091 %		0.1637	0.8700	0.804 %		0.6479	0.5173
5	-1.063 %	*	-1.9139	0.0562	-0.258 %		-0.1899	0.8495
6	0.047 %		0.0853	0.9320	-0.211 %		-0.1435	0.8859
7	0.453 %		0.8158	0.4150	0.242 %		0.1542	0.8776
8	0.151 %		0.2723	0.7855	0.393 %		0.2361	0.8134
9	0.448 %		0.8068	0.4202	0.841 %		0.4791	0.6321
10	-1.176 %	**	-2.1181	0.0347	-0.335 %		-0.1818	0.8558
11	0.825 %		1.4859	0.1380	0.490 %		0.2549	0.7989
12	-0.057 %		-0.1027	0.9183	0.433 %		0.2164	0.8288
13	0.219 %		0.3951	0.6930	0.653 %		0.3141	0.7536
14	-0.333 %		-0.6002	0.5487	0.319 %		0.1485	0.8820
15	0.458 %		0.8246	0.4100	0.777 %		0.3499	0.7265
16	-0.288 %		-0.5188	0.6042	0.489 %		0.2137	0.8309
17	0.357 %		0.6434	0.5203	0.846 %		0.3593	0.7195
18	-0.326 %		-0.5875	0.5571	0.520 %		0.2149	0.8299
19	-0.153 %		-0.2761	0.7826	0.367 %		0.1477	0.8826
20	0.357 %		0.6437	0.5201	0.724 %		0.2846	0.7760
21	-0.843 %		-1.5186	0.1295	-0.119 %		-0.0457	0.9636
22	0.156 %		0.2810	0.7788	0.037 %		0.0139	0.9889
23	0.045 %		0.0803	0.9361	0.082 %		0.0300	0.9761
24	-0.671 %		-1.2089	0.2273	-0.590 %		-0.2124	0.8319
25	-2.388 %	****	-4.3018	0.0000	-2.978 %		-1.0519	0.2934
26	-0.719 %		-1.2951	0.1959	-3.697 %		-1.2815	0.2006
27	0.465 %		0.8375	0.4027	-3.232 %		-1.1001	0.2718
28	-0.737 %		-1.3282	0.1848	-3.969 %		-1.3276	0.1849
29	-0.362 %		-0.6514	0.5151	-4.331 %		-1.4242	0.1550
30	1.152 %	**	2.0742	0.0386	-3.179 %		-1.0285	0.3042
31	0.969 %	*	1.7459	0.0815	-2.210 %		-0.7037	0.4820
32	-0.811 %		-1.4602	0.1449	-3.021 %		-0.9471	0.3441
33	-0.558 %		-1.0046	0.3156	-3.578 %		-1.1054	0.2696
34	-0.291 %		-0.5244	0.6002	-3.870 %		-1.1781	0.2393
35	-1.964 %	****	-3.5372	0.0004	-5.833 %	*	-1.7512	0.0806
36	0.488 %		0.8786	0.3801	-5.346 %		-1.5829	0.1141
37	-1.514 %	***	-2.7264	0.0066	-6.859 %	**	-2.0042	0.0456
38	-4.878 %	****	-8.7854	0.0000	-11.737 %	****	-3.3852	0.0008
39	1.332 %	**	2.3989	0.0168	-10.405 %	***	-2.9633	0.0032
40	-3.119 %	****	-5.6184	0.0000	-13.524 %	****	-3.8044	0.0002

41	0.779 %		1.4040	0.1610	-12.745 %	****	-3.5421	0.0004
42	-1.522 %	***	-2.7409	0.0064	-14.266 %	****	-3.9187	0.0001
43	-1.272 %	**	-2.2908	0.0224	-15.538 %	****	-4.2193	0.0000
44	2.227 %	****	4.0119	0.0001	-13.311 %	****	-3.5741	0.0004
45	-2.035 %	****	-3.6651	0.0003	-15.346 %	****	-4.0754	0.0001
46	1.374 %	**	2.4742	0.0137	-13.972 %	****	-3.6709	0.0003
47	0.508 %		0.9147	0.3608	-13.464 %	****	-3.5004	0.0005
48	-1.127 %	**	-2.0293	0.0430	-14.591 %	****	-3.7544	0.0002
49	-0.220 %		-0.3971	0.6915	-14.811 %	****	-3.7728	0.0002
50	0.424 %		0.7632	0.4457	-14.388 %	****	-3.6288	0.0003
51	0.860 %		1.5495	0.1219	-13.527 %	****	-3.3789	0.0008
52	0.380 %		0.6850	0.4937	-13.147 %	***	-3.2528	0.0012
53	0.817 %		1.4709	0.1420	-12.330 %	***	-3.0223	0.0026
54	0.147 %		0.2646	0.7915	-12.183 %	***	-2.9590	0.0032
55	0.518 %		0.9330	0.3513	-11.665 %	***	-2.8078	0.0052
56	1.159 %	**	2.0883	0.0373	-10.506 %	**	-2.5065	0.0125
57	0.614 %		1.1051	0.2697	-9.893 %	**	-2.3397	0.0197
58	1.401 %	**	2.5240	0.0119	-8.491 %	**	-1.9912	0.0470
59	0.587 %		1.0574	0.2909	-7.904 %	*	-1.8380	0.0667

The AARs and CAARs of the event window are visually described in Figure 6. The graph addresses six announcements that had an impact on the returns. The CAAR has a downward sloping trend which strengthens significantly when the infection status of Europe worsens. The volatility of AAR indicates the uncertainty the market is experiencing. It also indicates the correction of prices after large decreases, as the indicator changes between positive and negative AARs.

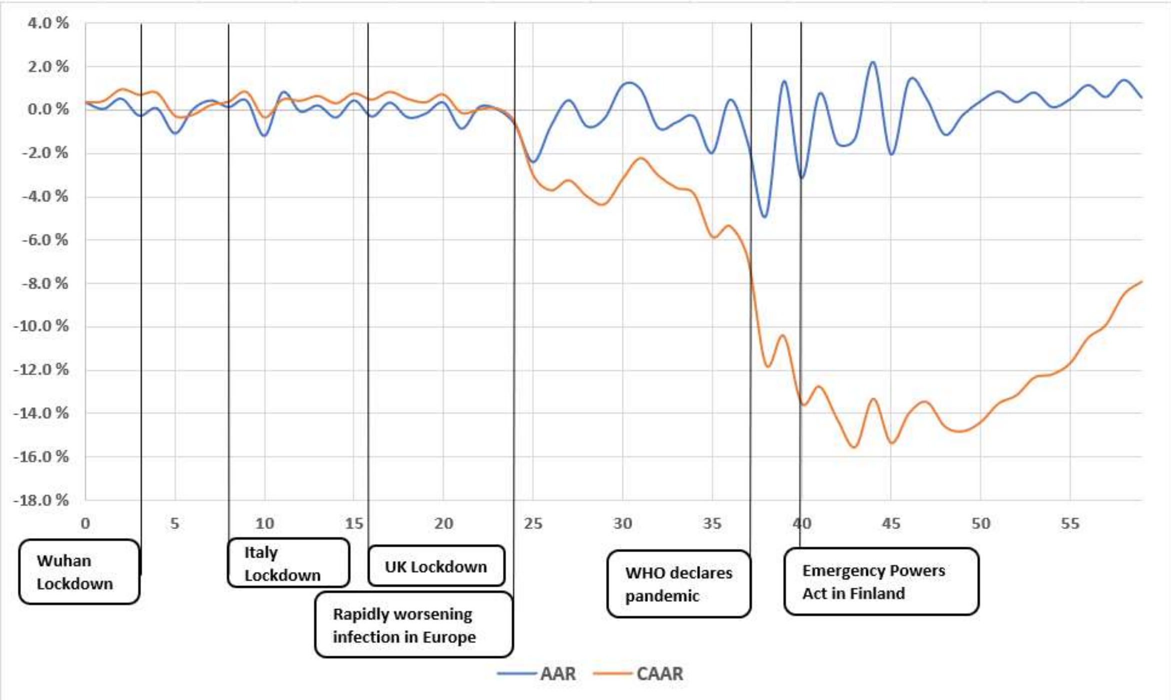

Figure 6: Average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) of the dataset during the event window

4.2 The Covid-19 reactions of volatility portfolios

This section measures the short-term effect of COVID-19 on the ten constructed volatility portfolios. Table 3 shows the summary of the constructed volatility portfolios before the buy-and-hold decision. These ten volatility portfolios (*deciles*) are constructed based on the beta value of the stock (Equation (3)). The stocks are weighted to the portfolios by their median monthly turnover ratio seen in Equation (2) with a max weight of 20% (see Appendix 1). To clarify the effect of beta during the “normal” performance in the pre-event window, the quintiles and halves are shown in Table 3. The quintiles and halves increase the diversification, therefore, making results more valid.

During the estimation window of 417 trading days, there is a trend of higher annualized returns for low-volatility portfolios. When measuring risk-adjusted performance with Sharpe ratio and Jensen’s alpha the same phenomenon is discovered as the low-volatility half has a moderately positive Sharpe ratio of 0.366 and Jensen’s alpha of 0.028 while the high-volatility half has both negative -0.381 and -0.064.

