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Abstract

This thesis examines the relationship between the OBX Index and NOK/EUR exchange rate, exploring both the short-term dynamics and long-term relationships between these variables. With a dataset including these two main variables and four other control variables from the period of 2000 to 2022, the research employs a comprehensive methodology, including a VAR model where we implement different tests such as a Granger causality test, cointegration analysis, and an impulse response function.

In the short-term analysis, the results reveal bidirectional causal relationships between the stock market and the exchange rate. Turning to the long run, the analysis provides robust evidence of a significant relationship between the variables, implying a long-term trend between the stock market and the exchange rate. The findings highlight the interplay between short- and long-term relationship, which contributes to a comprehensive understanding of the relationship between the Norwegian stock market and the NOK/EUR exchange rate.

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1. Introduction

This thesis aims to investigate if fluctuations in exchange rate can predict changes on the Norwegian stock market. The topic holds great importance for various reasons. As a small country heavily reliant on exports, Norway has a prominent position as a major exporter of oil and fish. This reliance exposes many key industries in Norway to exchange rate risk, which can significantly impact the demand for Norwegian goods and services in foreign markets. Moreover, the movements of the exchange rates can also have implications for Norwegian firms operating internationally or have foreign currency denominated revenues or expenses.

The stock market provides insight into the economic performance a country and is important for capital allocation. Knowledge about the relationship between movements in the exchange rate and changes in the stock market, is thus important to investors to make informed decisions and better manage risk associated with exchange rate exposure. Identifying the relationship, will alert investors with ownership in the Norwegian stock market if changes in the exchange rate will influence their assets, and thus affect their return.

To investigate this relationship, we will study the NOK/EUR exchange rate with the OBX index, as the Euro is a major currency as well as an important one for Norway due to its significant trade with the European Union. Fluctuations in this exchange rate can have an impact on firms' profitability and the return investors receive on their portfolios. According to the efficient market hypothesis, it is expected that the stock market prices, and exchange rates incorporate all available information, and that any new information is immediately reflected in the price. Knowledge about how the stock market reacts to fluctuations in the exchange rate can therefore contribute to a broader understanding of how efficient the market is, which is important in international trade and investments and can be helpful for investors in composing hedging strategies.

Due to Norway being a small, open economy with high exports, the fluctuations in exchange rates can affect the economy and consequently the stock market. There are multiple factors that simultaneously influence the performance of the stock market and therefore it can be hard to isolate the impact exchange rate fluctuations have on the stock market due to the complexity of the economy. The price of oil and electricity, the interest rate differential and the Stoxx 600 Index are added as control variables, as these potentially influence both the stock market and the exchange rate, to retrieve a more accurate determination of the impact between the two main variables.

To address this issue, we will collect historical data from Bloomberg on the OBX Index, containing the 25 most traded companies on the Oslo Stock Exchange as well as historical data on NOK/EUR exchange rate in the period of 2000-2022. We will use a Vector Autoregressive Model (VAR) to examine if there is relationship between the OBX Index and the exchange rate in the data, and if the exchange rate is a useful prediction for the performance of the OBX Index. To enhance our analysis, we conduct a Granger causality test on VAR to explore whether there is a correlation between past values and current values. An Engle-Granger two-step approach and Johansen´s test has also been conducted to analyze whether there is a presence of cointegration, which implies that there is a significant long-term relationship between the OBX Index and the respective variables. To better understand the dynamic behavior between these variables, it is helpful to implement an impulse response function to study how the OBX Index reacts when there is a shock in the exchange rate.

In the short-term dynamics, the Granger causality test revealed bidirectional causal relationships between the OBX Index and NOK/EUR, whereas in the long-term the cointegration analysis indicated a robust and significant relationship between these variables. From the impulse response function, we observed short-term effects of shocks in the exchange rate on the stock market were negative, while in the long run, a positive relationship. These results from our analysis highlights the complex dynamics between the OBX Index and the NOK/EUR exchange rate.

The thesis is organized as follows. We will present theories and review literature that are relevant for our thesis. An overview of the data is provided followed by the hypothesis we want to test and the different methods we use to test this hypothesis. The results of our analysis are thus presented before the thesis is summarized and a conclusion is reached.

2. Theory

In this chapter, we will look into the theoretical framework that form the foundation of this analysis. By exploring different concepts, we aim to develop a comprehensive understanding of the factors and theories that shape the behavior of the stock market and the exchange rate. This theoretical framework will lay the groundwork for subsequent literature review, where we will delve into existing empirical studies surrounding the relationship between the stock market and exchange rates. In the following sections we will present theories that explain the determination of exchange rates and the stock market separately.

2.1 Stock Market

Efficient Market Hypothesis

The efficient market hypothesis states that the stock price incorporates all available information and changes in stock prices is caused by new unpredictable information being made available. If the changes in price were not random and unpredictable, it would indicate that not all available information would be reflected in the stock price and thus the market would not be efficient. Current available information that could be used to predict changes in the stock prices should already be reflected in the price in an efficient market. (Bodie et.al., 2020, p. 332)

Random Walk Hypothesis

The random walk hypothesis states that stock prices can be explained by a random walk model, which is presented as follows (Godfrey et.al., 1964):

$$x_t - x_{t-1} = \varepsilon_t \tag{1}$$

The difference between the stock price today x_t and the previous value x_{t-1} is the term ε_t, which is an independent, random number drawn from a zero-mean distribution. The hypothesis states that information incorporated in past values of the variable are not helpful in prediction of future values. (Godfrey et.al., 1964)

Flow Oriented model

The relationship between exchange rates and stock prices can be illustrated by the flow-oriented framework presented by Dornbusch and Fischer (1980). The model is based on the idea that exchange rates affect the stock price, and that stock prices represent the present value of a company's expected cash flows. Exchange rate fluctuations affect the competitiveness of the company and its cash flows, thus impacting stock market prices. A depreciation in domestic currency is beneficial for companies with high exports since this will make it cheaper and more appealing for foreign investors to purchase their goods or services. Increased revenue increases lead to higher company value and thus higher stock price. For companies that have high imports, the opposite is true. An appreciation of domestic currency is positive as it will make importing from other countries relatively cheaper, and this will cause increased value and in turn a higher stock price.

2.2 Exchange rate

Exchange rate is the rate at which one currency will be exchanged for another currency (Chen, 2022). The exchange rate is an important factor in the global economy and affects trade and movements of money between countries. There are different factors influencing the changes in the exchange rate, such as interest rates, inflation, economic growth, and a country´s balance of trade. The exchange rate could either be fixed or floating. A fixed exchange rate is the rate the government sets as the official exchange rate. Since this currency is not pegged with any of the other currencies we are going to observe, the exchange rates are floating. This means that the exchange rate is determined by market factors, such as the supply and demand, and is constantly changing (The Investopedia team, 2022).

Uncovered Interest Rate Parity

The uncovered interest rate parity theory states that there is a relationship between exchange rates and interest rate differentials, in which a difference in interest rates between two countries should equal the expected change in the exchange rates of the countries' currencies.

$$E_t[\frac{S_{t+1}}{S_t}] = \frac{1+i}{1+i^*} \tag{2}$$

Where: S is the current spot rate, i is the domestic interest rate, and $i^*$is the foreign interest rate.

According to the uncovered interest rate parity theory, investors will expect a depreciation of the currency of a country with higher interest rates relative to a country with lower interest rates. The interest differential between two countries is compensated for by the depreciation, to eliminate the possibility of investors exploiting an arbitrage opportunity. Due to this compensation, the expected return of a foreign money market investment will be equal to that of a domestic money market investment, despite uncertainty of the future exchange rate value. (Bekaert & Hodrick, 2011, p. 211-212)

Unbiasedness Hypothesis

An important part of the theoretical foundation of the uncovered interest rate parity theory is the unbiasedness hypothesis. It states that the expected future spot rate equals the forward rate, thus providing the assumption that the forward rate is an unbiased predictor of the future spot rate. For the unbiasedness hypothesis to hold, both the seller and the buyer of the forward contract must expect zero profits, which incorporates the assumption of an efficient market in which investors rationally process all available information, as no one would be expected to enter a forward contract whilst expecting a loss. (Bekaert & Hodrick, 2011, p. 212)

$$F_t = E_t[S_{t+1}] \tag{3}$$

Stock Oriented Model

The stock-oriented model presented by (Branson, 1981) and (Frankel, 1984) moves in the opposite direction of the flow model, i.e. from the stock market to the exchange rate. According to the model it will be more attractive to invest in the stock market when it is performing well, and when attracting foreign investors, the demand for domestic currency will increase, which in turn can lead to an appreciation. Vice versa will a bad performing stock market not attract as many investors and some might also sell, this will cause a decreased demand for domestic currency which can lead to a depreciation.

3. Literature Review

In this section, we will outline previous literature that is relevant for our investigation. We focus on literature that analyzes the relationship between exchange rates and the stock market performance in other countries and build on this research to investigate the same relationship in Norway, of which there is little previous research.

Several previous studies have found a significant relationship between exchange rates and stock market prices. A study of the relationship between the two variables in the United Kingdom, the United States and Japan found that changes in exchange rates influence the stock market (Phylaktis & Ravazzolo, 2005). A study of capital markets in the United States under floating exchange rates found that the value of the US dollar was positively correlated with stock prices in the US (Aggarwal, 1981). In South Africa, a study found that the relationship between the exchange rates and stock market performance is negative in the long run (Javangwe & Takawira, 2022). Richards et al., (2009) found evidence that the relationship between stock prices and exchange rates were positively cointegrated in Australia in the sample period 2003 to 2006 using the Johansen cointegration test. From the same sample period, Granger causality was found to run from stock prices to exchange rates.

There are also examples of studies that get different results than our hypothesis. One is a study using data for 42 countries seeks to investigate the correlation between exchange rate movements and equity returns. The trading strategy is to go long in the indices with the highest expected equity returns, and short those with the lowest. The strategy seeks to exploit violations of the Uncovered Equity Parity condition, that depreciation of a currency will offset the equity return. Results from the trading strategy show that the returns are driven by local equity market returns, and that stock market performance does not respond to exchange rates. The study concludes that stock market returns do not explain much about exchange rates. (Sarno et al., 2016, p. 1045-1080)

In the period our data covers, there have been two financial crises, the financial crisis in 2008 and the Eurozone debt crisis that occurred in the aftermath of the 2008 crisis. The eurozone debt crisis particularly affected Spain, Portugal, Ireland, Greece, and Italy (Krugman et al., 2014, p 691-692). Previous studies have shown that findings of a relationship between exchange rates and stock market performance can vary based on macroeconomic circumstances, such as a financial crisis. One example is a study from Spain where no causal relationship was found in the period 1997-2007, but for the period 2008-2015 after the financial crisis of 2008, there were significant causal relationships (Luzarraga-Goitia et al., 2021). Another example is a study examining the relationship between exchange rates and the stock market found that the relationship between the two variables were higher during the banking crisis in the period 2007 to 2010, than in the years prior. The study included the US, the UK, Switzerland, Canada, Japan, and the euro area. (Caporale et.al., 2014)

There is a substantial amount of literature focusing on the relationship between stock markets and exchange rates. However, as the relationship is complex and can be affected by many factors as well as macroeconomic conditions the results of studies differ, which can be caused by what countries and time periods are chosen for the study, as well as which and how many factors that are investigated (Bahmani-Oskooee & Saha, 2015). Thus, we find it interesting to investigate the relationship from a Norwegian perspective.

4. Data

In this chapter, we transition from the theoretical foundations and relevant literature discussed in the previous chapters to the practical implementation of our research. We provide an overview of the data utilized in our study, including its sources, variables, and the sample period covered.

The data used in our research is crucial for testing our research question and drawing meaningful conclusions. To ensure its reliability and relevance, we carefully selected and obtained the data from reputable sources. Additionally, we outline the specific variables considered in our analysis. Along with our main variables of interest, such as the NOK/EUR exchange rate and the Norwegian stock market index, we also include control variables that may influence the relationship under investigation. These control variables are selected based on prior research and theoretical considerations.

4.1 Data Collection

We collect our data from Bloomberg and investing.com. From Bloomberg, we extract the OBX Index, oil price, NIBOR, EURIBOR, Stoxx Europe 600 and electricity price. Exchange rates are extracted from investing.com, which is a financial website that provides a range of market data, analysis, charts and other tools for investors and traders. The period for our data is from year 2000 to year 2022. We have selected this period due to the availability of the data, as data for the OBX Index were not available before year 2000.

4.2 Data Analysis Tools

In this section, we introduce the tools employed for the analysis of our research question and hypothesis. The Python programming language has been utilized extensively throughout our study to construct and implement various models, tests, and statistical techniques. Python is a highly adaptable and popular programming language known for its simplicity, readability, and extensive collection of libraries and packages. It provides a comprehensive ecosystem for data analysis, statistical modeling, and visualization, making it an ideal choice for our research. We will refer to different functions in python that are used in the different models when we explain our approach in the analysis.

4.3 Variables

If we only investigate the correlation between the exchange rate and the stock exchange index without controlling for other factors, we might falsely assume that changes in the exchange rate are the only cause of changes in the stock exchange. However, there may be other factors that influence both the exchange rate and the stock exchange, such as commodity prices, the interest rate level in Norway, relevant market index etc. By including additional variables in the analysis, it could lead to a more accurately determination of the impact the exchange rate has on the stock exchange, while controlling for the effects of other relevant factors.

