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The Economics of Technology Stock Prices

An empirical study of the relationship between macroeconomic variables and the Norwegian technology index

Henrik Forfang Huuse & Steinar Pedersen

Supervisor: Professor Svein-Arne Persson

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NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Many of today's largest and most influential companies are in the technology sector. In recent years, these firms have experienced enormous growth in their stock price. For investors, this has been an excellent opportunity to make abnormal returns by investing in technology stocks. In the same period as the technology stock prices increased, there also were major changes in the economic environment. This suggests that the macroeconomic development has an impact of the prices of technology stocks. The purpose of our thesis is therefore to examine the relationship between chosen economic variables and the performance of the Oslo Stock Exchange technology index by answering the following research question:

How do macroeconomic determinants affect the development of the Norwegian technology index?

To answer the research question, we use quarterly time series data over a period spanning from 2000-2021. Based on earlier research and economic theory, seven macroeconomic variables are included. These are the 3-month NIBOR rate, inflation, the oil price, NOK/USD exchange rate, gross domestic product per capita, gross fixed capital formation and credit to the private sector.

Previous literature has to a large extent examined the relationship between macroeconomic factors and the market as a whole. Our research differs from previous literature by focusing on the development of one specific sector. This can contribute to explain how the economics of technology stock prices differ from the overall stock market and how investors can exploit these differences to decide how and when to invest in the technology sector.

The results of our analysis confirm that there exists a relationship between the macroeconomic factors and the Norwegian technology index. Several different relationships are found in our models. However, both models suggested a significant relationship from the 3-month NIBOR rate, inflation, the oil price and exchange rate to the value of the technology index, making those relationships robust. Investors should therefore be aware of the development of these factors when investing in the Norwegian technology stock market. Further, our analysis found no relationships from the technology index to any of the macroeconomic variables, implying that the index is a bad indicator for predicting the development of the macroeconomic variables.

Preface

This thesis is conducted as a final assignment to complete our Master of Science in Economics and Business Administration at the Norwegian School of Economics. Our major profile has been Financial Economics.

The thesis intends to examine how macroeconomic variables affect the performance of the Norwegian technology index. The selection of topic can be explained by our interest in financial markets, as well as our desire to write a quantitative paper. Writing this thesis has been challenging and required a considerable amount of work, but also educational and inspiring. It has been an excellent opportunity to challenge our analytical abilities and apply the knowledge we acquired during our years at NHH.

We wish to express our gratitude to our supervisor, Professor Svein-Arne Persson, for the valuable and constructive feedback throughout the entire process. His support has been impeccable.

Bergen, December 2022

Norwegian School of Economics

Henrik Forfang Huuse

Steinar Pedersen

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1. Introduction

1.1 Background

The technology index at the Oslo Stock Exchange was established in year 2000. At the same time, the dot-com bubble burst, leading to severe losses in value for several technology companies. In the time following the crash, the development of the technology index was relatively stable, and the number of listed companies on the index increased. However, during the COVID-19 pandemic in 2020-2021, the price of the Norwegian technology index rose by nearly 150%, from around NOK 260 to approximately NOK 600. The pandemic highlighted the many benefits of adding more technology to our lives. As we are more dependent on technological solutions today than ever before, one would imagine this to be good news for the technology companies. Therefore, their stock price should be increasing. However, despite the high demand, technology stock prices started to decline at the end of 2021. This development makes it interesting to investigate whether there are other factors that significantly influence the stock price of technology companies.

Figure 1. Sector indexes at the Oslo Stock Exchange

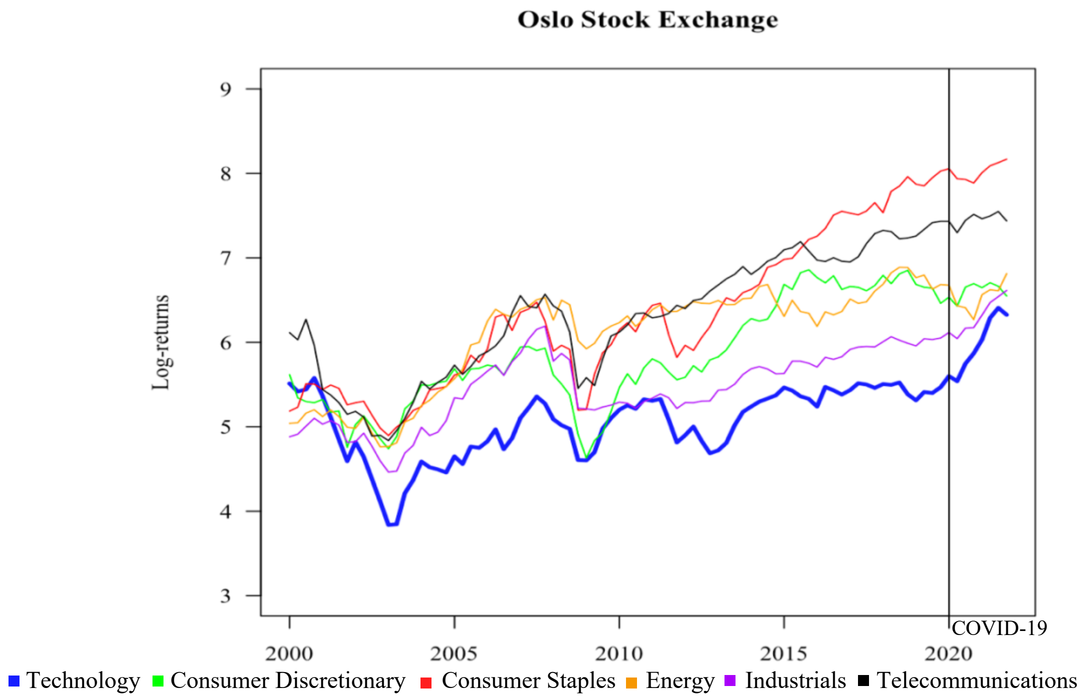


Figure 1: Development of different sector indexes at the Oslo Stock Exchange. Logarithmic returns for Q1 2000 – Q4 2021. The vertical line in 2020 marks the beginning of the COVID-19 pandemic.

Figure 1 exhibits the development of the Norwegian technology index compared to other sector indexes at the Oslo Stock Exchange from 2000 until the end of 2021. The figure shows that the return of technology stocks outperformed other sectors in 2020 and 2021. This suggests that investors could exploit the benefits of industry diversification and make an abnormal return by investing in technology stocks during this period. We believe one main reason the sector indexes have developed differently over the years is that they respond differently to changes in fundamental economic indicators. To understand why technology stocks have outperformed other sectors, and be able to exploit future opportunities to invest, it is important to gain knowledge of how the technology sector is affected by macroeconomic conditions and how this differs from the market in general.

Usually, technology stocks are valued at very high price-to-earnings multiples, and over time, they are considered to have the potential to exceed the return of the overall market due to their future potential and unique products. Today, many of the largest and most followed publicly listed shares are classified as technology stocks. The shares are divided into various subsectors, from hardware and software to internet and semiconductors. A relevant commonality for all these subsectors is the rapid changes that occur in the market. The prospects of a given technology company will change as rapidly as the underlying technology that drives the business. Therefore, the technology sector tends to be a very volatile sector to invest in when compared to other industries with more stable and predictable businesses.

Many of the characteristics of technology stocks are similar to those used to describe growth stocks. In Figure 2, we compare the Norwegian technology index to the US S&P 500 growth index. The figure reveals that the indexes exhibit a very similar path. Growth stocks differ from value stocks by making little to no current earnings. Instead, growth companies are considered to have a good potential for substantial expansion over a certain number of years. On the other hand, value stocks have more predictive cash flows instead of promised uncertain future cash flows. The S&P 500 growth index acts as a proxy for growth stocks included in the S&P 500 and consists primarily of technology companies. Based on the resemblances between the indexes, it appears that the technology stocks at the Oslo Stock Exchange primarily are growth stocks.

Figure 2. Oslo Stock Exchange technology index vs. S&P 500 growth index

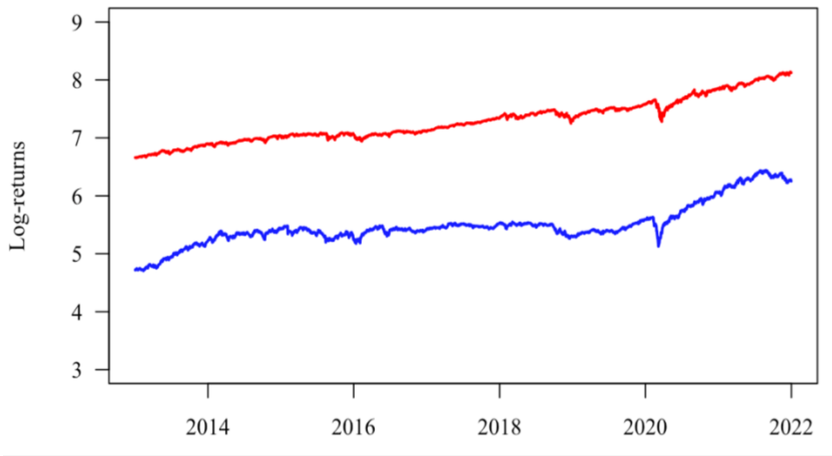


Figure 2: Development of the Oslo Stock Exchange technology index (blue) and S&P 500 growth index (red). Logarithmic returns of daily observations from 2013 – 2022. The period 2013-2022 is chosen due to the availability of data for the S&P 500 growth index.

Figure 1 shows that the technology index reached its all-time high in the fall of 2021. During the same period, interest rate were historically low at 0% in order to boost the economy and increase investment activities. As of 2022, the aftermath of the pandemic and war in Ukraine has caused high inflation across the world's economies. As a result, interest rates have increased to stabilize the economy and reduce inflation. At the same time, after a long period in which the technology index outperformed other indexes, the value of the Norwegian technology index has recently declined massively. From this, it seems evident that there is a strong relationship between interest rates and technology stocks.

The most prominent way to explain how stock markets can be affected by changes in interest rates is by using a discounted cash flow approach. The premise of the discounted cash flow approach is that the value of a financial asset is determined from its expected future cash flows discounted at the current rate of interest. This can form an intuition of why growth and technology stocks have been hit the hardest by a rise in interest rates. Because of the potential to outperform the overall market, growth stocks usually have higher expected future earnings than value stocks. These future earnings will be worth more to investors today when interest rates fall. The growth comes at a premium when the interest rate is low. This theory is intuitive, but, as we see from Figure 3, it does not always work in practice.

Figure 3. Development in the Oslo Stock Exchange technology index and 3-month NIBOR rate

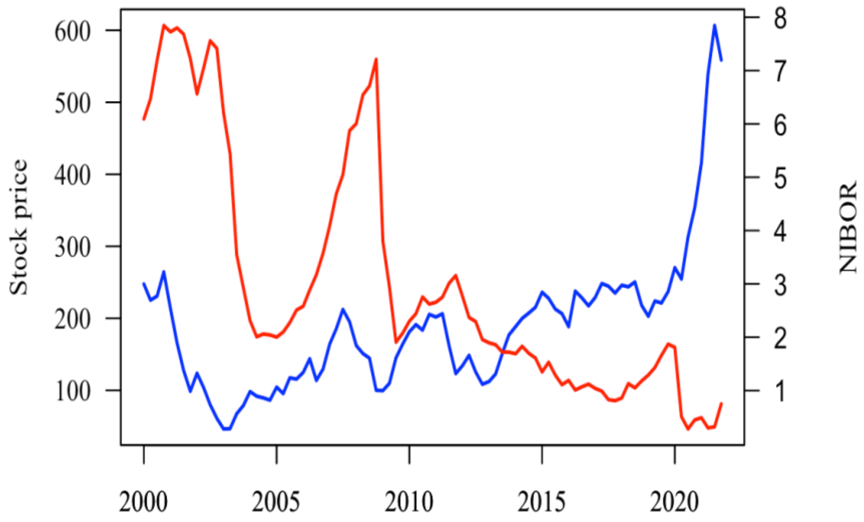


Figure 3: Oslo Stock Exchange Technology Index (blue) in NOK and NIBOR (red) in % for Q1 2000 – Q4 2021. The y-axis on the left-hand side shows the development of the technology index, while the evolvement of the three-month NIBOR rate applies to the y-axis on the right-hand side.

Figure 3 provides a good overview of how the Norwegian technology index and the interest rate have developed since 2000. When studying the entire period, we found it interesting that interest rates have decreased steadily while the technology stock prices have not increased accordingly. The interest rate fell from almost 8% in the early 2000s to just over 2% a few years later. At that time, the return of technology stocks also declined drastically. Further, the financial crisis from 2007-2009 saw a drop in interest rates to increase investing activities. As a result, one could expect technology stock prices to rise. However, the stock price declined along with the interest rates. From 2005 through 2007, the interest rate almost tripled from 2% to 6%. Correspondingly, the value of Norwegian technology stocks increased sharply during this period.

This suggests that there are other determinants affecting the stock price in addition to the interest rate. Many studies have previously been conducted on which variables that have an impact on the stock market. Still, there is no extensive research regarding the economic determinants of Norwegian technology stock prices. The purpose of our research will therefore be to contribute to empirically assess the extent to which a relationship exists between the Norwegian technology index and our chosen variables. If returns from the technology stock market consistently reflect macroeconomic information, the Norwegian technology market should be cointegrated with the set of macroeconomic variables. Thus, changes in these variables should contribute significantly to the cointegrating relationship. In economic terms, this would imply that the Oslo Stock Exchange technology index is sensitive to changes in economic factors and that investors, to some degree, can make large profits from investments in technology stocks by studying the macroeconomic environment.

1.2 Research Question

Our research supplements previous literature on how macroeconomic variables affect the stock market. By including variables previously studied and, at the same time, adding some new ones, the study aims to fill the gap of extensive research regarding the relationship between macroeconomic determinants and the return of Norwegian technology stocks. The objective with the analysis is to investigate the presence of long-run equilibrium relationships between our chosen variables and the technology index and, at the same time, examine if there are any short-run causalities among the variables. In addition, we aim to forecast how the technology index will react to an unexpected change in one of the variables and to what extent these unexpected changes are significant for the variation in stock returns. The practical goal of this study is to investigate whether our chosen macroeconomic factors are among the determinants of Norwegian technology stock prices and whether they are influential in predicting future stock returns. Hence, the following research question has been defined:

How do macroeconomic determinants affect the development of the Norwegian technology index?

Recognizing the lack of relevant studies examining the technology sector, this thesis investigates the dynamic relations between the Oslo Stock Exchange technology index and seven macroeconomic variables. These are the 3-month NIBOR interest rate, inflation, oil price, the NOK/USD exchange rate, gross domestic product per capita, gross fixed capital formation and credit to the private sector. With this, we aim to discover which systematic factors that are most important in determining the development of technology stock prices. Econometric techniques are used to conduct the analysis. We also apply financial theory to discuss the results obtained from the analysis. Comparing the results from our models with previous research conducted on other markets makes it possible to study whether already established relations also can be made valid for the technology sector.

