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Predicting Realised Volatility Around Covid-19
in Nordic Markets

Bachelor Thesis 15 hp
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Abstract

This study evaluates the performance of different models in predicting volatility in the Finnish and Swedish stock markets, particularly focusing on their adaptation to the Covid-19 pandemic. The study covers the period between 2018 and 2023. The model set contains a variety of methods, ranging from historical and implied volatility to the GARCH(1,1) model. The overall model performance is assessed using robust measures such as RMSE and MAE, along with regression analysis. Our findings reveal that the GARCH(1,1) model was the superior forecasting method for the OMXH25, with implied volatility proving to be the least effective forecasting method. Interestingly, the implied volatility forecast was the most reliable method for the OMXS30, with the historical volatility forecast being the weakest forecasting method. Additional research shows that both indices' volatility was significantly affected by Covid-19, with increased cases and deaths related to Covid-19 leading to increased volatility and increased vaccinations against Covid-19 leading to decreased volatility.

Keywords: Covid-19, Volatility, Volatility Forecasting, OMXS30, OMXH25

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1. Introduction

1.1 Background

The Covid-19 virus was first observed in China in late 2019. In March 2020 the World Health Organisation (WHO) declared it as a pandemic and as one of the biggest crises of the century. Because the virus had an extraordinary rate of death towards the elderly and the vulnerable in society, many countries chose to adopt social distancing and home isolation in order to decrease infection rates. However, these measures had large social, political, and economic consequences. Among the countries that drew attention to their divergent approaches were Finland and Sweden, which are neighbouring Nordic countries but with distinct strategies for combating the virus.

Finland adopted the more conventional route, swiftly implementing strict public health measures to contain the spread of the virus. Sweden, however, gathered global interest in its relatively unique approach, characterised by minimal restrictions and an emphasis on individual responsibility. The strategies implemented led to a significantly different number of recorded cases, with Sweden recording around five times more daily cases per thousand in the first four months of the pandemic (Yarmol-Matusiak et al., 2021). This higher case incidence corresponded to an overall higher rate of Covid-19 specific mortality rate, with Sweden having almost nine times higher Covid-19 attributed death toll compared to Finland.

The Covid-19 pandemic spurred substantial turbulence in global financial markets, including stock market plunges and volatility spikes in equity markets. The volatility of the US stock market in early 2020 was found to be more sensitive to the news regarding Covid-19 than to news regarding economic indicators (Baek et al., 2020). Since volatility acts as a barometer of financial risk or uncertainty surrounding investments in financial assets it is critical to the operations of financial markets and of interest to not only individual investors but also mutual fund managers, financial industry regulators, and policymakers. When looking at the possibility of predicting realised volatility, our study wants to include how different models have performed in predicting realised volatility on indices in Finland and Sweden. Additionally, we want to analyse how these models are affected by Covid-19 variables.

Our paper makes several contributions. It focuses on determining how different volatility measures perform when predicting realised volatility during a time of great distress. One of our contributions is determining the intensity and direction of different Covid-19 variables that affect the different volatility measure models. Additionally, our study expands the literature on the impact of the Covid-19 pandemic on Swedish and Finnish stock market volatility by investigating the impact of the pandemic's uncertainty on predicting realised volatility.

Our results show that the GARCH(1,1) is the superior forecasting method for all the periods studied of the OMXH25. Conversely, for the OMXS30, the implied volatility forecast was the superior forecasting method for all periods studied, except after the Covid-19 pandemic, where the historical volatility forecast was superior. We find that increased cases and deaths related to Covid-19 increase volatility and that increased vaccinations against Covid-19 decrease volatility. However, we found no significant trend among the estimates that cases, deaths, or vaccinations impacted the forecasting errors.

The remaining sections are organised as follows: Section 2 provides some preliminaries, such as the definition and measurement of volatility and hypothesis development. Section 3 discusses past literature. Section 4 introduces the three methods that have been used to evaluate the forecasts. Section 5 presents our data. Section 6 is the core section of this paper and presents our results. Section 7 discusses our views about our research and achievement in volatility forecasting and provides some directions for future research. Section 8 summarises and concludes.

1.2 Purpose

This thesis aims to evaluate the effectiveness of different volatility measures in predicting realised volatility before, during, and after the Covid-19 pandemic. By analysing historical, implied, and GARCH volatility metrics, the research seeks to identify the most reliable predictor of realised volatility amidst the market turbulence during the Covid-19 pandemic. It further aims to understand how Covid-19 factors affect volatility, as well as how they affect their ability to predict realised volatility. The findings could offer valuable insights for investors, risk managers, and policymakers, aiding in better risk assessment and derivative pricing strategies during periods of financial instability from future pandemics.

To help guide the process, we have formulated two research questions based on the above stated purpose of the study.

I. What volatility measure best predicts realised volatility during and around the Covid-19 pandemic in Finland and Sweden?
II. How do different Covid-19 data points, such as the number of persons sick, dead, and vaccinated for Covid-19 affect the volatility measures?

2. Theoretical Framework

2.1 Option Theory

Option contracts are a financial derivative that involves a buyer and a seller. They are divided into two contract types: call and put options (Hull, 2017). Where the call option provides the buyer the right to buy the underlying asset by a certain date, the maturity date, for a specific price, the strike price, whereas the put option gives the buyer the right to sell. Option contracts distinguish themselves from forwards and futures in giving the contract holder the right, but not the obligation, to exercise the contract. Options can furthermore be divided into American and European options, where American options can be exercised at any time up until the maturity date. In contrast, European options can only be exercised at the maturity date. Index options are usually European options, where one contract usually buys or sells 100 times the index at the specified strike price.

There are six factors affecting option prices, according to Hull:

1. The current price of the underlying asset, S_0
2. The strike price, K
3. The time to expiration, T
4. The volatility of the price of the underlying asset, σ
5. The risk-free interest rate, r
6. The dividends expected during the life of the option

Hull refers to options as in-the-money, at-the-money, or out-of-the-money. Call options are in-the-money when $S > K$, at-the-money when $S = K$, and out-the-money when $S < K$; the notations are reversed for put options. Options will only be exercised when they are in-the-money, as it is at that point they are profitable.

2.2 Black-Scholes-Merton Model

In the early 1970s, there was a significant advancement in the pricing of European Stock Options (Hull, 2017). This breakthrough, known as the Black-Scholes-Merton model, was introduced by its founders Fisher Black, Myron Scholes, and Robert Merton. The Black-Scholes-Merton model was the first model that became widely used for option pricing and is to this day an essential concept in modern financial theory with its considerable influence on financial engineering and on how traders hedge options.

The Black-Scholes-Merton model allows users to calculate European stock option prices with all observable inputs except stock price volatility (Hull, 2017). The variables that appear in the Black-Scholes-Merton model are the current stock price, time to expiration, stock price volatility and risk-free interest rate. The input stock price volatility is the underlying asset's volatility during the option's remaining life. It is an ex-post variable, meaning it is calculated based on past stock returns. Since current volatility can not be observed, a record of historical stock price movements can instead be used to estimate volatility. This historical stock price data is usually observed over a fixed interval, such as daily, weekly, or monthly. The Black-Scholes-Merton formula gives a risk-neutral valuation of European options since all inputs are independent of risk preferences.

The pricing formulas for European call and put options by Black-Scholes-Merton are:

$$c = S_0 N(d_1) - Ke^{-rt} N(d_2) \tag{1}$$

$$p = Ke^{-rt} N(-d_2) - S_0 N(-d_1) \tag{2}$$

where,

$$d_1 = \frac{ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} \tag{3}$$

$$d_2 = \frac{ln(S_0/K) + (r - \sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} \tag{4}$$

The price of a European call option is denoted as c, and the price of a European put option is denoted as p (Hull, 2017). S_0, K, T, r, and σ have all been defined in 2.1; however, in these formulas, σ is assumed to be constant. The function N(x) is defined as the probability that a random variable, following a standard normal distribution, takes a value less than x.

The Black-Scholes-Merton model assumes that stock prices are normally distributed under short periods of time; however, when considering long periods of time, it assumes that stock prices follow a lognormal distribution (Hull, 2017). Further assumptions for the Black-Scholes-Merton model are that there are no riskless arbitrage opportunities, no transaction costs or taxes and all securities are perfectly divisible, the trading of a security is continuous, investors can borrow or lend at the same risk-free rate, and that the short-term risk-free rate of interest is constant, short selling of securities with full use of proceeds is permitted, and that there are no dividends during the life of the option. However, it is possible to modify the model to incorporate expected dividends.

2.3 Volatility

The volatility, denoted as σ, of an underlying asset measures both the uncertainty of future movements while also working as a measure of the deviation from the mean return (Hull, 2017). It is an ex-post variable, meaning it is calculated on past stock returns and since current volatility can not be observed, a record of historical stock price movements can instead be used to estimate volatility. However, whereas more data generally leads to more accuracy, it comes with changes over time, and too old data could be irrelevant for predicting future volatility.

2.4 Historical & Realised Volatility

Historical volatility, also referred to as realised volatility, measures the volatility over a specific past time interval (Hull, 2017). The time period used when measuring volatility varies from intraday to daily, weekly, monthly, or yearly. It is important to establish an appropriate time frame when estimating volatility in order to get accurate measurements. It has been shown that volatility is much higher when the exchange is open than when it is closed; therefore, practitioners tend to ignore the days when the exchange is closed when estimating volatility from historical data, which means that they use trading days instead of calendar days.