Table 3: Summary of the volatility portfolios

Pre-Event Window						
Portfolio	**Beta**	**Geometric Annualised Returns**	**Annualised Std. Dev.**	**Median monthly Turnover-ratio**	**Sharpe Ratio**	**Jensen's Alpha**
Low	0.134	-4.71 %	12.658 %	34 %	-0.451	-0.059
2	0.239	2.71 %	13.121 %	5 %	0.130	0.013
3	0.326	-0.29 %	12.842 %	21 %	-0.101	-0.018
4	0.387	14.92 %	19.379 %	45 %	0.718	0.133
5	0.485	9.92 %	10.982 %	85 %	0.812	0.081
6	0.534	4.89 %	12.259 %	149 %	0.317	0.030
7	0.594	-8.73 %	16.058 %	25 %	-0.606	-0.107
8	0.741	-0.36 %	14.581 %	337 %	-0.093	-0.026
9	0.943	6.00 %	15.316 %	566 %	0.326	0.034
High	1.491	-19.43 %	23.411 %	1000 %	-0.872	-0.229
Low	0.187	-1.07 %	10.050 %	20 %	-0.206	-0.024
2	0.356	7.04 %	12.689 %	33 %	0.476	0.055
3	0.509	7.38 %	9.993 %	117 %	0.638	0.055
4	0.667	-4.64 %	13.356 %	181 %	-0.422	-0.067
High	1.217	-7.58 %	17.917 %	783 %	-0.479	-0.106
Low	0.314	4.27 %	8.949 %	38 %	0.366	0.028
High	0.861	-4.02 %	13.146 %	415 %	-0.381	-0.064
OMXH GI	**1.000**	**2.67 %**	**10.029 %**		**0.266**	**0.000**

Average returns during the pre-event, event, and post-event windows are illustrated in Table 4, which divides the three windows into their panels for a detailed comparison. The pre-event window (Panel A) is from May 2, 2018, to December 30, 2019, describing the normal performance of the portfolios. The mean returns of portfolios 1,3,7,8 and 10 are negative with portfolios 10 (-0.0857%) and 7 (-0.0363%) having the lowest ones. The most positive returns are those of portfolios 4 (0.0552%) and 5 (0.0375%). The standard deviations describe the risk of the portfolios. During the pre-event window portfolios 4 (1.2207%), 7 (1.0116%), and 10 (1.4747%) had the highest risk when measured with the standard deviation. The standard deviations of the portfolios are in support of the ranking by stock beta as the standard deviation increases in higher beta portfolios.

The immediate reaction of portfolios to Covid-19 announcements are shown in Panel B. All the portfolio returns and the market return are strongly negative with high standard deviation during the 60-day event window. The most impacted portfolios were 6 and 7 which average daily decreases were -0.4262% and -0.4203% while the least impacted were portfolios 4 and 5 with decreases of -0.1359% and -0.2525%. Standard deviations multiplied in all portfolios with the maximum being portfolio 10's 3.5263% and minimum portfolio 2's 2.3388%.

Panel C addresses the performance of the portfolios after the initial market decline from April 15, 2020, to December 30, 2021. The timespan of 433 trading days illustrates the long-term performance during the Covid-19 pandemic. However, this exposes the examination to other events which are not included in this empirical study. Therefore, the long-term returns of the portfolios need to be examined cautiously. The mean returns of Panel C indicate the boost of financial markets despite the roaming pandemic. The returns are all positive and at best ten times higher than the normal returns of Panel A. The highest mean return is portfolio 4’s 0.1758% and the lowest portfolio 5’s 0.0909%. The two extremes of mean returns are the consecutive portfolios which means the betas of portfolios 4 and 5 are close to each other. The standard deviations vary between portfolio 5’s 0.9564% and portfolio 10’s 1.4852%.

In all panels of Table 4, a trend of moderately greater return and smaller risk (*standard deviation*) on portfolios ranked under 6 in beta rankings is detected. The standard deviations multiply due to the event and stay on average 24.4% higher than during the estimation window.

Table 4: Mean returns of the volatility portfolios and the market indicator (OMXH GI) during pre-event (panel A), event (panel B), and post-event (panel C) windows.

Panel A: Pre-event window (2.5.2018-30.12.2019)			
Portfolio	**Number of trading days**	**Mean daily return**	**Standard Deviation**
Low	417	-0.0191 %	0.7974 %
2	417	0.0106 %	0.8266 %
3	417	-0.0012 %	0.8090 %
4	417	0.0552 %	1.2207 %
5	417	0.0375 %	0.6918 %
6	417	0.0190 %	0.7722 %
7	417	-0.0363 %	1.0116 %
8	417	-0.0014 %	0.9185 %
9	417	0.0231 %	0.9648 %
High	417	-0.0857 %	1.4747 %
OMXH GI	417	0.0104 %	0.8477 %

Panel B: Event window (20.1.2020-14.4.2020)			
Portfolio	**Number of trading days**	**Mean daily return**	**Standard Deviation**
Low	60	-0.3422 %	2.5866 %
2	60	-0.2953 %	2.3388 %
3	60	-0.3375 %	2.8192 %
4	60	-0.1359 %	3.0668 %
5	60	-0.2525 %	2.7740 %
6	60	-0.4262 %	2.4525 %
7	60	-0.4203 %	2.6586 %
8	60	-0.4058 %	2.7003 %
9	60	-0.3953 %	2.5801 %
High	60	-0.4121 %	3.5263 %
OMXH GI	60	-0.3455 %	2.7014 %

Panel C: Post-event window (15.4.2020-30.12.2021)			
Portfolio	**Number of trading days**	**Mean daily return**	**Standard Deviation**
Low	433	0.1543 %	1.3146 %
2	433	0.1348 %	1.0233 %
3	433	0.1689 %	1.2023 %
4	433	0.1758 %	1.2848 %
5	433	0.0909 %	0.9564 %
6	433	0.1171 %	0.9669 %
7	433	0.1111 %	1.0822 %
8	433	0.1083 %	1.0423 %
9	433	0.1107 %	1.1230 %
High	433	0.1077 %	1.4852 %
OMXH GI	433	0.1181 %	1.0664 %

In the event study, we calculated the abnormal returns (*AR*) of each volatility portfolio to measure the daily performance of different beta-level stocks in relation to OMXH GI during the 60-day event window. Figure 7 portrays the daily change in each portfolio's ARs. The graph indicates major volatility during the whole event window as the abnormal returns of all portfolios show both positive and negative numbers. During the event window, there are highly positive, over 6% daily ARs, but also highly negative, under -10% daily ARs. This phenomenon suggests there are possible overachiever and underachiever portfolios when measured by risk-adjusted returns.

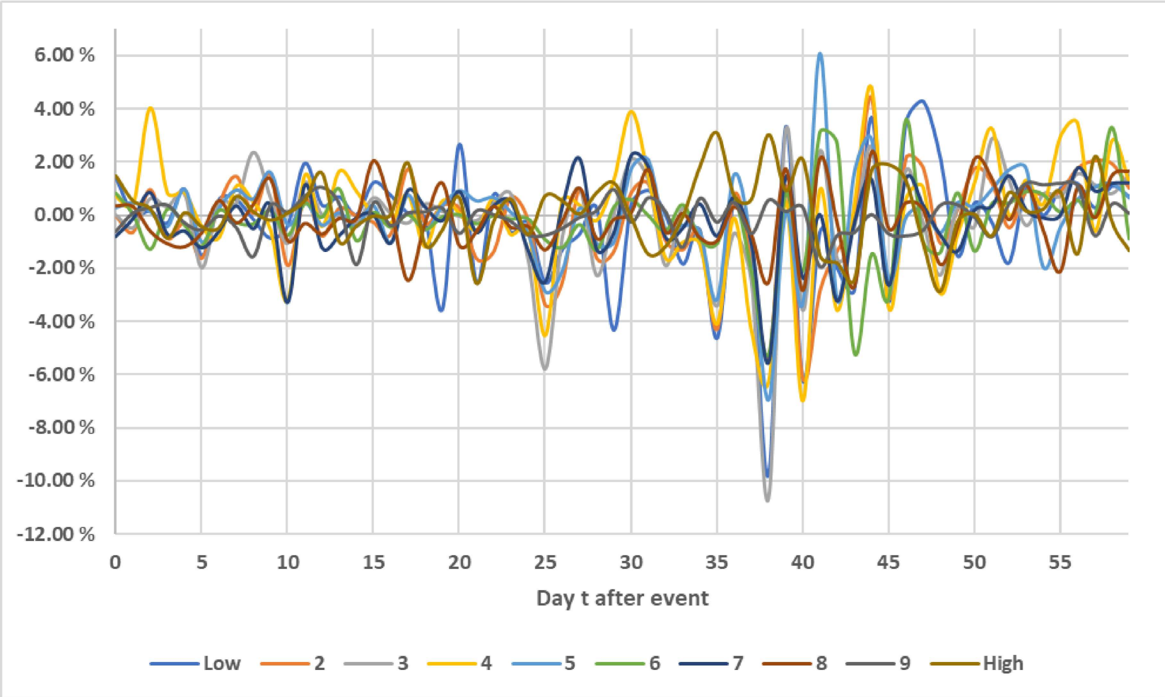

Figure 7: Abnormal returns (AR) of each volatility portfolio during the event window

The cumulative abnormal returns (*CAR*) are shown in Figure 8 which illustrates individual portfolio performance more clearly. On day 20 there are six portfolios from different beta levels with positive CARs. During days 20 to 37 most portfolios obtain negative CARs except for the highest volatility portfolio 10 which remains positive during the whole event window. The biggest risk-adjusted declines are experienced by the lowest volatility portfolios 1 and 2 which dive to -31.53% and -31.13% while the smallest declines are those of portfolio 10's 9's. This phenomenon is due to the nature of the decline. COVID-19 has a negative effect on most stocks which means the beta or standard deviation does not necessarily have a magnifying or decreasing effect on the actual returns as seen earlier in panel B of Table 4. The calculation of abnormal returns with the market model is done by including beta, as seen in Equation (8), which naturally leads to the same negative actual returns showing substantially lower risk-adjusted returns (AR and CAR) in lower beta portfolios.