1.3 Outline

This thesis consists of six parts, including the first introductory chapter. In the second chapter, relevant literature and theory is presented. Chapter three introduces the data collected and used in the analysis. We will give an overview of where the data were retrieved from, the reasoning for choosing the respective variables, and come up with expectations of how the variables impact the Norwegian technology index. In chapter four, we describe the empirical methods used before chapter 5 present our findings from the analysis. We discuss the results of each statistical test in depth and in light of established theory and previous literature. Finally, in chapter six we give some concluding remarks, discuss the limitations of our analysis and provide suggestions for further studies.

2. Literature Review and Theory

2.1 Literature Review

The relationship between macroeconomic variables and stock returns is a topic that has been relevant for many decades. As a result, the research is abundant and consists of a variety of studies from different countries conducted with several econometric methods. However, according to our knowledge, research on the relationship between macroeconomic determinants and the performance of technology stocks has barely been carried out.

In one of the first acknowledged studies of the topic Fama (1981) examined the correlation between the US economy and the stock market for the period 1953-1977 using regression methods. The study found a positive correlation between stock returns and real activity and provided strong evidence that an increase in inflation decreases the return of the stock market. In more recent research Kim (2003) used a vector error correction model on a sample spanning from 1974-1998 and discovered that the return of the US stock market had a positive relationship to industrial production and a negative relation to interest rate, real exchange rate and inflation, supporting the finding of Fama (1981). Consistent with these results, Humpe and Macmillan (2009) applied a cointegration analysis on US data for the last 40 years and found that stock prices had a positive relation to industrial production while they were negatively associated with the consumer price index and the long-term interest rate. Jareño and Negrut (2015) obtained quarterly data from 2008-2014 and detected that the US stock market was significantly affected by the development in GDP, industrial production and the long-term interest rate. Similarly, Faisal et al. (2016) examined the Chinese market from 1999 to 2015. They discovered stock prices were sensitive to a change in GDP, foreign direct investments and the level of credit to the private sector.

The research done by Gjerde and Sættem (1999) is highly relevant to our study. They investigated to what extent the relationships between macroeconomic variables and stock returns from more extensive and evolved markets are valid in Norway, which is a small and open economy. The authors used a Vector Autoregressive (VAR) approach to inspect whether there were any causal relationships between their chosen economic variables. The data were monthly observations over 20 years from 1974-1994. Variables included in the analysis were interest rate, inflation, oil price, the exchange rate (USD/NOK), industrial production, consumption, and the OECD industrial production index. Gjerde and Sættem found that changes in the real interest had an impact on stock returns and inflation. In addition, they observed that the return from the Norwegian stock market immediately increased when the oil price rose.

A significant negative correlation between inflation and stock returns is a well-established result. Sukruoglu and Temel Nalin (2014) studied the macroeconomic determinants of the stock market in 19 European countries in the period 1995-2011. The researchers found that a rise in inflation and the monetization ratio had a negative impact on the stock market development.[1] On the other hand, an increase in the income level, savings rate and liquidity ratio had a positive effect. Opposite to this, Lee (1992) used a vector autoregressive approach to study causal relations among asset returns, interest rates, inflation and real activity in the post-war United States. The results suggested no causal relationship running from stock returns to inflation. However, allowing for a separate role of the interest rate, the authors found a causal relationship between interest rates and inflation, indicating that an increase in interest rates would result in declining inflation.

Research conducted by Rigobon and Sack (2004) identified the impact of monetary policy on the US stock market performance. The research established that a 25-basis point increase in the three-month interest rate on average would result in a 1.7% decline in the S&P 500 index, while the NASDAQ technology index would decline by 2.4%. The NASDAQ index showed a considerably larger reaction indicating that technology stocks are more sensitive to changes in monetary policy. An inverse relation between stock prices and interest rates was also strongly documented by Bernanke and Kuttner (2005), who found that a 25-basis-point cut in the Federal Funds rate was associated with about a 1% increase in broad stock indexes. However, this research discovered that the high-tech and telecommunication sectors exhibit a response half as large as the broad market.

Jones and Kaul (1996) used quarterly data to investigate how international stock markets would react to changes in the oil price. They found that a change in the oil price had an impact on US and Canadian firms´ current and future cash flows. Thus, they concluded that oil price changes could be used to forecast stock returns in the US and Canada. Sadorsky (1999) used a vector autoregressive model with monthly data covering 1947-1996 to show that changes to

[1] Monetization ratio is a measure of the development of the financial system. It is defined as liquid liabilities (M3) to GDP ratio and is a determinant of the size of the financial system in relation to the whole economy (Sukruoglu and Temel Nalin, 2014).

the oil price could be important in affecting stock returns. The estimated results suggested that an increased oil price would depress real stock returns. Further, Sadorsky (2003) aimed to establish a relationship between technology stock price movements and oil price movements. The data were monthly and covered the period from 1984 to 2000. The study concluded that the volatility of the oil price is an important factor in explaining the volatility of technology stock returns. Sadorsky´s hypothesis was that oil price volatility is an important source of business cycle uncertainty. Technology stocks do not perform well in periods of uncertainty since investors will turn to stocks with secure earnings instead of technology stocks with uncertain cash flows further into the future. The results help to understand how oil price movements affect the return of technology stocks.

According to Dornbusch and Fischer (1980) and Frankel (1983), two main theories are the basis for empirical studies regarding the relations between exchange rates and stock markets. The goods market hypothesis states that the exchange rate has an impact on the stock market. A depreciation of the home currency is beneficial for stock prices because many firms are exporting their goods to other countries. A currency depreciation will therefore increase the demand for exports. As a consequence, earnings and thereby share prices will increase. On the other hand, the portfolio balance approach advocates that it is the stock market that causes changes in the exchange rate. More foreign capital inflow to the stock market would result in an increased demand for domestic currency. When the demand increases, the home currency will appreciate. Additionally, Kim (2003), in his study, found that foreign investors´ expectations regarding the performance of the stock market had a significant impact on stock prices. Good news in the economy will make US investors want to switch from foreign to American stocks, putting pressure on the currency to appreciate and the US equity prices to increase. The author refers to this as the portfolio adjustment effect.

Bahmani-Oskooee and Saha (2015) used an Autoregressive Distributed Lag (ARDL) approach with monthly data spanning from January 1973 to March 2014 to investigate the impact exchange rates have on stock prices in the US. Stock prices are estimated as a function of the exchange rate, industrial production, consumer price index and money supply. The research implied that an appreciation of the dollar had a negative impact on US firms´ stock prices. In another study, Bahmani-Oskooee and Saha (2016) used the ARDL approach to examine how exchange rates affected the stock market in 10 different European economies, including the United Kingdom, from January 1973 to March 2014. The study failed to find a significant effect from exchange rates to stock returns in the UK market. Kollias et al. (2015) adopted a cointegration methodology to study the relationship between stock markets and exchange rates in eight European economies. The sample included four countries with national currencies: Sweden, Denmark, Norway and the UK. Using monthly data from the period 2000-2014, the researchers found a causal relationship from the exchange rate to the stock market and simultaneously a causal relationship from the performance of the stock market to exchange rates. This is referred to as a bidirectional causality.

A paper by Belo and Yu (2013) empirically explored the effect of government investments in public sector physical capital on US stock returns. The empirical results showed that US public investments had a significant relationship with US stock market excess returns. The findings suggested that public investments are positively correlated with the return of the stock market, which means that an increase in the level of investments will lead to higher stock returns.

The relationship between macroeconomic variables and stock returns has been amply examined. However, little research has been performed regarding the relationship between the technology sector and various macroeconomic determinants. As far as our knowledge goes, the most relevant study on this area is the research of Bhuiyan and Chowdhury (2020), which investigated how different sectors of the stock market in the US and Canada were influenced by the macroeconomic variables money supply, interest rate and real economic activity. By analyzing monthly data over the 2000-2018 period, the authors concluded that the technology sector did not possess any long-term equilibrium with macroeconomic variables, neither in the US or Canada.

Our contribution to this literature will be to analyze how macroeconomic factors affect the technology stock prices at the Oslo Stock Exchange. We believe our results can be useful as they extend the current research on macroeconomic factors and stock returns. Previous studies of the Norwegian stock market, especially the work of Gjerde and Sættem (1999), have focused on the economy as a whole, while this study looks at one specific industry. Using the results from previous studies makes it possible to investigate how technology stock prices moves compared to the overall stock market. If tech stocks behave differently, there might exist diversification opportunities. This thesis also uses more recent data and contains some variables not widely used in macroeconomic studies.

2.2 Theory – Discounted Cash Flow

In addition to previous studies, it is appropriate to introduce the theoretical foundation for our analysis, which primarily consists of common approaches to equity pricing. The established theories will provide additional aspects when discussing our findings. We will use this as a framework when examining how macroeconomic variables affect the prices of technology stocks. The financial theory contains how stock prices are determined based on expected cash flows and the discount rate.

Based on a discounted cash flow approach, Chen et al. (1986) argue that external factors can significantly affect the price of a stock. Any systematic factor affecting either the expected cash flows or discount rate would also influence the stock price. Chen et al. (1986) argue that these external factors are macroeconomic. The Discounted Cash Flow (DCF) model is a common way of valuing a business. This theory states that the price of a stock is derived from the present value of its expected future free cash flows to equity ($\mathrm{FCF_E}$). The $\mathrm{FCF_E}$, as presented by Berk and DeMarzo (2020), is given by:

FCF_E = (Unlevered net income + Depreciation – Cap. Expenditures – Change in net working capital) – after tax interest payments + Net borrowing

We find the stock price by calculating the present value of future cash flows, using equation (1),

$$\mathrm{P_0} = \sum_{t=1}^{t=n} \frac{\mathrm{E(FCF_t)}}{(1 + \mathrm{k_e})^{\mathrm{t}}}\,, \tag{1}$$

where $\mathrm{k_e}$ is the required return on equity derived by the Capital Asset Pricing Model (CAPM). CAPM was initiated independently by Sharpe (1964), Lintner (1965) and Mossin (1966). It is recognized as a single-factor model, meaning it only takes the market factor into account when determining stock returns. An investor requires compensation for the risk he/she is taking and compensation for the time value of money. Since an investor can eliminate risk by holding a diversified portfolio, he/she is not compensated for firm-specific risk. Only the systematic risk is compensated. In CAPM, the time value of money is represented by the risk-free rate, compensating investors for placing money in an investment over a certain period.

Fama and French (2004) in their paper used empirical tests to prove that the CAPM does not hold. This is because the CAPM is a very simplistic model that relies on a set of unrealistic assumptions to be met in the real world. It is assumed that a perfect capital market exists, meaning there are no taxes and perfect information is available to all investors. As a result, all investors have the same expectations regarding risk and expected returns. Furthermore, the systematic risk is assumed to be constant, while it actually may vary significantly over time. The model is also heavily reliant on historical data to compute future stock returns. Nevertheless, the CAPM is still a commonly used model due to its intuitive measurement of risk and its simplicity.

Stocks are subdivided into two categories: value and growth. Value stocks have strong current cash flows and steady low growth over time. By contrast, growth stocks may yield small cash flows today. However, their value is based on the potential to make returns above the market´s average over a longer horizon. Different stocks have different characteristics and will be affected by changes in the discount rate in dissimilar ways. According to the DCF model, higher discount rates produce lower equity values, but the effect will vary across different types of stocks. Because the cash flows of growth stocks are further into the future, the value of these stocks will be more sensitive to a rising discount rate compared to value stocks.

In practice, multiples are often used to value a company's equity. The price-earnings multiple is the most common approach for valuing stocks (Koller et al., 2020). The model uses the ratio between price and earnings for comparable firms and multiplies it with the firm´s earnings to find the appropriate value.

The stock market is efficient if the price of a stock instantly responds to new information about a company´s expected future earnings. The efficient market hypothesis (EMH) presented by Fama (1970) states that a market is efficient if prices fully reflect all available information and economic indicators will therefore be unable to impact stock returns. The theory distinguishes between three forms of market efficiency, depending on the type of information reflected in the prices. Weak-form efficiency means that a share's historical prices and trading volume determine the current stock price. Semi-strong form efficiency states that the stock price, in addition to reflecting previous prices and volume, also will reflect information publicly available at all times. Lastly, strong form efficiency is when the stock price, as well as reflecting publicly available information, also reflects private information.

The empirical question of whether macroeconomic factors can be influential in determining and predicting stock prices is well documented in the literature. A causal relationship between stock prices and macroeconomic variables indicates whether the market exhibits informational efficiency. The establishment of a relationship between macroeconomic variables and stock prices contradicts the efficient market hypothesis (Fama, 1970) and Granger (1986) stated that asset prices could not be cointegrated when the market was efficient. On the other hand, Samuelson (1998) found evidence that the EMH may be suitable for individual stocks but does not hold for the aggregate stock market. However, the interpretation of cointegrated relationships depends on the definition of efficiency. Dwyer and Wallace (1992) defined efficiency as the absence of arbitrage opportunities and established that the existence of cointegration not automatically will violate the notion of information efficiency, which is defined by Fama (1991). Further, Fama (1991) argues that the possibility to forecast changes in stock prices is compatible with an efficient stock market in the presence of time-varying expected returns. Since the economy runs in business cycles, predictable and time-varying risk premiums are produced. Yet it is not certain that this predictability will provide arbitrage profit opportunities.

3. Data

In the following chapter, we elaborate on our data collection, the reasoning for variable selections and how they have been adjusted for our analysis. Furthermore, we comment on our predictions for the relationship between each variable and the technology index. Lastly, we discuss the potential challenges with our data.

The variables included in this analysis are selected based on relevant previous studies, as highlighted in the literature review, and established financial theory. For instance, the NIBOR rate, inflation, oil price, exchange rate and gross domestic product are variables several previous studies have found to be related to stock prices.[2] These are standard economic determinants that are easy to measure, and we want to investigate if the established relationships also are valid for technology stocks. In addition, we include the gross fixed capital formation and credit to the private sector, variables not widely used in macroeconomic studies. When studying the time series of these variables, we observe that significant changes occur simultaneously as major fluctuations in technology stock prices. Hence, we find it interesting to examine the existence of a causal relationship between these variables.

Table 1. Descriptive Statistics

Variable	Abbreviation	Mean	Standard deviation	Min	Max
Oslo Stock Exchange Technology Index	OTECG	187.99	98.84	46.40	606.66
NIBOR 3-month interest rate	NIBOR	3.01	2.25	0.28	7.85
Inflation	INF	93.12	12.04	74.50	117.20
Price of Brent Crude Oil	OIL	63.67	29.73	18.38	132.72
Exchange rate NOK/USD	EXCH	7.24	1.31	5.06	10.44
Gross Domestic Product per capita	GDP	133.95	144.42	122.61	144.42
Gross Fixed Capital Formation	GFCF	152.91	54.90	68.33	250.23
Credit to the Private Sector	CRDT	215.09	33.17	156.50	282.10

Table 1: Descriptive statistics of the variables for the period Q1 2000 – Q4 2021. Oslo Stock Exchange Technology Index (OTECG) in NOK, NIBOR 3-month interest rate in percentage (%), Inflation (INF) baseline value = 100, Price of Brent Crude Oil (OIL) per barrel in US Dollars ($), Exchange rate NOK/USD (EXCH) in NOK, Gross Domestic Product per capita (GDP) in thousands NOK, Gross Fixed Capital Formation (GFCF) in billions NOK, Credit to the Private sector (CRDT) in the percentage of GDP (%).