The formula for the annualised version of historical volatility and realised volatility is:

$$\sigma = \sqrt{\frac{\Sigma(r_t - r_m)^2}{N-1}} \times \sqrt{252} \tag{5}$$

where,

$$r_m = \frac{\Sigma ln(\frac{S_t}{S_{t-1}})}{N} \tag{6}$$

$$r_t = ln(\frac{S_t}{S_{t-1}}) \tag{7}$$

In the formula σ, N, r_t, r_m, and S_t are defined as historical volatility, number of observations, realised return at time t, mean return, and price of the underlying asset at time t, respectively (Hull, 2017). The number 252 represents the number of trading days in one calendar year and taking the square root of it makes the daily volatility annualised. This is necessary to be able to compare it to the implied volatility since implied volatility is expressed in annualised terms.

2.5 Implied Volatility

Implied volatility, denoted as σ^{IV} refers to the volatility implied by the option prices observed in the market (Hull, 2017). Implied volatility is often used to monitor the market's expectations and opinions about the volatility of a particular asset. Unlike historical volatility, which is backwards-looking, implied volatility is forward-looking. It is possible to estimate the implied volatility by knowing all the observable variables included in the Black-Scholes-Merton model and the option's current market price. However, although volatility is a part of the Black-Scholes-Merton model, it can not be found by rearranging the formula so that the implied volatility is a function of other inputs. To estimate the implied volatility, an iterative process has to be used until the implied volatility that equates the formula to the market price is found.

2.6 GARCH(1, 1) Model

GARCH (1,1) is a variance measure model proposed by Bollerslev in 1986 (Hull, 2017). The equation for GARCH(1,1) is:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{8}$$

where,

$$\omega = \gamma V_L \tag{9}$$

$$u_n = \frac{S_n - S_{n-1}}{S_{n-1}} \tag{10}$$

$$\gamma + \alpha + \beta = 1 \tag{11}$$

In the equation, un is defined as the percentage change in the market variable from the end of day n – 1 to the end of day n (Hull, 2017). VL is defined as the long-run average variance and σ_{n-1}^2 as the most recent estimate of the variance rate. For a GARCH(1,1) process to be stable, it requires that $\alpha + \beta < 1$ and that $\alpha \geq 0$ and $\beta \geq 0$. If $\alpha + \beta > 1$, the weight applied to the long-term variance is negative. The parameter β can be described as a "decay rate" as the weights of older observations decline exponentially at rate β, and therefore β defines the relative importance of the observations in the u's when determining the current variance rate.

The forecasts for one day ahead σ_{n+1}^2 of the GARCH(1,1) model are obtained through:

$$\sigma_{n+1}^2 = \omega + \alpha u_n^2 + \beta \sigma_n^2 \tag{12}$$

Since the formula gives the daily variance, we take the square root to get the standard error and multiply it by the square root of 252 to convert it to annual volatility.

3. Literature Review

3.1 Previous Studies

Implied volatility's predictability of realised volatility has been widely tested against historical volatility and different GARCH models in research papers. Many of these papers, produced in the 1980s and 1990s, have produced mixed results and conclusions, where the larger part of the studies and papers cover the American market indices.

Day and Lewis (1992) studied sample data consisting of closing prices and contract volumes for S&P 100 call options and daily closing prices of the underlying S&P 100 index between 1983 and 1989. In the study, they find that weekly volatility is difficult to predict. They also find that implied volatility, GARCH, and EGARCH forecasts work as unbiased predictors of future volatility. However, they are not able to make a strong statement regarding the relative information content of GARCH forecasts and implied volatilities. In a similar vein, Christensen and Prabhala (1998) delve deeper into the relation between implied and realised volatility of S&P 100 index option prices. Challenging the prevailing notion in the scientific literature that implied volatility was biased and an inefficient forecast of future volatility compared to historical volatility forecasts; they discovered that implied volatility actually outperforms historical volatility in forecasting future volatility. Moreover, their approach to measuring the relation between implied and realised volatility differed from how it had been measured before by employing a lower sampling frequency that looks at a longer period of time.

Poon and Granger (2003) compare the result of 93 studies about volatility forecasting methods. Within these studies, 34 of them compare the volatility forecasts from implied volatility to the forecasts from historical volatility. 26 out of the 34 studies conclude that implied volatility provides a superior forecast of realised volatility over historical volatility. The remaining eight studies conclude the opposite. The historical volatility measures include random walks, absolute returns, historical averages of squared returns and more. The Black-Scholes-Merton model and its various generalisations was the foundation for the implied volatility forecasts. From their study, they conclude that most of the papers find implied volatility as a better forecast than historical volatility for forecasting realised volatility. When they compare implied volatility, historical volatility and GARCH models, they conclude that implied volatility is the best forecast with historical volatility and GARCH roughly equal, although historical volatility did somewhat better in the comparisons. They conclude that the success of implied volatility as a forecast should not be surprising since it uses a larger, more relevant information set than alternative methods as it uses option prices.

Szakmary et al. (2003) analysed data from 35 futures options markets and eight different exchanges in order to test the implied volatility's predictable power of the realised volatility of their underlying asset. The study uses an unweighted average of the implied volatility from at-the-money put and call options because they found that the implied volatilities were almost identical. In the study, they use daily data on futures, and the implied volatility and the realised volatility are measured from 10 to around 70 trading days. When calculating the historical volatility they use a 30-day window. They find that for most of the futures studied, implied volatility outperforms historical volatility when it comes to predicting realised volatility. Moreover, the study finds that historical volatility does not contain any significant predictive information beyond what is already included in the implied volatility.

Basouny et al. (2021) studied the impact of the Covid-19 pandemic on stock returns and conditional volatility. They examine a sample of international stock market indices between 2013 and 2020; the indices are chosen from the nine countries with the most confirmed Covid-19 cases between March and June 2020. The study utilises an EGARCH model since it can capture the asymmetric effects of positive and negative shocks on conditional volatility. They find that the indices studied have an unprecedented increase in their conditional volatilities during the Covid-19 pandemic. Additionally, they found that negative news from deaths had a larger negative effect than the positive effect from recovered cases.

Albulescu (2020) and Baig et al. (2021) also studied the US markets. Similarly, they found that new confirmed cases during Covid-19 were associated with higher volatility. Furthermore, Baig et al. (2021) also found that new confirmed cases hurt market illiquidity. Baek et al. (2020) also conducted a study on the US stock market between January 2020 and April 2020, analysing the effect of Covid-19 on US stock market volatility at the industrial level. It similarly finds that volatility is affected by specific economic indicators but is also sensitive to Covid-19 news. Moreover, they found that both positive and negative Covid-19 news are significant, but that negative news is more impactful than positive news, which made them suggest that there is a negative bias. Zaremba et al. (2020) investigate the relationship between policy response to the Covid-19 pandemic and stock market volatility. They explore the stringency of policy responses in 67 countries and find that non-pharmaceutical interventions such as information campaigns and event cancellations are two of the largest contributors to the volatility's growth. The effect they find is independent of the role of the Covid-19 pandemic itself.

Li et al. (2023) studied the 2008 crisis and the Covid-19 pandemic since they both led to a decrease in economic growth and high uncertainty in global stock markets. They believe that financial distress information is closely linked to financial crises, and to improve the predictability of realised volatility of global equity indices during crises they examine the predictable power of the Global Financial Distress Index. In their study, they find that using more comprehensive models performs better when predicting realised volatility when incorporating the predicting power of financial distress information during a crisis. They believe their findings provide a positive case against the forecast combination puzzle.

Yarmol-Matusiak et al. (2021) conducted a study comparing Covid-19 epidemiological indicators in Denmark, Finland, Norway, and Sweden. By studying the initial phases, they found that policy decisions resulted in different trajectories of the Covid-19 pandemic. They also found that Sweden's public health responses to Covid-19 were less restrictive and instituted more slowly than those of their Nordic counterparts. Due to the Nordic countries' broader similarities, it is possible to conduct useful comparisons to determine the impacts of different policies. The strategies implemented resulted in the number of recorded cases being significantly different between the countries, with Sweden recording around five times more daily cases per thousand in the first four months of the pandemic than Finland. This higher case incidence corresponded to an overall higher Covid-19-specific mortality rate, with Sweden having an almost nine times higher Covid-19-attributed mortality rate than Finland.

3.2 Hypothesis Development

Many studies have previously been conducted on the predictable power of different forecasting methods; however, the empirical results for which forecasting method that have the most predictable power have varied. Although the results have differed in older studies, one part that almost all studies have in common is that both implied, historical, and GARCH volatility measures are significant and have some predictive power for realised volatility. Most studies revolve around well-established markets like the S&P indices. However, this study wants to examine two smaller markets: the Finnish and the Swedish markets. It will investigate what volatility measure has the most predictive power of realised volatility in these markets, but also investigate how Covid-19 variables change the predictive power of the measures.