Stock market prices and exchange rates can be exposed to daily fluctuations driven by various factors such as news or geopolitical events. To mitigate some of this volatility and gain broader perspective, we have chosen to utilize monthly data for our analysis. This also allows us to explore a dataset that spans a longer time period compared to using daily or weekly data, while still providing relatively frequent observations. By working with monthly data, we can effectively capture underlying trends in the economy without having an overwhelming amount of data to interpret. The interest rates are based on interbank offered rates, and these have one month maturity. The monthly maturity gives us insight into the expectations for the economy for the next month and is chosen because this time horizon matches our other data.

OBX Index

The OBX Index serves as a prominent performance indicator for the Norwegian stock market in this thesis. This index consists of the 25 most liquid and traded companies on the Oslo Stock Exchange. The listed companies are revised twice a year, in June and December. The OBX Index is tradable, both exchange traded options and futures are available. The index is composed of companies from numerous industries and is a widely followed benchmark for the Norwegian stock market. The dataset contains monthly data of the returns on the OBX Index in the period from January 31st, 2000, to December 30th, 2022. (Euronext, 2023) The visual representation below portrays the fluctuation pattern in the OBX index throughout this specific time frame, offering valuable insights into its dynamic movements.

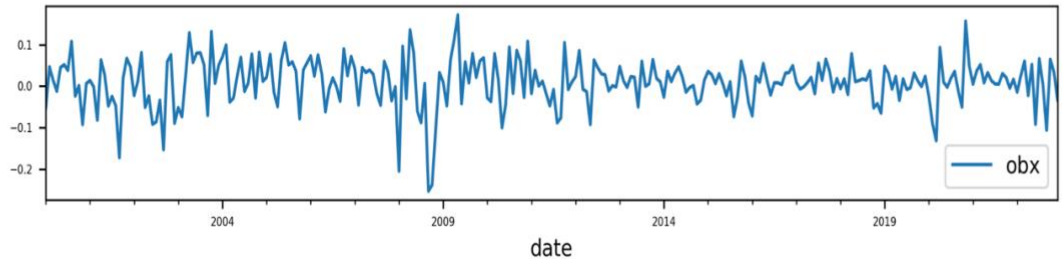

Figure 1: OBX Index

Exchange Rate

The NOK-EUR exchange rate is employed in this thesis, utilizing monthly data spanning from 01.02.2000-01.01.2023. In our dataset, exchange rate data is available on the first day of the month while the other variables in are reported from the end of each month. To ensure consistency, we adopted the approach of using the exchange rate on the first day of the month to represent the exchange rate for the preceding month. The exchange rate is denoted in Norwegian Krone as the domestic currency. The accompanying plot below visually captures the fluctuations in the exchange rate over the specified time period, shedding light on its inherent dynamic and trends.

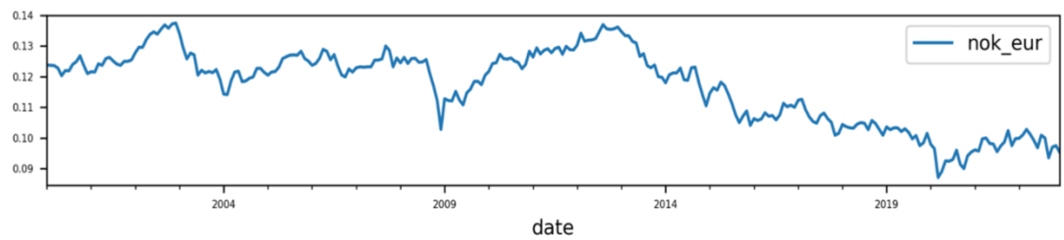

Figure 2: NOK/EUR Exchange Rate

Interest Rate Level

The Euro Interbank Offered Rate (Euribor) is used as a reference interest rate for the Eurozone, while the Norwegian Interbank Offering Rate (NIBOR) is the corresponding benchmark for the Norwegian market (The European Money Market Institue, n.d.; Nore, n.d.). In our analysis, we calculate the interest rate differential by subtracting the 1-month Euribor from the 1-month NIBOR to assess the disparity in interest rate levels between Norway and the Eurozone. The dataset includes Euribor and NIBOR data from January 31st, 2000, to December 30th, 2022.

NIBOR represents the average interest rate at which selected Norwegian banks can borrow from each other, serving as a vital indicator of the Norwegian financial system's condition (NoRe, n.d.). Fluctuations in NIBOR can give insight into the state of the financial markets, including the Norwegian stock exchange. Lower NIBOR suggests improved credit conditions, while higher NIBOR indicates increased perceived lending risk among banks. Consequently, rising NIBOR may lead to more expensive borrowing, potentially reducing investment and economic activity and negatively affecting the stock exchange.

Changes in the policy rate from the central bank can influence the NIBOR as well. An increase in the policy rate signals a tightening of the monetary policy, and thus the perceived risk of lending amongst banks can be increased which can lead to a higher NIBOR. Vice versa will a decrease in the policy rate stimulate the economy and make it more affordable for banks to lend, which can cause a decrease in the NIBOR.

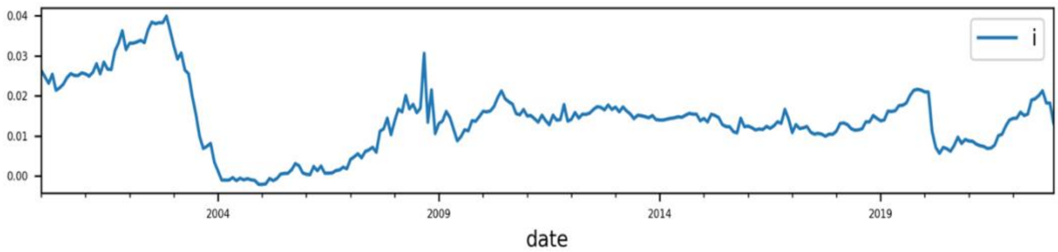

Figure 3: Interest Rate Differential

The plot above illustrates the fluctuations and trends in the interest rate differential between the 1-month NIBOR and 1-month Euribor over the specified time frame. This differential provides insights into the disparities between interest rates in Norway and the Eurozone, highlighting the relative borrowing costs and credit conditions between the two regions.

Commodities

Commodity prices can have a direct impact on the Norwegian economy, as Norway is a major exporter of natural resources such as oil and gas. Fluctuations in commodity prices can therefore have significant effects on the country's trade balance, government revenues, and overall economic performance. They can also have an indirect impact on the stock market and exchange rates, as changes in commodity prices can affect investor sentiment and expectations about future economic conditions.

Oil prices are an important control variable as they are a major driver of the Norwegian economy, given that Norway is a significant oil producer. An increase in oil prices can positively impact the Norwegian stock exchange by increasing revenue for oil companies and improving economic prospects for other industries, and vice versa. Brent crude oil price is widely used as a reference for prices of oil in Europe. Monthly data from January 2000 to December 2022, is collected from Bloomberg. As Norway is a large exporter of oil, we believe it is necessary to account for changes in the oil price as these can also affect the OBX index and the exchange rate. The plot below depicts the fluctuations and trends in the oil price over the specified time frame.

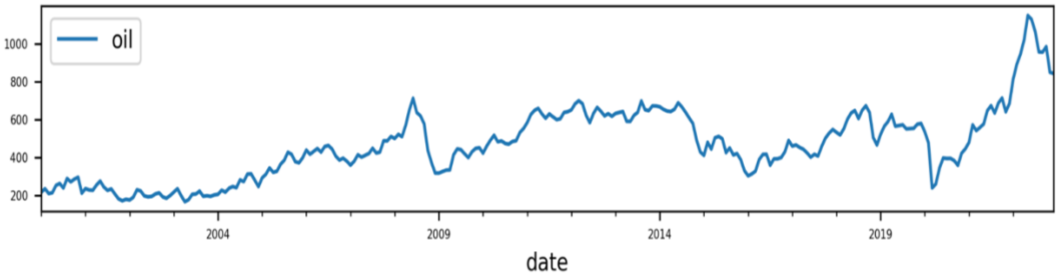

Figure 4: Oil Price

Electricity prices are also an important control variable as energy prices have a significant impact on the Norwegian economy and stock market. As Norway is a major exporter of energy, fluctuations in energy prices can affect the profitability of Norwegian energy companies and, consequently, have an impact on the OBX index.

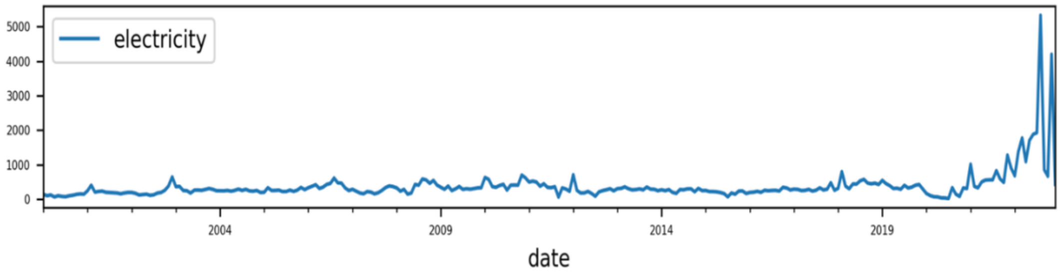

Figure 5: Electricity Price

The plot above showcases the fluctuations in electricity prices over the specified time period. It is noteworthy to observe a significant fluctuation in the electricity price, particularly towards the end of the time span after 2022. This notable fluctuation in electricity prices is also evident in the oil price plot, demonstrating a similar pattern. Additionally, we can observe a comparably less pronounced fluctuation in the OBX index during the same period. These observations suggest potential interconnectedness among electricity prices, oil prices, and the behavior of the OBX index.

Foreign Market Index

Including a market index in the analysis is important as changes in the index can affect investors' risk aversion and affect stock exchanges around the world. In the context of analyzing the relationship between the NOK/EUR exchange rate and the OBX index, it is appropriate to use an index that is closely related to the Norwegian stock market. The Stoxx Europe 600 is a broad-based European stock market index that includes stocks from 17 European countries with a fixed number of 600 components (Qontigo, n.d.). Including the Stoxx Europe 600 as a control variable can help capture the spillover effects of changes in the European stock market on the OBX index and the NOK/EUR exchange rate. An increase in the Stoxx Europe 600 index could signal positive sentiment and confidence in the European economy, which could lead to increased investments in the Norwegian stock exchange and strengthen the Norwegian krone against the euro, vice versa. By including a market index as a control variable, we can account for these broader market movements and better isolate the effects of the exchange rate on the OBX index. The visual representation below portrays the fluctuation pattern in the Stoxx600 market index throughout the specific time frame, with insights into its dynamic movements.

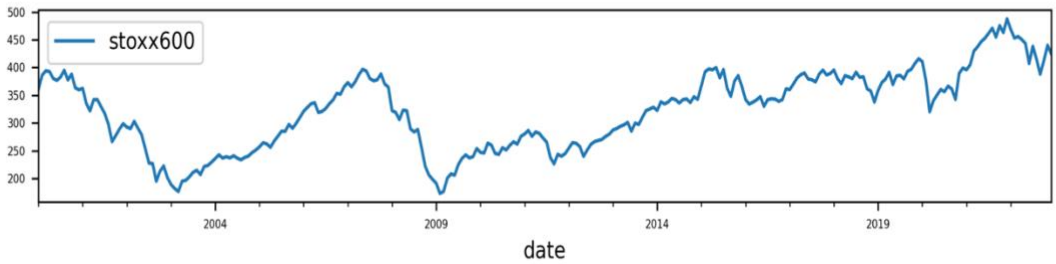

Figure 6: Stoxx600 Market Index

4.4 Summary of Data

The table below presents a comprehensive overview of the data used in our thesis. The dataset consists of various variables collected over a specific period, each capturing an essential aspect of our research. The table 1 below presents the name of these variables, the corresponding observations, and the time span covered.

Period	Name of variable		Observations
31.01.2000 - 30.12.2022	obx	OBX index	276
01.02.2000 - 01.01.2023	nok_eur	NOK/EUR exchange rate	276
31.01.2000 - 30.12.2022	oil	Oil price	276
31.01.2000 - 30.12.2022	i	Interest rate differential	276
31.01.2000 - 30.12.2022	stoxx600	Stoxx600 market index	276
31.01.2000 - 30.12.2022	electricity	Electricity price	276

Table 1: Data Summary

4.5 Data Plot

Having introduced the data variables, we proceed to analyze and visualize the time series data. By examining the plot over the OBX Index and the NOK/EUR exchange rate and identifying potential patterns or trends, we aim to gain insights into the behavior of the variables over the selected time span. This analysis will provide valuable context for our subsequent empirical analysis and help us interpret the results in a meaningful manner. From observing the plot, it becomes evident that the dynamics between the NOK/EUR exchange rate and the OBX index differ in terms of the frequency and magnitude of fluctuations.