[2] For example, Gjerde and Sættem (1999), Kim (2003), Humpe and Macmillan (2009) and Jareño and Negrut (2015).

Table 1 presents the descriptive statistics of the macroeconomic variables we have chosen to include in our analysis and the abbreviations frequently used in the thesis. This thesis uses quarterly time series data from the first quarter of 2000 to the fourth quarter of 2021, with a total of 88 observations per variable. The data is collected from various sources highlighted in the following subsections. All the data is easily accessible to others, which we believe increases the reliability of the study.

The data has been processed for our analysis by taking the natural logarithm for all the variables. Re-scaling the data to a logarithmic form can solve problems with inconsistent variances and help the data to a normal distribution. From Table 1, we observe that the financial time series contains differing base values that can be difficult to compare. Our data consists of percentages, differing currencies and extreme values. Logarithmic first difference returns are often applied to compare the variables and interpret all the results as relative changes. The log-transformed model will help stabilize and detrend the time series making it more adequate for forecasting. Also, extreme values are not as influential as before the data was transformed, which can reduce heteroskedasticity. For our analysis, the dependent and independent variables are transformed into logarithmic first differences using equation (2),

$$\Delta Y_t = \ln(Y_t) - \ln(Y_{t-1}), \tag{2}$$

where Y_t is the observation at time t, and Y_{t-1} is the observation in the previous period.

3.1 Definition of Variables

3.1.1 Oslo Stock Exchange Technology Index

The Oslo Stock Exchange Technology Index (OTECG) is the dependent variable in our analysis and is a part of the Oslo Stock Exchange Benchmark Index (OSEBX).[3] As of September 2022, the index consists of 25 technology companies registered at Oslo Stock Exchange. The quarterly gross returns were retrieved from the database of the Oslo Stock Exchange, and the index's development compared to the benchmark index is displayed in Figure 4.

Figure 4. Oslo Stock Exchange Technology Index compared to the Benchmark Index

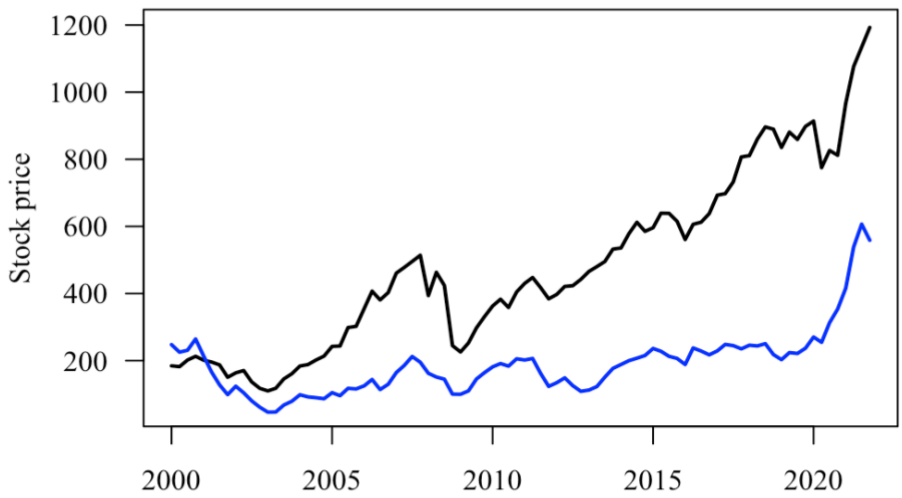


Figure 4: Oslo Stock Exchange in NOK for Q1 2000 – Q4 2021. Oslo Stock Exchange Benchmark Index (OSEBX) is in black, and Oslo Stock Exchange Technology Index (OTECG) is in blue.

We observe that fluctuations in the technology index follow OSEBX fluctuations to some degree. When the dot com bubble busted in 2000, severe losses in market value for the companies listed on the technology index occurred in the following years. The OSEBX also declined during the same period, as all stock markets worldwide were trembling. The financial markets started to recover in 2003, and there was consecutive annual growth, both for the benchmark- and technology index until the global financial crisis occurred in 2007. During the financial crisis, the whole financial system nearly broke down and the world´s stock markets suffered severe damage. There was probably nothing particularly wrong with the

[3] OSEBX is a value-weighted index compiled from a representative selection of all shares on the Oslo Stock Exchange.

technology sector. Finally, the technology index has seen massive growth in the last two years. Tech stocks seem to have profited from the COVID-19 pandemic and the central bank's subsequent stimulation of the economy.

As the need for technology has increased drastically in the last decade, one would expect the index to increase accordingly. However, in the study period, the growth in OSEBX is significantly higher than in the technology index. We find this particularly interesting and want to investigate further which factors that affect the technology index. This thesis aims to identify and explain the influence of macroeconomic variables on the Norwegian technology index, and we will include seven independent macroeconomic determinants for our further analysis.

3.1.2 NIBOR

The Norwegian Interbank Offered Rate (NIBOR) is included as an independent variable and reflects the cost of borrowing between banks and the money market. The 3-month NIBOR rate consists of the market's expected average overnight rate that follows the Norwegian policy rate and a risk premium (Kloster & Syrstad, 2019). As previously exhibited in Figure 3, the NIBOR rate decreased drastically after the 2008 financial crisis and has been declining steadily ever since. The 3-month NIBOR rate for Q1 2000 – Q3 2013 was collected from the database of the Norwegian Bank, while the remaining data was collected from Statistics Norway (SSB).

As presented in the theory section, growth stocks are expected to perform contrary to changes in interest rates. An increase in interest rate is expected to increase the discount rate and based on the discounted cash flow model, we expect NIBOR rate to have a negative impact on the technology index. Additionally, an increased interest rate may raise financing costs, reducing a firm´s profitability and, consequently, its stock price.

3.1.3 Inflation

The inflation rate (INF) is obtained by looking at the changes in the Norwegian consumer price index (CPI). We follow Chen et al. (1986), who use CPI as a proxy for inflation. The consumer price index can be defined as the rate at which prices increase over time and is often used to calculate inflation. For our analysis, we look at changes in CPI from one quarter to the next. As a measure of economic activity, an increase in inflation would mean reduced purchasing power and lower returns. We collected the CPI from the database of the Federal Reserve Bank of Saint Louis (FRED),[4] and calculated the inflation rate by using equation (3),

$$\Delta\text{INF} = \ln(CPI_t) - \ln(CPI_{t-1}), \quad (3)$$

where CPI_t is the observation at time t, and CPI_{t-1} is the observation in the last quarter.

Figure 5 presents the evolution of the consumer price index, and one can observe that it increases over time, as stated in theory. A higher inflation rate usually leads to stricter economic policies. Hence, interest rates would increase and, thereby, the discount rate in the discounted cash flow model. Based on this, we expect the rate of inflation to have a negative impact on the value of the technology index.

Figure 5. Consumer Price Index

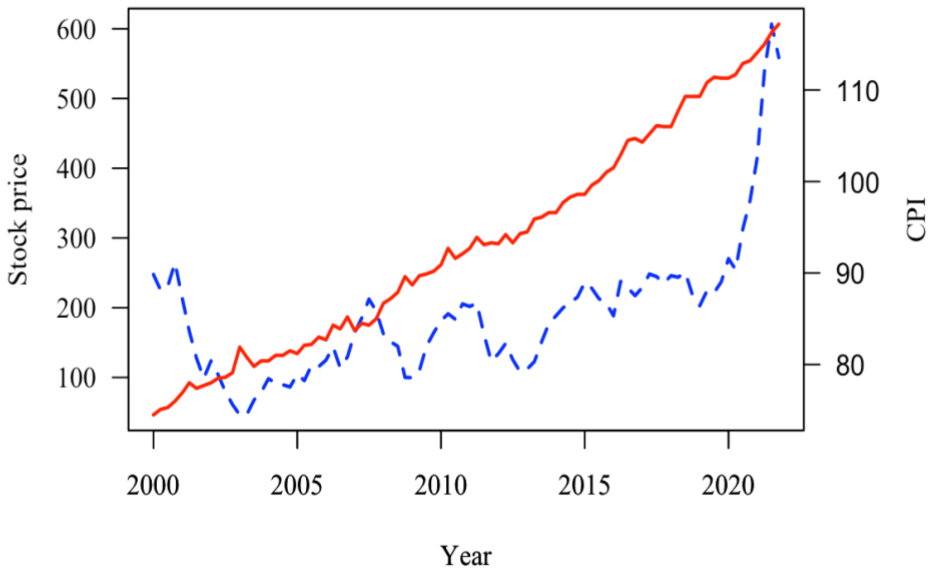


Figure 5: The Norwegian Consumer Price Index (CPI) for Q1 2000 – Q4 2021. Baseline value: 2015 = 100. OTECG (stippled blue) in NOK.

3.1.4 Oil Price

Norway is an energy-exporting country, and the stock exchange is thought to be heavily influenced by changes in oil prices. To determine oil prices (OIL) in our model, we obtained the Brent Crude Oil spot prices from the FRED database, reported in US Dollars per barrel.

[4] FRED (Federal Reserve Economic Data) is an online database which consists of hundreds of thousands economic time series developed by the Research Department at the Federal Reserve Bank of St. Louis.

Figure 6 presents the changing oil prices in our analysis period, and as one can observe, the oil prices are heavily influenced in periods of crisis.

Previous studies discussed in the literature review suggest that oil prices are important in impacting the business cycle. Sadorsky (1999) found a negative response to changes in oil prices in the US stock market, while Gjerde and Sættem (1999) found a positive response to oil price changes in the Norwegian stock market. We expect the Norwegian technology index to respond similarly to the findings of the Norwegian stock market and be positively influenced by oil prices.

Figure 6. Oil Price

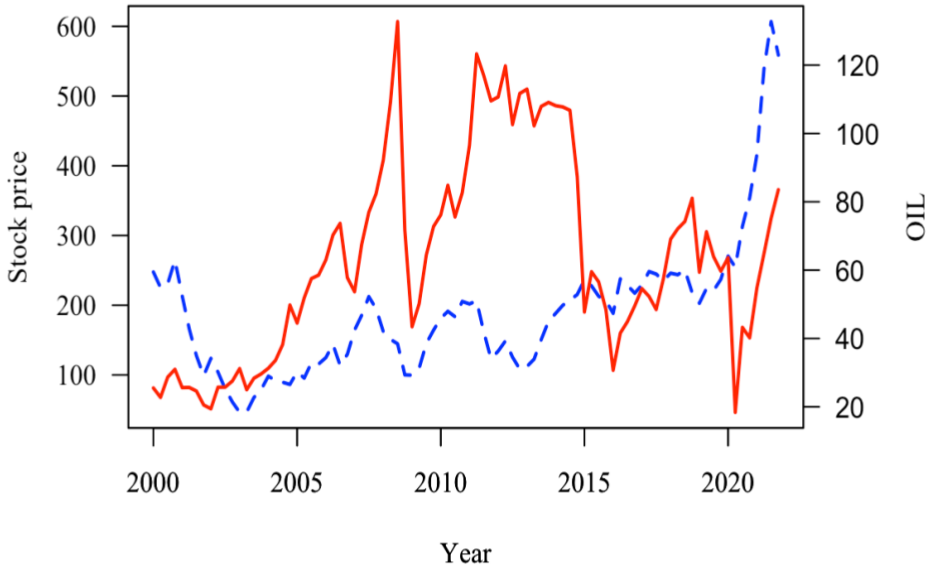


Figure 6: The Brent Crude Oil spot price (OIL) per barrel in US Dollars ($) for Q1 2000 – Q4 2021. OTECG (stippled blue) in NOK.

3.1.5 Exchange Rate

The foreign exchange rate (EXCH) was retrieved from the database of the Norwegian Central Bank and contains the exchange rate of the Norwegian Krone (NOK) to US dollars (USD). As the companies listed in the Norwegian technology index get revenues in currencies other than NOK, the exchange rate can influence the value of their international sales. As most exports are traded in USD, we decided to include the NOK/USD exchange rate as an explanatory variable in our analysis.

The exchange rate is displayed in Figure 7, and we observe that the rate fluctuates over time. There are two different approaches to how a rise in the exchange rate, which means a depreciation in NOK to USD, will impact the Norwegian Technology Index. One possible expectation is that a weak home currency is beneficial for the stock prices because many tech companies get their revenues not just in Norway but also in foreign countries. With a weak home currency, the companies will gain value from international sales when the earnings are repriced in the home currency. The other approach is that a depreciation of NOK will lower the demand for investments in the Norwegian technology market and thereby lower the future expected earnings of the tech companies.

Figure 7. NOK/USD Exchange Rate

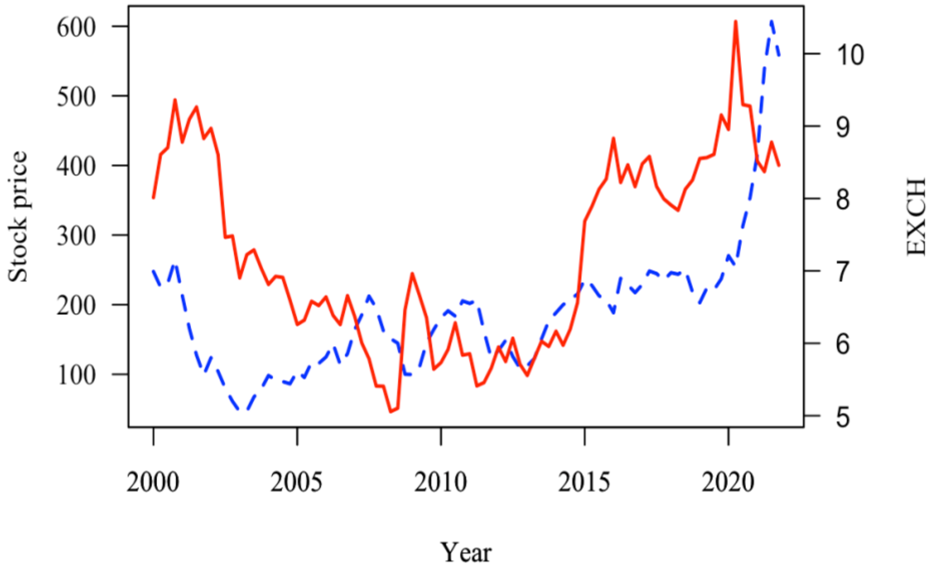


Figure 7: Exchange rate NOK/USD (EXCH) in NOK for Q1 2000 – Q4 2021. OTECG (stippled blue) in NOK.