Previous studies, such as Poon and Granger (2003), have found that both implied and historical volatility measures have predictive power for realised volatility in larger markets. However, since this study will look into the smaller markets of Sweden and Finland, which may have different market dynamics than the larger markets, the question is whether the traditional volatility measures hold the same predictive power in these markets. Additionally, the volatile circumstances brought about by the Covid-19 pandemic may have disrupted typical market behaviour, potentially changing conventional volatility measures to be less effective. Therefore, Hypothesis 1 is formulated to explicitly test whether our volatility measures contain significant predictive power for realised volatility in the Swedish and Finnish stock markets amidst the Covid-19 pandemic.

Hypothesis 1

H_0: Implied, historical, and/or GARCH(1,1) volatility estimates contain no significant information in predicting future realised volatility.

The global stock market has been volatile and turbulent during the Covid-19 pandemic. Basouny et al. (2021) and Baek et al. (2020) highlight that both positive and negative news relating to Covid-19 affect the stock market volatility. Finland's and Sweden's different strategies in response to the pandemic make them an excellent pair to examine whether the impact of Covid-19 on volatility remains consistent across different markets and volatility measures. Therefore, hypothesis 2 aims to assess whether Covid-19 variables impact volatility in the Finnish and Swedish markets, providing insights into how external events like pandemics influence market volatility.

Hypothesis 2

H_0: Covid-19 factors do not impact realised, implied, historical, and/or GARCH(1,1) volatility.

As noted by Basouny et al. (2021), Baek et al. (2020), and Baig et al. (2021), the number of Covid-19 cases and deaths significantly impacts market volatility. However, whether these enhance or reduce the predictability of volatility forecasting methods remains unclear. Therefore, Hypothesis 3 seeks to investigate whether Covid-19 variables affect the ability of the volatility measures to forecast future realised volatility in the Finnish and Swedish markets, contributing to the understanding of how external shocks impact the volatility prediction models.

Hypothesis 3

H_0: Covid-19 variables do not impact implied, historical, and/or GARCH(1,1)'s ability to predict future realised volatility.

By formulating and testing these hypotheses, the study aims to provide valuable insights into the effectiveness of different volatility measures in predicting realised volatility in periods with higher market turbulence and how external factors like Covid-19 variables influence volatility dynamics in the Finnish and Swedish stock markets.

4. Method

A quantitative, empirical study on volatility measures has been conducted by using different volatility measures and backtesting the predicted volatilities with the realised volatility of the indices. Different measures, such as root mean squared error and mean absolute error have been used to evaluate forecast performance, as well as single-variable regression analysis and multivariable regression analysis.

The data that have been collected include closing prices of indices and implied volatility in two markets: OMXS30 (Sweden) and OMXH25 (Finland). Data on Covid-19, such as the number of sick, dead, and vaccinated persons, as well as data on inflation, policy rate, M3, and relative unemployment rate, have also been collected.

4.1 Root Mean Squared Error (RMSE)

Root mean squared errors are calculated by taking the difference between predicted values and realised values. This measure allows for easy comparison between different forecasting methods.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t - \sigma_t)^2} \tag{13}$$

4.2 Mean Absolute Error (MAE)

Mean absolute errors are calculated similarly to the root mean squared errors, but instead of taking the square root, we take the absolute value of the difference between predicted values and realised values. This measure allows for easy comparison between different forecasting methods.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|\hat{\sigma}_t - \sigma_t| \tag{14}$$

4.3 Regression Analysis

A single-variable regression analysis can be made to analyse the forecasted volatility compared to the actual volatility at a future date. Mincer and Zarnowitz (1969) proposed the Mincer-Zarnowitz regression, which is a regular linear regression widely employed for evaluating forecasts. The forecasts are compared to the actual volatility at time t; in their study, they regress the realised volatility on the implied volatility estimate. In our, we will use the same method to test our volatility forecasts over different periods:

$$\sigma_t^{RV} = \beta_0 + \beta_1 \sigma_{t-1}^{VF} + e_t \tag{15}$$

With a perfect prediction, $\beta_0 = 0$ and $\beta_1 = 1$, the prediction is assumed to be unbiased. To test the volatility estimate over three periods (before, during and after the Covid-19 pandemic), a multivariate regression will be used where before and after are added as dummy variables, making it possible to examine the different time segments. The regressions will look like this:

$$\sigma_t^{RV} = \beta_0 + \beta_1 \sigma_{t-1}^{VF} + \beta_2\, Before\ X\ \sigma_{t-1}^{VF} + \ \beta_3\, Post\ X\ \sigma_{t-1}^{VF} + e_t \tag{16}$$

The study will conduct single-variable and multivariate regressions to see how different Covid-19 variables affect the specific volatility estimates and realised volatility. Additionally, we have done similar regressions to see the effect on the absolute residuals between the estimate and the realised volatility. The Covid-19 variables are cases, deaths and vaccinations, and the control variables are the inflation rate, the relative unemployment rate, the size of M3, and the policy rate. First, single-variable regressions have been made to observe the effect of the Covid-19 variables on the volatilities, and then a multivariate regression was made, introducing the control variables.

5. Data

5.1 Definitions

A lot of effort has been put into finding high-quality data to ensure that the results gained from the regressions are as valuable as possible. We, therefore, chose as many official sources for the data as possible. We first defined the entire period as the years 2018-2023. We then divided the data into three separate periods: before, during, and after Covid-19. Before is defined as February 2018 until February 2020, during is defined as March 2020 until May 2023 and after is defined as May 2023 until December 2023. The defined periods are based on WHO's declaration of the start and the end of the Covid-19 pandemic**.** In total, there are 72 observations for each index/country representing monthly data. However, since no information was available for OMXS30 implied volatility during April 2023, we removed that observation from the regression analysis for all categories, making it 71 observations used for the analysis.

The data collection process can be divided into two parts, where the first part consisted of downloading data on implied volatility, as well as closing prices of the two indices, OMXH25 and OMXS30. The second part consisted of collecting macroeconomic data from different official government sources and other reliable sources.

5.2 Data Sources

5.2.1 Volatility and Index Prices

The implied volatility, as well as the closing prices of the indices, were collected through the database Refinitiv Eikon, which is a database that contains a multitude of customisable financial data. The data between the defined dates were chosen and downloaded as Excel files. The closing prices of the indices were then used to calculate the daily percentage change in prices, which was then used to calculate the historical/realised volatility and fit the GARCH(1,1) model as specified in the theoretical framework.

5.2.2 Covid-19 and Macroeconomic Data

The Covid-19 data was collected from different government websites and Our World in Data. The Finnish data on Covid-19 cases was collected from the Finnish Institute for Health and Welfare, and data on deaths and vaccinations related to Covid-19 was collected from Our World in Data. The Swedish data on Covid-19 cases and deaths was collected from the Public Health

Agency of Sweden, and data on vaccinations related to Covid-19 was collected from Our World in Data.

The macroeconomic variables collected are inflation, relative unemployment rate, size of M3, and policy rate. The Finnish data on inflation and the relative unemployment rate were collected from Statistics Finland. The policy rate was collected from the Central Bank of Finland, and the size of M3 was collected from FXEMPIRE. The Swedish data on inflation, relative unemployment rate, and size of M3 were collected from Statistics Sweden and policy rate data from the Central Bank of Sweden.

5.3 Descriptive Statistics

This section provides a description of key statistics of the variables used in our regression models for both markets; the results of the Finnish market are presented in Appendix A. This summary includes the number of observations, the minimum and the maximum values, the standard deviation, the mean, the median, and the IQR of the data set. The table also describes kurtosis and skewness, which measure the number of outliers present in the distribution and the extent to which a variable’s distribution is not symmetrical about the mean, respectively.

Table 1. Descriptive Statistics Sweden

	N	Mean	SD	Median	IQR	Min	Max	Skewness	Kurtosis
Realised Volatility	70	0.1751	0.0795	0.1601	0.0797	0.0990	0.6246	3.0107	16.2858
Implied Volatility Forecast	70	0.1819	0.0552	0.1688	0.0769	0.1152	0.4048	1.5758	5.7731
Historical Volatility Forecast	70	0.1730	0.0793	0.1594	0.0832	0.0947	0.6246	3.0853	16.7453
GARCH(1,1) Volatility Forecast	70	0.1746	0.0592	0.1569	0.0428	0.1209	0.5219	3.3583	18.5229
Logarithmised Cases	46	9.7641	1.8032	9.7622	1.5051	2.6391	13.6502	-1.1018	6.8360
Logarithmised Deaths	45	5.4165	1.1741	5.2219	1.7895	3.2852	7.9059	0.3076	2.3975
Logarithmised Vaccinations	35	12.8214	1.5774	13.2848	2.4141	8.9839	14.8562	-0.8112	2.7333
Inflation	70	0.0035	0.0061	0.0027	0.0055	-0.0144	0.0207	0.0953	4.4436
Relative Unemployment	70	0.0765	0.0114	0.0765	0.0170	0.0580	0.1050	0.4665	2.5599
Policy Rate	70	0.0057	0.0141	0	0.005	-0.0050	0.0400	1.5249	3.7467
Logarithmised M3	70	15.2595	0.1486	15.3021	0.2898	15.0016	15.4414	-0.3700	1.5501

When analysing the kurtosis of the volatility estimates in the Swedish market, a high kurtosis is found for all of them. This relates to Brooks (2008) in that financial series often are characterised by a leptokurtic distribution[1] indicating a greater tendency of outliers. The skewness of the volatility estimates are all found to be highly positively skewed. Regarding the Covid-19 variables, it's only Covid-19 cases that have a leptokurtic distribution, with deaths and cases having platykurtic distribution[2]. Covid-19 deaths are approximately symmetric, with Covid-19 cases and vaccinations being highly and moderately negatively skewed. The control variables are all approximately symmetric except for the policy rate, which is highly positively skewed. The policy rate and the inflation have a leptokurtic distribution, and the relative unemployment rate and the M3 have a platykurtic distribution.