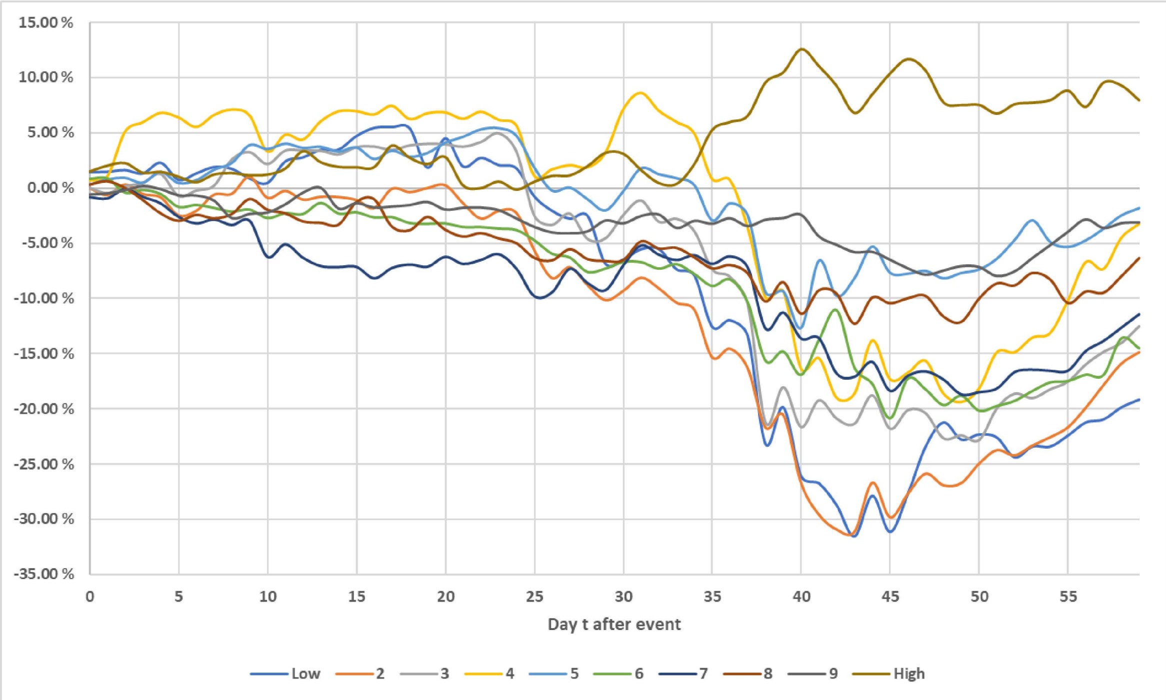

Figure 8: Cumulative abnormal returns (CAR) of each volatility portfolio during the event window.

The cumulative abnormal returns (*CAR*) of 10-day intervals are shown in Tables 4-6. The start of the event in Table 5 (0-19) shows only zero statistically significant CARs. The trend of the first 20 days moderately favors low-volatility portfolios. This trend changes during days 20 to 29 when the statistical significance of low-volatility portfolios becomes strong and the CARs negative. The most negatively affected are portfolios 2 and 1 with CARs of -10.1508% (p-value 0.0013) and -8.6787% (p-value 0.0130) while the high-volatility portfolio 10 has an unaffected CAR of 1.0280% (p-value 0.6980). The same trend continues during days 30-39 as portfolio 3 is the lowest with -13.4774 (p-value 0.0001) with portfolios 1, 2, and 4 within about three percentage points more CARs. Portfolio 10 increases its CAR to +7.3373% which is a strongly statistically significant increase (p-value 0.0058). Compared to the results of earlier studies of Table 1, our dataset indicates a significantly smaller decline in our volatility portfolios than in average national indices during the largest COVID-19 downfall on days 20-39.

The CARs of days 40-49 are negative except for portfolio 5. The recovery of the market starts between days 42 and 50 which is confirmed by Table 7's CARs of days 50-59. They are all positive with statistically significantly the largest abnormal returns being portfolio 4's 16.1200% (p-value 0.0002) and portfolio 2's 11.8411% (p-value 0.0002). This finding is consistent with the event window dividing into two stages suggested by Singh et al. (2020, 16). The second stage is an indication of the recovery of the market. When comparing the recovery of the volatility portfolios to the results of Singh et al. (2020, 17)

*Table 5: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (0-9 and 10-19). (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Portfolio	CAR(0,9)		t-stat	p-value
Low	0.8428 %		0.2422	0.8088
2	0.9975 %		0.3182	0.7505
3	3.2127 %		0.9693	0.3329
4	6.5696 %		1.5321	0.1262
5	3.8737 %		1.5143	0.1306
6	-1.9635 %		-0.7831	0.4339
7	-2.9366 %		-0.9697	0.3327
8	-0.9635 %		-0.4008	0.6888
9	-2.3562 %		-1.3227	0.1866
High	1.1353 %		0.4288	0.6683

Portfolio	CAR(10,19)		t-stat	p-value
Low	0.9755 %		0.2803	0.7794
2	-1.0151 %		-0.3238	0.7462
3	0.7623 %		0.2300	0.8182
4	0.2185 %		0.0510	0.9594
5	-0.7120 %		-0.2783	0.7809
6	-1.2778 %		-0.5096	0.6105
7	-4.1626 %		-1.3746	0.1699
8	-1.6138 %		-0.6712	0.5024
9	1.0676 %		0.5994	0.5492
High	1.0139 %		0.3829	0.7020

*Table 6: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (20-29 and 30-39). (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Portfolio	CAR(20,29)		t-stat	p-value
Low	-8.6787 %	**	-2.4938	0.0130
2	-10.1508 %	***	-3.2380	0.0013
3	-8.5512 %	**	-2.5800	0.0102
4	-3.5609 %		-0.8304	0.4067
5	-5.2073 %	**	-2.0357	0.0423
6	-4.0620 %		-1.6201	0.1059
7	-2.1341 %		-0.7047	0.4813
8	-3.9962 %	*	-1.6622	0.0971
9	-1.6636 %		-0.9339	0.3508
High	1.0280 %		0.3882	0.6980

Portfolio	CAR(30,39)		t-stat	p-value
Low	-13.0044 %	****	-3.7367	0.0002
2	-10.4151 %	****	-3.3223	0.0010
3	-13.4774 %	****	-4.0663	0.0001
4	-12.5773 %	***	-2.9331	0.0035
5	-7.3394 %	***	-2.8691	0.0043
6	-7.5271 %	***	-3.0021	0.0028
7	-2.0312 %		-0.6708	0.5027
8	-1.9239 %		-0.8002	0.4240
9	0.2181 %		0.1224	0.9026
High	7.3373 %	***	2.7710	0.0058

*Table 7: Cumulative abnormal returns (CAR) of the volatility portfolios in the event window (40-49 and 50-59). (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Portfolio	CAR(40,49)		t-stat	p-value
Low	-2.9038 %		-0.8344	0.4045
2	-6.1427 %	*	-1.9594	0.0506
3	-4.3581 %		-1.3149	0.1892
4	-9.9908 %	**	-2.3299	0.0202
5	1.6629 %		0.6500	0.5160
6	-4.0018 %		-1.5961	0.1111
7	-7.4213 %	**	-2.4507	0.0146
8	-3.5871 %		-1.4920	0.1364
9	-4.3247 %	**	-2.4278	0.0156
High	-2.9959 %		-1.1314	0.2584

Portfolio	CAR(50,59)		t-stat	p-value
Low	3.6089 %		1.0370	0.3003
2	11.8411 %	****	3.7771	0.0002
3	9.8760 %	***	2.9797	0.0030
4	16.1200 %	****	3.7593	0.0002
5	5.8760 %	**	2.2971	0.0221
6	4.3100 %	*	1.7190	0.0863
7	7.2675 %	**	2.3999	0.0168
8	5.7803 %	**	2.4043	0.0166
9	3.9434 %	**	2.2138	0.0273
High	0.4474 %		0.1690	0.8659

To measure the different reactions of the volatility portfolios individually, we calculated the abnormal returns (*AR*) of the portfolios to seven individual announcements on announcement day and the day after. From those ARs, the average abnormal return (*AAR*) is calculated to observe possible differences in initial reactions. The results are shown in

Table 8. Individually examined events show the variation between each announcement. The AARs of event day (t0) indicate three statistically significant portfolios which are portfolio 2's -1.3137% (p-value 0.0184), portfolio 4's -1.3991% (p-value 0.0121) and portfolio 7's -0.9509% (p-value 0.0874). All volatility portfolios except for portfolio 10, have negative AARs in t0 of the event. The day after the announcement (t1) shows higher AARs than the t0. Therefore, according to the AAR reactions, the market is not instantly reflecting new information to the prices correctly. T1 shows a trend of low-volatility portfolios having statistically significant negative AARs as portfolios 1, 2, 3, and 4 all experienced over one percent decrease during the t1. Portfolio 3 shows a statistically significant negative AAR of -1.8648% (p-value 0.0008) in t1, which is the highest average abnormal return of the analysis period. The effects of announcements were more negative on lower-volatility portfolios. The examination of individual announcements concludes that the reactions to announcements were delayed and overreacted which is consistent with the findings of Scherf et al. (2022). The results contradict the semi-strong efficient market hypothesis as the prices did not reflect all public announcements correctly and immediately.