3.1.6 GDP per Capita

Gross domestic product (GDP) is widely used as a standard measure of economic activity within a country. It consists of all value created through the production of goods and services over a certain period. We calculated the Gross Domestic Product per capita (GDP per capita) by collecting real GDP and dividing it by the Norwegian population data for each quarter. Since both GDP and GDP per capita are good indicators for economic growth, we chose to use GDP per capita in our model due to its logical presentation. Real GDP was obtained from the FRED database and is inflation adjusted, while the population data was retrieved from Statistics Norway (SSB).

The evolution of the Norwegian GDP per capita is presented in Figure 8 and shows that it has been increasing for the past two decades. One could also observe economic shocks that have negatively impacted Norway's GDP per capita. The most visible ones are the 2008 financial crisis and the beginning of the COVID-19 pandemic in 2020. As an increase in GDP per capita induces increased purchasing power and the ability to invest in the stock market, we expect it to impact the technology index positively.[5]

Figure 8. GDP per Capita

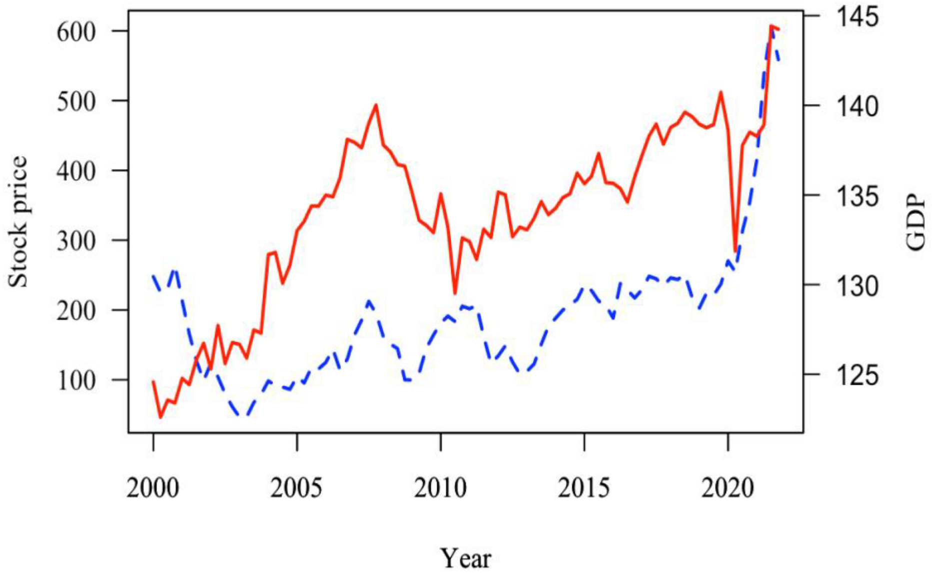


Figure 8: Gross Domestic Product per capita (GDP per Capita) in thousands NOK for Q1 2000 – Q4 2021. OTECG (stippled blue) in NOK.

3.1.7 Gross Fixed Capital Formation

Gross fixed capital formation (GFCF) is included as an independent variable as investments significantly contribute to GDP growth. The current price data for the variable gross fixed capital formation was retrieved from the FRED database and contains data on domestic investments of produced assets used for over a year in production. This includes assets used repeatedly by producers. The variable only includes assets that are output from a production process. Thus it does not include investments in assets not used in production, such as land or natural resources (OECD, 2022).

The growth in GFCF can be seen in Figure 9 and shows that domestic investments in fixed assets have increased rapidly during the past two decades. We believe increased investment activities will have a beneficial effect on economic growth and activity, which again can lead to higher stock prices. Thereby, the variable is included to observe how increasing investment

[5] From this point and onwards, the thesis uses GDP as the abbreviation for GDP per capita.

activities affect the Norwegian technology index. We expect GFCF to have a positive effect on the technology index.

Figure 9. Gross Fixed Capital Formation

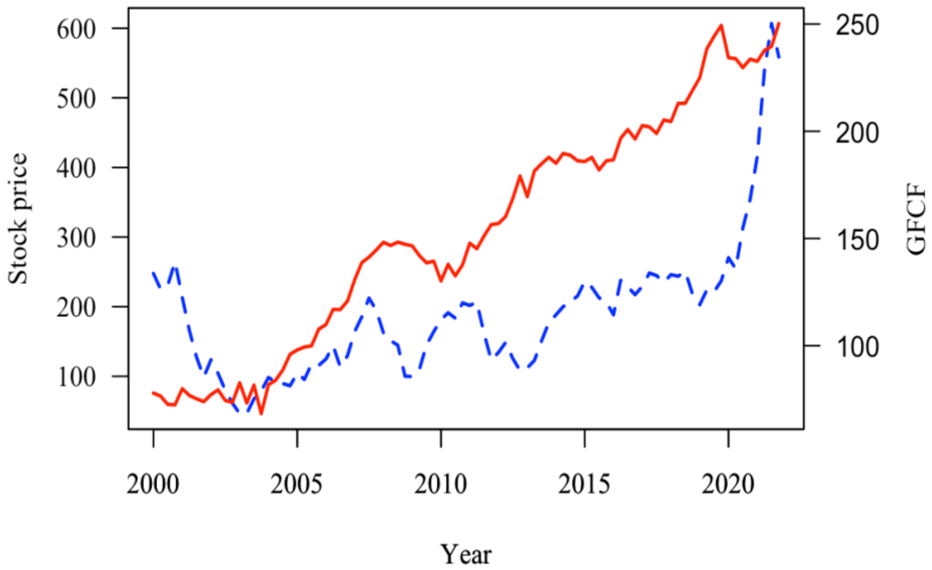


Figure 9: The Norwegian Gross Fixed Capital Formation (GFCF) in billions NOK for Q1 2000 – Q4 2021. OTECG (stippled blue) in NOK.

3.1.8 Credit to Private the Sector

The variable credit to the private sector (CRDT) is included as it measures financial resources provided to the private sector as a percentage of GDP. These resources include loans, non-equity security purchases or other accounts receivable offered by financial institutions such as banks, authorities and other financial corporations. Providing credit to the private sector affects economic activity. As Norway is among the countries with the highest CRDT ratios in the world, we include the variable to help explain movements in the technology index. For our analysis, we use the data retrieved from the FRED database on the Norwegian domestic credit to the private sector. As displayed in Figure 10, we observe that it has increased during the timespan we investigate in this thesis.

As financial resources are offered to the private sector, we expect that more money will make its way to the stock market and therefore increase the expected future earnings of companies. On the other hand, with a high level of credit, people get more vulnerable to interest rate changes. Increased repayment of interest rates means that less money will be invested in the stock market and thereby reduce the valuation of the firm's future cash flows. This could especially hurt technology companies, valued at high P/E multiples and relying on funds to be reinvested to generate growth.

Figure 10. Credit to the Private Sector

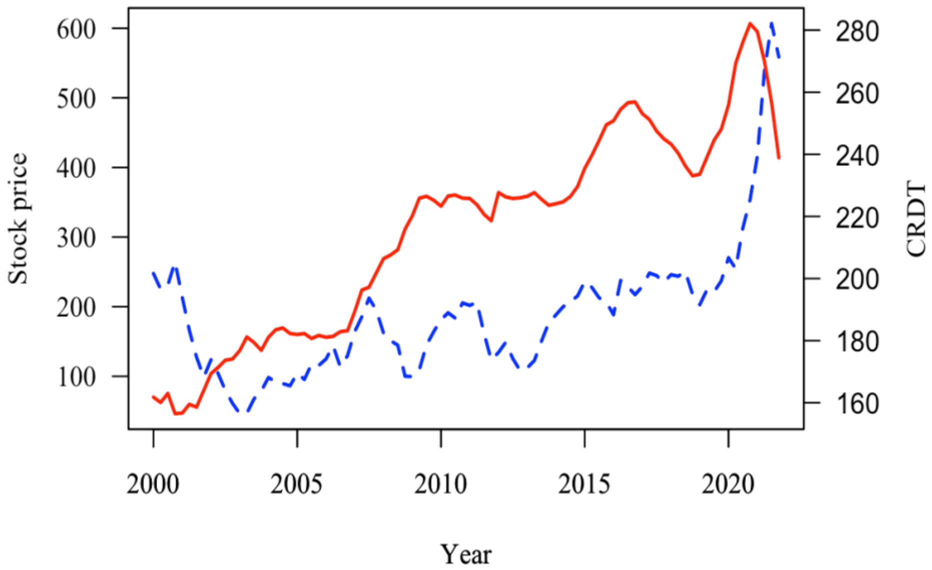


Figure 10: Credit to the Private sector (CRDT) in percentage (%) of GDP for the period Q1 2000 – Q4 2021. OTECG (stippled blue) in NOK.

Table 2 provides a summary of our expectations of the relationship between the Norwegian technology index and each of the macroeconomic variables.

Table 2. Summary of the expected relationship between the technology index and an increase in macroeconomic variables analyzed.

Expected impact	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
OTECG	-	-	+	+/-	+	+	-

3.2 Potential challenges with our data

This thesis uses macroeconomic variables selected based on previous literature and theory. When this study was conducted, interest rates were rising, and there was a high level of inflation due to aftershocks from the COVID-19 pandemic and the war in Ukraine. Since our data is limited to Q1 2000 – Q4 2021, it excludes data from Q1 2022 to the present day and thereby does not capture the current market effects. We do not have historical data for a more extended period due to the index being established in year 2000. During the period chosen for the study, there has been a financial crisis, a drop in oil prices and a pandemic. One could argue that these unusual periods should've been excluded from our data as they caused abnormal results in both the technology index and the macroeconomic variables. However, we chose to include all periods and economic shocks to analyze the previous 20 years as they actually have been.

Another potential challenge with our data is that we use quarterly data for the analysis. Government Fixed Capital Formation and Credit to the Private Sector were only available quarterly, and consequently, we decided to use quarterly data for all our variables. As a result, the number of observations may be somewhat limited. Thus, the results of our study could be inaccurate and lack significant relationships between the variables included.

Other macroeconomic variables could also have been included in the analysis. We considered including the variable money supply (M2) as we thought this could cause variations in interest rates and inflation. However, Lee (1992) argued that money supply is so strongly correlated with interest rate changes and inflation that one of the variables would have been redundant in the models. Industrial production is also widely used in explaining stock returns. Still, we did not find it appropriate to include this variable as our analysis solely focuses on the technology sector, which is a service-based, and not a manufacturing-based, industry.

4. Empirical Methodology

In this section, we present the methodology used to answer the empirical research question. Financial time series often operate under the prerequisite that previous observations will affect current values. This means that the past value of a variable can have large explanatory power. In an attempt to solve this problem, autoregressive models have been developed. An autoregressive model is a linear regression model of today's value of a time series against more than one previous value. The method reduces the risk that past values of a variable will increase the explanatory power of a model without increasing the causality. Considering that our purpose is to model causal relationships, two econometric models are of particular interest, namely the Autoregressive Distributed Lag Model (ARDL) and the Vector Error Correction Model (VECM). Both models lead to efficient estimates of long- and short-run relationships. Before we can run the models, our variables need to be checked for stationarity and the existence of cointegrated relationships. A cointegration test is a process to check if there is a common pattern between variables that are changing over time. Lastly, we run the respective forecasts of each model, and impulse response functions (IRF) are created. Since these are econometric methods that perhaps not all the readers are familiar with, we find it appropriate to go through them in detail. The subsequent results are presented in chapter 5.

4.1 Stationarity

Many financial time series exhibit a trend or non-stationary behavior. Non-stationary variables are variables with a probability distribution that is dependent on time. This means that the variables are either increasing or decreasing in time. Hence, the time series are not random. Using a non-stationary time series, i.e., a time series that contains a unit root, in financial modeling produces unreliable and spurious results,[6] and leads to poor understanding and forecasting because the independency assumption of the ordinary least square (OLS) is violated.[7] Therefore, before the econometric models can be utilized, it is required that the macroeconomic variables are tested for stationarity. A stationary time series process is "*a process in which the probability distributions are stable over time*" (Wooldridge, 2020, p.

[6] A spurious regression is a statistical model that indicates a relationship between two or more unrelated time series. (Wooldridge, 2020).

[7] Independent observations in a regression means that there is no relation between the variables. This might not be the case with time series data as the value today is closer to the previous observation than an observation a long time ago.

367). A variable is stationary if it has a constant mean and a constant variance. Further, the covariance between two time periods should not depend on the time at which it is estimated. The normal distribution of a process must be stable over time to make assumptions that the relationships found between the variables in the data will have the same effect over different periods. If a time-series variable is stationary in level, it is considered as integrated of order 0, or I (0). A non-stationary process is transformed into a stationary process by differencing. Variables that are stationary after taking the first difference are integrated of order 1, or I (1). Generally, a variable whose k^{th} difference is stationary is referred to as integrated of order k, or I (k).

Several approaches can be adopted to examine the stationarity properties of time series data. In this research, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests are performed. All the tests can be conducted assuming the time series are either trend- or level stationary. Various unit root tests are conducted to make a robust conclusion about the order of integration. Schwert (1989), in his paper, criticizes the ADF for having low power and the PP test for having poor size properties. Because the ADF and PP tests usually give the same conclusion, the KPSS test has also been conducted as a complementary model to confirm the results of the ADF and PP tests. The results of the three tests are compared to check if the same conclusion is reached.

The Dickey-Fuller test was created by Dickey and Fuller (1979) and is based on linear regression. Because serial correlation might be an issue, Dickey and Fuller (1981) came up with the Augmented Dicky Fuller Test (ADF), which was developed to handle bigger models. The form of the ADF test with constant but no trend is presented in equation (4), and the ADF test with constant and trend is presented in equation (5),

$$\Delta y_t = \alpha_0 + \theta\, y_{t-1} + \sum_{i=1}^{N} \alpha_i\, \Delta y_{t-1} + \varepsilon_t, \tag{4}$$

and

$$\Delta y_t = \alpha_0 + \beta T + \theta\, y_{t-1} + \sum_{i=1}^{N} \alpha_i\, \Delta y_{t-1} + \varepsilon_t, \tag{5}$$

where α_0 is the intercept and T represents a linear time trend, $\theta = (\rho - 1)$, and y_t is the variable of interest. Δ represents the first difference operator, while ε_t is the error term, which is identically and independently distributed.[8] Asymptotic normality of the idiosyncratic error term is assumed by the ADF test. The null hypothesis of the presence of a unit root (H_0: $\theta = 0$) is tested against the alternative hypothesis of no unit root (H_1: $\theta < 0$). H_0 is rejected if the t-statistics are lower than the critical values taken from MacKinnon (1994).