The results of the Finnish market are similar to the results of the Swedish market. However, particularly the implied volatility forecast appears to be one variable that does not share similar characteristics to the Swedish market, displaying a platykurtic distribution and being moderately negatively skewed. The Covid-19 variables are also similar, except for Covid-19 deaths showing negative skewness. All the control variables show similar characteristics.

5.4 Autocorrelation, Heteroscedasticity, Multicollinearity

When conducting Lagrange Multiplier tests for autocorrelation, it was found that autocorrelation was present in almost all regressions. Therefore, in the regression analysis, robust standard errors were used for the regressions to provide reliable estimates even when the assumption of heteroscedasticity is violated, which means that our regression outputs will be less sensitive in the presence of heteroscedasticity in the data. Furthermore, the usage of robust standard errors will help against false rejections of the null hypothesis that could arise because of a smaller standard error from autocorrelation. To handle possible biases from multicollinearity, we've included the average variance inflation factor (VIF) for all multivariate regressions in our analysis. All observed average VIFs were between one and five, meaning they are moderately correlated, but there is no need for correction due to it.

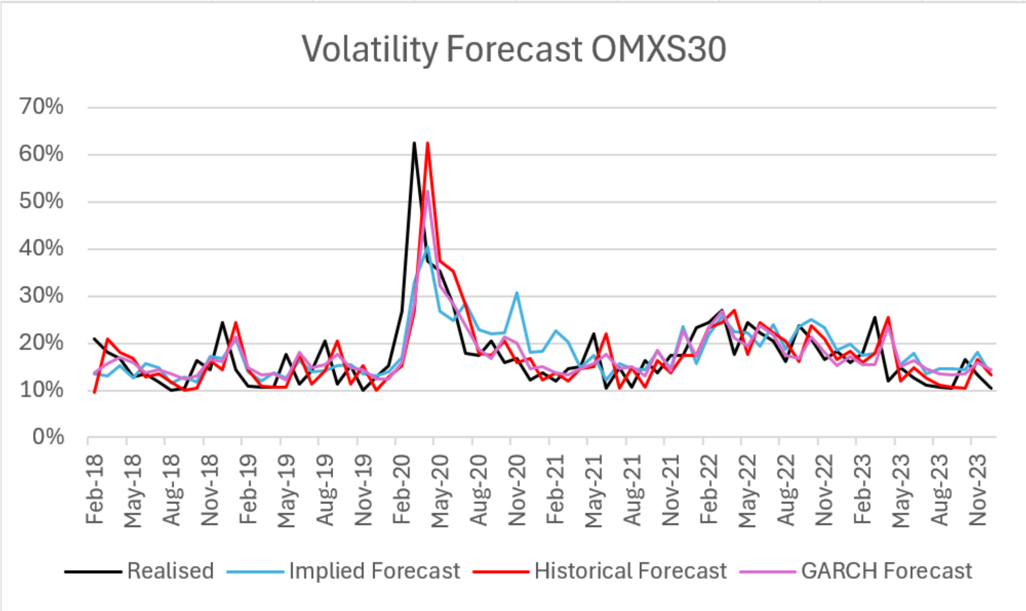
[1] Kurtosis higher than three
[2] Kurtosis less than three

6. Results

In this section, graphs and tables of the results of the OMXS30 index are presented. These results are compared to the results of the OMXH25, which are presented in appendix A. The analysis includes analysis of RMSE, MAE, and regression analysis.

Firstly, a time series plot of the realised volatility and the different volatility forecasts is presented.

Figure 1. Time Series Plot of the OMXS30 index volatilities between 2018 - 2023



When analysing the time series no abnormal trends in the volatility forecasts are identified nor in the realised volatility for the OMXS30. However, the implied volatility forecast of the OMXH25 displays an abnormal trend after October 2019 where it continuously remains around 30% for the remaining period.

6.1 Estimation Errors

In this section, an analysis of the Mean Absolute Error and Root Mean Square Errors is conducted. The analysis is divided into four parts: one for the whole period between 2018 and 2023 and three others for the time periods defined as before, during, and after Covid-19.

Table 2. Root Mean Square Errors and Mean Absolute Errors between the volatility forecasts and realised volatility for the OMXS30 index

	2018-2023		Before COVID		During COVID		After COVID	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Implied Volatility Forecast	0.0595	0.0427	0.0257	0.0124	0.0523	0.0266	0.0120	0.0037
Historical Volatility Forecast	0.0735	0.0489	0.0340	0.0159	0.0644	0.0303	0.0100	0.0027
GARCH(1,1) Volatility Forecast	0.0614	0.0405	0.0275	0.0132	0.0539	0.0241	0.0101	0.0032

The analysis of forecasting errors over the time period 2018 to 2023 indicates that the implied volatility estimate consistently outperforms both the GARCH(1,1) and the historical volatility estimates in predicting realised volatility, regardless of the presence or absence of the Covid-19 pandemic. Specifically, before and during the pandemic, the implied volatility estimate was the most accurate predictor, followed by the GARCH(1,1) estimate in the second position and the historical volatility estimate as the least accurate. However, post-pandemic, the historical volatility estimate surpassed both the GARCH(1,1) and the implied volatility estimates in forecasting realised volatility, where GARCH(1,1) remained second, and the implied volatility estimate was the least accurate. The analysis of the OMXH25 differed from the OMXS30 in that the GARCH(1,1) volatility forecast outperformed both historical and implied volatility forecasts over all periods, and that the implied volatility forecast performed the worst over all periods.

6.2 Predictive Power of Volatility Forecasts

In this section, the predictive power of the volatility forecasts against realised volatility is analysed. The analysis is divided into two parts per forecasting method; the first displays the whole period 2018-2023, and the second displays the three time periods within defined as before, during and after Covid-19 where the before and after periods are dummy variables.

Table 3. Predictive Power of the Volatility Forecasts against Realised Volatility for the OMXS30 index

	Implied		Historical		GARCH	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0014	-0.0021	0.0744***	0.1012***	0.0221	0.0474
	(0.0406)	(0.0542)	(0.0170)	(0.0150)	(0.0356)	(0.0355)
Volatility Estimate	0.9552***	0.9698***	0.5820***	0.5130***	0.8760***	0.7953***
	0.2485	(0.2962)	(0.1195)	(0.1026)	(0.2267)	(0.2167)
Estimate X Before COVID		0.0628		-0.2001**		-0.1270
		(0.1183)		(0.0911)		(0.0896)
Estimate X After COVID		-0.1402		-0.3335***		-0.2637***
		(0.0899)		(0.0881)		(0.0796)
R-squared	0.4399	0.4529	0.3372	0.3793	0.4261	0.4505
VIF		1.40		1.13		1.18
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Between 2018 and 2023 we observe significant predictive power across all estimates. Notably, the implied volatility forecast shows the most predictive power, followed by the GARCH(1,1) volatility forecast, with the historical volatility showing the least predictive power. In regards to the OMXH25, all of the volatility forecasts showed significant predictive power, with the GARCH(1,1) forecast having the highest predictive power, followed by the historical and implied volatility forecast.

Regarding significant parameters, a parameter value equal to one signifies a perfect estimate for realised volatility. When examining specific time periods, only the historical volatility forecast demonstrated consistent significant predictive power in all periods. The historical volatility forecasts predictive power becomes significantly lower before and after Covid-19 compared to during the Covid-19 pandemic, displaying the lowest predictive power after Covid-19. However, its information content was comparatively lower than the other volatility forecasts overall. The implied volatility forecasts showed significant predictive power during the Covid-19 pandemic but not before or after. The GARCH(1,1) volatility forecast showed significant predictive power during and after Covid-19, displaying lower predictive power after Covid-19 than during Covid-19. Moreover, the implied volatility forecast contained more information than the GARCH(1,1) volatility forecast during the Covid-19 pandemic. Similarly to the OMXS30, the historical volatility forecast was the only forecasting method to have significant predictive power over all the specific time periods for the OMXH25, displaying the same pattern for the size of the parameters as the OMXS30. The GARCH(1,1) estimate displayed similar characteristics, being significant during and after the Covid-19 pandemic, but having the highest predictive power of all the forecasting methods for the OMXH25, displaying the highest predictive power during the Covid-19 pandemic. The implied volatility forecast was only significant before Covid-19 and displayed the lowest predictive power out of all the forecasting methods.