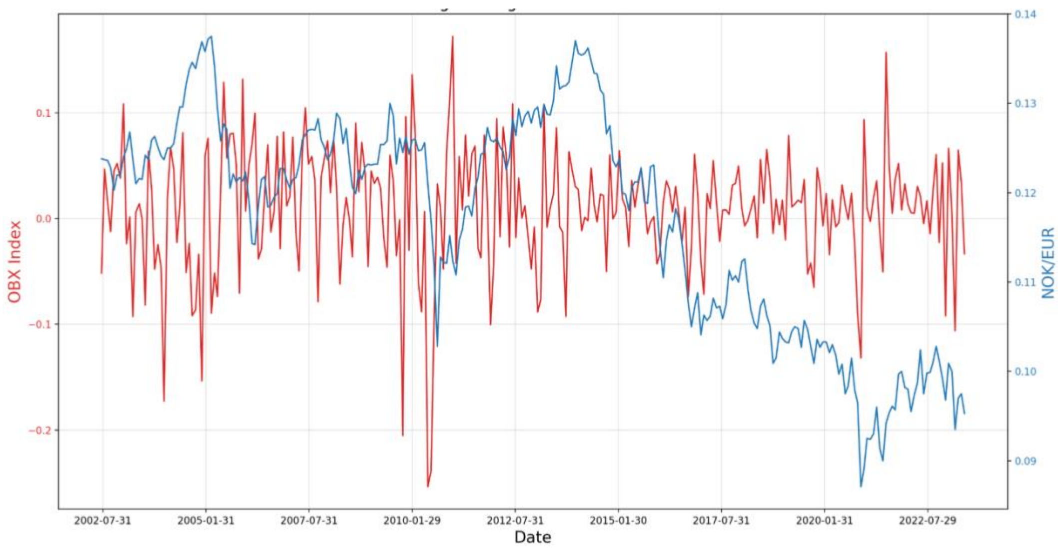

Figure 7: OBX Index and NOK/EUR Exchange Rate

The OBX index exhibits more pronounced fluctuations compared to the NOK/EUR exchange rate in the short run. This suggests that the stock market index experiences more rapid and volatile movements, with frequent ups and downs, compared to the relatively smoother changes in the exchange rate during shorter time periods. In the long run, the NOK/EUR exchange rate demonstrates larger fluctuations compared to the OBX index. These long-term fluctuations in the exchange rate tend to be more gradual and sustained, indicating a gradual decrease or increase over time.

That the exchange rate shows greater long-term variations, while the stock market index exhibits more rapid and pronounced short-term movements, could have some implications to our analysis. When examining the causal relationship between the two variables, it could be important to consider the appropriate time frame for analysis. Short-term fluctuations may indicate a more immediate impact, while long-term fluctuations may reflect broader economic trends. The differences in the fluctuations could also suggest that they may respond to different underlying factors and dynamics. It could therefore be interesting to study the relationship between the OBX index and the other variables included in our analysis that could have a great impact on the stock market.

5. Hypothesis & Empirical Method

In this chapter, we outline the empirical methods employed to address our research question. Our aim is to establish the causal relationship between the exchange rate and the Norwegian stock exchange while considering the influence of other pertinent factors. To achieve this, we incorporate four control variables in our analysis.

To examine the short-term dynamics among the variables, we utilize a VAR model. Furthermore, we employ a Granger causality test, which is a condensed representation of the coefficients in the VAR model. This test enables us to assess the existence and direction of causal relationships between the variables. In addition to investigating short-term dynamics, we also explore long-term relationships between the variables through cointegration analysis. Cointegration assesses whether the variables have a stable and lasting relationship, indicating a common long-term trend. To delve further into the dynamic interactions within the system, we employ impulse response functions. These functions employ the VAR model to illustrate the impact of shocks to one variable on the others, providing insights into the transmission of effects over time.

It is important to note that while these methodologies may appear distinct, they are all employed within the framework of the VAR model. The VAR serves as the foundation for analyzing both short-term dynamics and long-term relationships, while the different techniques within the VAR framework offer various perspectives and insights.

5.1 Hypothesis

We want to test a specific hypothesis related to the impact of exchange rate fluctuations on the Norwegian stock market and investigate if it is possible to determine that fluctuations in the exchange rate can predict changes in the stock market performance.

$$H0: Fluctuations\ in\ the\ exchange\ rate\ have\ a\ significant$$

$$impact\ on\ the\ Norwegian\ stock\ market.$$

This hypothesis is interesting because it is a fundamental question in international finance and has significant implications for investors and policymakers. Depreciation of the Norwegian currency causes Norwegian goods and services to be cheaper for foreign investors and can thus lead to more export for Norwegian businesses. This can in turn lead to better results for the businesses and subsequently increased stock prices. Vice versa, an appreciation of the Norwegian currency will make it more expensive for foreign investors and can lead to worse results for Norwegian businesses and in turn lower the stock prices. If we find evidence to support this hypothesis, it suggests that changes in the exchange rate can be used to predict changes in the Norwegian stock market. This would be valuable information for investors and could help policymakers understand the transmission of shocks between the exchange rate and the stock market. On the other hand, if we fail to find evidence to support this hypothesis, it suggests that other factors are more important in driving changes in the Norwegian stock market.

5.2 Vector Autoregressive Model

A Vector Autoregressive (VAR) model is an extension of the traditional univariate autoregression model and is used to analyze and understand the dynamic relationships between multiple time series variables. (Brooks, 2008, p. 290). The model has many advantages, such as it allows us to analyze a wide range of data, but it also encounters some limitations and problems relative to other models. The model uses little theoretical information about the relationship between the different variables, encounter issues in deciding lag length, includes too many parameters, and requires all components in the model to be stationary (Brooks, 2008, p. 292). VAR can be specified by the following equations, where *g* denote the number of variables in the system and *k* the number of lags:

$$\underset{g\times 1}{y_t} = \underset{g\times 1}{\beta_0} + \underset{g\times 1\, g\times 1}{\beta_1 y_{t-1}} + \underset{g\times 1\, g\times 1}{\beta_2 y_{t-2}} + \cdots + \underset{g\times 1\, g\times 1}{\beta_k y_{t-k}} + \underset{g\times 1}{u_t} \qquad (4)$$

(Brooks, 2008, p.291)

For this thesis the VAR model can look at the historical relationship between the given exchange rate and the OBX index to estimate how a change in the exchange rate can predict changes in the Norwegian stock market. In the model we can use the historical exchange rates and stock market index as the dependent variable, and their past values as independent variables. Once the coefficients of the independent variables are estimated, the VAR model can be used to make predictions about how changes in the exchange rate will affect changes in the OBX index in the future.

One advantage of the VAR model is that one does not need to identify which variables that are exogenous and endogenous since all variables are endogenous. The VAR model captures this dynamic interrelationship among these endogenous variables which also includes the four control variables. By including these control variables in the model, we can better understand the impact of external factors on the stock market index, and potentially improve the accuracy of our forecasts.

5.2.1 Testing for Unit Roots

When implementing VAR, the model requires the time series to be stationary. Stationary time series are characterized with a constant mean, variance, and covariance for each lag (Brooks, 2008, p.318). Using non-stationary data could lead to spurious regressions. A unit root test therefore needs to be conducted to check for stationarity in the given time series. The test used in this analysis are the Augmented Dickey Fuller (ADF) test. The null hypothesis of the ADF test is that the time series are non-stationary versus the alternative hypothesis which state that the time series is stationary. The model for the unit root test can be written as follows:

$$y_t = \phi y_{t-1} + \mu + \lambda t + u_t \tag{5}$$

$$test\ statistic = \frac{\hat{\psi}}{\widehat{SE\hat{\psi}}} \tag{6}$$

The ADF test statistic, stated above, measures the strength of evidence against the null hypothesis of a unit root. If the null hypothesis is not rejected, the time series are non-stationary, and y_t needs to be differenced before it becomes stationary. (Brooks, 2008, 327-329)

5.2.2 Optimal Lag Length

The optimal lag length is the number of lags that provides the best balance between capturing the relevant dynamics in the data and avoiding overfitting the model. To identify the optimal lag length in a time series model one possible approach is to use information criteria. The information criteria include a term which is a function of the residual sum of squares as well as penalty for the loss of degrees of freedom from adding extra parameters. The goal is to choose the number of parameters which minimizes the value of the information criteria. There are several different criteria one can use. In this thesis the Akaike´s information criterion stated below are used. In the criteria below the $\hat{\sigma}^2$ represent the residual variance and quantifies the amount of unexplained variation or noise in the model. (Books, 2008, p.232)

$$AIC = \ln{(\hat{\sigma}^2)} + \frac{2k}{T} \tag{7}$$

5.3 Granger Causality Test

A disadvantage with VAR is that it is difficult to interpret which variables that have, or do not have, significant effects on the dependent variable. To get a more meaningful result from the VAR, a Granger causality test can be conducted on VAR.

Granger causality does not prove that changes in one variable directly causes change in another, but with statistically significant results from the Granger test it is reasonable to state that such a relationship appear to exist between the variables (Brooks, 2008, p. 311-312). The test examines whether there is a correlation between the current value of stock returns and past values of the exchange rate, and thus if the exchange rate can be useful in forecasting changes in the stock returns. (Brooks, 2008, p.297-298)

The test seeks to determine whether changes in y_1 cause changes in y_2. If y_1 granger-causes y_2, lagged values of y_1 should be statistically significant in the equation of y_2. This implies a unidirectional causality from y_1 to y_2. Conversely, if y_2 causes y_1, lagged values of y_2 should be significant in the equation for y_1. If both sets of lags in the test are significant, this indicates a bi-directional causality. If neither set of lagged values is statistically significant, it suggests that y_1 and y_2 are independent. The Granger causality test does not imply a causal relationship in the traditional sense but rather assesses the correlation between the current value of one variable and past values of others. (Brooks, 2008, p.298)

5.4 Cointegration

The concept of cointegration in econometrics suggests that if two or more series are connected by a long-run equilibrium relationship, they will exhibit a close relationship over time, despite containing stochastic trends or being non-stationary individually. The difference between these series, known as the residuals or disequilibrium error, remains constant and stationary. This notion reflects the idea that an economic system tends to converge towards a long-run equilibrium over time, with the residuals representing the deviation from this equilibrium at any given point in time (Harris & Sollis, 2003, p.34).

Engle-Granger Two-step Approach

Cointegration can be tested by using a several cointegration tests. The Engle-Granger two-step approach is a method used to test for cointegration between two variables and involves two main steps. In step one, all individual variables need to be integrated of order one to become stationary. Then estimate the OLS to determine the relationship between the variables in levels. The residual from this cointegration regression is saved and tested for any unit roots to ensure stationarity. (Brooks, 2008, p.341).

In step two, the residuals from step one is used as one variable in the error correction model, as presented below.

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 \hat{u}_{t-1} + u_t \tag{8}$$

Where $\hat{u}_{t-1} = y_{t-1} - \hat{\gamma} x_{t-1}$

(Brooks, 2008, p.341)

In this model the differenced variables, Δy_t and Δx_t, are regressed on the lagged residuals, $\hat{u}_{t-1}$. The estimated coefficient β_1 represent the short-term relationship between the variables, while the coefficient $\hat{\gamma}$ represent the long-term relationship. The coefficient β_2 examines the speed at which the variables adjust back to their long-term equilibrium after a shock. (Brooks, 2008, p.338-339)

Johansen´s Test for Cointegration

The Johansen´s test can test for cointegration among multiple time series at once. The VAR model must be transformed into a vector error correction model (VECM) to perform the Johansen test (Brooks, 2008, p. 350):

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \ , \tag{9}$$

$$where\ \Pi = (\textstyle\sum_{i=1}^{k} \beta_i) - I_g \ \text{ and } \Gamma_i = \left(\textstyle\sum_{j=1}^{i} \beta j\right) - I_g$$

The Johansen approach defines the following two test statistics (Brooks, 2008, p. 351):

$$\lambda_{trace}(r) \ = \ -T \textstyle\sum_{i=r+1}^{g} \ln\left(1 - \widehat{\lambda_i}\right) \tag{10}$$

and

$$\lambda_{max}(r, r+1) \ = \ -T \ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{11}$$

λ_i represents the eigenvalues from the Π matrix. $\widehat{\lambda_i}$ is the estimated value of the Π matrix *i*th ordered eigenvalue. For each eigenvalue there is a cointegrating vector, and these are eigenvectors. If the eigenvalue is significant and different from zero, that is an indication of the cointegrating vector being significant. We see from the formula that a higher $\widehat{\lambda_i}$ causes a higher test statistic. The null hypothesis of the test postulates that the number of cointegrating vectors equal to r and is rejected if the test statistic exceeds the critical value. λ_{trace} is a jozint test with the null hypothesis is that there are less than or *r* number of cointegrating vectors, with the alternative hypothesis that the number of cointegrating vectors exceeds r. λ_{max} performs separate tests, using the hypothesis stated below. (Brooks, 2008, p. 351-352)

$$H_0\!: \ r = 0 \ vs \ H_1\!: \ 0 < r \leq g. \tag{12}$$

$$H_0\!: \ r = 1 \ vs \ H_1\!: \ 1 < r \leq g$$

$$H_0\!: \ r = 2 \ vs \ H_1\!: \ 2 < r \leq g$$

$$\vdots \qquad\qquad \vdots$$

$$H_0\!: \ r = g - 1 \ vs \ H_1\!: \ r = g$$

Once cointegration is established, it can be used to estimate a long-term relationship between the series by using the error correction model which estimates the short-term and long-term relationship between the series (Brooks, 2008, p.338).