Before performing an ADF test, we need to select the optimal lag length. Lags are interpreted as the previous values of a time series.[9] The inclusion of lags is intended to remove serial correlation in Δy_t (Wooldridge, 2020). An insignificant number of lags included will decrease the forecast accuracy of the model since valuable information is lost, and the size of the test would be incorrect. Too many lags included increase the estimation uncertainty. There is no unequivocal rule for choosing the appropriate lag length. One approach is to select the lag length based on the frequency of the data. (4 lags for quarterly data, 12 for monthly data, etc.). Schwert (1989), in his work, suggests the following rule of thumb to find the optimal lag length,

$$\rho_{max} = 12\left(\frac{n}{100}\right)^{\frac{1}{4}}. \tag{6}$$

In equation (6), ρ refers to the number of lags and n equals the number of observations. With a large sample size, this would result in a relatively long lag length.[10] Another common approach when determining the optimal lag length is to use an information criterion such as Akaike´s Information Criterion (AIC) or Schwarz´s Bayesian Information Criterion (SBIC). In this thesis, we used the AIC, which applies the test described in equation (7) to decide the optimal lag length. T equals the sample size, and SSR(p) refers to the sum of squared residuals of the relevant autoregressive model,

$$\mathrm{AIC(p)} = \ln\left(\frac{\mathrm{SSR(p)}}{\mathrm{T}}\right) + (\mathrm{p}+1)^{\frac{2}{\mathrm{T}}}. \tag{7}$$

[8] The ADF test can also be conducted with no constant and no trend: $\Delta y_t = \theta\, y_{t-1} + \sum_{i=1}^{N} \alpha_i\, \Delta y_{t-1} + \varepsilon_t$.

[9] Considering our data, one lag equals one previous quarter.

[10] In our case with 88 observations, this would result in a lag length of: $\rho_{max} = 12\left(\frac{88}{100}\right)^{1/4} = 11{,}623 \approx 12$.

The Phillips Perron (PP) unit root test, developed by Phillips and Perron (1988), is a modified Dickey-Fuller test. Equation (8) presents the form of the PP test with constant and trend,

$$\Delta y_t = \alpha_0 + \beta T + \theta y_{t-1} + \varepsilon_t. \tag{8}$$

All the parameters are interpreted as in equation (5). Compared to the ADF test, the PP test is more robust to heteroskedasticity in the error term. If a variable is integrated of order one in the ADF test, the error term is integrated of order zero, and therefore, it might be heteroskedastic. In addition, the PP test uses Newey and West (1987) standard errors to account for serial correlation.[11] Thus, the lag length in the test regression does not need to be specified to account for serial correlation.

Kwiatkowski et al. (1992) proposed the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test as an alternative test to circumvent the problem of the low power of the ADF test. Opposite of the ADF and PP test, the KPSS test is assumed to be stationary under the null hypothesis. The KPSS test is a Lagrange multiplier test, and the test statistic is given in equation (9),

$$\text{KPSS LM} = \sum_{t=1}^{T} \frac{S_t^2}{\sigma_\varepsilon^2}, \tag{9}$$

where S_t is the partial sum of the OLS residuals for all t and σ_ε^2 is the estimated error variance from the regression in equation (10),

$$y_t = \alpha + \varepsilon_t, \text{ or } y_t = \alpha + \beta_t + \varepsilon_t. \tag{10}$$

4.2 Autoregressive Distributed Lag Model

The Autoregressive Distributed Lag model (ARDL) is adopted to examine the relationship between macroeconomic variables and the return of the Oslo Stock Exchange technology index. The ARDL model combines elements from an autoregressive (AR) and a distributed lag (DL) model, making it a more general dynamic regression model. The lagged values of both the dependent and explanatory variables can capture significant structures in the dependent variable that can be caused by several factors.

[11] For more detailed information, see the paper of: Newey and West (1987).

Based on the ARDL model, Pesaran et al. (2001) developed a method known as the ARDL bounds test. The bounds test approach is used to test for cointegrated relationships among the variables employed in the study. The method does not require that the variables have the same order of integration. However, the variables must be stationary at level I (0) or first difference I (1). In the presence of variables being integrated in second difference I (2), the F-statistics of the bounds test becomes invalid (Pesaran et al., 2001). To conclude whether cointegration exists or not, the F-statistic of the bounds test is compared to the critical F-values developed by Pesaran et al. (2001). An F-stat below the lower bound critical value suggests an absence of cointegration. By contrast, an F-stat above the critical value for the upper bound confirms that cointegration exists in the long run. If there are cointegration among the variables, the estimated relationship cannot be spurious.

We can perform the ARDL model on stationary or non-stationary variables as long as the data does not exceed I (1). Pesaran et al. (2001) argued that in the presence of difference-stationarity variables in a model, the ARDL approach could still be employed with a small augmentation. The specification of the ARDL model needs to be augmented with an adequate number of lags prior to conducting estimation and inference on the model. The estimation of the model is based on the number of lags suggested by Akaike's Information Criterion (AIC). Once the optimal lag lengths are identified, the ARDL model enables the cointegrated variables to be estimated by the ordinary least squares method. This allows us to estimate the long- and short-run relationships of the model simultaneously. Also, the technique removes any potential problems with autocorrelation and variables being omitted. In addition, the ARDL model is useful in research where the samples of data are smaller or limited since it enables reasonable inferences on long-run relationships.

When the possible relationships between two or more variables are analyzed, it is often assumed that the dependent variable is a function of the independent variables. Specifications are made according to equation (11), where Y is the dependent variable and X is a vector of independent variables. f is some function,

$$Y = f(X). \tag{11}$$

The ARDL model tries to capture the relationship in $f(X)$. When we have established that a long-run relationship exists, the conditional ARDL (p, q1, … qn) in equation (11) can be specified in equation (12). $\mathrm{Y_t}$ is the dependent variable and $\mathrm{X_t}$ is the set of explanatory variables. q and p are the respective number of lags for each variable. This approach follows the papers of Pesaran and Shin (1999) and Pesaran et al. (2001),

$$\Delta Y_t = \beta_0 + C_0 t + \sum_{i=1}^{q} \tau_i \, \Delta Y_{t-i} + \sum_{j=1}^{p} \omega \, X_{t-j} + \gamma_1 \, Y_{t-1} + \varepsilon_t, \tag{12}$$

where β_0 and C_0 are the drift and trend coefficients. ε_t exhibit the error term. Following the description in equation (12), the ARDL model we apply is given in equation (13),

$$\begin{gathered} \Delta OTECG_t = \beta_0 + \textstyle\sum_{i=1}^{n} \beta_{1i} \Delta OTECG_{t-i} + \sum_{i=0}^{n} \beta_{2i} \Delta NIBOR_{t-i} + \\ \textstyle\sum_{i=0}^{n} \beta_{3i} \Delta INF_{t-i} + \sum_{i=0}^{n} \beta_{4i} \Delta OIL_{t-i} + \sum_{i=0}^{n} \beta_{5i} \Delta EXCH_{t-i} + \sum_{i=0}^{n} \beta_{6i} \Delta GDP_{t-i} + \\ \textstyle\sum_{i=0}^{n} \beta_{7i} \Delta GFCF_{t-i} + \sum_{i=0}^{n} \beta_{8i} \Delta CRDT_{t-i} + \beta_{9i} OTECG_{t-1} + \beta_{10i} NIBOR_{t-1} + \\ \beta_{11i} INF_{t-1} + \beta_{12i} OIL_{t-1} + \beta_{13i} EXCH_{t-1} + \beta_{14i} GDP_{t-1} + \beta_{15i} GFCF_{t-1} + \\ \beta_{16i} CRDT_{t-1} + \varepsilon_t, \end{gathered} \tag{13}$$

where β_0 is the intercept and n are the chosen number of lags. ε_t is the error term, while the rest of the coefficients describe the long- and short-run relationships.

The ARDL test aims to create the best linear unbiased estimator (BLUE). To validate the results from the model diagnostic tests are being conducted. Tests are carried out for serial correlation, normality in the residuals and heteroskedasticity. Finally, a CUSUM test is conducted to ensure the dynamic stability of the model.

4.3 Johansen Cointegration Test

There is cointegration between two variables if each of the variables, in level, are non-stationary, but a linear combination of the variables is stationary. This means there is long-term continuing relationship between the variables. The development of the variables may diverge in the short run, but over time they always follow a similar path. When the order of integration and the appropriate lag length is determined, the Johansen cointegration test is adopted to investigate whether cointegration exists between the technology index at the Oslo Stock Exchange and our chosen explanatory variables.

A cointegration test for bivariate models was introduced by Engle and Granger (1987). However, in this study, we use the Johansen test for cointegration as described by Johansen (1988) since this works better for multivariate analysis. Before the development of cointegration analyses, linear regressions were applied to non-stationary time series data. However, Granger and Newbold (1974) showed that this approach could lead to spurious correlations. The Johansen multivariate cointegration method makes it possible to study the long-term equilibrium relations between the variables without problems with spurious correlations arising and is used to determine the number of existing cointegrated relations. If the variables are cointegrated, the vector error correction model can be implemented to examine the dynamic relationships among the variables.

We use the work of Johansen (1991) and Johansen (1995) to decide the number of cointegrated vectors present in the regressions. Two different likelihood ratio tests are implemented to calculate the number of appropriate ranks. These are the Trace test and the Maximum Eigenvalue test. The null hypothesis for both tests states that there is no more than *r* cointegrated relationships. The alternative hypothesis for the Trace test is that more than r cointegrated relationships exist. For the Maximum Eigenvalue test, the alternative hypothesis is that there are exactly *r* + 1 cointegrating relations (Enders, 2015). This makes it possible to determine if cointegration is present and how many cointegrating equations there are. The definition of the Trace- and Maximum Eigenvalue test statistics are presented in equations (14) and (15),

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln (1 - \lambda_i) \qquad r = 0, 1, \ldots n - 1, \tag{14}$$

and

$$\lambda_{max} = -T \ln(1 - \lambda_{r+1}) \qquad r = 0, 1, \ldots n - 1, \tag{15}$$

where T is the number of observations and n is the number of I (1) variables. r is the number of cointegrated equations while λ_i is the estimated eigenvalues. The testing starts by checking whether zero cointegrating relationships exist (r = 0). If the null hypothesis is rejected, the test checks for the existence of one or less cointegrating relations (r ≤ 1) and so on until we fail to reject the null hypothesis. The null hypothesis is rejected if the computed test statistics are above the critical values obtained from Osterwald-Lenum (1992). Johansen (1991) argues that when the Trace- and Max-Eigenvalue statistics show different estimators, one should proceed with the Maximum Eigenvalue results.

There is no formal agreement on how to select the optimal number of lags in a Johansen test. The purpose of including lags is to remove any autocorrelation in the error terms. Too few lags could lead to losing observations and errors in the forecasts (Stock & Watson, 2001). On the other hand, Juselius (2007) argues that, even with evidence for autocorrelation, one should only include two lags. This is justified by the fact that two lags are, in most cases, sufficient to describe a rich and dynamic structure. Further, Juselius (2007) suggests that including too many lags is more damaging than accepting a moderate autocorrelation in the error terms. However, the most common approach is to select the lag length based on an information criterion (AIC or SBIC) or a combination of these. In this thesis, we use Akaike's Information Criterion (AIC) to decide the optimal lag length of the Johansen Test.

4.4 Vector Error Correction Model

The Vector Error Correction Model (VECM) is a suitable method for examining causal relationships when the variables are non-stationary and cointegrated. While the cointegration regression only considers long-run relationships between the time series, an error correction model (ECM) is also developed to measure any dynamic effect between the first differences of the variables. The VECM is developed from the Vector Autoregressive Model (VAR). When the time-series data is non-stationary, the VAR model needs to be modified for the relationships among the time series to be sufficiently and consistently estimated.[12] In the VECM, the cointegration term is called the error correction term. This is because a series of short-run adjustments gradually corrects the deviation from the long-run equilibrium. In equation (16) the mathematical form of the VECM is derived from the Johansen cointegration test, which is a VAR model of order p,

$$y_t = \mu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t, \tag{16}$$

where y_t is a $k \times 1$ vector of variables that are I (1). μ is a $k \times 1$ vector of constants, while ε_t is a $k \times 1$ vector of error terms which is independently and normally distributed. Finally, $A_1 - A_p$ are $k \times k$ matrices of parameters. k is the number of variables in the VAR. If the variables are cointegrated and integrated of order one, it is possible to take the first difference of the VAR model and derive the VECM. Equation (16) is re-written to VECM form in equation (17),

[12] A VAR model assumes stationary variables. When the stationarity assumption is violated, the framework does not hold. The VECM is an advanced VAR framework for variables that are stationary in their differences.

$$\Delta y_t = \mu + \prod y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta y_{t-1} + \varepsilon_t, \tag{17}$$

where μ and ε_t are the same as in equation (16). $\prod = \sum_{i=1}^{p} A_i - I_k$ (I is the $k \times k$ identity matrix) and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$.[13] Engle and Granger (1987) showed that if the variables A_t are integrated of order one, the matrix $\prod$ will have the rank $0 \leq r \leq K$, where r is the number of cointegrated vectors. For the VECM, there is at least one cointegrated vector. In that case $\prod$ can be decomposed as,

$$\Pi = \alpha\beta', \tag{18}$$

where α and β are $r \times K$ matrixes with a rank of r. Matrix α is interpreted as the adjustment parameters in the model and gives insight to how fast the variables will adjust in disequilibrium. Matrix β is a vector of cointegration parameters. Thus, equation (17) can be rewritten as,

$$\Delta y_t = \mu + \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta y_{t-1} + \varepsilon_t. \tag{19}$$

From equation (19), we see that the VECM contains information about the short-run relations between the variables as well as the equilibrium in the long run. The specifications of the VECM puts a restriction on the long-run behavior of the variables to ensure that they still can allow for short-run dynamics as they converge towards the cointegrating relationships. $\beta' y_t$ represents the long-run relationship between the variables. When there is cointegration, a linear combination of $\beta' y_t$ is stationary, even when y_t is non-stationary. $\sum_{i=1}^{p-1} \Gamma_i \, \Delta y_{t-1}$ describes the short-term dynamics of the model (Johansen, 1995). Further, Johansen (1995) used the maximum likelihood method to estimate the VECM by default, which requires that a constant, μ, is defined.

Given the model specification in equation (19), the following VECM model is estimated for further analysis,

[13] For more information, see Lütkepohl (2005) (p. 244-256).

$$\Delta\text{OTECG} = \pi_0 + \sum_{i=1}^{p} \pi_1 \Delta\text{OTECG}_{t-1} + \sum_{i=1}^{p} \pi_2 \Delta\text{NIBOR}_{t-1} + \sum_{i=1}^{p} \pi_3 \Delta\text{INF}_{t-1} + \sum_{i=1}^{p} \pi_4 \Delta\text{OIL}_{t-1} + \sum_{i=1}^{p} \pi_5 \Delta\text{EXCH}_{t-1} + \sum_{i=1}^{p} \pi_6 \Delta\text{GDP}_{t-1} + \sum_{i=1}^{p} \pi_7 \Delta\text{GFCF}_{t-1} + \sum_{i=1}^{p} \pi_8 \Delta\text{CRDT}_{t-1} + \delta ECT_{n\,t-1} + \varepsilon_t, \tag{20}$$

where ΔOTECG represent changes in the dependent variable and p denotes the number of lagged differences. The factor π captures the short-run changes between the variables. δECT represents the error correction term that measures how fast the variables adjust back to the long-run equilibrium after a deviation has occurred.

To check for autocorrelation in the residuals, model stability and the normality condition, diagnostic tests are performed on the VECM model.