Comparing the volatility estimates across the different time periods and the whole time period, both the historical and the GARCH(1,1) volatility estimates performed worse during the Covid-19 pandemic and even more so after it, in contrast to the entire time period. Surprisingly, the implied volatility forecast performed better during the pandemic compared to the overall period. The OMXH25 displayed the same characteristics for the GARCH(1,1) and the historical volatility estimates; the implied volatility forecast was only significant before the Covid-19 pandemic where it performed worse than over the whole period.

6.3 Impact of Covid-19 on Volatility Estimates

In this section, the relationship between Covid-19 cases, deaths, vaccinations, and their influence on realised, implied, historical, and GARCH(1,1) volatility is analysed. Firstly, the Covid-19 variables effects are tested alone in a single variable regression, before the same regressions are done with control variables.

Table 4. Impact of Covid-19 on the Realised Volatility for the OMXS30 index

	Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1482***	0.1421***	0.1794***	5.3480	3.9124*	-4.2282*
	(0.0087)	(0.0093)	(0.0170)	(3.3117)	(2.2824)	(2.3537)
Logarithmised Cases	0.0042***			0.1513*		
	(0.0013)			(0.0078)		
Logarithmised Deaths		0.0095***			0.0250**	
		(0.0034)			(0.0116)	
Logarithmised Vaccinations			-0.0006			-0.0058
			(0.0015)			(0.0035)
Inflation				0.4308	0.5981	0.9256
				(1.3552)	(1.2588)	(1.3056)
Relative Unemployment				-1.2922	-1.4768	0.7309
				(1.2997)	(1.2775)	(0.8256)
Policy Rate				-0.3588	-0.9584*	-1.1960*
				(0.5565)	(0.4976)	(0.6148)
Logarithmised M3				-0.3388	-0.2430	0.2876*
				(0.2150)	(0.1470)	(0.1576)
R-squared	0.0665	0.1097	0.0030	0.1812	0.2507	0.1029
VIF				3.56	2.45	2.68
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

The single variable regression analysis reveals a significant correlation between increased Covid-19 cases and deaths and elevated realised volatility. However, upon introducing control variables, only Covid-19 deaths maintain significance, maintaining its increasing effect on realised volatility. Notably, the parameter of Covid-19 deaths increases with the addition of control variables. The findings were the same regarding the OMXH25 index, however, Covid-19 vaccinations also become significant upon introducing control variables, indicating a decrease in realised volatility with increased vaccinations for the OMXH25.

Table 5. Impact of Covid-19 on the Implied Volatility Forecast for the OMXS30 index

	Implied Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1440***	0.1397***	0.1792***	3.6553**	2.3867*	-6.0504***
	(0.0044)	(0.00515	0.0115	(1.6863)	(1.2033)	(1.7846)
Logarithmised Cases	0.0059***			0.0139***		
	(0.0009)			(0.0037)		
Logarithmised Deaths		0.0121***			0.0231***	
		(0.0021)			(0.0053)	
Logarithmised Vaccinations			0.0004			-0.0070***
			0.0010)			(0.0023)
Inflation				-0.3074	-0.1535	0.2533
				(0.9285)	(0.8184)	(0.9455)
Relative Unemployment				-1.0810*	-1.2707**	0.7921
				(0.6479)	(0.5888)	(0.6606)
Policy Rate				-0.3559	-0.9110**	-1.1567**
				(0.4169)	(0.3772)	(0.4806)
Logarithmised M3				-0.2278**	-0.1430*	0.4077***
				(0.1105)	(0.0787)	(0.1200)
R-squared	0.2727	0.3719	0.0024	0.4006	0.5292	0.3352
VIF				3.56	2.45	2.68
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Analysis of the single variable regressions shows that increasing Covid-19 cases and deaths correlate with increased implied volatility, with deaths having the largest effect. When introducing control variables, all three variables (cases, deaths, vaccinations) emerge as significant factors, with cases and deaths contributing to heightened implied volatility and vaccinations with a relieving effect. The size of the Covid-19 parameters increases with the introduction of control variables. For the OMXH25, we got similar results in the single variable regressions; however, when introducing control variables, all of the Covid-19 factors stopped being significant.

Table 6. Impact of Covid-19 on the Historical Volatility Forecast for the OMXS30 index

	Historical Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1419***	0.1315***	0.1790***	3.6159	3.8921	-6.1613***
	(0.0078)	(0.0101)	(0.0014)	(3.1124)	(2.6106)	(2.1946)
Logarithmised Cases	0.0049***			0.0116*		
	(0.0015)			(0.0064)		
Logarithmised Deaths		0.0119***			0.0262***	
		(0.0042)			(0.0116)	
Logarithmised Vaccinations			-0.0009			-0.0088**
			(0.0014)			(0.0035)
Inflation				-0.1727	-0.2928	0.4887
				(1.4156)	(1.2761)	(1.3233)
Relative Unemployment				-0.0421	-0.7917	1.5559
				(0.8696)	(0.9239)	(0.9337)
Policy Rate				-0.6075	-1.0309**	-1.3232**
				(0.5701)	(0.4428)	(0.5485)
Logarithmised M3				-0.2300	-0.2453	0.4114***
				(0.2055)	(0.1711)	(0.1453)
R-squared	0.0896	0.1746	0.0058	0.1771	0.3243	0.2283
VIF				3.56	2.45	2.68
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Analysis of the single variable regressions indicates that an increased number of Covid-19 cases and deaths are associated with higher historical volatility estimates, with deaths having the largest effect. With control variables, Covid-19 deaths and vaccinations emerge as significant factors. Specifically, increasing Covid-19 deaths correlates to an increased historical volatility, while increased vaccinations act as a decreasing factor. The size of Covid-19 parameters increases with the introduction of control variables. The OMXH25 have similar results for the single variable regressions, however, when introducing control variables, both cases and deaths remain significant. Similarly to the OMXS30, the Covid-19 vaccinations become significant for the OMXH25, correlating increased vaccinations with a decrease in historical volatility.

Table 7. Impact of Covid-19 on the GARCH(1,1) Volatility Forecast for the OMXS30 index

	GARCH(1,1) Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1495***	0.1424***	0.17856***	2.9996	2.8477	-4.9860***
	(0.0045)	(0.0066)	(0.0128)	(2.3651)	(1.9684)	(1.6455)
Logarithmised Cases	0.0039***			0.1005**		
	(0.0011)			(0.0050)		
Logarithmised Deaths		0.0093***			0.0208**	
		(0.0031)			(0.0089)	
Logarithmised Vaccinations			-0.0006			-0.0067***
			(0.0011)			(0.0027)
Inflation				-0.09771	0.0225	0.4182
				(1.1186)	(1.0239)	(1.0661)
Relative Unemployment				-0.4518	-0.9295	0.9259
				(0.6191)	(0.6657)	(0.6687)
Policy Rate				-0.5697	-0.9492***	-1.1771***
				(0.4121)	(0.3336)	(0.3898)
Logarithmised M3				-0.1868	-0.1749	0.3367***
				(0.1559)	(0.1289)	(0.1091)
R-squared	0.1049	0.1885	0.0047	0.2063	0.3532	0.2363
VIF				3.56	2.54	2.68
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Examining the single variable regressions of Covid-19 variables reveals a significant increasing effect on the GARCH(1,1) volatility estimate by Covid-19 cases and deaths, with deaths having the largest effect. Upon the introduction of control variables, the significance of all three variables (cases, deaths, vaccinations) becomes significant, where higher cases and deaths increase GARCH(1,1) volatility, and increased vaccinations decrease GARCH(1,1) volatility. The size of Covid-19 parameters becomes larger when introducing control variables to the regressions. For the OMXH25 we have similar findings from both the single variable analysis and multivariate regressions.

Comparing significant parameters across different volatility forecasts and the realised volatility of the OMXS30, it is found that the implied volatility forecast emerges as the volatility that is influenced the most by Covid-19 cases and deaths, particularly without control variables. Subsequently, the historical volatility estimate emerges as the most affected, followed by realised volatility and GARCH(1,1) volatility, this order is the same for the OMXH25 index. However, the introduction of control variables leads to variations in both the parameters' significance and magnitude. Notably, Covid-19 deaths become the most influential factor for the historical volatility estimate, followed by realised, implied, and GARCH(1,1) volatilities, respectively for the OMXS30. However, for the OMXH25 Covid-19 variables are no longer significant for the implied volatility. Covid-19 deaths affect the realised volatility most, followed by the historical volatility estimate and the GARCH(1,1) volatility estimate respectively. Covid-19 cases retain significance for implied and GARCH(1,1) volatility forecasts, exerting the greatest impact on implied volatility for the OMXS30. For the OMXH25 Covid-19 cases retain significance for historical and GARCH(1,1) volatility forecasts, exerting the greatest impact on historical volatility when introducing control variables. Moreover, Covid-19 vaccinations exhibit a significant negative parameter across all volatility forecasts, with historical having the largest effect followed by the implied, GARCH(1,1) and realised volatility for the OMXS30. Similarly, Covid-19 vaccinations exhibit a significant negative parameter across all volatility forecasts except in the implied volatility forecast, with realised being the most affected, followed by the historical and GARCH(1,1) volatility forecasts for the OMXH25.

In summary, our analysis demonstrates significant relationships between Covid-19 variables and various different volatility estimates. While initial findings highlight the impact of cases and deaths on volatility, the introduction of control variables reveals variations in significance and magnitude, with Covid-19 deaths emerging as the most influential factor in affecting volatility.