5.5 Impulse Response Function

Impulse response function (IRF) is a tool used to study the dynamic behavior of a VAR model. It shows the response of each variable in the model to a one-time shock to another variable. More specifically, the IRF traces out the responsiveness of each dependent variable in the VAR to a one-unit shock to one of the independent variables (Brooks, 2005, p.299). The dynamic effects of a shock to a variable on the variables in the VAR model over time can be written as:

$$y_t = A(L)^{-1}u_t = u_t + \sum_{i=1}^{\infty} \Phi_i u_{t-i} \tag{13}$$

From this equation, the VAR model is simulated tracing the marginal effect of a shock to one variable by setting one component of u_t equal to one while keeping all other variables unchanged. We evaluate the response of each variable y_t to this impulse as time progresses, where these responses are captured in the elements of Φ matrices. (Lütkepohl, 2010, p.145)

6. Results and Analysis

In this chapter, we delve into the results and analysis of our study aimed at examining our hypothesis. As highlighted in the literature review, previous research has yielded mixed findings regarding the relationship between exchange rates and stock prices.

Given Norway's status as a significant oil exporter, it is plausible that both exchange rates and stock market performance in the country are more influenced by fluctuations in oil prices rather than a direct relationship between exchange rates and stock market prices. In this context, it becomes essential to consider the role of other variables that may have a stronger impact on both exchange rates and stock market performance. These additional factors could potentially overshadow the direct relationship between exchange rates and stock prices, highlighting the need for a comprehensive analysis that explores the influence of various variables on the observed dynamics.

In the following sections, we present the detailed test results, discuss their implications, and provide a comprehensive analysis of the observed patterns and dynamics between exchange rates and stock market performance.

6.1 Exploring Stationarity and Optimal Lag Order

Before conducting statistical tests such as Granger causality, cointegration, and VAR, it is essential to ensure that the time series data used in the analysis is stationary. One common approach to achieve stationarity is by differencing the data. To determine whether differencing is required, an ADF test is commonly employed. The ADF test checks for the presence of unit roots in the data, which indicates non-stationarity. To implement this test, we apply the *adfuller_test* function in python. This function calculates the test statistic, p-value, number of lags, and number of observations for each variable. It then compares the p-value to the significance level at 5% and determine the time series stationarity. The table below presents the results from the test.

Variable	P-value	Reject H0
obx	0.0000	Yes
nok_eur	0.2449	No
i	0.1164	No
oil	0.0980	No
stoxx600	0.2373	No
electricity	0.0014	Yes

Table 2: Results from ADF test

In our case, the ADF test results indicate that the variables nok_eur, i, *stoxx600*, and *oil* have one unit root. To make the data stationary, we apply first-order differencing to the data. Differencing removes the trend component and can help stabilize the statistical properties of the time series.

We employ the AIC to select the optimal lag order. When considering all six variables in the analysis, the AIC suggests that the optimal lag order is 8. This means that the past eight observations of each variable are considered for modeling. However, in the case of VECM between obx and nok_eur, using only these two variables, the AIC indicates that a lag order of 6 is optimal.

By performing unit root tests, differencing the data, and selecting appropriate lag orders using the AIC, we ensure that our time series analysis is based on stationary data and considers the relevant temporal dependencies in the variables under investigation.

6.2 VAR Model

The VAR model is a commonly used time-series model that estimates the interdependent relationship among multiple variables. From earlier in our analysis, we have already ensured the stationarity of the dataset using an ADF test. The appropriate lag order of 8 was selected based on the AIC criterion. Using Python, we implement the VAR model with the *model.fit (8)* command which estimates the parameters of the VAR model using an OLS method. From this command we retrieve a summary of the VAR model, which provides valuable insights into the estimated coefficients, standard errors, significance levels, and other relevant statistical information.

Regression on obx

Using a significance level of 0.05, the statistically significant coefficients for the *obx* equation are summarized in table 3. The entire regression result is presented in appendix B.

Results for equation obx

	Prob	Coeff	St. Error	T-stat
L1.obx	0.000	-0.7921	0.0710	-11.155
L1.i	0.027	4.1129	1.8602	2.211
L2.obx	0.000	-0.7257	0.1214	-5.978
L3.obx	0.000	-0.6094	0.1416	4.184
L4.obx	0.009	-0.4038	0.1543	-2.617
L5.obx	0.001	-0.4996	0.1531	-3.263
L6.obx	0.026	-0.3363	0.1511	-2.226
L6.i	0.014	-5.1216	2.0871	-2.454
L7.oil	0.031	0.0003	0.0001	2.157

Table 3: Results from Equation on obx

There is a total of eight lags, we see that for the first seven lags of *obx* the coefficients are statistically significant with a p-value lower than 0.05 and a T-stat outside of the interval [-1.96, 1.96]. The coefficients are all negative, which tells us that the lags of *obx* have a negative relationship with the dependent variable *obx*. For example, an increase of one unit in L1 *obx* would lead to a decrease of 0.7921 in the dependent variable, with all other variables held constant. We see that apart from the lags of *obx*, the first and sixth lag of the interest level *i* are statistically significant with a positive coefficient for lag 1 and a negative coefficient for lag 6. The coefficients are also high compared to the other presented in the table, implying that the interest rate level possibly has quite a high impact on the *obx*. However, as there are only two of the eight lags that are statistically significant, it could be special events in these two lags that cause this seemingly large impact on the *obx*, and we do not conclude based on these results that the interest rate level in general have a high impact. The seventh lag of *oil* also is statistically significant, but with a very small coefficient, so it does not appear to have an important effect on the *obx*.

The results of the VAR regression tell us that the *nok_eur* for the chosen eight lags are not statistically significant when *obx* is the dependent variable. Thus, lagged values of the exchange rate are not able to predict changes in the stock market, based on these results.

Regression on nok_eur

For the equation with *nok_eur* as the dependent variable the statistically significant variables are presented present the variables are presented in table 4, also here using a significance level of 0.05. The entire regression result is presented in appendix B.

Results for equation nok_eur

	Prob	*Coeff*	*St. Error*	*T-stat*
L1.obx	0.000	-0.0126	0.0026	-4.780
L1.nok_eur	0.000	-0.2685	0.0719	-3.736
L1.i	0.001	0.2372	0.0690	3.438
L1.oil	0.025	0.0000	0.0000	2.243
L2.obx	0.003	-0.0132	0.0045	-2.939
L2.nok_eur	0.012	-0.1868	0.0746	-2.505
L2.i	0.000	0.2869	0.0740	3.876
L3.obx	0.011	-0.0137	0.0054	-2.532
L4.obx	0.013	-0.0142	0.0057	-2.482
L5.obx	0.045	-0.0114	0.0057	-2.002
L6.stoxx600	0.014	0.0000	0.0000	2.468
L7.nok_eur	0.044	0.1467	0.0727	2.017
L8.obx	0.025	0.0084	0.0037	2.249

Table 4: Results from Equation on nok_eur

We see that the *obx* is statistically significant for all the lags except lag six and seven. The lags of *obx* have a negative relationship with *nok_eur* expect from in lag eight. The coefficients are quite small in all cases for *obx*, and do not have large explanatory power for *nok_eur*. The *nok_eur* is significant for the two first lags and lag seven, the first two are positive while the seventh is negative. This tells us that the first two lags have a negative effect on *nok_eur* while in lag seven the effect is positive.

The first two lags for *i* are statistically significant, with a relatively high explanatory power of 0.2374 and 0.2869, respectively. Lag one for *oil* and lag six for *stoxx600* are statistically significant as well, but both have coefficients so close to zero that the effect is extremely small on *nok_eur*.

We see from the results that there are more statistically significant lags of *obx* when *nok_eur* is the dependent variable, than the other way around. This challenges our hypothesis that fluctuations in the exchange rate can predict changes in the stock market. It seems from our results in the VAR model that *nok_eur* is not able to predict changes in the stock market performance. However, as the economy is complex and a lot of factors influence each other, this result can be due to the variables, model, and time period we have chosen, and does not rule out the possibility that such a relationship exist.

Correlation Matrix

The correlation matrix of residuals is an important output of the VAR model analysis. It shows the correlations between the residuals of the different variables in the model, after accounting for the effect of the other variables. It therefore shows how much of the variation in each variable is explained by the other variables in the model, and how much remains unexplained. In our analysis we have a VAR model with six variables which is shown below in table 5.

Correlation matrix of residuals

	obx	**nok_eur**	**i**	**oil**	**stoxx600**	**electricity**
obx	1.0000	-0.1344	-0.1295	-0.2705	0.0991	-0.1383
nok_eur	-0.1344	1.0000	0.2910	0.1838	0.2080	-0.0385
i	-0.1295	0.2910	1.0000	0.1460	0.1008	0.1203
oil	-0.2705	0.1838	0.1460	1.0000	0.1043	0.0052
stoxx600	0.0991	0.2080	0.1008	0.1043	1.0000	-0.0022
electricity	-0.1383	-0.0385	0.1203	0.0052	-0.0022	1.0000

Table 5: Correlation Matrix - VAR

From the matrix, we can see that there are both positive and negative correlations between the residuals of the different variables. For example, the residual of obx is positively correlated with the residual of $stoxx600$, 0.0991, indicating that changes in the stock market index in Europe may have an impact on the Oslo stock exchange. On the other hand, the residual of *oil*, as well as the residual of *electricity*, is negatively correlated with the residual of obx, suggesting that changes in the price of oil and the price of electricity may have a weakening effect on the Oslo stock exchange.

The correlation matrix reveals that the residuals of obx and nok_eur exhibit a correlation coefficient of -0.1344. This negative correlation suggests an inverse relationship between the residuals of these variables. However, it is important to note that the magnitude of the correlation of -0.1344 indicates a relatively weak association between the residuals of the obx and nok_eur. This suggests that changes in the exchange rate may have only a modest impact on the fluctuations observed in the Norwegian stock market. they may not strongly predict changes in the Norwegian stock market. To gain further insights into the relationship between the exchange rate and the stock market, it may be beneficial to conduct additional analyses, such as impulse response functions or other statistical techniques, that can provide a more comprehensive understanding of their interdependencies.

6.3 Short-term Dynamics

Granger causality tests is employed to investigate the influence of variables on each other. The test assesses the null hypothesis that past values of the variables in the regression do not have a causal effect on the dependent variable, implying that the coefficients of the variables equal zero. In our analysis, we utilize a VAR model with six variables. The implementation of the test is accomplished through the utilization of the *granger_causation_matrix* function in python. This function iterates over each variable in the dataset, conducting pairwise tests to examine the causal relationships between the variables. As we have a total of six variables, the resulting matrices will provide insights into the causality dynamics among them. This section presents these matrices and proceeds to analyze the obtained results in the context of our research question.

The lag order in the granger causality test, presented in table 7, determines the number of lagged values considered and is chosen to capture the appropriate temporal relationship between the variables.

Lag Orders

	obx_x	nok_eur_x	i_x	oil_x	stoxx600_x	electricity_x
obx_y	1.0	12.0	9.0	2.0	7.0	2.0
nok_eur_y	1.0	1.0	3.0	9.0	1.0	3.0
i_y	1.0	6.0	1.0	2.0	2.0	3.0
oil_y	1.0	6.0	4.0	1.0	6.0	1.0
stoxx600_y	1.0	1.0	4.0	12.0	1.0	3.0
electricity_y	2.0	1.0	4.0	1.0	1.0	1.0

Table 6: Lag Orders from Granger Causality Test

The lag order of 12 for *obx_y* suggests that the previous 12 values of the obx have a significant impact on the current value of the exchange rate. On the other hand, the lag order of 1 for *obx_x* indicates that only the immediately preceding value of the exchange rate has a significant impact on the current value of the OBX Index. By considering the different lag orders, we gain insight into the specific lags that have the most significant influence on the dependent variable.

Causal Relationships and Directionality of Variables

The results presented in table 7 show the p-values, and table 8 present the coefficient resulting from the test. These tables present the Y-variables as the dependent variables and the X-variable as the independent variable for all the six variables in our analysis. When analyzing the results from the granger causality test one should consider both the p-value and the coefficient to assess if a variable is significant in relation to another. The p-values associated with the Y-variables indicate the statistical significance of their coefficients in the X-equation. If the p-values are below the significance level of 5%, we can conclude that the coefficient is significantly different from zero. This means that there is a statistically significant relationship between the X- and Y-variables. The coefficients in the coefficient table represents the strength and direction of the causal effect between the variables. If the coefficient is significantly different from zero, it suggests that the variable has a causal effect on the other variable. If the null hypothesis is rejected, it suggests that the Y-variable Granger cause the X-variable. We will examine the p-values of both the Y-variable and the X-variables to determine the direction of the causal relationship between the different variables.