4.5 Impulse Response Functions and Variance Decomposition

The causal relations found in the vector error correction model will tell us which variables that have a significant impact on the other variables in the system. However, the VECM cannot tell how long these effects will take place. The answer to this question is provided by studying the impulse response functions and forecast error variance decomposition.

An impulse response investigates how one variable will respond to an impulse in another variable in the system (Lütkepohl, 2005, p. 51). Plotting the impulse response function (IRF) is a practical way to investigate in which direction, to what extent and for how long a variable is affected by a shock in itself or another variable in the model. The approach of this thesis is that we plot the response of the Norwegian technology index (OTECG) to an unexpected change in each of the variables and the response of all variables to an unexpected change in OTECG.

Variance decompositions trace out the proportion of movements in the dependent variable that can be accounted for by a shock in itself and shocks to the other variables. The method clearly shows the components of variance in the dependent variable. A variance decomposition analysis is a good tool for predicting future changes in financial time series. The decomposition of variance is included to confirm the impulse response analysis. In general, a variance decomposition analysis should offer quite similar information to the impulse response analysis.

5. Empirical results and analysis

In this section, the analyses introduced in section 4 are presented and discussed in conjunction with previous literature. First, we check if our time series are stationary and applicable for analysis by the econometric models introduced. The results of the autoregressive distributed lag model will then be discussed. Further, the Johansen test is performed to determine if there exists cointegration among our variables. Following the cointegration test, the vector error correction model is introduced, and we discuss the relationships found among the variables in depth. Additionally, we examine the effects of dynamic shocks in the variables using the impulse response functions and the forecast error variance decompositions.

5.1 Stationarity tests

When analyzing time series, it is pivotal to determine whether the series are stationary or nonstationary. That is because financial time series could exhibit trend and seasonality behavior, causing invalid or misleading results. As elaborated in section 4.1, the idea behind the stationarity test is to check that the properties of the series are independent of when the observations are made. A stationary time series should not be predictable or pattern-based, i.e., the last year's observations of the technology index should not be predictive for future prices of the index.[14] To test the properties of our time series, we apply the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979), Phillips-Perron (PP) (Phillips & Perron, 1988) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) unit root tests to ensure valid results. We choose optimal lags based on Akaike's Information Criterion (AIC) and test for unit roots in level and first differences for each variable.

The ADF-test from equation (4) and (5) and the PP-test from equation (8) with the null hypothesis of variables having unit roots, thus being nonstationary, are performed with a constant and trend component, and the results are presented in Table 3. We fail to reject the null hypothesis at any significance level when the variables are in level, and a constant component is included. In first difference we can reject the null hypothesis at the 1% significance level for all variables, indicating that the included variables are stationary when

[14] For time series that apply to stock returns, one could argue that if the observations were dependent on each other, it would be possible for an investor to implement a trading strategy to gain abnormal returns. When neither investors nor computers are able to uncover such a pattern in returns, a reasonable explanation is that the observations are independent of each other.

integrated of order one. When including a trend component in the ADF-test, the results imply that OTECG is stationary in level at a 5% significance level and thus integrated of order zero. In comparison, the PP-test finds OTECG stationary at the 1% significance level when the variable is integrated of order one. For both tests, the remaining variables are stationary in first difference at a 1% significance level and integrated of order one.

We apply the KPSS unit root test from equation (9) to confirm our findings. The null hypothesis should be interpreted inversely of the ADF and PP tests, and the results are presented in Table 3. The results imply that with a constant component, all variables are stationary in first difference, as we fail to reject the null hypothesis of no unit roots. Testing with a trend component, we fail to reject the null hypothesis in OTECG and NIBOR, indicating that the variables are stationary in level. For the remaining variables, we fail to reject the null hypothesis of no unit roots in first difference, implying that the variables are stationary. However, one should be careful of concluding with OTECG and NIBOR being stationary in level based on differing results from the three tests. The KPSS-test supports our findings that all variables are stationary in first difference and integrated of order one. This enables us to use the autoregressive distributed lag model and the Johansen cointegration tests.

Table 3. Unit Root Tests

Augmented Dickey-Fuller (ADF) unit root test				
	Constant		Constant and trend	
Variable	Level	First difference	Level	First difference
OTECG	-1.3678	-5.491***	-3.604**	-5.716***
NIBOR	-1.135	-3.725***	-3.326*	-3.696***
CPI	1.021	-4.941***	-2.010	-5.064***
OIL	-2.241	-7.264***	-2.241	-7.232***
EXCH	-1.557	-5.506***	-1.874	-5.816***
GDP	-1.663	-5.762***	-2.213	-5.734***
GFCF	-1.257	-5.064***	-1.858	-5.116***
CRDT	-1.680	-3.804***	-0.575	-4.109***
Phillips-Perron (PP) unit root test				
	Constant		Constant and trend	
Variable	Level	First difference	Level	First difference
OTECG	-0.975	-6.719***	-2.837*	-6.881***
NIBOR	-1.386	-5.792***	-3.006	-5.785***
CPI	-0.585	-13.465***	-3.225*	-13.526***
OIL	-2.326	-11.264***	-2.447	-11.264***
EXCH	-1.458	-9.186***	-1.691	-9.283***
GDP	-1.280	-11.979***	-2.420	-11.908***
GFCF	-0.615	-13.490***	-2.152	-13.443***
CRDT	-1.570	-4.169***	-1.725	-4.251***
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit roots test				
	Constant		Constant and trend	
Variable	Level	First difference	Level	First difference
OTECG	1.619***	0.303	0.163*	0.064
NIBOR	1.019***	0.047	0.081	0.047
CPI	1.856***	0.109	0.274***	0.042
OIL	1.536***	0.065	0.778***	0.042
EXCH	1.166***	0.176	0.928***	0.057
GDP	1.498***	0.085	0.245***	0.086
GFCF	2.177***	0.083	0.305***	0.074
CRDT	1.133***	0.153	0.176***	0.050

***significant at 1%, **significant at 5%, * significant at 10%
Table 3: Augmented Dickey-Fuller and Phillips-Perron hypothesis: H_0: Existence of unit root, H_1: No unit root. Kwiatkowski-Phillips-Schmidt-Shin hypothesis: H_0: No unit root, H_1: Existence of unit root.
For plots of the time series in logarithmic level and logarithmic first difference, see Appendix II.

5.2 Autoregressive Distributed Lag Model

To implement the Autoregressive distributed lag (ARDL) model, we must determine the appropriate lag length for each term in the equation. The appropriate number of lags in the model is chosen based on the Akaike Information Criterion (AIC). The selection of ARDL (3, 3, 5, 1, 0, 2, 4, 2) is based on the value that minimizes the AIC.

The ARDL bounds test is used to examine if there is a long-run relationship among the variables. If the F-statistic is below the lower bound, no cointegration is possible. If the F-statistics surpass the upper bound, the conclusion is that we have cointegration. No conclusion can be drawn if the computed F-value lies between the lower and upper bound. The results from the ARDL bounds test are displayed in Table 4.

Table 4. ARDL Bounds Test

F-Statistic	ARDL bound test at 95%		ARDL bound test at 99%	
6.137606	Lower bound: 2.32	Upper bound: 3.5	Lower bound: 2.96	Upper bound: 4.26

Table 4: Critical values obtained from Pesaran et al. (2001)

From the results, we observe that the F-statistic for joint significance exceeds the upper bound at a 95% and 99% significance level. We thus have sufficient reasons to reject the null hypothesis of no long-run relationship and conclude that a long-run level equilibrium relationship exists among the macroeconomic variables employed in the analysis.

The ARDL model is estimated using the OLS method. All variables have a quarterly frequency, and the inclusion of a lag will therefore tell how last quarter´s values affect today's value of the Oslo Stock Exchange technology index (OTECG). To determine which of the variables that explain changes in the technology index, we examine the p-values, where the chosen significance levels are 1% and 5%. If a variable is significant, the associated coefficient can be interpreted as the percentage change in the dependent variable from a one percent change in an explanatory variable, all else equal. The results from the ARDL model are presented in Table 5.

Table 5. Autoregressive Distributed Lag Model

ARDL Model Estimation Results

Variable		COEF.	STD.ERR.	t-value	Pr(>|t|)
Intercept		-8.369	8.766	-0.955	0.349
OTECG	L1.	0.958	0.108	8.969	0.000 ***
	L2.	-0.144	0.150	-0.961	0.341
	L3.	.0352	0.105	0.337	0.737
NIBOR		-0.197	0.081	-2.451	0.017 **
	L1.	0.139	0.115	1.215	0.230
	L2.	-0.060	0.107	-0.571	0.570
	L3.	-0.095	0.078	-1.232	0.223
INF		-4.267	1.674	-2.549	0.014 **
	L1.	-1.970	1.825	-1.079	0.285
	L2.	1.583	1.966	0.805	0.424
	L3.	6.273	2.079	3.018	0.004 ***
	L4.	5.711	1.948	2.932	0.005 ***
	L5.	1.829	1.827	1.001	0.321
OIL		0.080	0.105	0.767	0.446
	L1.	-0.215	0.069	-3.128	0.003 ***
EXCH		-0.629	0.264	-2.382	0.021 **
GDP		1.624	1.252	1.298	0.200
	L1.	1.628	1.430	1.139	0.260
	L2.	-2.750	1.261	-2.181	0.033 **
GFCF		-0.106	0.339	-0.312	0.756
	L1.	-0.192	0.361	-0.531	0.598
	L2.	0.135	0.393	0.345	0.732
	L3.	-0.520	0.352	-1.480	0.144
	L4.	1.094	0.325	3.366	0.001 ***
CRDT		-0.795	1.057	-0.752	0.456
	L1.	3.252	1.657	1.962	0.055
	L2.	-3.467	1.099	-3.154	0.003 ***
R^2 Adj = .957 F-Stat = 69.11					

***significant at 1%, **significant at 5%.

Table 5: The baseline for the model is expressed as: $OTECG = f(NIBOR, INF, OIL, EXCH, GDP, GFCF, CRDT)$ – see equation 11.

The model hypothesizes that the Oslo Stock Exchange Technology Index is a function of the NIBOR rate, inflation, oil price, the NOK/USD exchange rate, GDP, gross fixed capital formation and credit to the private sector. The F-statistic is significant, which implies that the independent variables jointly explain the performance of the Norwegian technology index. The value of the adjusted R^2 suggests that the predetermined variables can explain approximately 96% of the variation in the model, while the remaining 4% is unaccounted for.

Lags of the dependent variable (OTECG) are included as explanatory variables in the model. This is because we see a significant effect, and therefore the lags can contribute to explain the value of OTECG today. We find a positive effect between the dependent variable and its first lag, which is significant at the 1% level. The finding indicates that today's value of the Oslo Stock Exchange technology index relies on its value in the last period. According to the results, with all other variables held constant, a one percent increase in the technology index from the previous quarter is associated with an increase in the value of the technology index in the present quarter by around 0.96%.

From the results presented in Table 5, we learn that a significant negative relationship exists between the three-month NIBOR rate and the technology index at the Oslo Stock Exchange. An increase in the interest rate by one percent causes the value of the technology index to fall by about 0.2%. This inverse relation supports our expectation and is in line with the theory that a higher interest rate will decrease the present value of future discounted cash flows. An increase in the discount rate has consequences for technology companies, which often are valued on projected earnings delivered years in the future. Thus, investors must pay more for growth when the interest rate rises. Also, rising rates diminishes businesses´ cash flows to equity, reducing their opportunity to reinvest into growth prospects. During times of economic uncertainty, when interest rates usually rise, investors will turn towards companies where they expect a steady level of income. This will hurt tech stocks due to their usually low dividend payments. The finding of a negative relation corresponds with the results of Rigobon and Sack (2004), who found a 2.4% decline in the NASDAQ technology index from a 25-basis point increase in the three-month interest rate. Our findings indicate that the value of OTECG is less sensitive than the NASDAQ index to a change in interest rates.

We find a negative relationship between inflation and the Norwegian technology index in the ARDL model. A percentage increase in inflation in the current quarter causes the value of OTECG to fall by 4.27% in the same quarter. The negative relation is consistent with several studies such as; Fama (1981) and Humpe and Macmillan (2009). On the other hand, the model shows a positive relationship between the tech index and inflation three and four quarters back in time, which is statistically significant at a 1% error level. This means that an increased inflation will lead to increased stock prices. A reasonable explanation is that investors believe higher inflation will lead to a higher interest rate. Hence, the discount factor will increase. By other words, it is the higher interest rates, not the inflation, that sink the market. The findings suggest there exists an expectation that higher future rates will hurt the value of technology stocks. Over time the technology stocks benefit from inflation, as their growth capacity seems to be judged more important than a slightly higher discount rate. Inflation means that the economy is growing, and tech stocks benefit from expanding the economic environment.

The results demonstrate a negative relationship between the Oslo Stock Exchange technology index and the lagged value of the oil price. A percentage increase in the oil price in the previous quarter causes the technology index to fall by 0.215 percent and is statistically significant at a 99% confidence level. The negative relationship supports the hypothesis of Sadorsky (2003) that changes in the oil price impact technology stock prices and that a higher oil price will decrease the value of the technology stocks.

From Table 5, we find a negative relationship between the NOK/USD exchange rate and the Norwegian technology index. The relation is significant at a 5% error level and shows that an increase of one percent in the exchange rate causes the technology index to fall by 0.63%. A rise in the exchange rate means a depreciation of NOK against USD. In other words, a weaker home currency negatively impacts the value of the technology index. This finding contradicts the study of the US stock market, where Bahmani-Oskooee and Saha (2015) find that an appreciation of the home currency has a negative effect on stock prices. Our finding also contradicts the results from the UK market, where Bahmani-Oskooee and Saha (2016) couldn’t find a significant effect between the exchange rate and stock prices. A possible explanation for why a weak home currency is bad for the technology stock prices could be that the development of the technology index probably is correlated with the development of the overall market, which Figure 4 also suggests. Foreign investments are usually associated with exchange rate fluctuations. An appreciation of NOK against USD means that the return on domestic assets is favorable. This will increase foreign investors' demand for domestic assets in the Norwegian indexes. A depreciation of NOK against USD causes foreign investors' demand to fall as the return on Norwegian assets isn’t favorable. This supports that there is a portfolio adjustment effect (Kim, 2003). Good news in the Norwegian economy relative to the US makes investors want to switch to the Norwegian market, and vice versa for bad news.

We find a negative and significant relationship between the technology index and the second lag of GDP. On average, OTECG will experience a drop in value by 2.75% if the level of GDP increases by one percent two quarters back in time. The results contradict the initial hypothesis of a positive relationship between GDP and the value of the technology index and do not support the findings from the study by Jareño and Negrut (2015), who found a positive correlation for the US stock market. A potential reason for this could be that GDP is calculated retrospectively, looking back at the time in question. In contrast, financial markets are forward-looking and affected by expectations of what will happen in the future. The level of GDP is treated as an indicator of the overall state of the economy. Over time, growth in GDP may result in inflation, which typically leads to increased interest rates. As previously mentioned, expectations of higher interest rates will result in a lower present value of future cash flows.