6.4 Impact of Covid-19 on Estimation errors

In this part, an analysis of Covid-19 cases, deaths, and vaccinations impact on the different volatility estimates performance in predicting realised volatility is conducted.

Table 8. Impact of Covid-19 on the Implied Volatility Forecasting Errors for the OMXS30 index

	Implied Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0785	-0.0076	0.0873***	6.3694*	6.1290	8.8846
	(0.1001)	(0.0227)	(0.0248)	(3.1387)	(3.6992)	(6.8224)
Logarithmised Cases	-0.0027			-0.0007		
	(0.0092)			(0.0067)		
Logarithmised Deaths		0.0104**			0.0029	
		(0.0047)			(0.0075)	
Logarithmised Vaccinations			-0.0038*			0.0019
			(0.0019)			(0.0033)
Inflation				-1.3168*	-1.3141*	-1.1328*
				(0.6527)	(0.6482)	(0.6567)
Relative Unemployment				-1.9856	-2.0201	-2.3103
				(1.2212)	(1.2638)	(1.5964)
Policy Rate				-0.4210	-0.4117	-0.2451
				(0.7714)	(0.6201)	(0.6223)
Logarithmised M3				-0.4000**	-0.3857	-0.5638
				(0.1958)	(0.2336)	(0.4382)
R-squared	0.0044	0.0534	0.1958	0.3799	0.3833	0.3903
VIF				1.52	1.46	3.22
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

When looking at Covid-19 cases, deaths, and vaccinations individually, we found significant results that increased Covid-19 deaths increase the implied volatility absolute error for the OMXS30. However, when introducing control variables, there were no longer any significant results that the Covid-19 variables affected the implied volatility's ability to forecast the realised volatility of the OMXS30. For the OMXH25 we found no significant results for the single variable regression analysis; however, for the multivariate regression analysis, we found that increased vaccinations increase the implied volatility forecasting error.

Table 9. Impact of Covid-19 on the Historical Volatility Forecasting Errors for the OMXS30 index

	Historical Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.2417**	0.0145	-0.0912**	6.3931	7.9327	13.4447
	(0.1179)	(0.0514)	(0.0356)	(4.2186)	(5.0906)	(9.0345)
Logarithmised Cases	-0.0182*			-0.0183*		
	(0.0107)			(0.0092)		
Logarithmised Deaths		0.0072			-0.0023	
		(0.0103)			(0.0105)	
Logarithmised Vaccinations			-0.0038			0.0044
			(0.0027)			(0.0042)
Inflation				-0.9095	-0.6610	-0.2588
				(1.1397)	(0.9362)	(0.9874)
Relative Unemployment				-1.6877	-1.8624	-2.6226
				(1.6060)	(1.8575)	(2.2130)
Policy Rate				-1.0807	0.0877	0.3711
				(0.8261)	(0.6564)	(0.7446)
Logarithmised M3				-0.3909	-0.5022	-0.8610
				(0.2644)	(0.3219)	(0.5803)
R-squared	0.1138	0.0149	0.1141	0.3442	0.2531	0.2855
VIF				1.52	1.46	3.22
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

When looking at Covid-19 cases, deaths, and vaccinations individually, we found no significant results that the Covid-19 variables affected historical volatility's ability to forecast realised volatility of the OMXS30. When introducing control variables, there were no significant results that the Covid-19 variables affected the historical volatility estimate's ability to forecast realised volatility of the OMXS30. The same results were found for the OMXH25.

Table 10. Impact of Covid-19 on the GARCH(1,1) Volatility Forecasting Errors for the OMXS30 index

	GARCH(1,1) Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1785	0.0253	0.0724**	6.5408*	7.7906	15.0086*
	(0.1129)	(0.0322)	(0.0310)	(3.7691)	(4.6504)	(8.2347)
Logarithmised Cases	-0.0131			-0.0105		
	(0.0103)			(0.0084)		
Logarithmised Deaths		0.0032			-0.0050	
		(0.0064)			(0.0080)	
Logarithmised Vaccinations			-0.0030			0.0059
			(0.0023)			(0.0038)
Inflation				-0.8095	-0.6581	-0.1219
				(1.0617)	(0.8741)	(0.7820)
Relative Unemployment				-2.1518	-2.2189	-3.2571
				(1.5718)	(1.6920)	(2.0344)
Policy Rate				-0.3964	0.3201	0.6793
				(0.8996)	(0.7241)	(0.7401)
Logarithmised M3				-0.4042	-0.4908	-0.9613*
				(0.2346)	(0.2935)	(0.5285)
R-squared	0.0796	0.0039	0.0970	0.3494	0.3164	0.3896
VIF				1.52	1.46	3.22
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

When looking at Covid-19 cases, deaths, and vaccinations individually, we found no significant results that the Covid-19 variables affected the GARCH(1,1) volatility estimate’s ability to forecast. When introducing control variables, there were no significant results that the Covid-19 variables affected the GARCH(1,1) volatility estimate’s ability to forecast. The same results were found for the OMXH25.

To summarise the impact of Covid-19 variables (cases, deaths, vaccinations) on the ability of different volatility measures to forecast realised volatility, we initially identified a significant association between increased Covid-19 deaths and higher absolute errors in implied volatility forecasts of the OMXS30’s realised volatility. However, upon introducing control variables, we found no significant effects of Covid-19 variables on the implied volatility's predictive accuracy. When examining how the historical and the GARCH(1,1) volatility forecasts are affected by Covid-19 variables we did not observe any significant relationships between the Covid-19 variables and forecasting errors of the OMXS30’s realised volatility. The results of the OMXH25 were similar, but the only significant observation was that increased Covid-19 vaccinations are correlated with an increased forecasting error for implied volatility.

7. Discussion

The study investigates the efficiency of different volatility estimates in forecasting realised volatility before, during and after the Covid-19 pandemic in the Finnish (OMXH25) and Swedish (OMXS30) stock markets. When looking at the first research question "What volatility measure best predicts realised volatility during and around the Covid-19 pandemic in Finland and Sweden?" the results demonstrate that the GARCH(1,1) volatility estimation consistently outperforms historical and implied volatility in forecasting the realised volatility of the OMXH25 index during the pandemic. The results align with the findings of Basouny et al. (2021), who investigated the suitability of the GARCH models in capturing the volatility dynamics during crises, but they also align with Li et al. (2023) in that more comprehensive methods perform better when predicting realised volatility during times of crises. Conversely, for the OMXS30 index, the implied volatility estimation was the most accurate volatility predictor as it beat both the GARCH(1,1) and the historical volatility estimates. Surprisingly, the historical volatility estimate showed the highest accuracy after the pandemic period for the OMXS30. Our results align with those of Poon and Granger (2003) in that implied volatility is a better predictor of realised volatility compared to historical and GARCH(1,1) volatility estimates when we examined the OMXS30.

When looking at our second research question "How do different Covid-19 data points, such as the number of persons sick, dead, and vaccinated for Covid-19 affect the volatility measures?" the research reveals a significant correlation between Covid-19 dynamics and volatility measures, with Covid-19 cases, deaths, and vaccinations being the examined factors. Our results are similar to the findings of Basuony et al. (2021), Baek et al. (2020), Albulescu (2021), Zaremba et al. (2020) and Baig et al. (2021), who noticed that volatility increased when the number of deaths and Covid-19 cases rose during the pandemic.

This study considers a new Covid-19 variable by introducing vaccination's effect on market volatility, which was found to have a decreasing effect on volatility. These results align with Baek et al. (2020) in that positive news surrounding Covid-19 decreases volatility. As such, our study expands the understanding of the impact of Covid-19 variables on the different volatility measures and reveals the possibly different significances and magnitudes of these explanatory variables across volatility estimates.

Among the more surprising observations is that volatility forecasts are not similarly reliable for all time periods and indices. Whilst implied volatility always produced good results for the OMXS30 index, the GARCH(1,1) model outperformed the other volatility forecasting methods during the pandemic for the OMXH25 index. This stresses the need to give more attention to the market-specific elements when forecasting volatility. Moreover, the result showed that the only volatility forecast in which the predictive power was affected by a Covid-19 variable was the implied volatility forecast for the OMXH25 index. The implied volatility forecasts absolute residuals became larger with increased Covid-19 vaccinations, something we believe goes against our findings that Covid-19 vaccinations decrease volatility. However, it could be that the realised volatility was affected more by the decrease in Covid-19 vaccinations than the implied volatility forecast, which would make the absolute residual larger.

To conclude, our study helps to understand the predictive power of volatility measures during the Covid-19 pandemic period as well as before and after the period in Finnish and Swedish stock markets. Our hypotheses state that we want to find significant predictors of realised volatility and determine how Covid-19 variables affect the predictors' effectiveness and how they influence volatility as a whole. The results of our research highlight the relevance of taking into account the influence of exogenous shocks, such as the Covid-19 pandemic, for volatility prediction since it affects volatility. One strength is that our study is performed on smaller markets, which provides valuable insights into how different volatility measures perform in less-studied markets. Additionally, incorporating Covid-19 dynamics adds relevance and timeliness to the analysis and the literature regarding a pandemic’s impact on market volatility. However, restrictions have to be recognised. The linear relationship between regression analysis and variables overlooks the possible nonlinearities in volatility dynamics, which could be a limitation. We also believe that other shocks, such as Russia's invasion of Ukraine, could be confounding variables affecting our findings in the during and after periods.