P-values

	obx_x	**nok_eur_x**	**i_x**	**oil_x**	**stoxx600_x**	**electricity_x**
obx_y	1.0000	0.0435	0.0001	0.1181	0.2133	0.0379
nok_eur_y	0.0000	1.0000	0.0001	0.0027	0.0192	0.0230
i_y	0.4609	0.0060	1.0000	0.0093	0.0039	0.0865
oil_y	0.0000	0.1865	0.0553	1.0000	0.0090	0.0000
stoxx600_y	0.0000	0.1863	0.0012	0.0002	1.0000	0.0000
electricity_y	0.0130	0.0005	0.0645	0.0000	0.0176	1.0000

Table 7: P-values from Granger Causality Test

Coefficients						
	obx_x	**nok_eur_x**	**i_x**	**oil_x**	**stoxx600_x**	**electricity_x**
obx_y	4.2481	1.6221	3.5464	2.0976	1.2929	3.2128
nok_eur_y	30.3398	6693.8516	6.8478	2.6065	5.4267	3.0942
i_y	0.5378	2.8677	3496.4424	4.5950	5.4562	2.1376
oil_y	47.2183	1.3926	2.2346	5636.6225	2.7089	117.9034
stoxx600_y	381.5915	1.7274	4.3847	2.8435	6851.9575	7.7971
electricity_y	4.2634	12.0522	2.1439	42.3733	5.5776	65.1137

Table 8: Coefficients from Granger Causality Test

Looking at the P-values for the *nok_eur_x*-variable, it has p-value of 0.0435 for the variable *obx_y*, which suggests that there is a significant relationship between the exchange rate and the OBX Index. This implies that nok_eur Granger causes obx since the coefficient on *obx_y* is significantly different from zero. On the other hand, the p-value of 0.00 for the variable *nok_eur_y* suggests a significant relationship in the opposite direction, implying that obx Granger causes nok_eur. Therefore, based on these results, there appears to be a bidirectional causal relationship between obx and nok_eur.

Besides the exchange rate, two other variables, namely the interest rate differential and the electricity price, exhibit significant Granger causality with the OBX Index. However, none of the other variables show statistically significant causality. It is important to note that obx does not Granger cause the interest rate differential, but it does granger cause the electricity price. This implies a one-way Granger causality from the interest rate differential to the OBX Index, and a two-way Granger causality between the electricity price and the OBX Index. Specifically, changes in the interest rate differential influence the OBX Index, while changes in the OBX Index influence the electricity price.

The results indicate a significant granger causality between the NOK/EUR exchange rate and all the variables in the model. This implies that all variables have a causal influence on the exchange rate. Conversely, the variable *nok_eur_x* shows statistical significance only with obx, the interest rate differential, and the electricity prices. This suggests a bidirectional causal relationship between the exchange rate and these variables. Furthermore, the causal relationship between the exchange rate and the oil prices, as well as the market index, is unidirectional. In other words, the exchange rate influences these variables, but they do not significantly impact the exchange rate in return.

Since our dataset is based on returns, the coefficient of 1.6221 for *obx_y* would indicate that a 1% increase in the exchange rate would lead to a 1.6221% increase in the obx. Similarly, a coefficient of 30.3398 for *obx_x* would suggest that a 1% increase in the obx leads to a 30.3398% increase in the exchange rate in the long run. Both coefficients are significantly different from zero which implies that both variables have a causal effect on the other variable. The magnitude of these coefficient indicates that a 1% increase in the obx lead to a stronger influence of the exchange rate than what a 1% increase in the exchange rate influences the OBX Index.

6.4 Long-Term Relationship

We conducted a cointegration test to examine the existence of a long-term relationship between the different time series. Initially, we focused on examining the bivariate cointegration between the OBX Index and each individual variable separately using the Engle-Granger two-step approach. This approach allows for the inclusion of multiple variables to capture potential drivers of the OBX Index. We chose to focus on bivariate relationships for the initial analysis to gain insights into the individual contributions of each variable.

First Step – OLS Regression

The first step regression estimates the individual relationships between the obx variable and each of the independent variables. It involves running separate regressions for each independent variable against the dependent variable and obtaining the coefficients, standard errors, t-statistics, and p-values for each regression. This step helps to examine the individual long-term relationships between the variables. The results from the first step regression are presented in table 9 below.

	nok_eur	i	oil	stoxx600	electricity
Coefficients	5.5289	- 3.2252	0.0001	0.0031	0.0000
St. errors	1.9096	1.9467	0.0001	0.0003	0.0000
T-stat	2.8952	- 1.6567	1.2520	10.8748	0.5572
P-value	0.0041	0.0987	0.2116	4.02e-23	0.5779

Table 9: First Step Regression Results

From the first step regression, we investigate the long-term relationship between the OBX Index and the NOK/EUR exchange rate. The coefficient reflects the expected change in the obx for a one-unit increase in the exchange rate. The exchange rate exhibits the highest coefficient between the variables and implies that changes in the exchange rate have a substantial influence on the OBX Index´s movement. The statistically significant t-statistic of 2.89 and the lox p-value of 0.004 suggest that the relationship between these two variables is robust and unlikely to be due to random chance.

After examining the long-term relationship between the obx and the control variables we find that only one additional variable, besides the exchange rate, is statistically significant. The positive coefficient and t-statistic at 1.25 for the oil variable indicate a potential positive relationship, but it is not statistically significant as the p-value exceeds the 5% significant level. Therefore, there is insufficient evidence to support a robust long-term relationship between the OBX Index and oil price. Similarly, for the interest rate differential and the electricity price variables, the t-statistics are negative, and their respective p-values are higher than the significance level, indicating inadequate evidence to support a significant long-term relationship. However, in the case of the market index, we observe a positive t-statistic and a low p-value, suggesting a strong positive long-term relationship between the OBX Index and the Stoxx600 Market Index.

Second Step – Cointegration Test

The second step in the Engle-Granger method involves testing for cointegration based on the residuals obtained from the first step regression. These residuals capture the unobserved long-term relationship between the OBX Index and the exchange rate and the control variables, accounting for any omitted variables or short-term dynamics that were not captures in the first step. The test was performed by defining all the variables of interest and then applied the *coint ()* function in python. This test gives us the p-values, test statistic and the critical values. The cointegration test compares the test statistic with these critical values to assess the presence of cointegration, whether the p-value measures the statistical significance of the test. The results from the second step are presented in the table 10 below.

Significance levels	[1%, 5%, 10%]
Critical values	[-3.9368, -3.3585, -3.0599]
Test result between OBX and the Exchange rate	
Test statistic	-10.3138
P-value	4.05e-17
Test result between OBX and the Interest rate differential	
Test statistic	-9.1229
P-value	4.22e-14
Test result between OBX and Oil Prices	
Test statistic	-9.4649
P-value	5.65e-15
Test result between OBX and Market Index	
Test statistic	-21.4092
P-value	0
Test result between OBX and Electricity Prices	
Test statistic	-8.7517
P-value	3.75e-13

Table 10: Cointegration Test using Engle Granger 2-step Approach

The cointegration test between the obx and nok_eur reveals a test statistic of -10.3138, which surpasses the critical values, indicating a significant negative relationship between the two variables. As well as a low P-value at 4.05e-17, this suggests strong evidence of cointegration between these two variables. The presence of cointegration between the obx and the exchange rate implies a long-term relationship, highlighting the interplay between the stock market and currency dynamics in the Norwegian economy. Based on the other results in table 8, all the tested variables exhibit strong cointegration with the OBX Index. The highly negative test statistics and very small p-values indicate a robust and significant long-term relationship between the OBX Index and the respective variables.

For example, if there is a positive shock to the OBX, indicating a rise in stock market performance, it could be expected to have an impact on the value of the Norwegian Krone relative to the Euro. This could happen if foreign investors perceive the Norwegian stock market as attractive and invest in Norwegian stocks, leading to an appreciation of the Krone against the Euro. Conversely, if there is a significant depreciation of the Norwegian Krone relative to the Euro, it might signal a weaker economic outlook for Norway, potentially impacting the performance of the Oslo Børs Index. The cointegration result indicates that such changes in the exchange rate could have long-term implications for the stock market.

Comparing the results from the two steps, we can conclude that while the first step regression identified a statistically significant long-term relationship only between the OBX Index and exchange rate, and the Market Index, the second step cointegration test indicates a robust and significant long-term relationship between the OBX Index and all the tested variables. This suggests that the second step analysis, which accounts for the presence of cointegration, provides stronger evidence of the long-term relationships between the OBX Index and the variables. Therefore, the cointegration analysis supports the notion that these variables are jointly determined and move together in the long run, providing a more comprehensive understanding of their interrelationships.

Vector Error Correction Model

In our recent analysis, using the Engle-Granger two-step approach, we found a statistically significant long-term relationship between the OBX Index and the NOK/EUR exchange rate. This provides a strong motivation for us to investigate this specific relationship further using a more comprehensive model like VECM. The VECM model allows us to analyze the interdependencies among multiple variables. However, by focusing on the specific relationship between the obx and nok_eur, we simplify the analysis and can draw a more precise conclusion about their long-term equilibrium and short-term dynamics.

To conduct the VECM analysis, we utilize Python and employ several steps. We apply the *coint_johansen* function on the differenced variables to test for the presence of cointegrations and extract the eigenvectors from the cointegration test results. Next, we create a DataFrame with these eigenvectors and another with the differenced variables. We use the *VECM class* from the Python library to fit the model and retrieve a model summary. This summary provides information such as the coefficients, standard errors, and p-values, which are all presented in the table 11 below.

	Coef.	St. Error	P-value
Equation: OBX			
Constant	0.0002	0.004	0.954
L1.obx	0.3064	0.061	0.000
L1.nok_eur	2.7888	1.194	0.019
Equation: NOK/EUR			
Constant	7.41e-06	0.000	0.966
L1.obx	0.0068	0.003	0.009
L1.nok_eur	- 0.4512	0.051	0.000
Cointegration relations			
α: equation OBX	- 1.8614	0.100	0.000
α: equation NOK/EUR	- 0.0225	0.004	0.000
Cointegration relations for loading-coefficients			
Beta.1	1.0000	0.000	0.000
Beta.2	3.1260	1.218	0.010

Table 11: VECM between OBX and NOK/EUR

The lag coefficient L1.obx is statistically significant, indicating that the lagged value of obx is an important determinant of its own current value. Similarly, the lag coefficient L1.nok_eur shows statistical significance, implying that the past value of nok_eur influences its present level. These significant lag coefficients suggest the presence of autocorrelation in both obx and nok_eur.

When we are examining the cointegration equation, we are looking at the beta coefficients. The beta.1 coefficient indicates the weight of the obx variable in the cointegration relationship, while the beta.2 coefficient represent the weight of the nok_eur variable in the cointegration relationship. The coefficient of 3.126, signifies the impact of nok_eur on the long-term equilibrium relationship between obx and the exchange rate. The alpha coefficient of -1.8614 and -0.025 is part of the error correction term, representing the speed of adjustment towards the long-term equilibrium.

The analysis of the VECM model provides compelling evidence of a significant relationship between OBX Index and NOK/EUR exchange rate. The negative coefficients found in the model indicate that any deviations from the equilibrium level between the variables will be gradually corrected over time. Moreover, the inclusion of error correction terms in the equations highlights the existence of a corrective mechanism that drives the variables back to their long-term equilibrium. Overall, these findings underscore the strong connection between obx and nok_eur

and highlight the role of both lagged values and error correction in shaping their dynamic relationship.

Comparing our cointegration results, the Engle-Granger two-step approach suggests a long-term relationship between the OBX Index and the exchange rate, while the VECM provides additional evidence of cointegration and offers a more nuanced understanding of the short-term dynamics and adjustments between the variables.

6.5 OBX Responses to Shock in the Exchange Rate

To understand the significance of the correlation between the obx and nok_eur, we can analyze the impulse response function (IRF) between these variables. From the IRF figure 8 below, the x-axis represents the number of periods after the shock, and the y-axis represent the response of the obx and nok_eur variables. The blue shaded area represents the 95% confidence interval of the response.

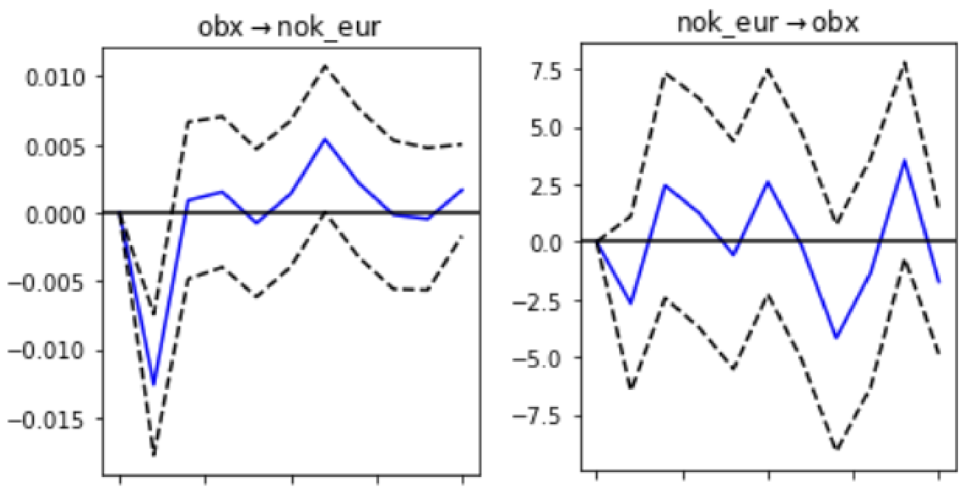

Figure 8: Impulse responses

If we were to shock the obx variable, we can see from the first table of the IRF above that there is a short-term negative effect on the nok_eur variable, which then gradually increases to a positive effect over time. This indicates that in the short term, a negative shock to the obx leads to a decrease in nok_eur, but in the long term, there is a positive relationship between these two variables.