*Table 8: Abnormal returns (AR) and average abnormal returns (AAR) of specific announcement days (t0) and the day after (t1) (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Portfolio #	ARs							
	Announcement of human-to-human transmission		Wuhan lockdown		Italy lockdown		UK lockdown&WHO announcement	
	20/01/2020	**21/01/2020**	**23/01/2020**	**24/01/2020**	**30/01/2020**	**31/01/2020**	**10/02/2020**	**11/02/2020**
Low	1.4101 %	0.0396 %	-0.3028 %	0.9640 %	-0.1650 %	-0.8694 %	1.2185 %	0.7388 %
2	-0.0275 %	-0.6379 %	-0.8619 %	-0.3070 %	0.0817 %	1.5368 %	-0.2705 %	-0.7201 %
3	0.0010 %	-0.4851 %	0.3135 %	0.7983 %	2.3616 %	0.6560 %	0.6496 %	0.0575 %
4	0.7090 %	0.3692 %	0.8464 %	0.8503 %	0.4849 %	-0.5419 %	0.0088 %	-0.2923 %
5	0.2811 %	0.4743 %	-0.4298 %	0.9755 %	0.6165 %	1.6184 %	0.3631 %	-1.0473 %
6	0.8319 %	0.0362 %	0.2341 %	-0.3718 %	-0.3298 %	0.1775 %	0.1034 %	-0.4541 %
7	-0.7909 %	-0.1168 %	-0.7087 %	-0.5911 %	-0.5003 %	0.3793 %	0.0215 %	-1.0400 %
8	0.3428 %	0.3084 %	-1.0870 %	-1.2036 %	0.3961 %	1.3501 %	2.0372 %	0.2543 %
9	-0.6097 %	0.0934 %	0.3876 %	-0.2892 %	-1.5584 %	0.3705 %	0.4773 %	-0.3871 %
High	1.4740 %	0.5314 %	-0.8777 %	0.0836 %	0.1247 %	-0.1980 %	-0.0310 %	0.0101 %

Portfolio #	ARs						AARs			
	Worsening infection in Europe		WHO declares pandemic		Finnish Government announcement of Emergency powers act		Average abnormal reactions of the portfolios			
	21/02/2020	**24/02/2020**	**11/03/2020**	**12/03/2020**	**16/03/2020**	**17/03/2020**	**t0**	**p-value**	**t1**	**p-value**
Low	-0.2923 %	-2.5367 %	-1.4299 %	-9.7576 %	-6.2245 %	-0.6387 %	-0.8266 %		-1.7229 %	0.0020
2	-0.1830 %	-3.3774 %	-1.7857 %	-5.3488 %	-6.1491 %	-2.8540 %	-1.3137 %	0.0184	-1.6726 %	0.0027
3	-1.6620 %	-5.7958 %	-2.4923 %	-10.6938 %	-3.5949 %	2.4090 %	-0.6319 %		-1.8648 %	0.0008
4	-0.5164 %	-4.5343 %	-4.3285 %	-6.2817 %	-6.9982 %	0.9653 %	-1.3991 %	0.0121	-1.3522 %	0.0152
5	-0.6918 %	-2.8705 %	-1.1005 %	-6.9618 %	-3.3128 %	6.0927 %	-0.6106 %		-0.2455 %	
6	-0.1318 %	-0.9260 %	-2.1068 %	-5.2592 %	-2.1026 %	3.1527 %	-0.5002 %		-0.5207 %	
7	-1.3096 %	-2.4895 %	-1.0209 %	-5.5294 %	-2.3473 %	0.0278 %	-0.9509 %	0.0874	-1.3371 %	0.0164
8	-0.4388 %	-1.3189 %	-0.7596 %	-2.5416 %	-2.8512 %	2.1237 %	-0.3372 %		-0.1468 %	
9	-0.7494 %	-0.7582 %	-0.6968 %	0.5712 %	0.2966 %	-1.9451 %	-0.3504 %		-0.3349 %	
High	-0.7365 %	0.7242 %	0.5846 %	3.0276 %	2.0914 %	-1.5385 %	0.3757 %		0.3772 %	

An Ordinary Least Squares regression (OLS) was conducted to estimate the linear relationship between the abnormal return of the portfolio and the factors affecting it. The dependent variable is the abnormal return (*AR*) of the portfolio and the independent variables are return of the portfolio (*Return(P)*), return of the OMXH GI (*Return(M)*), portfolio beta (*Beta(P)*) and to examine the reaction of volatility portfolios to new Covid-19 cases we added logarithmic confirmed cases of Finland (*Log(Fin Cases)*) as well as globally (*Log(Glob Cases)*). To account for the problem of heteroskedasticity we used the robust standard errors in the statistical model. The Variance Inflation Factors (VIF) of independent variables are 2.24 which means collinearity is not an issue in the model. Table 9 shows the summary of the used panel data. As the table and earlier examination of the abnormal returns indicate, all the return factors are negative. The regression model formula is seen in Equation (18).

Table 9: Summary of short-term panel data

Variable	AR	RP	RM	Beta	Log(Fin Cases)	Log(Glob cases)
Observations	600	600	600	600	600	600
Mean	-0.13 %	-0.36 %	-0.35 %	0.5874	12.42 %	15.04 %
Std. Dev.	1.72 %	2.86 %	2.70 %	0.3762	22.30 %	19.37 %
MIN	-10.69 %	-15.35 %	-10.76 %	0.1340	-69.31 %	0.00 %
MAX	6.09 %	12.18 %	6.19 %	1.4910	81.09 %	119.01 %

$$AR_{it} = \alpha + \beta_1 Return(P)_{it} + \beta_2 Return(M)_{it} + \beta_3 Beta(P)_{it} + \beta_4 Log(Fin\ Cases)_{it} + \beta_5 Log(Glob\ Cases)_{it} + \varepsilon_{it} \tag{18}$$

The independent variables of the regression model during the event window explain 56.0% of the variation of abnormal returns. The results of OLS regression in Table 10 indicate that the largest significance to abnormal returns is returns of the portfolio 0.6745 and returns of the market -0.3157. The disparity between the effects of the portfolio and market returns is due to the nature of the abnormal returns. The ARs increase when portfolio returns grow and reduce when market returns grow as seen in Equation (8). The beta of the portfolio has a weak statistically significant (p-value 0.084) positive effect on the ARs.

OLS regression’s result’s positive effect on the return of the portfolio and the negative effect on the return of the market are consistent with the results of Liu et al. (2020) and Ji et al. (2022). Singh et al. (2020) found a weak statistically significant positive relationship between ARs and the return of the market which is inconsistent with our results.

The COVID-19 pandemic is the instigator of the decline in the market, but the regression results suggest that the change in confirmed cases nationally or globally did not affect the abnormal returns statistically significantly. This finding differs from the results of Liu et al. (2020), Singh et al. (2020), and Ji et al. (2022) who all found a statistically significant (p<0.10) negative relationship between abnormal returns and COVID-19 cases. This discrepancy is a result of our long event window and the data of Finnish confirmed cases as the first cases are confirmed on day 34 of the event window. The long event window of our dataset includes part of the market recovery which influences the negative relationship that the earlier studies discovered. Our short-term findings are consistent with Scherf et al. (2022) as they discovered the negative statistically insignificant (p=0.12) relationship between national cases and abnormal returns. The results are inconsistent with Scherf et al's. results of a statistically insignificant (p=0.26) positive relationship. The differences are partly explained by the different nature of COVID-19 data and return data in each study. Another OLS regression with the same variables is completed in Section 4.3 to examine ARs of the post-event window.

*Table 10: OLS panel regression of short-term abnormal returns (AR) with robust standard errors in parentheses (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Variable	Abnormal Return (Event Window)	
Return (Portfolio)	0.6745	****
	(0.0638)	
Return (Market)	-0.3157	****
	(0.0453)	
Beta (Portfolio)	0.0037	*
	(0.0021)	
Log(Finnish Cases)	-0.00105	
	(0.0019)	
Log(Global Cases)	-0.00169	
	(0.0019)	
Constant	-0.0018	
	(0.0012)	
Observations	600	
R-squared	0.560	****

4.3 Long-term performance of volatility portfolios

Having examined the immediate short-term effects of COVID-19 on the volatility portfolios, we move to the long-term effects. The long-term effects are the essence of this empirical study as the objective of the thesis is to measure the performance of low-volatility portfolios during and after the Covid-19 decline. The measurement of low-volatility anomaly is the secondary objective of this section. The timespan of this section is the event window and post-event window shown in Figure 4 (January 20, 2020 – December 30, 2021).

Figure 9 shows the actual returns of each volatility portfolio during the analysis period. The graph indicates a strong performance of volatility portfolios 4 (yellow) 3 (light grey) and 1 (blue). The lowest performance portfolios are 5 (light blue), 8 (brown), and 9 (dark grey). The high-volatility portfolio 10 (light brown) is an average performer. The COVID-19 decline forecasts of OECD (2020b) were not realized because the actions of policymakers and central banks had an immense effect on the economy. This phenomenon is seen in Figure 9 where all the volatility portfolios perform abnormally well.

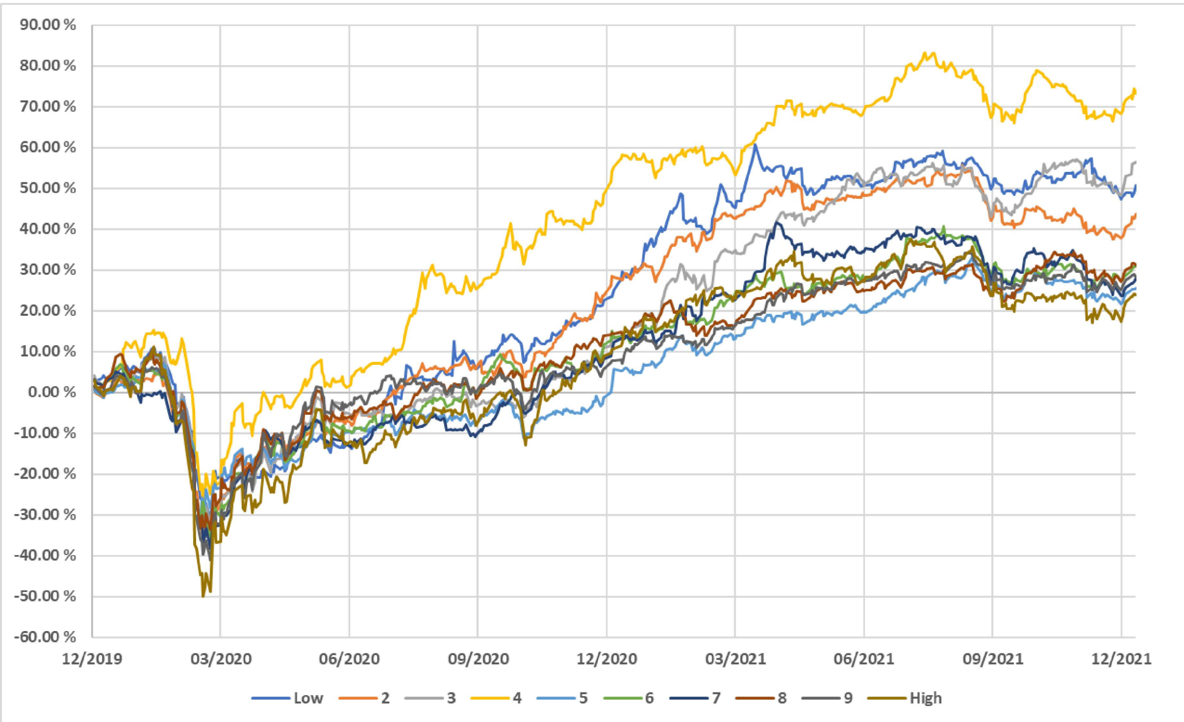

Figure 9: The realized returns of the volatility portfolio during the event window & post-event window