Future research could further investigate the determinants of volatility forecasting performance and include alternative volatility forecasting methods which could offer valuable insights into enhancing prediction accuracy in volatile market environments. Further research could include news events such as lockdowns, quarantine days and more in order to further investigate how different policies may have affected volatility during the Covid-19 pandemic.

8. Conclusion

We investigate the impact of the Covid-19 pandemic on volatility forecasting. Firstly, we investigate the performance and predictive power of implied, historical, and GARCH(1,1) volatility forecasts for realised volatility. Our results found that the GARCH(1,1) volatility estimate was superior for the OMXH25 but that the implied volatility forecast was superior for the OMXS30 index in all periods except after Covid-19, when the historical volatility forecast was the best.

Our results regarding the impact of Covid-19 suggest that increases in confirmed cases and deaths due to Covid-19 are associated with an increase in volatility, and increases in Covid-19 vaccinations are associated with a significant decrease in volatility. However, we only found two significant results regarding how Covid-19 affected the prediction errors, with vaccinations' increasing effect on implied volatility forecasting errors for the OMXH25 and deaths increasing the implied volatility forecasting errors for the OMXS30.

The insights from the study can provide guidance for policymakers in future pandemics by its highlighting the different impacts of Covid-19 factors on volatility. Moreover, the study highlights the importance of limiting deaths associated with the pandemic, suggesting that timely and good public health responses can have significant benefits in reducing market volatility.

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Appendix A

Below, all the tables and figures regarding the OMXH25 will be presented.

Table 11 provides a description of key statistics of the variables used in our regression for the OMXH25. This summary includes the number of observations, the minimum and the maximum values of the variables, the standard deviation, the mean, the median, and the IQR of the data set. The table also contains a description of kurtosis as well as skewness.

Table 11. Descriptive Statistics Finland

	N	Mean	SD	Median	IQR	Min	Max	Skewness	Kurtosis
Realised Volatility	70	0.1746	0.0819	0.1509	0.0634	0.0872	0.6525	3.3351	18.4180
Implied Volatility Forecast	70	0.2689	0.0887	0.3143	0.2026	0.1215	0.2467	-0.8745	1.8740
Historical Volatility Forecast	70	0.1723	0.0829	0.1480	0.0654	0.0851	0.6535	3.2754	17.9849
GARCH(1,1) Volatility Forecast	70	0.1729	0.0616	0.1527	0.0535	0.1126	0.4966	2.7854	13.2220
Logarithmised Cases	46	9.0667	1.9840	9.1802	2.7089	2.0794	12.3982	-0.8823	4.8208
Logarithmised Deaths	45	4.8170	1.4952	4.9708	1.8706	1.1451	6.8459	-0.8570	3.1531
Logarithmised Vaccinations	35	11.6253	2.5872	12.0188	3.0170	5.9269	16.8076	-0.4204	2.8552
Inflation	70	0.0026	0.0040	0.0023	0.0042	-0.0071	0.01448	0.7265	4.0322
Relative Unemployment	70	0.7226	0.0108	0.0700	0.0100	0.0540	0.1090	1.1617	4.4028
Policy Rate	70	0.0098	0.0147	0.0025	0	0.0025	0.0475	1.7502	4.3891
Logarithmised M3	70	12.2571	0.1225	12.2965	0.2077	12.0196	12.3952	-0.6434	2.0348

Figure 2 provides the time-series plot for the OMXH25 between 2018-2023. In it we find that the implied volatility forecast displays an unusual trend after October 2019 remaining around 30%.

Figure 2. Time Series Plot of the OMXH25 index volatilities between 2018-2023

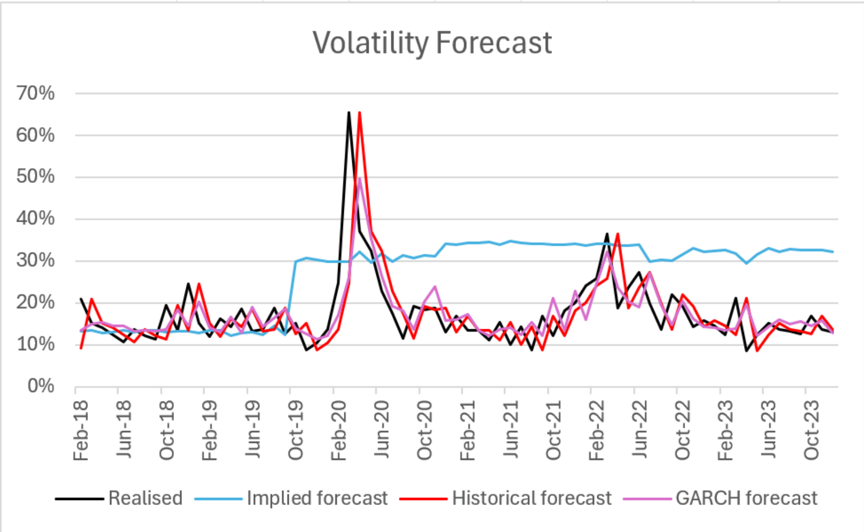

Table 12 presents the RMSE and MAE for between the volatility forecasts and realised volatility for the OMXH25. The table is divided into four parts, one for the whole period between 2018-2023, and three for the time periods defined as before, during, and after Covid-19.

Table 12. Root Mean Square Errors and Mean Absolute Errors between the volatility forecasts and realised volatility for the OMXH25 index

	2018-2023		Before COVID		During COVID		After COVID	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Implied Volatility Forecast	0.1464	0.1223	0.0488	0.0189	0.1230	0.0824	0.0626	0.0210
Historical Volatility Forecast	0.0820	0.0552	0.0340	0.0165	0.0741	0.0363	0.0088	0.0025
GARCH(1,1) Volatility Forecast	0.0657	0.0419	0.0257	0.0123	0.0601	0.0279	0.0062	0.0017

Table 13 presents the predictive power of the volatility forecasts against realised volatility for the OMXH25. Each forecasting method has two parts. The first part displays the whole period 2018-2023 and the second part displays the three time periods defined as before, during, and after Covid-19.

Table 13. Predictive Power of the Volatility Forecasts against Realised Volatility for the OMXH25 index

	Implied		Historical		GARCH	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1373***	0.1737***	0.0880***	0.1107***	0.0321	0.0490**
	(0.0150)	(0.0268)	(0.0139)	(0.0137)	(0.0253)	(0.0238)
Volatility Estimate	0.1388**	0.0719	0.5026***	0.4534***	0.8240***	0.7744***
	(0.0692)	(0.0839)	(0.1024)	(0.0880)	(0.1731)	(0.1606)
Estimate X Before COVID		-0.1990*		-0.2035**		-0.1051
		(0.1130)		(0.0935)		(0.0888)
Estimate X After COVID		-0.1793***		-0.2476***		-0.1596**
		(0.05279		(0.0934)		(0.0777)
R-squared	0.0226	0.0930	0.2585	0.2940	0.3832	0.3944
VIF				1.10		1.15
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 14 presents the relationship between Covid-19 cases, deaths, and vaccinations, and their influence on realised volatility of the OMXH25. First, we test the Covid-19 variables alone in a single variable regression, and then we do the same regression with control variables.

Table 14. Impact of Covid-19 on the Realised Volatility for the OMXH25 index

	Realised Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1495***	0.1509***	0.1789***	1.3905	2.5519*	-3.6846**
	(0.0088)	(0.0088)	(0.0165)	(1.3091)	(1.3832)	(1.6740)
Logarithmised Cases	0.0042***			0.0066*		
	(0.0014)			(0.0036)		
Logarithmised Deaths		0.0077***			0.2185**	
		(0.0027)			(0.0089)	
Logarithmised Vaccinations			-0.0007			-0.0054**
			(0.0016)			(0.0027)
Inflation				0.7346	-1.2491	2.0401
				(3.2288)	(3.4264)	(2.8861)
Relative Unemployment				0.0654	0.4060	0.6601
				(0.8483)	(0.7478)	(0.6945)
Policy Rate				-1.1266**	-2.1345***	-1.0925**
				(0.4322)	(0.7449)	(0.4921)
Logarithmised M3				-0.1023	-0.2000*	0.3140**
				(0.1061)	(0.1133)	(0.1382)
R-squared	0.0568	0.0597	0.0031	0.1035	0.1904	0.1369
VIF				2.72	2.23	1.69
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 15 presents the relationship between Covid-19 cases, deaths, and vaccinations and their influence on implied volatility forecast of the OMXH25. First, we test the Covid-19 variables alone in a single variable regression, and then we do the same regression with control variables.