The second table of the IRF, shows how a shock to the nok_eur variable influences the obx variable. From the plot, we can see that a positive shock to nok_eur initially causes obx to increase slightly. However, this effect is not statistically significant as the confidence interval overlaps zero. After the increase, the response of the obx to the shock becomes negative and statistically significant. This means that a positive shock to the nok_eur leads to a significant decrease in the obx in the long run.

Overall, the weak negative correlation between the obx and nok_eur in the VAR model, as well as the short-term negative effect and the long-term positive relationship observed in the IRF, suggest that these two variables are weakly related but still have some impact on each other. A shock in the exchange rate can predict changes in the Oslo stock exchange with a negative effect in the long run.

6.6 Summary and Interpretation of Findings

In our analysis, we employed a range of methods to investigate the dynamics among the variables and provide insights into our research question. We began by utilizing a VAR model to examine the short-term dynamics, finding that lagged values of *nok_eur* were not statistically significant in predicting changes in *obx*. This challenges our hypothesis that fluctuations in the exchange rate can predict stock market performance. However, we acknowledged that the complexity of the economy and other factors may influence this relationship.

Moving beyond short-term dynamics, we conducted a Granger causality test, which revealed bidirectional causal relationships between *obx* and *nok_eur*, indicating an interdependence between the variables. Additionally, we observed unidirectional causality from the interest rate differential to the OBX Index, as well as a bidirectional causality between the electricity price and the OBX Index. These findings further supported the presence of causal relationships and highlighted the interconnectedness among the variables. To explore long-term relationships, we employed cointegration analysis, which indicated a robust and significant long-term relationship between the OBX Index and all tested variables. This suggests that the variables are jointly determined and move together in the long run, providing a comprehensive understanding of their interrelationships.

Moreover, impulse response functions illustrated the dynamic interactions within the system. We observed a weak negative correlation between *obx* and *nok_eur* in the VAR model. The short-term effects of shocks in the exchange rate on the stock market were negative, while in the long run, we found a positive relationship. This implies that changes in the exchange rate can impact the stock market in the long term.

In summary, the general VAR model and Granger causality test provided evidence of causal relationships and short-term dynamics, cointegration analysis highlighted the enduring relationships among the variables. The impulse response functions further illustrated the dynamic interactions over time. Collectively, these findings enhance our understanding of the interdependencies and dynamics among the variables, offering valuable insights into our research question.

7. Conclusion

Based on our findings, we have reached the conclusion that exchange rate fluctuations have a significant impact on the stock market performance, affirming our initial hypothesis. Our results demonstrates that these effects persist not only in the short run but also in the long run, indicating a robust relationship between the stock market and the exchange rate.

In the short run, a bidirectional causal relationship between the variables was observed, suggesting that changes in the exchange rate can influence the stock market and vice versa. The time series plot also visualized that the OBX Index exhibits more pronounced fluctuations compared to the exchange rate, suggesting short-term movements in the stock market may be influenced by immediate changes in the exchange rate. This finding aligns with the flow-oriented model, which emphasizes the role of current information and investor sentiment in driving short-term market behavior.

In the long run, the exchange rate demonstrates larger fluctuations compared to the OBX Index, implying long run variations in the exchange rate may reflect broader economic trends and structural factors, which could have implications for investment decision and overall economic stability. This observed long run relationship may indicate that a weakening of the Norwegian krone could potentially benefit the Norwegian stock market as this could enhance the competitiveness of export-oriented firms in the foreign market.

As previously discussed in the thesis, the economy is incredibly complex which makes it difficult to establish a relationship between two variables. Our thesis focuses on a specific set of variables for the time period 2000-2022, and different results could be obtained by including more variables or choosing different variables altogether. We suggest future research to incorporate specific events such as shocks and crises, to see if results vary based on macroeconomic conditions. Further research could also explore the development of forecasting models that incorporate the identified relationships, allowing for more accurate predictions of stock market behavior based on exchange rate fluctuations.

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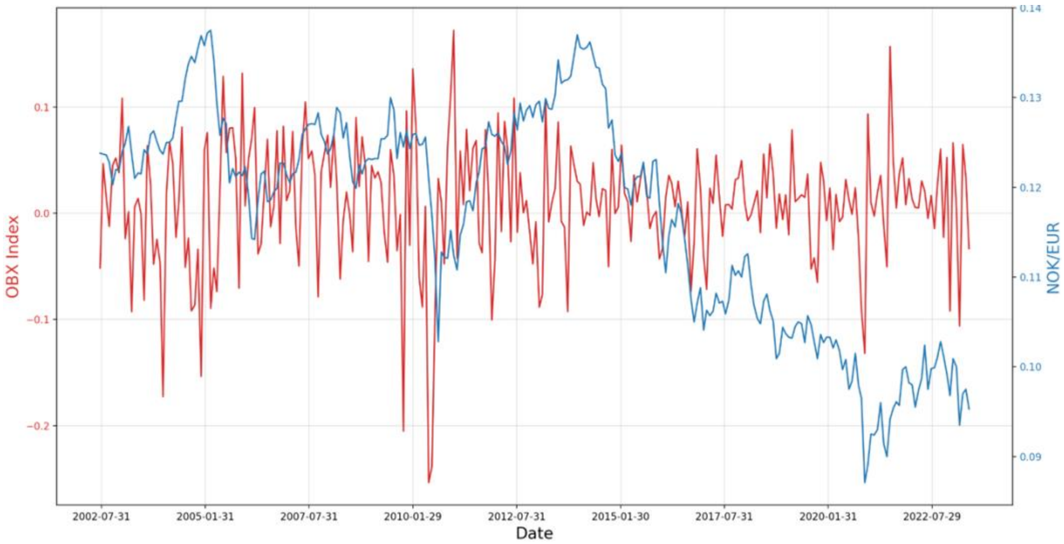
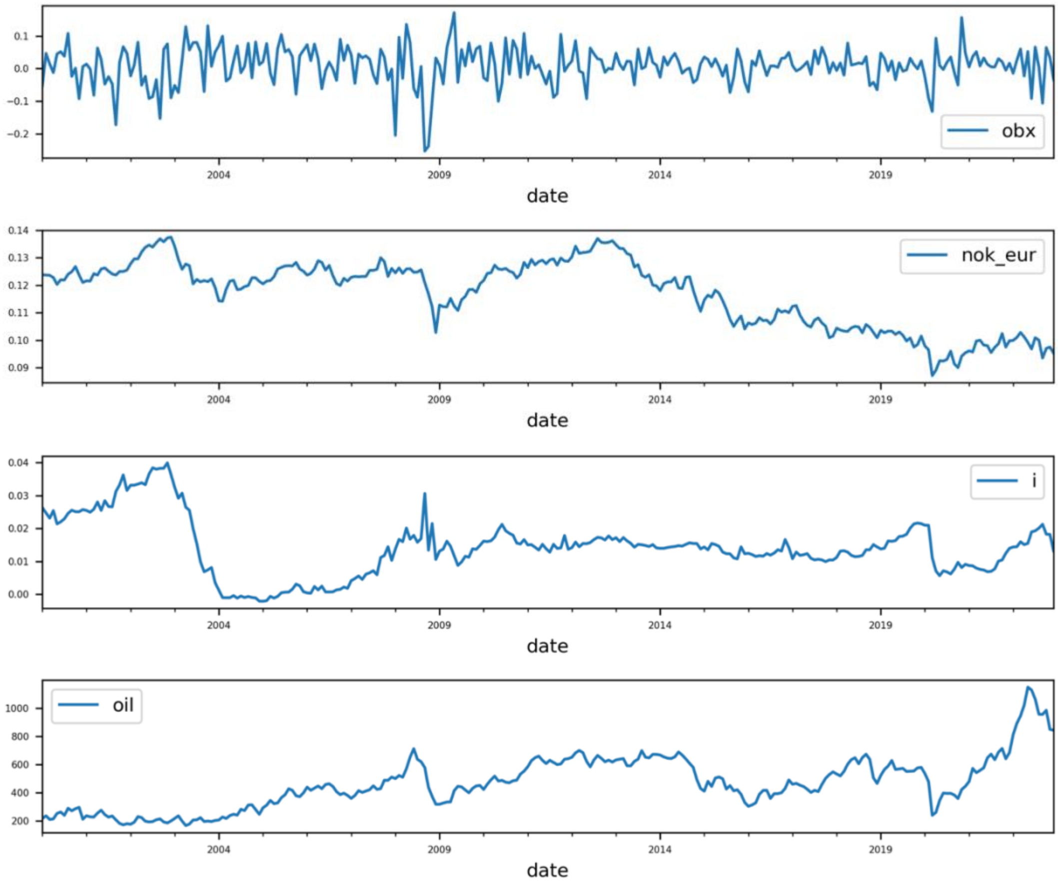
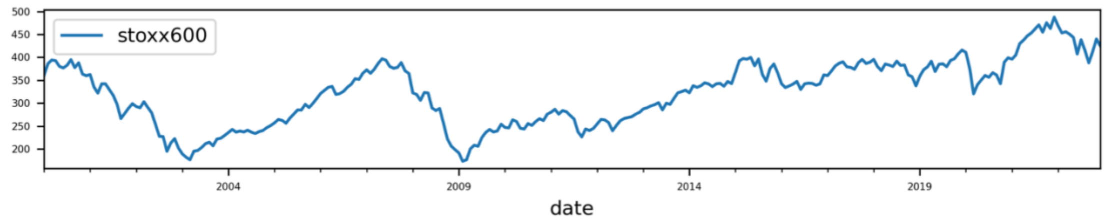
Appendix A: Data Plots

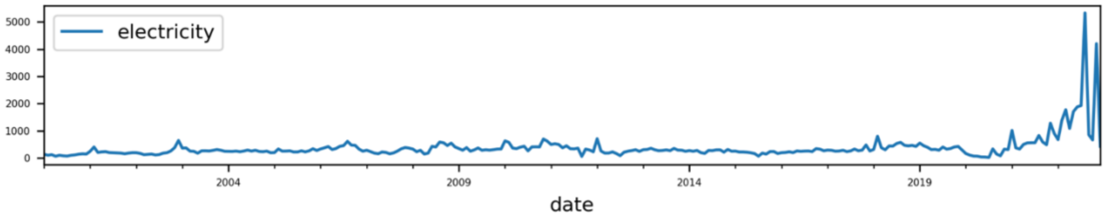
OBX and NOK/EUR Plot



Time series Plot







Appendix B: Results from Analysis

Results from ADF test:

```
    Augmented Dickey-Fuller Test on "obx"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -14.5729
 No. Lags Chosen        = 0
 Critical value 1%      = -3.454
 Critical value 5%      = -2.872
 Critical value 10%     = -2.572
 => P-Value = 0.0. Rejecting Null Hypothesis.
 => Series is Stationary.
```

```
    Augmented Dickey-Fuller Test on "nok_eur"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -2.0992
 No. Lags Chosen        = 0
 Critical value 1%      = -3.454
 Critical value 5%      = -2.872
 Critical value 10%     = -2.572
 => P-Value = 0.2449. Weak evidence to reject the Null
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "i"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -2.4963
 No. Lags Chosen        = 6
 Critical value 1%      = -3.455
 Critical value 5%      = -2.872
 Critical value 10%     = -2.573
 => P-Value = 0.1164. Weak evidence to reject the Null
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "stoxx600"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -2.118
 No. Lags Chosen        = 1
 Critical value 1%      = -3.454
 Critical value 5%      = -2.872
 Critical value 10%     = -2.572
 => P-Value = 0.2373. Weak evidence to reject the Null
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "oil"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -2.5765
 No. Lags Chosen        = 1
 Critical value 1%      = -3.454
 Critical value 5%      = -2.872
 Critical value 10%     = -2.572
 => P-Value = 0.098. Weak evidence to reject the Null
 => Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "electricity"
    -----------------------------------------------
 Null Hypothesis: Data has unit root. Non-Stationary.
 Significance Level     = 0.05
 Test Statistic         = -3.9946
 No. Lags Chosen        = 2
 Critical value 1%      = -3.455
 Critical value 5%      = -2.872
 Critical value 10%     = -2.572
 => P-Value = 0.0014. Rejecting Null Hypothesis.
 => Series is Stationary.
```

Regression results VAR model – Equation OBX

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Thu, 08, Jun, 2023
Time:                     17:59:01
--------------------------------------------------------------------
No. of Equations:         6.00000    BIC:                   -5.00275
Nobs:                     267.000    HQIC:                  -7.36606
Log likelihood:          -783.947    FPE:                0.000132687
AIC:                     -8.95275    Det(Omega_mle):     4.82807e-05
--------------------------------------------------------------------
Results for equation obx
==========================================================================
======
                   coefficient       std. error           t-stat
  prob
--------------------------------------------------------------------------
------
const                 0.001302         0.003724            0.350
0.727
L1.obx               -0.792164         0.071016          -11.155
0.000
L1.nok_eur           -2.678092         1.937864           -1.382
0.167
L1.i                  4.112929         1.860249            2.211
0.027
L1.oil                0.000062         0.000122            0.512
0.608
L1.stoxx600           0.000289         0.000467            0.618
0.537
L1.electricity       -0.000049         0.000034           -1.461
0.144
L2.obx               -0.725746         0.121413           -5.978
0.000
L2.nok_eur            0.471464         2.010361            0.235
0.815
L2.i                 -0.518100         1.995496           -0.260
0.795
L2.oil                0.000186         0.000123            1.512
0.131
L2.stoxx600          -0.000046         0.000456           -0.100
0.920
L2.electricity        0.000025         0.000035            0.704
0.481
L3.obx               -0.609360         0.145646           -4.184
0.000
L3.nok_eur            0.391417         2.030377            0.193
0.847
L3.i                 -3.795968         2.061876           -1.841
0.066
L3.oil                0.000210         0.000122            1.722
0.085
L3.stoxx600           0.000251         0.000460            0.545
0.586
L3.electricity       -0.000032         0.000034           -0.943
```