Given the risk of the portfolio, the performances change greatly. The long-term market model risk-adjusted returns, or cumulative abnormal returns (CAR), are illustrated in Figure 10. During the post-event window, the low-volatility portfolios perform visibly better than the high-volatility portfolios. The CAR of high-volatility portfolio 10 remains negative for almost the entirety of the analysis period ending up at -12.40% while the CAR of low-volatility portfolio 1 rises momentarily to over +40% ending up at +34.29%. As earlier announced in Section 3.2, the estimation of normal returns of portfolios to examine long-term abnormal returns is challenging. The large estimation sample size and the event window including the calculation of test statistics do not remove the high sensitivity and other basic issues of a long-horizon event study (Kothari and Warner, 2007, 14). To compare the long-term performance of the portfolios reliably, we emphasize the examination of risk-adjusted realized returns.

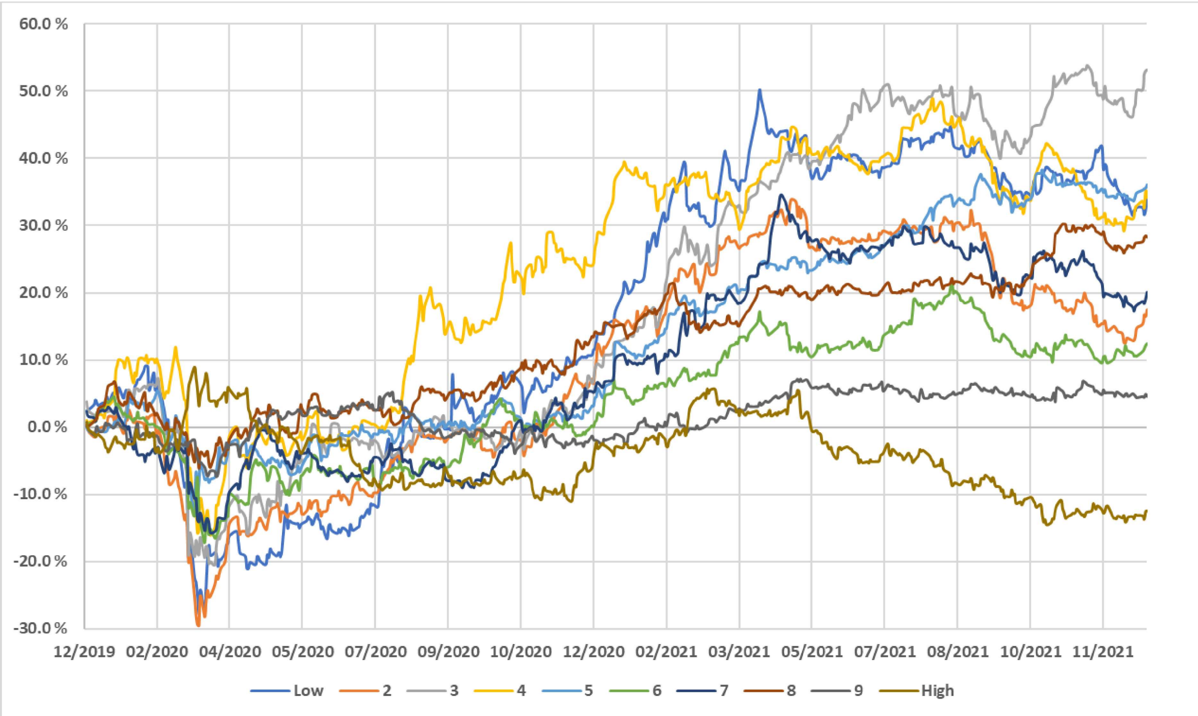

Figure 10: The cumulative abnormal returns (CAR) of the volatility portfolio during the event window & post-event window

To test the effect of the same factors as in section 4.2 on long-term ARs, the regression model of Equation (18) is utilized in the panel data of the post-event window. The summary of the regression variables is visible in Table 11. The addition of observations and the decreased Covid-19 uncertainty of this analysis period increases the adjusted R-squared to 0.652 as seen in the results in Table 12. The collinearity of the model is rejected as the Variance Inflation Factors (VIF) of independent variables is 1.44. Statistically significant return of the portfolio and return of the market have the same effect as in short-term regression in section 4.2.

The OLS regression indicates that an increase in portfolio returns grows abnormal returns while a decrease in market returns has the same effect. These results are consistent with our short-term OLS regression (section 4.2) and the results of Liu et al. (2020) and Ji et al. (2022). As an opposite to short-term regression, the beta has a strongly statistically significant negative effect on the ARs. Larger ARs when beta decreases are an indication of the inconsistency of CAPM on this dataset. The excessive abnormal performance of low-volatility portfolios supports low-volatility anomaly.

Table 11: Summary of long-term panel data

Variable	AR	RP	RM	Beta	log(Fin cases)	log(Global cases)
Observations	0	4330	4330	4330	4330	4330
Mean	0.07 %	0.13 %	0.12 %	0.5951	0.99 %	1.16 %
Std. Dev.	0.87 %	1.25 %	1.07 %	0.3965	1.05 %	1.52 %
MIN	-5.97 %	-6.81 %	-4.24 %	0.1298	0.00 %	0.00 %
MAX	8.16 %	12.01 %	4.57 %	1.5702	7.51 %	12.50 %

*Table 12: OLS panel regression of long-term abnormal returns (AR) with robust standard errors in parentheses (Significance levels: *p<0,1; **p<0,05; ***p<0,01 and ****p<0,001)*

Variable	Abnormal Return (Post-Event Window)	
Return (Portfolio)	0.7120	****
	(0.0081)	
Return (Market)	-0.3921	****
	(0.0095)	
Beta (Portfolio)	-0.0010	****
	(0.0002)	
Log(Finnish Cases)	0.011247	
	(0.0087)	
Log(Global Cases)	-0.00308	
	(0.0060)	
Constant	0.000717	****
	(0.0002)	
Observations	4330	
R-squared	0.652	****

Theoretically, as the CAPM and the EMH assume the return should increase as the risk increases. The summary of the realized performance of each volatility portfolio in Table 13 reveals the opposite nature in our dataset. Six volatility portfolios generated annualized returns below the market indicator OMXH GI's 16.81% in the long-term examination. The largest annualized returns are portfolio 4's 41.53% and portfolio 3's 31.04%, while the lowest are portfolio 10's 11.84% and portfolio 8's 12.22%. When accounting for the annualized standard deviation of portfolios (Equation (4)) the Sharpe ratios are constructed. The highest Sharpe ratios are portfolio 4's 1.582 and portfolio 3's 1.257.

Table 13 shows deciles (alias volatility portfolios) but additionally, quintiles and halves which illustrate the trends more visually. The Sharpe ratio of 1.565 of quintile 2 is higher than that of the low-volatility quintile 1 (1.223). That difference is explained by the nature of decile 1 (the low-volatility portfolio) as the portfolio betas are largely statistically insignificant (see Appendix 1), which means the variances of stocks do not correlate strongly with the variance of the market indicator OMXH GI. This phenomenon is possibly caused by the higher annualized standard deviation of the low-volatility portfolio (1) than the second-lowest-volatility portfolio (2).

The turnover ratios of volatility halves in Table 13 reveal that the liquidity of low-volatility stocks has increased significantly. The pre-event turnover ratio of the low-volatility half was 38% and the high-volatility was 415% (seen in Table 3). During Covid-19 they grew to 127% and 493% indicating the increased demand for low-volatility stocks. The trading volume illustrates a proxy for market activity, meaning that the COVID-19 decline increased the market activity, especially concerning the low-volatility stocks.

The theoretical background suggests that investors can pick a spot in the Security Market Line shown in Figure 11 where the addition of systematic risk yields more expected returns. As seen in the graph during the COVID-19 analysis period of roughly two years, this hypothesis is rejected. The low-volatility portfolios overachieved greatly their results, while the high-volatility portfolios underachieved theirs. The abnormal returns that differed from the CAPM's expected returns are illustrated with Jensen's alpha as it indicates the amount of actual returns that deviated from the security market line. The results suggest that the market is inefficient in the weak level of EMH as the technical analysis of beta produced significantly higher returns than the market portfolio.