Table 15. Impact of Covid-19 on the Implied Volatility Forecast for the OMXH25 index

	Implied Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1704***	0.1860***	0.2115***	-5.7216***	-6.9766***	-7.8083***
	(0.0127)	(0.0135)	(0.0145)	(1.1704)	(0.6709)	(0.4996)
Logarithmised Cases	0.0165***			0.0058*		
	(0.0014)			(0.0031)		
Logarithmised Deaths		0.0268***			0.0057	
		(0.0026)			(0.0039)	
Logarithmised Vaccinations			0.0099***			0.0005
			(0.0012)			(0.0010)
Inflation				-2.7670***	-2.7668***	-2.4772**
				(0.9146)	(1.0149)	(1.0994)
Relative Unemployment				0.2780	0.4213	0.4693
				(0.3788)	(0.4204)	(0.4355)
Policy Rate				0.1686	-0.0407	0.1936
				(0.2474)	(0.2799)	(0.3357)
Logarithmised M3				0.4847***	0.5878***	0.6563***
				(0.0979)	(0.0563)	(0.0415)
R-squared	0.7433	0.6234	0.4663	0.8401	0.8299	0.8236
VIF				2.82	2.23	1.69
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 16 presents the relationship between Covid-19 cases, deaths, and vaccinations and their influence on the historical volatility forecast of the OMXH25. First, we test the Covid-19 variables alone in a single variable regression, and then we do the same regression with control variables.

Table 16. Impact of Covid-19 on the Historical Volatility Forecast for the OMXH25 index

	Historical Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1458***	0.1476***	0.1776***	2.2380	2.3599	-4.3361**
	(0.0085)	(0.0087)	(0.0167)	(1.6843)	(1.9205)	(1.7023)
Logarithmised Cases	0.0045***			0.0111**		
	(0.0015)			(0.0049)		
Logarithmised Deaths		0.0080**			0.0246**	
		(0.0033)			(0.0117)	
Logarithmised Vaccinations			-0.0009			-0.0053**
			(0.0016)			(0.0026)
Inflation				-3.5716	-4.6428	-1.1742
				(3.4725)	(3.6203)	(2.8999)
Relative Unemployment				0.3882	0.5351	0.8138
				(0.9845)	(0.9266)	(0.9202)
Policy Rate				-1.4755***	-2.4657***	-1.3071**
				(0.4806)	(0.8289)	(0.5183)
Logarithmised M3				-0.1743	-0.1849	0.3668***
				(0.1383)	(0.1584)	(0.1389)
R-squared	0.0616	0.0630	0.0046	0.1771	0.2523	0.1658
VIF				2.82	2.23	1.69
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 17 presents the relationship between Covid-19 cases, deaths, and vaccinations and their influence on GARCH(1,1) volatility forecast of the OMXH25. First, we test the Covid-19 variables alone in a single variable regression, and then we do the same regression with control variables.

Table 17. Impact of Covid-19 on the GARCH(1,1) Volatility Forecast for the OMXH25 index

	GARCH(1,1) Volatility Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1496***	0.1521***	0.1760***	1.6961	1.6347	-3.6347***
	(0.0055)	(0.0058)	(0.0120)	(1.1491)	(1.2705)	(1.1700)
Logarithmised Cases	0.0039***			0.0089***		
	(0.0011)			(0.0033)		
Logarithmised Deaths		0.0067***			0.0188***	
		(0.0024)			(0.0078)	
Logarithmised Vaccinations			-0.0005			-0.0044**
			(0.0012)			(0.0019)
Inflation				-2.3262	-3.1147	-0.3547
				(2.6766)	(2.6769)	(2.4308)
Relative Unemployment				0.1825	0.3079	0.5243
				(0.8408)	(0.7927)	(0.7674)
Policy Rate				-1.2526***	-2.0066***	-1.1144***
				(0.3487)	(0.5796)	(0.3632)
Logarithmised M3				-0.1282	-0.1236	0.3106***
				(0.0942)	(0.1048)	(0.0949)
R-squared	0.0866	0.0816	0.0028	0.2125	0.2850	0.2060
VIF				2.82	2.23	1.69
No. observations	70					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 18 presents the relationship between Covid-19 cases, deaths and vaccinations, and their influence on the performance of the implied volatility forecast of the OMXH25. First we test the Covid-19 variables alone in a single variable regression, then we do the same regression with control variables.

Table 18. Impact of Covid-19 on the Implied Volatility Forecasting Errors for the OMXH25 index

	Implied Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.2312***	0.2056***	0.1361***	-2.6812	-1.7074	15.1183*
	(0.0758)	(0.0364)	(0.0279)	(6.9416)	(6.5316)	(7.5627)
Logarithmised Cases	-0.0083			-0.0089		
	(0.0074)			(0.0096)		
Logarithmised Deaths		-0.0113			-0.0119	
		(0.0068)			(0.0097)	
Logarithmised Vaccinations			0.0018			0.0093***
			(0.0024)			(0.0022)
Inflation				-4.4834*	-4.1505*	-5.3611***
				(2.4629)	(2.4121)	(1.9660)
Relative Unemployment				-0.9550	-0.9711	-1.5364
				(1.5043)	(1.4398)	(1.3674)
Policy Rate				-0.1801	0.5836	1.4254*
				(1.2019)	(0.9707)	(1.0445)
Logarithmised M3				0.2436	0.1620	-1.2094*
				(0.5642)	(0.5276)	(0.6088)
R-squared	0.0439	0.0680	0.0231	0.1159	0.1395	0.2926
VIF				1.80	1.54	2.41
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 19 presents the relationship between Covid-19 cases, deaths and vaccinations, and their influence on the performance of the historical volatility forecast of the OMXH25. First we test the Covid-19 variables alone in a single variable regression, then we do the same regression with control variables.

Table 19. Impact of Covid-19 on the Historical Volatility Forecasting Errors for the OMXH25 index

	Historical Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1438*	0.0651**	0.1085***	11.7408	12.6860	10.4084
	(0.0811)	(0.0253)	(0.0384)	(8.5367)	(7.9601)	(11.2612)
Logarithmised Cases	-0.0082			0.0028		
	(0.0077)			(0.0075)		
Logarithmised Deaths		0.0002			0.0144	
		(0.0046)			(0.0089)	
Logarithmised Vaccinations			-0.0046			-0.0003
			(0.0030)			(0.0033)
Inflation				-1.3090	-2.3858	-1.0609
				(2.7332)	(2.7825)	(2.4108)
Relative Unemployment				-1.7302	-1.4799	-1.7829
				(1.1548)	(1.1285)	(1.2980)
Policy Rate				-0.0250	-0.4804	-0.2338
				(0.8882)	(0.8916)	(1.0481)
Logarithmised M3				-0.9373	-1.0180	-0.8265
				(0.6885)	(0.6415)	(0.9079)
R-squared	0.0343	0.0000	0.1236	0.2076	0.2611	0.2059
VIF				1.80	1.54	2.41
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Table 20 presents the relationship between Covid-19 cases, deaths and vaccinations, and their influence on the performance of the GARCH(1,1) volatility forecast of the OMXH25. First we test the Covid-19 variables alone in a single variable regression, then we do the same regression with control variables.

Table 20. Impact of Covid-19 on the GARCH(1,1) Volatility Forecasting Errors for the OMXH25 index

	GARCH(1,1) Volatility Forecast Absolute Errors					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0961	0.0520	0.0799	9.8907	10.2263	10.5171
	(0.0740)	(0.0237)	(0.0337)	(7.8103)	(7.6440)	(10.2317)
Logarithmised Cases	-0.0048			0.0026		
	(0.0069)			(0.0061)		
Logarithmised Deaths		-0.0003			0.0087	
		(0.0035)			(0.0063)	
Logarithmised Vaccinations			-0.0032			0.0008
			(0.0026)			(0.0026)
Inflation				-0.8237	-1.4018	-0.6102
				(1.7049)	(1.7732)	(1.6497)
Relative Unemployment				-2.0124*	-1.8863*	-2.1617*
				(1.1357)	(1.0629)	(1.2726)
Policy Rate				-0.2458	-0.5749	-0.3081
				(0.7998)	(0.7087)	(0.8212)
Logarithmised M3				-0.7868	-0.8157	-0.8353
				(0.6286)	(0.6150)	(0.8233)
R-squared	0.0167	0.0001	0.0845	0.2174	0.2438	0.2167
VIF				1.80	1.54	2.41
No. observations	37					

Robust standard errors are reported in parentheses.
*, **, *** indicate significance at the 90%, 95%, and 99% level, respectively.

Appendix B

Below, you will find a detailed description of all the variables used in the analysis.

Variable	Definition
Realised Volatility	The monthly realised volatility annualised, calculated on the daily change in the closing price of the indices.
Implied Volatility Forecast	The implied volatilty from the Black-Scholes-Merton model of a monthly at-the-money call option.
Historical Volatility Forecast	The lagged realised volatility.
GARCH(1,1) Volatility Forecast	The Volatility Forecast made from a Generalised Autoregressive Conditional Heteroskedasticity model annualised.
Covid-19 Cases	The monthly cases of Covid-19.
Covid-19 Deaths	The monthly deaths related to Covid-19.
Covid-19 Vaccinations	The monthly Covid-19 vaccinations
Inflation	The monthly inflation measured in percent.
Relative Unemployment Rate	The monthly relative unemployment rate in percent.
Policy Rate	The policy rate that became active in the month, or was active from before.
M3	The monthly M3, which includes the M2 plus large time deposits, institutional money market funds, short-term repurchase agreements, and larger liquid funds.