```
0.346
L4.obx              -0.403796         0.154285          -2.617
0.009
L4.nok_eur           1.735223         2.008140           0.864
0.388
L4.i                -1.445980         2.055433          -0.703
0.482
L4.oil               0.000247         0.000128           1.929
0.054
L4.stoxx600         -0.000746         0.000460          -1.625
0.104
L4.electricity      -0.000028         0.000030          -0.952
0.341
L5.obx              -0.499555         0.153117          -3.263
0.001
L5.nok_eur           3.571309         1.959402           1.823
0.068
L5.i                -3.408064         2.062515          -1.652
0.098
L5.oil               0.000037         0.000125           0.299
0.765
L5.stoxx600          0.000762         0.000462           1.651
0.099
L5.electricity      -0.000025         0.000025          -0.973
0.330
L6.obx              -0.336303         0.151111          -2.226
0.026
L6.nok_eur           3.144330         1.961164           1.603
0.109
L6.i                -5.121628         2.087080          -2.454
0.014
L6.oil              -0.000082         0.000121          -0.676
0.499
L6.stoxx600         -0.000094         0.000462          -0.205
0.838
L6.electricity      -0.000017         0.000025          -0.695
0.487
L7.obx              -0.243705         0.131876          -1.848
0.065
L7.nok_eur          -1.252025         1.960780          -0.639
0.523
L7.i                 0.443773         2.054463           0.216
0.829
L7.oil               0.000259         0.000120           2.157
0.031
L7.stoxx600          0.000725         0.000439           1.651
0.099
L7.electricity      -0.000014         0.000020          -0.673
0.501
L8.obx              -0.124662         0.100154          -1.245
0.213
L8.nok_eur           0.279802         1.903953           0.147
0.883
L8.i                -3.177215         1.936928          -1.640
0.101
L8.oil              -0.000148         0.000120          -1.240


0.215
L8.stoxx600          0.000545         0.000441           1.235
0.217
L8.electricity      -0.000010         0.000015          -0.673
0.501
============================================================================
======
```

Regression results VAR model – Equation NOK_EUR

Results for equation nok_eur

	coefficient	std. error	t-stat	prob
const	0.000144	0.000138	1.042	0.297
L1.obx	-0.012591	0.002634	-4.780	0.000
L1.nok_eur	-0.268524	0.071881	-3.736	0.000
L1.i	0.237246	0.069002	3.438	0.001
L1.oil	0.000010	0.000005	2.243	0.025
L1.stoxx600	-0.000020	0.000017	-1.145	0.252
L1.electricity	-0.000000	0.000001	-0.061	0.952
L2.obx	-0.013235	0.004504	-2.939	0.003
L2.nok_eur	-0.186826	0.074570	-2.505	0.012
L2.i	0.286902	0.074018	3.876	0.000
L2.oil	0.000008	0.000005	1.653	0.098
L2.stoxx600	-0.000008	0.000017	-0.445	0.656
L2.electricity	-0.000001	0.000001	-0.746	0.456
L3.obx	-0.013678	0.005402	-2.532	0.011
L3.nok_eur	-0.044341	0.075312	-0.589	0.556
L3.i	0.006758	0.076480	0.088	0.930
L3.oil	0.000007	0.000005	1.556	0.120
L3.stoxx600	-0.000012	0.000017	-0.678	0.498
L3.electricity	-0.000001	0.000001	-0.632	0.527
L4.obx	-0.014205	0.005723	-2.482	0.013
L4.nok_eur	-0.104000	0.074487	-1.396	0.163
L4.i	-0.090032	0.076241	-1.181	0.238
L4.oil	0.000004	0.000005	0.768	0.442
L4.stoxx600	0.000005	0.000017	0.272	0.785
L4.electricity	-0.000001	0.000001	-0.747	0.455
L5.obx	-0.011372	0.005680	-2.002	0.045
L5.nok_eur	0.117332	0.072679	1.614	0.106
L5.i	-0.008841	0.076504	-0.116	0.908
L5.oil	0.000004	0.000005	0.881	0.378
L5.stoxx600	0.000011	0.000017	0.649	0.516

```
L5.electricity          0.000000        0.000001          0.323
0.746
L6.obx                 -0.002491        0.005605         -0.444
0.657
L6.nok_eur              0.130829        0.072745          1.798
0.072
L6.i                    0.024453        0.077415          0.316
0.752
L6.oil                 -0.000003        0.000004         -0.754
0.451
L6.stoxx600             0.000042        0.000017          2.468
0.014
L6.electricity          0.000000        0.000001          0.168
0.867
L7.obx                  0.005846        0.004892          1.195
0.232
L7.nok_eur              0.146699        0.072731          2.017
0.044
L7.i                   -0.032837        0.076205         -0.431
0.667
L7.oil                  0.000000        0.000004          0.087
0.931
L7.stoxx600             0.000010        0.000016          0.586
0.558
L7.electricity         -0.000000        0.000001         -0.208
0.835
L8.obx                  0.008354        0.003715          2.249
0.025
L8.nok_eur              0.072021        0.070623          1.020
0.308
L8.i                   -0.008437        0.071846         -0.117
0.907
L8.oil                 -0.000002        0.000004         -0.529
0.597
L8.stoxx600            -0.000029        0.000016         -1.788
0.074
L8.electricity          0.000000        0.000001          0.016
```

Results from Correlation Matrix:

Correlation matrix of residuals

	obx	nok_eur	i	oil	stoxx600	electricity
obx	1.000000	-0.134351	-0.129484	-0.270541	0.099130	-0.138274
nok_eur	-0.134351	1.000000	0.290990	0.183812	0.207974	-0.038468
i	-0.129484	0.290990	1.000000	0.145927	0.100757	0.120329
oil	-0.270541	0.183812	0.145927	1.000000	0.104336	0.005207
stoxx600	0.099130	0.207974	0.100757	0.104336	1.000000	-0.002165
electricity	-0.138274	-0.038468	0.120329	0.005207	-0.002165	1.000000

Results from Granger Causality test:

P-values:

	obx_x	nok_eur_x	i_x	oil_x	stoxx600_x	electricity_x
obx_y	1.0000	0.0435	0.0001	0.1181	0.2133	0.0379
nok_eur_y	0.0000	1.0000	0.0001	0.0027	0.0192	0.0230
i_y	0.4609	0.0060	1.0000	0.0093	0.0039	0.0865
oil_y	0.0000	0.1865	0.0553	1.0000	0.0090	0.0000
stoxx600_y	0.0000	0.1863	0.0012	0.0002	1.0000	0.0000
electricity_y	0.0130	0.0005	0.0645	0.0000	0.0176	1.0000

Coefficients:

	obx_x	nok_eur_x	i_x	oil_x	stoxx600_x	electricity_x
obx_y	4.2481	1.6221	3.5464	2.0976	1.2929	3.2128
nok_eur_y	30.3398	6693.8516	6.8478	2.6065	5.4267	3.0942
i_y	0.5378	2.8677	3496.4424	4.5950	5.4562	2.1376
oil_y	47.2183	1.3926	2.2346	5636.6225	2.7089	17.9034
stoxx600_y	381.5915	1.7274	4.3847	2.8435	6851.9575	7.7971
electricity_y	4.2634	12.0522	2.1439	42.3733	5.5776	65.1137

Lag Orders:

	obx_x	nok_eur_x	i_x	oil_x	stoxx600_x	electricity_x
obx_y	1.0	12.0	9.0	2.0	7.0	2.0
nok_eur_y	1.0	1.0	3.0	9.0	1.0	3.0
i_y	1.0	6.0	1.0	2.0	2.0	3.0
oil_y	1.0	6.0	4.0	1.0	6.0	1.0
stoxx600_y	1.0	1.0	4.0	12.0	1.0	3.0
electricity_y	2.0	1.0	4.0	1.0	1.0	1.0

Results From Engle-Granger Two-step Approach:

1) **First Step regression**

```
Regression Results for OBX ~ Exchange Rate:
Coefficients:
const      -0.000639
nok_eur     5.528997
dtype: float64
Standard Errors:
const       0.004583
nok_eur     1.909664
dtype: float64
T-Statistics:
const      -0.139406
nok_eur     2.895272
dtype: float64
P-Values:
const       0.889232
nok_eur     0.004095
dtype: float64
```

```
Regression Results for OBX ~ Interest Rate
Coefficients:
const    0.000088
i       -3.225258
dtype: float64
Standard Errors:
const    0.004626
i        1.946731
dtype: float64
T-Statistics:
const    0.019066
i       -1.656756
dtype: float64
P-Values:
const    0.984802
i        0.098718
dtype: float64
```

```
Regression Results for OBX ~ Oil Price:
Coefficients:
const    0.000262
oil      0.000144
dtype: float64
Standard Errors:
const    0.004643
oil      0.000115
dtype: float64
T-Statistics:
const    0.056534
oil      1.252022
dtype: float64
P-Values:
const    0.954958
oil      0.211633
dtype: float64
```

```
Regression Results for OBX ~ Market Index:
Coefficients:
const       0.000644
stoxx600    0.003051
dtype: float64
Standard Errors:
const       0.003884
stoxx600    0.000281
dtype: float64
T-Statistics:
const        0.165735
stoxx600    10.874785
dtype: float64
P-Values:
const       8.684883e-01
stoxx600    4.019976e-23
dtype: float64
```

```
Regression Results for OBX ~ Electricity Prices:
Coefficients:
const         -0.000060
electricity    0.000005
dtype: float64
Standard Errors:
const          0.004646
electricity    0.000010
dtype: float64
T-Statistics:
const         -0.012962
electricity    0.557169
dtype: float64
P-Values:
const          0.989668
electricity    0.577869
dtype: float64
```

2) Second Step