Panel B of Figure 11 indicates the changes in beta and standard deviation from the estimation window to the analysis period are important discoveries. Betas of the low-volatility quintile (portfolios 1&2) more than tripled and the standard deviation doubled. The betas of the high-volatility quintile (portfolios 9&10) decreased moderately while the standard deviation increased by 46%. This result decreases the difference of volatilities in the whole dataset portraying the effect of COVID-19 on the average level of risk. These findings are in contradiction of static beta and therefore in support of Jagannathan and Wang's (1996) time-varying beta. Haritha and Rishad (2020) suggest that irrational investor sentiment is a significant factor in excessive stock market volatility. The low-volatility stocks outperformed high-volatility stocks significantly with realized and risk-adjusted returns which supports the low-volatility anomaly conclusions of Baker et al. (2014) and Frazzini and Pedersen (2014).

Table 13: Summary of the performance of volatility portfolios during the event window and post-event window

Event Window & Post-Event Window						
Portfolio	**Beta**	**Geometric Annualised Returns**	**Annualised Std. Dev.**	**Median monthly Turnover-ratio**	**Sharpe Ratio**	**Jensen's Alpha**
Low	0.640	26.70 %	24.379 %	158 %	1.054	0.156
2	0.660	23.09 %	20.112 %	12 %	1.099	0.117
3	0.760	31.04 %	23.887 %	44 %	1.257	0.180
4	0.789	41.53 %	25.621 %	276 %	1.582	0.281
5	0.774	13.18 %	21.014 %	143 %	0.579	-0.001
6	0.676	13.70 %	19.984 %	262 %	0.635	0.020
7	0.752	12.42 %	21.991 %	50 %	0.519	-0.005
8	0.842	12.22 %	21.707 %	381 %	0.517	-0.021
9	0.933	13.19 %	22.140 %	719 %	0.550	-0.026
High	1.249	11.84 %	29.612 %	1051 %	0.366	-0.089
Low	0.650	24.88 %	19.532 %	85 %	1.223	0.136
2	0.774	36.18 %	22.475 %	160 %	1.565	0.229
3	0.725	13.44 %	18.941 %	203 %	0.657	0.010
4	0.797	12.32 %	20.338 %	216 %	0.557	-0.013
High	1.091	12.51 %	24.970 %	885 %	0.461	-0.057
Low	0.725	26.76 %	19.308 %	127 %	1.334	0.143
High	0.890	12.67 %	20.649 %	493 %	0.565	-0.024
OMXH GI	**1.000**	**16.81 %**	**21.939 %**		**0.721**	**0.000**

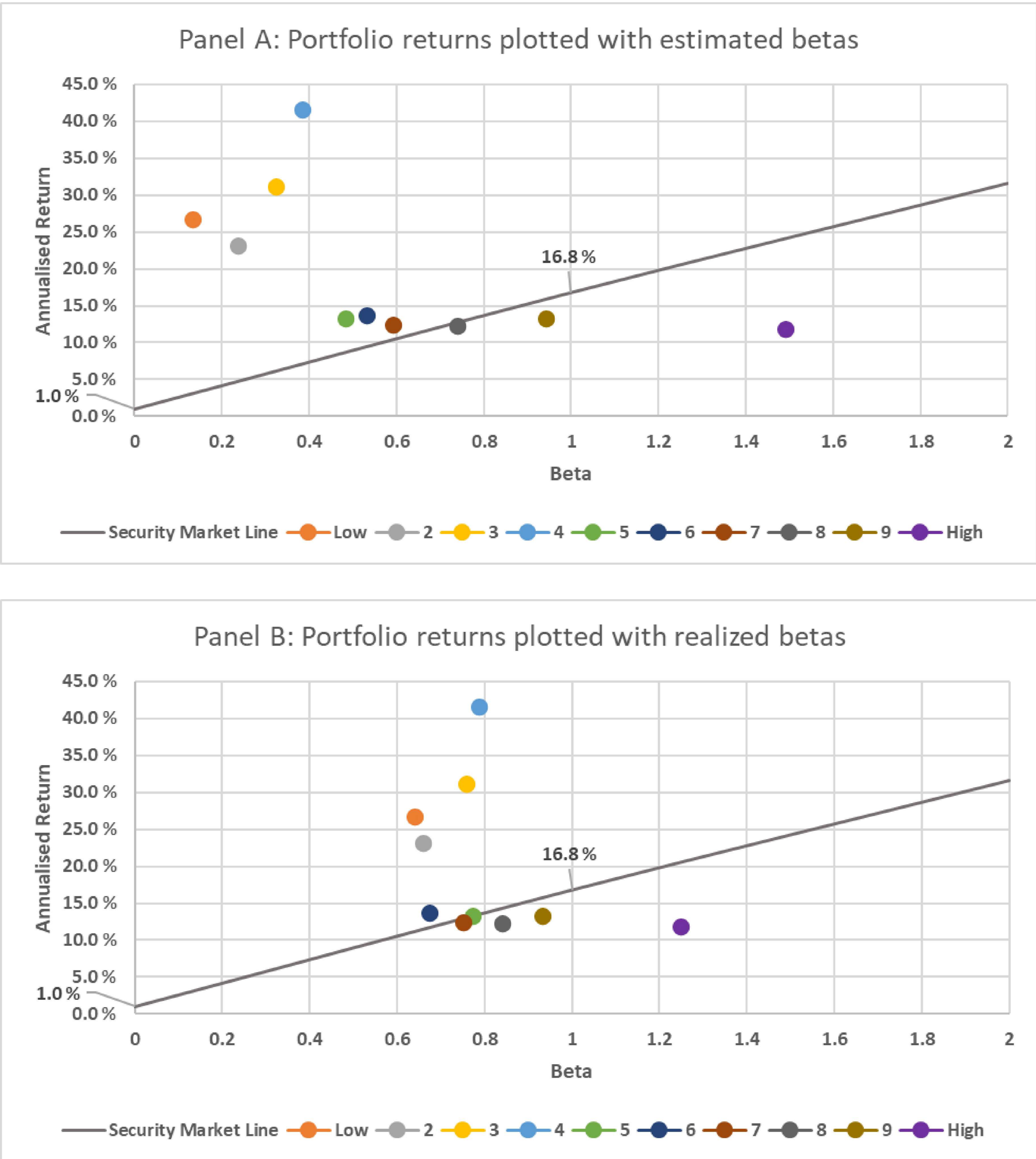

Figure 11: The Security Market Line (SML) and the portfolio returns plotted to estimated (Panel A) and realized (Panel B) betas.

5 Conclusions

This thesis' objective was to examine and measure the risk-return tradeoff during the Covid-19 pandemic in 2020-2022. The main hypothesis was that by minimizing the risk of a portfolio, investors can minimize the negative effect of market decline. The risk (volatility) indicator was selected as the beta of the Capital Asset Pricing Model as it measures the relationship between the variance of investment and the market. For an accurate and valid study, the dataset was selected as the Nasdaq's Helsinki Stock Exchange to define the limits clearly. As the earlier event studies of Ji et al. (2022); Scherf, Matschke, and Rieger (2022); Liu et al. (2020); and Singh et al. (2020) indicate, the COVID-19 pandemic event that had an extensive negative effect on the global economy. The earlier-mentioned event studies concentrated on the short-term market decline caused by the pandemic without examining the recovery from it. The motivation for this study came from the parallel rapid economic growth and the exponentially increasing pandemic infection. A key objective of this thesis was to examine the role of stock beta in changing market conditions and investor sentiments. If investors with a low-volatility investment strategy can earn larger than average returns, the results indicate market inefficiency and low-volatility anomaly.

The notes of OECD (2020b) in April 2020 predicted every month of strict containment measures inflicting a 2 percent decrease in annual GDP. They evaluated the widespread shutdowns resulting possibly in the GDP decreasing by 20-25% in advanced economies. This early announcement illustrates the uncertainty and increased risk in the economy which resulted in the stock market decline and inefficient market reactions found in empirical results. The investment strategy of buy and hold was selected to simplify the already complex study and to examine the changes in stock beta. With the utilization of event study, ordinary least squares regression, and other portfolio comparison indicators, the following research questions were answered:

1. How did the performance of low-volatility stock portfolios differ from high-volatility portfolios in OMX Helsinki during and after Covid-19 (2020-2022)?

2. How does beta affect the short-term returns of a portfolio during a market decline?

3. Does a low-volatility anomaly occur in OMX Helsinki?

The empirical result of our study confirms the delayed market response to COVID-19 announcements suggested by Scherf, Matschke, and Rieger (2022) as the first statistically significant AARs are seen on t5 and t10 after the event. The results support the results of

Scherf, Matschke, and Rieger’s (2022) post-announcement drift and overreaction, as the initial market reactions lasted multiple days after which statistically significant positive abnormal returns emerged to correct the overreaction. This pattern is inconsistent with the efficient market hypothesis, meaning OMX Helsinki was inefficient at the time of the event window. The largest immediate event-specific ARs were inflicted by the later events starting 24 trading days after the event date. The largest impact events were the worsening infection status in Europe (t24-25), the WHO declaring pandemic status (t37-38), and the Finnish Government announcing the Emergency Powers Act (t40-41). In the seven early negative news announcements, the AAR on the day after the announcement (t1) was 34.8% more negative than the day of the announcement (t0), emphasizing the market inefficiency.

The short-term results confirm that when measuring the negative effects of the event with actual returns, the high-volatility portfolios decreased more than the low-volatility portfolios as assumed. The low-volatility half of the data declined by -30.69% and the high-volatility half declined by -39.67%. When estimated with the market model, the low-volatility portfolios experienced significantly larger decreases than the high-volatility portfolios. During the deepest decline between t20 and t49, the low-volatility half of the dataset had an average of -22.94% in CARs while the high-volatility half had an average of only -7.42%. The reason low-volatility stocks have much more negative abnormal returns than high-volatility portfolios is the nature of the event. COVID-19 was unpredictable, and the substantial negative effects were on par between different volatility-level stocks. The event increased the volatility of low-volatility stocks more than the high-volatility stocks.