The results reveal that the return of the Oslo Stock Exchange technology index has a positive lagged relationship with gross fixed capital formation (GFCF), which is statistically significant at a 1% level. The coefficient of GFCF with four lags (i.e., one year) is 1.09, implying that a one percent increase in GFCF will lead to an increase in the Norwegian technology index by about 1.09%, ceteris paribus. The findings support the initial hypothesis that investments boost productivity and influence economic activity and growth. As mentioned, growth seems to be very important to technology companies. Our results are also consistent with findings from the US stock market (Belo & Yu, 2013).

Lastly, we discover a negative lagged relationship between the Norwegian technology index and the level of credit to the private sector. A percentage increase in credit to the private sector with a lag of two quarters causes a decrease of the OTECG by almost 3.5% and is significant at a 1% error level. The sign of the relation is negative, which means that our initial expectation is being supported. The results are also consistent with previous studies of the stock market in Europe (Sukruoglu & Temel Nalin, 2014) and China (Faisal et al., 2016).

5.2.1 Long Run Relationship Among the Variables

The ARDL bounds test revealed that relationships exist between the macroeconomic variables and the technology index. Testing the long-run relationships enables us to examine the direction and magnitude of the independent variables' impact to the technology index over a more extended period than the original ARDL test, which tests for five quarters (5 lags). The test will also provide insight regarding the speed of adjustment towards the long-run equilibrium. The long-run coefficients are estimated using the autoregressive distributed lag model, and the results are presented in Table 6.

Table 6. Long-Run Estimates for the ARDL

	Long-Run Estimates								
	Intercept	L.OTECG	L.NIBOR	L.INF	L.OIL	L.EXCH	L.GDP	L.GFCF	L.CRDT
Coef.	-8.369	-0.151***	-0.215***	9.159	-0.135	-0.629**	0.501	0.411*	-1.010**
ECT-1	-0.144***								

***significant at 1%, **significant at 5%, *significant at 10%.
Table 6: Dependent variable = OTECG.

The long-run results show that out of the seven explanatory variables, only the NIBOR rate, exchange rate and credit to the private sector are statistically significant. It can be seen from Table 6 that all three significant independent variables have a negative impact on the value of the technology index at the Oslo Stock Exchange. Gross fixed capital formation is statistically significant at a 10% error level and has a positive impact on the technology index in the long run. The ARDL model does not find any cointegrating relationships between the remaining explanatory variables and the technology index.

The coefficient of the error correction term (ECT) represents the Norwegian technology index´s speed of adjustment to its long-run equilibrium. The coefficient of the ECT is found to be negative and statistically significant at a 1% level. This confirms the stability of the model, meaning there is a significant adjustment towards the long-run equilibrium in any disequilibrium situation. The error correction term suggests that approximately 14% of the long-run disequilibrium is corrected in the short run, i.e., one period. The estimated coefficient of the error correction term shows that disequilibrium happens and that the OTECG´s speed of adjustment to the long-run equilibrium is relatively slow, based on its low absolute value. When the short-run deviation is corrected by 14% each period, it takes almost two years for the Norwegian technology index to adjust itself back to the long-run equilibrium.[15]

[15] (100% / 14% = 7,143). It takes approximately seven quarters (1 ¾ years) before 100% of the deviation is corrected.

5.2.2 Diagnostic Tests

Time series analysis requires certain assumptions to be fulfilled to ensure valid, efficient and consistent estimators.[16] Failing to meet the assumptions can cause spurious and invalid regression estimates. The estimated results may not be interpreted causally as the estimators might be biased. For the estimated autoregressive distributed lag model in Table 5, we apply diagnostic tests to investigate the reliability of the model. We perform tests for serial correlation and normality in the residuals to ensure that observations are random and that the model is stable. We also test if the model is misspecified or shows signs of heteroskedasticity to ensure efficient and valid estimators. If the diagnostic test provides adequate results, the ARDL model can be used for further analysis. Table 7 displays the test statistics and accompanying p-values of the performed diagnostic tests.

Table 7. Diagnostics Tests for the ARDL

	Test Statistics	P – Value
(a) Serial correlation	0.44493	0.5093
(b) Normality	0.9727	0.07414
(c) Functional form	0.95256	0.3943
(d) Heteroskedasticity	42.858	0.6447

Table 7: (a) Breusch-Godfrey test for serial correlation. (b) Shapiro-Wilk test for normality. (c) Ramsey RESET test for functionality, (d) Breusch-Pagan test for heteroskedasticity.

The Breusch-Godfrey test examines the serial correlation of the residuals to ensure that the error terms are uncorrelated. Line (a) shows a p-value of 0.5093, which clearly exceeds the 5% significance level. This means that we are not able to reject the null hypothesis of no serial correlation in the residuals. The result supports the assumption of no serial correlation of the error terms.

For the normality test, we used the Shapiro-Wilk statistics to study if the residuals are normally distributed. We see from line (b) that the p-value of 0.07414 exceeds the 5% significant level, and thus we cannot reject the null hypothesis of residuals being normally distributed. Based on the test, we can conclude that the residuals are normally distributed.

[16] For a complete list of assumptions, see Wooldridge (2020), p. (370-373).

The Ramsey RESET test is used to evaluate the functional form of the model. Line (c) shows a p-value of 0.3943, which clearly exceeds a 5% significance level. Hence, we are not able to reject the null hypothesis that the model has the correct functional form. Based on the RESET test, the model does not have evidence of misspecification.

In the ARDL model, homoskedasticity, i.e., that the residuals have a constant variance, is assumed. From line (d) in Table 7, the results of the Breusch-Pagan test show a p-value of 0.6447, which exceeds the 5% significance level. The null hypothesis of no heteroscedasticity in the residuals cannot be rejected, and we conclude that there is homoskedasticity.

The above diagnostic tests suggest that the model does not suffer from any problems with serial correlation, nonnormal distribution, incorrect functional form or heteroskedasticity. As the assumptions for times series data are satisfied, we can conclude that the results of the ARDL model are robust and that the model is the best linear unbiased estimator (BLUE).

5.2.3 CUSUM and CUSUMQ Test for Structural Stability

Model stability is necessary for economic inference and to ensure that the residuals do not deviate significantly from their mean value. Deviating residuals suggest that the autoregressive model is misspecified. We construct plots of the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMQ) to test for the structural stability of the ARDL model used in this thesis. Plots of the CUSUM and CUSUMQ statistics are presented in Figure 11. We reject the null hypothesis of no structural instability in the model if the test statistics do not remain inside the critical bound at a 5% significance level.

Figure 11. Plots of Cumulative Sum and Cumulative Sum of Squares of Recursive Residuals

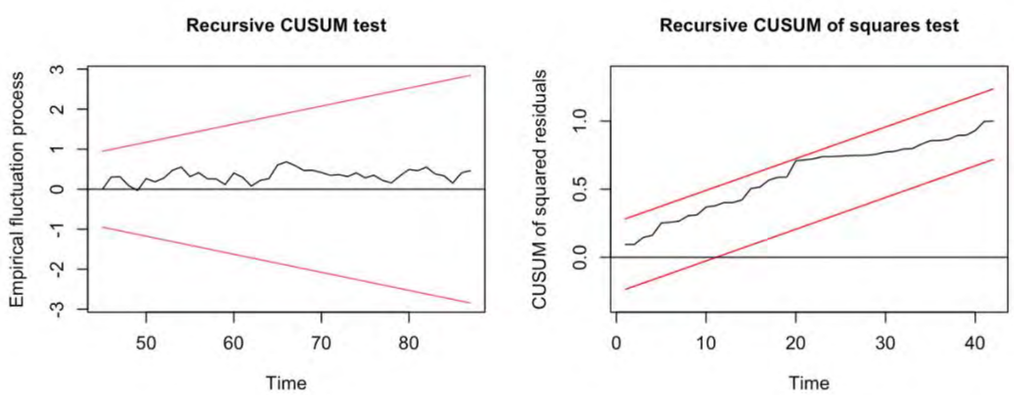


Figure 11: Plots of CUSUM (left) and CUSUMQ (right). Red lines represent the 5% significance level.

Figure 11 shows the systematic variation in the parameter estimates and both plots indicate that fluctuations in the parameter estimates are within a 5% significance level. Hence, we cannot reject the null hypothesis that the model does not suffer from any structural instability over the study period. We conclude that the model is stable.

5.3 Johansen Cointegration Test

In section 5.2 we found evidence of cointegration between the macroeconomic variables and the Norwegian technology index. As the macroeconomic variables included in this thesis seems to be closely related, we want to investigate further how many variables that are cointegrated. Also, if the Johansen test concludes that the technology index is cointegrated with the macroeconomic variables, we are allowed to estimate the VECM to further examine if the relationships are positive or negative (see section 5.4). The Johansen test also reveals the number of cointegrated relationships present in the system. This is important when estimating the VECM.

The results from the Johansen cointegration test are presented in Table 8. Test statistics for both the Trace and the Maximum Eigenvalue tests are included, with the optimal number of lags determined to 5 based on Akaike's Information Criterion (AIC). The cointegration rank, r, is tested using data integrated of order one with critical values on the 5% significance level. We reject the null hypothesis if the test statistic exceeds the critical values for each rank.

Table 8. Johansen Cointegration Test

Multivariate Johansen cointegration test for OTECG and macroeconomic variables				
H0: rank = r	Max Eigen test	Critical values 5%	Trace test	Critical values 5%
r = 0	88.63***	52.00	291.76***	165.58
r <= 1	61.31***	46.45	203.13***	131.70
r <= 2	42.40***	40.30	141.82***	102.14
r <= 3	31.58	34.40	99.42***	76.07
r <= 4	26.79	28.14	67.83***	53.12
r <= 5	17.33	22.00	41.04***	34.91
r <= 6	16.22	15.57	23.71***	19.96
r <= 7	7.49	9.24	7.49	9.24

Table 8: ***significant at 5% level. Critical values retrieved from Osterwald-Lenum (1992).

From the Maximum Eigenvalue test, we observe that the null hypothesis of r <= 0, 1 and 2 is rejected at the 5% significance level. Therefore, we accept the alternative hypothesis of exactly three cointegrated variables in our model. The rank of the matrix (Π) is above zero and smaller than the number of variables in our model, supporting our time series being cointegrated

(Johansen, 1988). As opposed to Bhuiyan and Chowdhury (2020), we find a long-term equilibrium relationship between the technology sector and our chosen variables. The Trace test rejects the null hypothesis of r <= 0, 1, 2, 3, 4, 5 and 6 at the 5% level, indicating at most seven cointegrated variables. For our further analysis, we use the cointegrated rank from the maximum eigenvalue test, r <= 2, based on its shaper alternative hypothesis (Enders, 2015).

5.4 Vector Error Correction Model

Since the Johansen cointegration test indicated at least two cointegrated equations, we can proceed with the vector error correction model (VECM). The error correction term in Table 9 is statistically significant and thus establishes the long-run equilibrium relationship between the Norwegian technology index and the chosen macroeconomic variables. The coefficient of the error correction term illustrates the speed of adjustment by which our dependent variable will return to equilibrium after a deviation. In the case of more than one cointegrated vector, the first eigenvector is based on the largest eigenvalue and is therefore regarded most useful (Maysami & Koh, 2000). The error correction term is obtained from the cointegrated vector and presented in equation (21),

$$\delta \mathrm{ECT}_{t-1} = \delta(\beta_1 \mathrm{OTECG}_t + \beta_2 \mathrm{NIBOR}_t + \beta_3 \mathrm{INF}_t + \beta_4 \mathrm{OIL}_t + \beta_5 \mathrm{EXCH}_t + \beta_6 \mathrm{GDP}_t + \beta_7 \mathrm{GFCF}_t + \beta_8 \mathrm{CRDT}_t). \tag{21}$$

Table 9 presents the estimated cointegration vector and the coefficients of the error correction terms, known as the speed of adjustment.

Table 9. Long-Run Coefficients in the VECM and ECT

	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
Long run	1.000	-0.782***	9.041	4.261	2.725	12.382	-12.629**	13.522
δ_1	-0.195***	-0.017	0.008**	0.124	-0.006	0.000	0.027	-0.004
δ_2	-0.204***	-0.029	-0.001	0.103	-0.041*	0.002	-0.018	-0.002

***significant at 1%, **significant at 5%, *significant at 10%.
Table 9: The first row of the table presents the normalized cointegration coefficients. The second and third rows show the error correction terms representing the variables' speed of adjustment.

The long-run relation is interpreted from the cointegrated vector, obtained from normalizing the technology index to one using Johansen normalization as shown in equation (22).

$$\mathrm{OTECG}_t = -0.782\mathrm{NIBOR}_t + 9.041\mathrm{INF}_t + 4.261\mathrm{OIL}_t + 2.725\mathrm{EXCH}_t + 12.238\mathrm{GDP}_t - 12.629\mathrm{GFCF}_t + 13.522\mathrm{CRDT}_t + 34.102. \tag{22}$$

The long-run results from the VECM show that the 3-month NIBOR rate has a significant negative effect on the value of the technology index. This is in accordance with the findings from the ARDL model and consistent with the study of Rigobon and Sack (2004). The result indicates that a 1% increase in the interest rate causes the technology index to decrease by 0.78%. We also find a significant negative long-run relationship from gross fixed capital formation to the index, meaning that an increase in investments might negatively impact the value of the technology index. A negative relationship contradicts the ARDL long-run estimates. Consequently, we are unable to draw an unequivocal conclusion regarding the long-run relationship between gross fixed capital formation and the technology index.

The coefficients of the error correction terms for the Norwegian technology index are negative and statistically significant. This is an assumption for the error correction terms to have a meaningful interpretation and confirms the stability of the model. The long-term adjustment coefficient is -0.195 for the first cointegrated vector and -0.204 for the second one. This suggests that the deviation of the technology index from the long-term equilibrium is corrected by about 20% each quarter, and the speed of adjustment is relatively slow. This largely coincides with the finding from the ARDL model, where it appears that 14% of long-run disequilibrium is corrected in the short run.

Table 10 presents the significant results from the VECM model at the ordinary 5% significance level. The short-run relationships are expressed by the significant coefficients of the lagged explanatory variables. We recognize that there is a probability that a random effect can occur. This needs to be considered when the results are interpreted.