```
Cointegration test result between OBX and the Exchange Rate:
Test statistic: -10.313761440448221
P-value: 4.0499130952242955e-17
Critical values: [-3.93685701 -3.35852052 -3.05996506]
Cointegration test result between OBX and the Interest Rate Differentials:
Test statistic: -9.122934309052608
P-value: 4.22197167487921e-14
Critical values: [-3.93685701 -3.35852052 -3.05996506]
Cointegration test result between OBX and Oil price:
Test statistic: -9.46486511915552
P-value: 5.6551902801164046e-15
Critical values: [-3.93685701 -3.35852052 -3.05996506]
Cointegration test result between OBX and Market Index:
Test statistic: -21.409195178181687
P-value: 0.0
Critical values: [-3.93685701 -3.35852052 -3.05996506]
Cointegration test result between OBX and Electricity price:
Test statistic: -8.751748059654743
P-value: 3.749192267544183e-13
Critical values: [-3.93685701 -3.35852052 -3.05996506]
```

Results from VECM:

Det. terms outside the coint. relation & lagged endog. parameters for equation obx

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0002	0.004	0.058	0.954	-0.008	0.008
L1.obx	0.3064	0.061	5.040	0.000	0.187	0.426
L1.nok_eur	2.7888	1.194	2.336	0.019	0.449	5.128

Det. terms outside the coint. relation & lagged endog. parameters for equation nok_eur

	coef	std err	z	P>|z|	[0.025	0.975]
const	7.409e-06	0.000	0.043	0.966	-0.000	0.000
L1.obx	0.0068	0.003	2.622	0.009	0.002	0.012
L1.nok_eur	-0.4512	0.051	-8.812	0.000	-0.552	-0.351

Loading coefficients (alpha) for equation obx

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-1.8614	0.100	-18.646	0.000	-2.057	-1.666

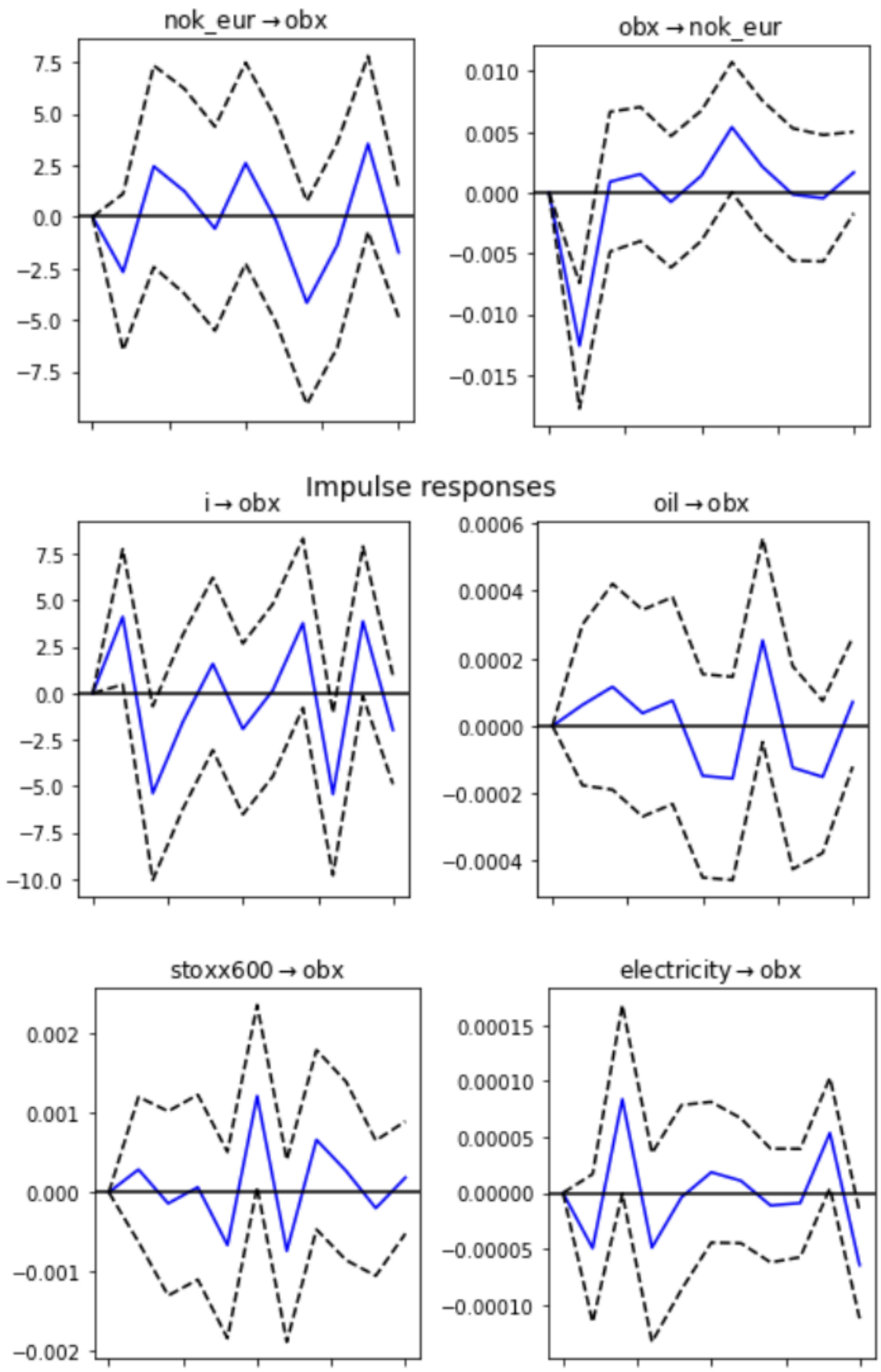
Loading coefficients (alpha) for equation nok_eur

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0225	0.004	-5.254	0.000	-0.031	-0.014

Cointegration relations for loading-coefficients-column 1

	coef	std err	z	P>|z|	[0.025	0.975]
beta.1	1.0000	0	0	0.000	1.000	1.000
beta.2	3.1260	1.218	2.567	0.010	0.739	5.513

Impulse response function:



Appendix C: Python Code

```
#### LIBRARY
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
import random
import pandas as pd

#### Import Statsmodels
from statsmodels.tsa.api import VAR
from statsmodels.tsa.stattools import adfuller
from statsmodels.tools.eval_measures import rmse, aic
from statsmodels.tsa.stattools import grangercausalitytests
from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.vector_ar.vecm import VECM
from statsmodels.tsa.stattools import coint
import statsmodels.api as sm
get_ipython().run_line_magic('matplotlib', 'inline')

#### IMPORT DATASET
df = pd.read_csv('/Users/karinamyhre/Documents/MASTER/MASTER
THESIS/DATA/dataset.csv' ,sep = ';', parse_dates=['date'], index_col='date')

#### PLOT DATA
fig, axes = plt.subplots(nrows=6, ncols=1, dpi=300, figsize=(8,10))
for i, (col,ax) in enumerate(zip(df.columns, axes.flatten())):

    df[col].plot(legend=True, ax=ax);
    ax.tick_params(labelsize=5)
plt.tight_layout();

#Plot OBX and NOK/EUR
x = df.index
y1 = df['obx']
y2 = df['nok_eur']

# Reverse the order of x and y data
x = pd.to_datetime(x[::-1])
y1 = y1[::-1]
y2 = y2[::-1]
```

```
# Plot Line1 (Left Y Axis)
fig, ax1 = plt.subplots(1, 1, figsize=(15, 8), dpi=200)
ax1.plot(x, y1, color='tab:red')

# Plot Line2 (Right Y Axis)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
ax2.plot(x, y2, color='tab:blue')

# ax1 (left Y axis)
ax1.set_xlabel('Date', fontsize=16)
ax1.tick_params(axis='x', rotation=0)
ax1.set_ylabel('OBX Index', color='tab:red', fontsize=16)
ax1.tick_params(axis='y', rotation=0, labelcolor='tab:red')
ax1.grid(alpha=0.4)

# ax2 (right Y axis)
ax2.set_ylabel("NOK/EUR", color='tab:blue', fontsize=16)
ax2.tick_params(axis='y', labelcolor='tab:blue')

# Format date labels
ax1.xaxis.set_major_locator(plt.MaxNLocator(10))
ax1.xaxis.set_major_formatter(plt.FixedFormatter(x[::30].strftime("%Y-%m-%d")))
ax2.set_title("Visualizing Leading Indicator Phenomenon", fontsize=16)
fig.tight_layout()
plt.show()

#### STATIONARITY TEST
# Running ADF-test
def adfuller_test(series, signif=0.05, name='', verbose=False):
    r = adfuller(series, autolag='AIC')
    output = {'test_statistic':round(r[0], 4), 'pvalue':round(r[1], 4),
              'n_lags':round(r[2], 4), 'n_obs':r[3]}
    p_value = output['pvalue']
    def adjust(val, length= 6): return str(val).ljust(length)

    # Summary
    print(f'    Augmented Dickey-Fuller Test on "{name}"', "\n   ", '-'*47)
    print(f' Null Hypothesis: Data has unit root. Non-Stationary.')
    print(f' Significance Level    = {signif}')
    print(f' Test Statistic        = {output["test_statistic"]}')
```

```
    print(f' No. Lags Chosen       = {output["n_lags"]}')
    for key,val in r[4].items():
        print(f' Critical value {adjust(key)} = {round(val, 3)}')
    if p_value <= signif:
        print(f" => P-Value = {p_value}. Rejecting Null Hypothesis.")
        print(f" => Series is Stationary.")
    else:
        print(f" => P-Value = {p_value}. Weak evidence to reject the Null Hypothesis.")
        print(f" => Series is Non-Stationary.")

# ADF Test on each variable
for name, column in df.iteritems():
    if column.name != 'DATE':
        adfuller_test(column, name=column.name)
        print('\n')

# Differencing the data
df_differenced = df.diff().dropna()

# Run ADF-test on our differenced data
for name, column in df_differenced.iteritems():
    adfuller_test(column, name=column.name)
    print('\n')

#### LAG ORDER SELECTION
model = VAR(df_differenced)
for i in [0,1,2,3,4,5,6,7,8,9,10]:
    result = model.fit(i)
    print('Lag Order =', i)
    print('AIC : ', result.aic)
    print('BIC : ', result.bic)
    print('HQIC: ', result.hqic, '\n')

#OPTIMAL LAG FOR ONLY OBX AND NOK/EUR
df_var = df_differenced[['obx', 'nok_eur']]
max_lag = 10

# Fit the VAR model with different lag orders

best_aic = float('inf')
best_order = None
```

```
for lag in range(1, max_lag + 1):
    model = VAR(df_var)
    results = model.fit(lag)
    aic = results.aic
    if aic < best_aic:
        best_aic = aic
        best_order = lag

print("Best lag order:", best_order)
print("AIC:", best_aic)

#### GRANGER CAUSALITY TEST
def grangers_causation_matrix(data, variables, maxlag=12, verbose=False):
df = pd.DataFrame(np.zeros((len(variables), len(variables))), columns=variables,
index=variables)

    coeffs = pd.DataFrame(np.zeros((len(variables), len(variables))), columns=variables,
index=variables)
    lag_order = pd.DataFrame(np.zeros((len(variables), len(variables))),
columns=variables, index=variables)
     for c in df.columns:
          for r in df.index:
            test_result = grangercausalitytests(data[[r, c]], maxlag=maxlag, verbose=False)
            p_values = []
            coef_values = []
            lag_values = []

            for i in range(maxlag):
              lag = i + 1
              p_value = round(test_result[i+1][0]['ssr_chi2test'][1], 4)
              coef = round(test_result[i+1][0]['params_ftest'][0], 4
               p_values.append(p_value)
               coef_values.append(coef)
               lag_values.append(lag)

               if verbose:
              print(f'Y = {r}, X = {c}, Lag = {lag}, Coef = {coef}, P-Value = {p_value}')

            min_p_value = np.min(p_values)
            min_coef = coef_values[np.argmin(p_values)]
```

```
        min_lag = lag_values[np.argmin(p_values)]
        df.loc[r, c] = min_p_value
        coeffs.loc[r, c] = min_coef
        lag_order.loc[r, c] = min_lag

    df.columns = [var + '_x' for var in variables]
    df.index = [var + '_y' for var in variables]
    coeffs.columns = [var + '_x' for var in variables]
    coeffs.index = [var + '_y' for var in variables]
    lag_order.columns = [var + '_x' for var in variables]
    lag_order.index = [var + '_y' for var in variables]
    return df, coeffs, lag_order

# Example usage
p_values, coefficients, lag_orders = grangers_causation_matrix(df, variables=df.columns,
maxlag=12, verbose=False)

# Print the p-values, coefficients, and lag orders
print("P-values:")
print(p_values)
print("\nCoefficients:")
print(coefficients)
print("\nLag Orders:")
print(lag_orders)

#### COINTEGRATION
obx = df_differenced['obx']
exchange_rate = df_differenced['nok_eur']
interest_rate_differentials = df_differenced['i']
oil_price = df_differenced['oil']
market_index = df_differenced['stoxx600']
electricity_prices = df_differenced['electricity']

# Perform first step regression: OBX ~ Other Variables
def run_regression(dependent_var, independent_vars):
    X = sm.add_constant(independent_vars)
    model = sm.OLS(dependent_var, X)
    results = model.fit()
    return results
```

```
# Run first step regression for each variable
reg_results = {}
variables = {'Exchange Rate': exchange_rate,
             'Interest Rate Differentials': interest_rate_differentials,
             'Oil Price': oil_price,
             'Market Index': market_index,
             'Electricity Prices': electricity_prices}

for var_name, var_data in variables.items():
    result = run_regression(obx, var_data)
    reg_results[var_name] = result

# Print regression results
for var_name, result in reg_results.items():

    print(f"Regression Results for OBX ~ {var_name}:")
    print("Coefficients:")
    print(result.params)
    print("Standard Errors:")
    print(result.bse)
    print("T-Statistics:")
    print(result.tvalues)
    print("P-Values:")
    print(result.pvalues)
    print("\n")

# Perform cointegration test
result = coint(obx, exchange_rate)
print("Cointegration test result between OBX and the Exchange Rate:")
print("Test statistic:", result[0])
print("P-value:", result[1])
print("Critical values:", result[2])

result = coint(obx, interest_rate_differentials)
print("Cointegration test result between OBX and the Interest Rate Differentials:")
print("Test statistic:", result[0])
print("P-value:", result[1])
print("Critical values:", result[2])
```

```
result = coint(obx, oil_price)
print("Cointegration test result between OBX and Oil price:")
print("Test statistic:", result[0])
print("P-value:", result[1])
print("Critical values:", result[2])

result = coint(obx, market_index)
print("Cointegration test result between OBX and Market Index:")
print("Test statistic:", result[0])
print("P-value:", result[1])
print("Critical values:", result[2])

result = coint(obx, electricity_prices)
print("Cointegration test result between OBX and Electricity price:")
print("Test statistic:", result[0])
print("P-value:", result[1])
print("Critical values:", result[2])

# VECM - COINTEGRATION BETWEEN OBX AND NOK/EUR

# Perform Johansen's cointegration test
johansen_result = coint_johansen(df_differenced[['obx', 'nok_eur']], det_order=0,
k_ar_diff=6)

# Extract the eigenvectors from the cointegration test results
eigenvectors = johansen_result.evec

# Create a DataFrame with the eigenvectors for the VECM
df_vecm = pd.DataFrame(eigenvectors, columns=['obx', 'nok_eur'])

# Create a DataFrame with the variables for the VECM
df_var = df_differenced[['obx', 'nok_eur']]

# Fit the VECM model
model = VECM(df_var, coint_rank=1, deterministic="co")
model_fit = model.fit()
print(model_fit.summary())

#### VAR MODEL
model_fitted = model.fit(8)
model_fitted.summary()
```

```
#### IMPULSE RESPONSE FUNCTION
import matplotlib.pyplot as plt
irf = model_fitted.irf()

# Plot the impulse response function
fig = irf.plot(orth=False)
fig.set_figheight(20)
fig.set_figwidth(20)
plt.xlabel('Time')
plt.ylabel('Response')
plt.title('Impulse Response Function')
fig.tight_layout()
plt.show()
```