The market model, as calculated with Equation (8), estimates the portfolio return using beta as an instrument to indicate the normal reaction of the portfolio in relation to the market reaction. As the market reacted to COVID-19 with a decline, the volatility portfolios experienced negative average realized returns of -34.26%. When measuring the abnormal performance, this is portrayed as a catastrophic return to low-volatility portfolios which is estimated to decrease significantly less than the market. The same market fluctuation is considered a minor decline in high-volatility portfolios which is estimated to decrease more than the market. Therefore, the short-term negative effects of COVID-19 on low-volatility portfolios are found more severe than those in high-volatility. The short-term examination of abnormal returns (Section 4.2) resulted in consistent findings with the OLS regression. Therefore, a statistically significant positive relationship between beta and abnormal returns during the market shock is concluded. This rejects the hypothesis of the low-volatility portfolio being a haven during the market decline of COVID-19.

The long-term examination measured the effect of beta on portfolio performance post-event. The average of portfolios reached the pre-event level in October 2020 indicating a 66% average increase from the decline's minimum value in March 2020. The empirical findings of actual returns indicate that during the post-event window, the low-volatility portfolios performed ultimately better as they produced more realized returns than the high-volatility portfolios (See table 13). Thus, the relationship of risk and return suggested by CAPM and EMH is found opposite (negative) in our data. When dividing the dataset into halves, the annualized returns, from the start of the event, of the low-volatility half were 14.1 percentage points greater than those of the high-volatility half.

The examination of long-term abnormal returns further increased the gap between the performance of low-volatility and high-volatility portfolios. At the end of the thesis' analysis period, estimated with the market model, the CARs of the lowest volatility portfolio were 46.7 percentage points higher than the CARs of the highest volatility portfolio. The low-volatility half of the dataset had 24.5 percentage points larger CAR than the high-volatility. The risk-adjusted portfolio performance indicators Sharpe ratio and Jensen's alpha both indicate that the low-volatility strategy yielded greater results than the market. Low volatility half of the data had a Sharpe ratio of 1.33 in relation to OMXH GI's 0.72, indicating the success of technical analysis during the market decline. Low-volatility half had 0.143 Jensen's alpha showing the excessive risk-adjusted returns gained by utilization of the low-volatility strategy. These findings support Frazzini and Pedersen's (2014) conclusions in global equity markets of high beta stocks having historically lower Sharpe ratios and Jensen's alphas.

The economic recovery of the whole market happened parallel to the increased spreading of the COVID-19 pandemic. The results of short and long-term OLS regressions of event and post-event windows indicated that Covid-19 cases globally or nationally did not affect the abnormal returns of portfolios which differs from the negative relationship found in studies of global indices by Ji et al. (2022), Liu et al. (2020) and Singh et al. (2020) but confirms the findings of Scherf, Matschke and Rieger (2022). As an opposite to low-volatility portfolios' event window's poor risk-adjusted performance, the regression pointed out that beta had a strong statistically significant negative effect on the abnormal returns of portfolios. This result means that the low-volatility portfolios performed significantly better in the long horizon than the high-volatility portfolios when measured with abnormal returns. Low beta value's long-term positive effect on abnormal returns is therefore confirmed supporting, pointing at a low-volatility anomaly.

The measuring of possible low-volatility anomaly in OMX Helsinki was a secondary objective of this thesis. Our empirical results indicate that during both, the estimation period of 417 trading days and the analysis period of 495 trading days, the low-volatility anomaly existed. With a 4-year dataset, there is evidence of low beta portfolios experiencing more statistically significant returns than the high beta portfolios. Risk-adjusted performance indicators of the Sharpe ratio and Jensen's alpha showed higher values in low-volatility portfolios. These results are highly inconsistent with the theories of CAPM and EMH as seen in Panel A of Figure 11.

A key phenomenon during the analysis window is the change of volatility indicators beta and standard deviation of portfolios. The betas of portfolios increase from the pre-event window to the event and post-event window which is largely caused by the upward trend of market returns due to economy reviving. This finding is in support of betas varying over time (Jagannathan and Wang, 1996). The same change on a smaller scale occurs in standard deviations. This is explained by the irrational investor sentiment suggested by Haritha and Rishad (2020). Our results indicate that the changes in volatility did decrease the abnormal returns of low-volatility stocks but not at as drastic scale as the significantly positive Sharpe ratios and Jensen's alphas indicate.

The main explanation for low-volatility stocks performing better in a decline than high-volatility stocks in a decline would be the lower risk of the investment. During the event window of COVID-19, the lower risk did not correlate with higher abnormal returns. Part of the reason for the low volatility not producing more stable abnormal returns was the economic panic caused by the early estimates of the decline. The great long-term performance of low-volatility stocks in the empirical study is possibly explained by investor sentiment. According to the paper of Baker and Wurgler (2006, 1677) when investor sentiment is high, the high-volatility portfolios tend to earn lower returns. Therefore, the large-scale economic reviving by central banks and the government possibly caused a high demand for lower-risk stocks in OMX Helsinki.

The empirical results indicated that low-volatility stocks had substantially lower liquidity (*turnover-ratio*) than high-volatility stocks during the estimation period, which according to Amihud (2002, 52) can lead to illiquidity premium (higher returns). The low liquidity changed greatly due to COVID-19 as the liquidity of low-volatility half of the data tripled from pre-event to post-event (see Tables 2 and 12). This is an indication of high investor sentiment and increased demand, especially for low-volatility stocks due to the pandemic.

Our examination ignores factors such as low market value (Banz, 1981), a high book-to-market value (Rosenberg, Reid and Lanstein, 1985), high profitability (Cohen, Gompers and Vuolteenaho, 2002), low investment rate (Fairfield, Whisenant and Yohn, 2003), high accruals (Sloan, 1996) and high momentum (Jegadeesh and Titman, 1993), which all have been proven to explain stock returns. The decision to ignore the before-mentioned factors was validated by the minimization of assumptions and conscious concentration on the effects of beta. Therefore, this thesis does not try to explain the returns of stocks but the effect of volatility on them.

The research methods of this thesis were conducted with theoretical support as large as possible. Nevertheless, there are factors such as estimation frequency, sensitivity of risk assessment, weighting, and diversification of portfolios that possibly affect the validity and reliability of the results. The investment strategy of the thesis was passive which means it is not necessarily applicable to active strategies. Active strategies may alter the results as the beta and portfolio weight (*turnover ratio*) are calculated continuously for each stock. Transactional costs are another element that affects active investment strategies as they consume a part of the returns. The portfolio weighting with turnover ratio was done to minimize the illiquidity of abnormal stocks. Different weighing techniques of the volatility portfolios alter the results but not significantly. As for diversification, the small market size of OMX Helsinki restricted possibilities to acknowledge industries' effect on beta and the Covid reaction.

To examine the topics of the thesis correctly, the comparison of portfolios was completed with both actual and abnormal returns. The long-term event study was conducted with theoretical support and simplifications for undisturbed examination (Kothari and Warner, 2007). The possible clustering of events and uncertain announcement dates may affect the results. The t-tests accounted for event window variation to avoid Type 1 error, which is rejecting the null hypothesis falsely (Kothari and Warner, 2007, 12).

The impacts of the COVID-19 pandemic on the economy and global well-being are complicated and deeply interconnected. Through the eyes of investors, market declines are unavoidable. This thesis' main objective was to examine the effect of COVID-19 on different volatility-level stocks in Nasdaq's Helsinki Stock Exchange. The hypothesis of low-volatility stocks being a short-term safe investment is rejected, especially in risk-adjusted comparison. Although, the long-term performance of low-volatility stocks was distinctly better than the high-volatility portfolios, underlining the low-volatility anomaly during the pandemic and recovery from it. This thesis' assumptions and restrictions encourage further research on the reasons for low-volatility stocks performing better during the analysis window. The evidence found in the Finnish stock market would be worthwhile to study on a larger scale by increasing the individual events for a broader understanding of the phenomena.

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Appendices

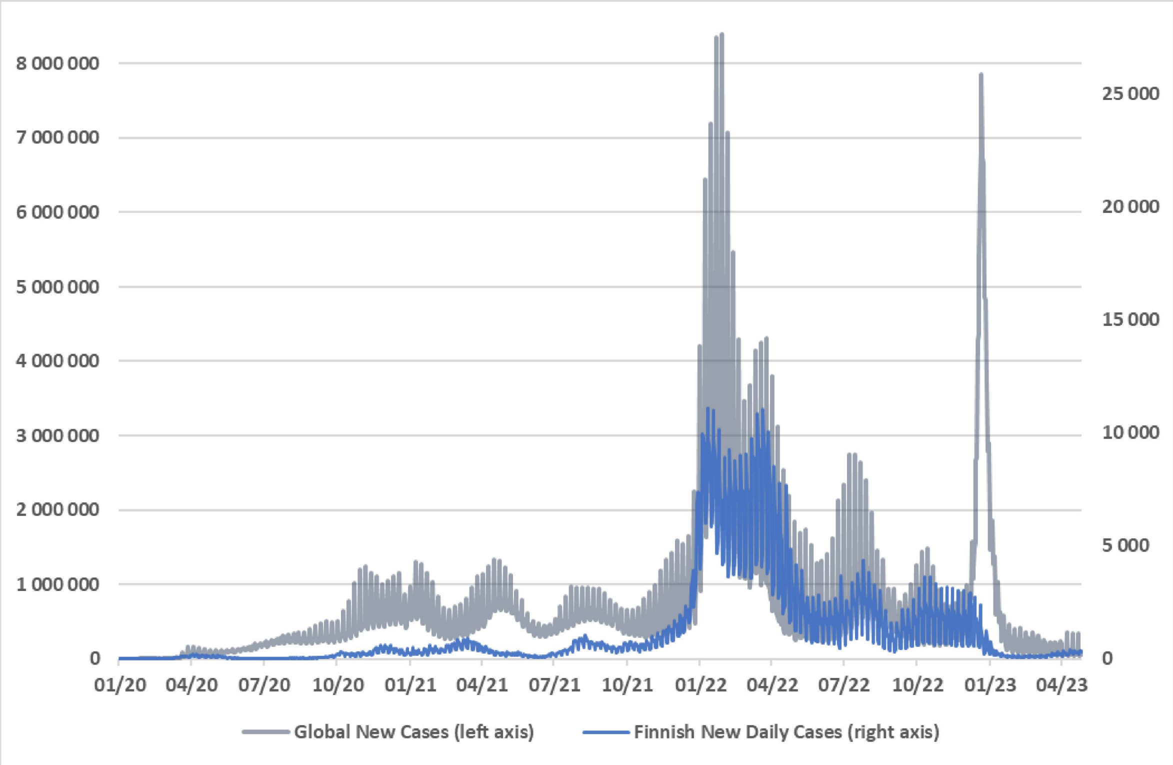
Appendix 1. List of the stocks in volatility portfolios

Name of the company	Portfolio #	Beta		Weight (max 20%)	Sector
Viking Line Abp	1	-0.035		5.2 %	Consumer Services
Wulff-Yhtiöt Oyj	1	0.025		4.0 %	Industrials
PunaMusta Media Oyj	1	0.067		4.4 %	Consumer Services
Boreo Oyj	1	0.083		13.2 %	Industrials
Enento Group Oyj	1	0.133		11.6 %	Financials
Apetit Oyj	1	0.151	**	5.0 %	Consumer Goods
United Bankers Oyj	1	0.159		5.5 %	Financials
Sotkamo Silver AB	1	0.159		5.0 %	Basic Materials
Elecster Oyj A	1	0.164		11.6 %	Industrials
Ålandsbanken Abp A	1	0.165	***	13.4 %	Financials
Rapala VMC Oyj	1	0.166	**	5.2 %	Consumer Services
Nurminen Logistics Oyj	1	0.175		5.5 %	Industrials
Enersense International Oyj	2	0.179		14.4 %	Industrials
Solteq Oyj	2	0.181		11.8 %	Technology
Exel Composites Oyj	2	0.183	*	3.8 %	Industrials
Panostaja Oyj	2	0.220	**	3.8 %	Financials
Pihlajalinna Oyj	2	0.235	*	4.4 %	Health Care
Investors House Oyj	2	0.241	***	18.3 %	Real Estate
Revenio Group Oyj	2	0.257	**	15.0 %	Health Care
Consti Oyj	2	0.258	**	4.8 %	Industrials
Ovaro Kiinteistösijoitus Oyj	2	0.267	****	15.3 %	Real Estate
Biohit Oyj B	2	0.270		5.5 %	Health Care
Harvia Oyj	2	0.288	***	14.4 %	Consumer Services
Gofore Oyj	2	0.291	**	5.5 %	Technology
Dovre Group Oyj	3	0.305	***	15.3 %	Industrials
Saga Furs Oyj C	3	0.307	**	3.8 %	Consumer Services
Siili Solutions Oyj	3	0.313	***	3.3 %	Technology
Nixu Oyj	3	0.322	**	14.5 %	Technology
eQ Oyj	3	0.326	****	14.9 %	Financials
Taaleri Oyj	3	0.327	****	9.9 %	Financials
Suominen Oyj	3	0.335	**	14.4 %	Consumer Goods
SSH Communications Security	3	0.336	**	13.4 %	Technology
Incap Oyj	3	0.340	**	3.8 %	Industrials
HKScan Oyj A	3	0.345	**	4.0 %	Consumer Goods
Afarak Group	3	0.353	***	5.0 %	Basic Materials
Anora Group Oyj	4	0.359	****	3.9 %	Consumer Goods
Olvi Oyj A	4	0.363	****	9.7 %	Consumer Goods
Tecnotree Oyj	4	0.367		11.6 %	Technology
Kamux Oyj	4	0.377	****	12.0 %	Consumer Services
Martela Oyj A	4	0.385	***	3.8 %	Consumer Services
Ilkka Oyj 2	4	0.386	****	19.0 %	Consumer Services
Digia Oyj	4	0.392	****	3.8 %	Technology
Keskisuomalainen Oyj A	4	0.408	****	4.8 %	Consumer Services
Honkarakenne Oyj B	4	0.414	***	3.9 %	Consumer Services
QPR Software Oyj	4	0.424	****	19.9 %	Technology
Aspo Oyj	4	0.451	****	14.9 %	Industrials

Remedy Entertainment Oyj	5	0.462	***	5.0 %	Consumer Services
Scanfil Oyj	5	0.464	****	4.8 %	Industrials
Glaston Oyj Abp	5	0.464	****	13.5 %	Industrials
Lassila & Tikanoja Oyj	5	0.468	****	5.0 %	Utilities
CapMan Oyj	5	0.482	****	4.4 %	Financials
Qt Group Oyj	5	0.483	****	3.8 %	Technology
Vaisala Oyj A	5	0.484	****	3.8 %	Industrials
Raute Oyj	5	0.485	****	11.8 %	Industrials
Elisa Oyj	5	0.491	****	13.5 %	Telecommunications
Digitalist Group Oyj	5	0.494	**	12.1 %	Technology
Kesla Oyj A	5	0.506	****	16.5 %	Industrials
Telia Company	5	0.508	****	3.3 %	Telecommunications
Oriola Oyj B	6	0.512	****	14.6 %	Health Care
Trainers´ House Oyj	6	0.515	**	19.9 %	Technology
Terveystalo Oyj	6	0.521	****	5.0 %	Health Care
Bittium Oyj	6	0.522	****	13.3 %	Technology
Tokmanni Group Oyj	6	0.525	****	9.2 %	Consumer Services
Kesko Oyj B	6	0.542	****	3.8 %	Consumer Goods
Tulikivi Oyj A	6	0.544	***	13.4 %	Industrials
Raisio Oyj Vaihto-osake	6	0.544	****	3.8 %	Consumer Goods
Citycon Oyj	6	0.546	****	9.9 %	Real Estate
Verkkokauppa.com Oyj	6	0.547	****	5.5 %	Consumer Services
Aspocomp Group Oyj	6	0.558	****	5.0 %	Technology
Fiskars Oyj Abp	7	0.563	****	4.8 %	Consumer Services
NoHo Partners Oyj	7	0.564	****	5.2 %	Consumer Services
SRV Yhtiöt Oyj	7	0.581	****	5.5 %	Industrials
Etteplan Oyj	7	0.586	****	4.8 %	Industrials
Talenom Oyj	7	0.588	****	13.4 %	Industrials
Innofactor Plc	7	0.590	****	4.4 %	Technology
Valoe Oyj	7	0.597		4.8 %	Industrials
Alma Media Oyj	7	0.609	****	3.9 %	Consumer Services
Atria Oyj A	7	0.609	****	13.3 %	Consumer Goods
Ponsse Oyj 1	7	0.610	****	4.0 %	Industrials
Teleste Oyj	7	0.612	****	16.8 %	Telecommunications
Stockmann Oyj Abp	8	0.616	****	10.6 %	Consumer Services
Aktia Bank Abp	8	0.621	****	4.8 %	Financials
Componenta Oyj	8	0.676	****	4.0 %	Basic Materials
Orion Oyj B	8	0.683	****	9.2 %	Health Care
Marimekko Oyj	8	0.696	****	20.9 %	Consumer Services
Sampo Oyj A	8	0.713	****	11.6 %	Financials
Reka Industrial Oyj	8	0.714	****	3.8 %	Industrials
Rovio Entertainment Oyj	8	0.786	****	12.1 %	Consumer Services
Sanoma Oyj	8	0.787	****	14.6 %	Consumer Services
TietoEVRY Oyj	8	0.816	****	4.4 %	Technology
Nokian Renkaat Oyj	8	0.818	****	4.0 %	Consumer Services
Fortum Oyj	9	0.845	****	15.3 %	Utilities
YIT Oyj	9	0.847	****	18.3 %	Industrials
KONE Oyj	9	0.863	****	19.0 %	Industrials
Wetteri Oyj	9	0.901	****	10.6 %	Consumer Services
Robit Oyj	9	0.905	****	7.9 %	Industrials
Caverion Oyj	9	0.923	****	11.6 %	Industrials
Kemira Oyj	9	0.976	****	5.2 %	Basic Materials
Huhtamäki Oyj	9	0.978	****	5.2 %	Industrials
Valmet Oyj	9	1.042	****	5.2 %	Industrials
Nordea Bank Abp	9	1.056	****	5.2 %	Financials
WithSecure Oyj	9	1.093	****	13.3 %	Technology
Uponor Oyj	9	1.096	****	5.5 %	Industrials

Lehto Group Oyj	10	1.195	****	11.5 %	Industrials
Neste Oyj	10	1.202	****	3.9 %	Energy
Nokia Oyj	10	1.223	****	4.8 %	Telecommunications
UPM-Kymmene Oyj	10	1.436	****	13.7 %	Basic Materials
Wärtsilä Oyj Abp	10	1.448	****	7.9 %	Industrials
SSAB B	10	1.552	****	5.2 %	Basic Materials
Konecranes Oyj	10	1.568	****	5.5 %	Industrials
Cargotec Oyj	10	1.570	****	3.9 %	Industrials
Metsä Board Oyj A	10	1.731	****	3.9 %	Basic Materials
Stora Enso Oyj R	10	1.803	****	3.8 %	Basic Materials
Metso Oyj	10	1.875	****	5.5 %	Industrials
Outokumpu Oyj	10	2.010	****	9.4 %	Basic Materials

Appendix 2. New COVID-19 cases daily in Finland and globally in 2020-2023 (World Health Organization, 2023)



Appendix 3. Proxies for risk-free return (Bank of Finland, 2023)