Table 10. Short-Run Causalities from the VECM

	Model Estimates
(a) $\Delta OTECG_t$:	$-19.027 - 0.439\Delta OIL_{t-1} - 1.368\Delta EXCH_{t-2} + 7.163\Delta INF_{t-3}$ (0.000) (0.015) (0.016) (0.050) $+ 10.052\Delta INF_{t-4} + 8.172\Delta INF_{t-5}$ (0.008) (0.006)
(b) $\Delta NIBOR_t$:	$+1.731\Delta GFCF_{t-1}$ (0.048)
(c) ΔINF_t:	$-0.601\Delta INF_{t-1} - 0.656\Delta INF_{t-2} - 0.618\Delta INF_{t-3} + 0.023\Delta OIL_{t-1}$ (0.004) (0.000) (0.001) (0.024) $- 0.019\Delta NIBOR_{t-2} - 0.265\Delta GDP_{t-2} - 0.1017\Delta GFCF_{t-2}$ (0.004) (0.012) (0.003) $- 0.078\Delta GFCF_{t-3} + 0.203\Delta CRDT_{t-5}$ (0.021) (0.019)
(d) ΔOIL_t:	$-0.933\Delta OIL_{t-1} - 0.850\Delta OIL_{t-2} - 1.955\Delta EXCH_{t-1} - 2.813\Delta EXCH_{t-2}$ (0.004) (0.020) (0.05) (0.006) $- 2.178\Delta EXCH_{t-4} - 8.245\Delta GRDT_{t-1} + 3.388\Delta GFCF_{t-1} + 2.337\Delta GFCF_{t-2}$ (0.013) (0.008) (0.006) (0.022)
(e) $\Delta EXCH_t$:	$-0.636\Delta GFCF_{t-1} + 2.232\Delta CRDT_{t-1} + 2.977\Delta INF_{t-2} + 2.446\Delta INF_{t-3}$ (0.005) (0.002) (0.038) (0.025)
(f) ΔGDP_t:	$-0.340\Delta CRDT_{t-1} - 0.025\Delta NIBOR_{t-2} - 0.124\Delta EXCH_{t-2} - 0.771\Delta INF_{t-5}$ (0.050) (0.031) (0.030) (0.011)
(g) $\Delta GFCF_t$:	$-0.167\Delta OIL_{t-1} - 0.372\Delta EXCH_{t-1} - 0.447\Delta EXCH_{t-2} + 2.455\Delta GDP_{t-3}$ (0.005) (0.041) (0.015) (0.001)
(h) $\Delta CRDT_t$:	$+ 0.479\Delta CRDT_{t-1}$ (0.021)

Table 10: Estimates at the 5% significance level for the VECM model with five lags. p-values in parentheses. Δ denotes changes in each variable. For the complete model, see appendix II (Table 15).

Table 10 shows that significant causal results at a 5% level occur in every line, revealing several short-run relations. The short-term analysis uses the differenced values of the variables to investigate the relationships to the VECM for up to five lags. In other words, we can examine the variables´ effect on each other for up to five quarters.

We learn from line (a) that the oil price, exchange rate and inflation are significant in explaining the movements in returns of the Oslo Stock Exchange technology index. The first lag of ΔOIL and the second lag of ΔEXCH are both negatively related to ΔOTECG, while the third, fourth and fifth lag of ΔINF impacts ΔOTECG positively. The results show the intricacy of fluctuations in the Norwegian technology index. Interestingly, the opposite causality does not occur for any of the mentioned macroeconomic variables. This suggests that the relationships are unidirectional, and that the Norwegian technology index does not seem to have a predictive ability on the mentioned macroeconomic factors.

Our results suggest that an increase in oil price has a disadvantageous effect to the value of the Norwegian technology index. The finding of a causal relationship supports the previous study of the US stock market (Sadorsky, 1999) and is consistent with the finding of Jones and Kaul (1996) that a change in oil price will affect the stock prices. However, our results contradict the study of Gjerde and Sættem (1999), who found that an increase in the oil price is beneficial for Norwegian stock prices. Thus, an immediate positive price effect occurs. The fact that a causal relationship between oil price and stock returns can be made valid for the Norwegian technology index makes the hypothesis of Sadorsky (2003) that oil price movements has an impact on technology stock prices more robust. Oil prices are an important factor of the market cycle, and technology stocks seem to be highly vulnerable to changes in market cycles.

The VECM further finds a negative unidirectional relationship from the NOK/USD exchange rate to the price of the technology index. This is in concordance with the finding from the ARDL model and suggests that there is a portfolio adjustment effect, meaning that a depreciation of the home currency will reduce the stock prices (Kim, 2003).[17] Another explanation for the negative relationship could be attributed to currency risk. The relative value of USD and NOK is important for the technology companies since their products and services often are exported and denominated in USD but must be reported in NOK. We expect that the technology index is more sensitive to a change in the exchange rate than the Norwegian benchmark index. This is because the benchmark index is more geographically diversified, so the sensitivity to overall currency risk should be reduced.

The finding of a unidirectional causality diverges from the findings of Kollias et al. (2015), where bidirectional causality is found between the exchange rate and the Norwegian stock market. The fact that we don´t find a causal relationship from the technology stock market to the exchange rate means that we fail to support the portfolio balance hypothesis, which states that increased stock prices lead to an appreciation of the home currency. This might be somewhat surprising as we expect that more capital inflow to the tech market would mean

[17] The portfolio adjustment effect is interpreted in more detail in section 5.2.

higher demand for domestic currency and, therefore, an appreciation of the NOK (Aysan et al., 2014).

The unidirectional causality from ΔINF to ΔOTECG indicates that when inflation rises, the value of the technology index also rises. A positive relationship from inflation to OTECG is contrary to the study by Gjerde and Sættem (1999), which suggests no significant causal relationship between the Norwegian stock market and inflation. However, a positive causal relationship supports our findings from the ARDL model. Based on these results, it seems that the characteristics of technology stocks differ from other groups of stocks. For tech stocks, economic activity seems to be important as this can help drive economic growth. Growth is crucial as many tech companies are valued based on their growth opportunities and ability to generate positive returns in the future.

The results do not support any unidirectional causalities from ΔOTECG to the other macroeconomic variables. ΔOTECG does not seem to cause movements in the other variables. This applies at least for the short run. We find that macroeconomic variables have a stronger ability to signal fluctuations in technology stock prices than what is the case the other way around.

Table 10 shows that the VECM suggests no significant causal relationship from ΔGDP to ΔOTECG. We expected to find a positive relationship between OTECG and GDP. This is because GDP in this context is a measure of economic activity, and higher economic activity usually leads to increased expected earnings.[18] This will boost the present value of future cash flows and thereby, the stock price. As Humpe and Macmillan (2009) found in their research, higher values of the stock market are associated with higher values for GDP, suggesting that good news in the real economy will lead to good news in the financial economy and vice versa.

From line (c), we also learn that there is a causal relationship from interest rates (ΔNIBOR) to inflation. Interest rates seem to be an important factor in explaining inflation, and the results suggest that inflation will decrease when interest rates rise, and vice versa. This is consistent with several studies such as Lee (1992) and Gjerde and Sættem (1999). As this relationship also occurs in the analysis of the Norwegian technology market when a more recent period is

[18] Gross domestic product is the most commonly used measure of a country´s economic activity. Chiripanhura, B. (2010). Measures of economic activity and their implications for societal well-being. *Economic & labour market review*, *4*(7), 56-65.

covered, the conclusion is that the relationship between interest rates and inflation is very robust. In counter-inflationary policy, raising the interest rates therefore seems to be an effective tool. Somewhat surprisingly, we find a negative causal effect from gross fixed capital formation to inflation. A negative relationship contradicts the established view that an increase in public spending and investments lead to a rise in price levels.

The results in line (c) illustrate the complexity of changes in inflation. ΔINF is significantly impacted by changes in all the macroeconomic variables except ΔOTECG and ΔEXCH. We find a bidirectional causal relationship between ΔINF and ΔGDP, ΔOIL and ΔGFCF and ΔEXCH and ΔGFCF. These are the only significant bidirectional causalities among our chosen macroeconomic variables, at least at a 5% significance level.

5.4.1 Diagnostic Tests

Diagnostic tests are performed to examine the adequacy of the vector error correction model. The tests are conducted to ensure that the model can be used for forecasting. As the model uses time series, we need to ensure that there is no serial correlation and heteroskedasticity in the residuals and that the residuals are normally distributed. We test the model for serial correlation to check if there is a relationship between one of our variables and its lagged version of itself over an interval. This is useful to determine if past values influence future values such that the observations might be non-random. For VECM, serial correlation in the error terms could cause the standard errors and statistics to be misleading (Wooldridge, 2020, p. 419). A heteroskedasticity test is also performed to ensure constant variance in the residuals. avoiding invalidation of our estimators. Finally, we test if the residuals are normally distributed to determine the stability and reliability of the model. The test statistics of the performed diagnostic tests on the vector error correction model are presented in Table 11, accompanied by their respective p-values.

Table 11. Diagnostic tests for the VECM

	Test Statistics	P – Value
(a) Serial Correlation	1033.4	0.071
(b) Heteroskedasticity	2268.0	1.000
(c) Normality	118.98	0.000

Table 11: (a) Portmanteau test (asymptotic) for serial correlation. (b) ARCH tests for heteroskedasticity. (c) Jarque Bera test for normality.

The Portmanteau test is applied to test for serial correlation in the residuals. The p-value in line (a) in Table 11 exceeds a 5% significance level. The test fails to reject the null hypothesis stating there is no serial correlation in the residuals and therefore concludes that the model is feasible and can be used for forecasting.

To test for heteroskedasticity, or ARCH effects, an ARCH test is performed. It is important to ensure that there are no ARCH effects because this would mean clustered volatility in the model.[19] From line (b) in Table 11, the test results show a p-value of 1. This clearly exceeds the 5% significance level, and thus the null hypothesis of no heteroskedasticity in the residuals cannot be rejected. There is no clustered volatility in the model.

The normality test of the residuals was carried out using the Jarque-Bera test. From line (c) in Table 11, we get a very small p-value, which does not exceed the 5% significance level. The null hypothesis is therefore rejected, and the conclusion is that the residuals are not normally distributed. With a small sample size, the Jarque-Bera test often indicates nonnormality in the residuals. However, failing the normality test has no implications on the validity of either tests or estimators in the VECM (Patterson & Mills, 2009). According to regression theory, the residuals follow the normal distribution when the sample size is sufficient. Although we failed to reject the hypothesis of nonnormality, the Portmanteau test and the ARCH test did not signal any significant violations of the standard model assumptions. This confirms that the model is valid for analysis purposes.

5.5 Dynamic Effects of Shocks

In this section, we investigate how an unexpected change, often referred to as a shock, to one of the macroeconomic variables will impact the other variables in our model. Both impulse response functions and variance decompositions are presented and discussed. The analysis primarily focuses on two contexts. Firstly, how the Oslo Stock Exchange technology index responds to one positive standard deviation shock in the macroeconomic variables. Secondly, we study how the macroeconomic determinants are impacted by a standard deviation shock in the Norwegian technology index.

[19] Clustered volatility is when the volatility changes over time, and its degree shows a tendency to persist. This means there are periods with high volatility and periods where the volatility is low, i.e., the variance of the residuals is not constant. (Wooldridge, 2020, pp. 417-418).

In section 5.4.1, diagnostic tests were performed, and we concluded that the vector error correction model was stable. When the assumptions of the model are fulfilled, we conclude that it is well specified. Thus, the analysis of impulse response functions and variance decomposition can be employed with consistent estimates.

We use the impulse response function, as it shows the effects of shocks on the adjusted path of the variables. Plotting the impulse response function reveals how an unexpected change in one variable will affect another variable and whether the effect is positive or negative. An advantage of the approach is that we can decide whether the shocks are permanent or transitory.[20] We have chosen a study period of 20 quarters (five years) since this allows us to study the effect of a shock both in the short and long run.

5.5.1 Impulse Response Analysis

The VECM analysis in section 5.4 revealed several short-run relations between our chosen variables and the Norwegian technology index. However, we are not able to determine how long these effects last and if the changes are permanent or transitory. We apply impulse response functions to forecast how the technology index will react to a shock in one of the independent variables. The impulse response function analyses the dynamic effects of the system when the model receives an impulse, enabling us to examine the direction of a shock in one of the variables and determine if the shock causes permanent changes in the technology index. We are also interested in investigating if shocks in the Norwegian technology index cause permanent changes to the included macroeconomic variables, covered in the latter part of the analysis.

Figure 12 (a) to (h) predicts how the Norwegian technology index will react to one standard deviation shock in the chosen macroeconomic determinants. The black line represents the impulse response function (IRF) constructed using the estimated coefficients from the VECM. For each figure, 95% confidence intervals are included to account for the parameter uncertainty inherent in the estimation process (Enders, 2015, p. 299). When a confidence interval includes zero, the interpretation is that after a shock in a variable, an effect in OTECG may or may not materialize, which means that a definite conclusion cannot be drawn. This must be considered when the results are interpreted.

[20] A shock is transitory if the effect of the shock dies out over time.

A positive shock to the technology index causes it to increase immediately. An unexpected change initially leads to a rise in OTECG with immediate effect. We see from figure (a) that the positive effect continues in the following periods before it, after approximately five quarters, reverts to the initial shock. The technology index responds aptly to its own innovations, but the effect somewhat fades off over time. A reasonable explanation for this could be that technology stocks experience a price momentum in the short run. Over time, the momentum will disappear, and the prices will somewhat decline. From figure (a), it seems like a shock has a positive, permanent effect on the technology index, which is statistically significant.

Figure (b) shows that a shock in interest rate (NIBOR) has a permanent negative impact on OTECG. This illustrates the importance of interest rate shocks to the technology stock market. The initial response supports the result of Gjerde and Sættem (1999), who found an initial negative response of the Norwegian stock market to a shock in NIBOR. Higher interest rates will lead to increased cost of capital and thus lower the value of the stock prices. This effect will probably be larger for technology stocks than value stocks because the expected cash flows of these securities are farther in the future, making the stock price more sensitive to the discount factor. From figure (c), we learn that OTECG has a positive response to an unexpected change in inflation, which is consistent with the findings from the VECM. However, the effect is very small and the result cannot be given much weight.

From figure (d), we see that OTECG has an initial negative effect on a standard deviation shock in the oil price. This is consistent with the research of Sadorsky (1999), who finds that a positive shock to the oil price depresses real stock returns. In the long run, a shock in the oil price seems to have a permanent negative effect to OTECG. Similar to the broad Norwegian stock market, the technology stock market also is sensitive to oil price changes. The findings from line (e) suggest that the effect of a shock in the exchange rate is positive but transitory. There is very little response in OTECG to a shock in the exchange rate. This is validated by the variance decomposition in section 5.5.2, where the explanatory power of EXCH is insignificant. The model fails to find supporting evidence for the negative relationship between EXCH and OTECG, which is accounted for in both the ARDL model and VECM.

We see from figure (f) that a shock in GDP leads to a modest negative and permanent response in OTECG. The negative relation supports our finding from the ARDL model but contradicts our initial hypothesis. Regarding gross fixed capital formation (GFCF), figure (g) shows there is very little response in OTECG to a shock in this variable. This finding is supported by the variance decomposition (see section 5.5.2), which shows that GFCF has little explanatory power to OTECG. It seems to be no influence from GFCF to technology stock prices. Lastly, figure (h) shows that a positive shock in the level of credit to the private sector has a significant permanent positive effect to the value of the technology index. A possible explanation for this relationship could be that with a higher level of credit, people will have more money available and, therefore, a greater capacity to invest in the stock market. This will affect the earnings of the listed companies and thereby raise the stock price. The effect will probably be somewhat larger for technology stocks priced at high price-earnings multiples compared to traditional value stocks.

Figure 12. Impulse Response Functions for the Technology Index

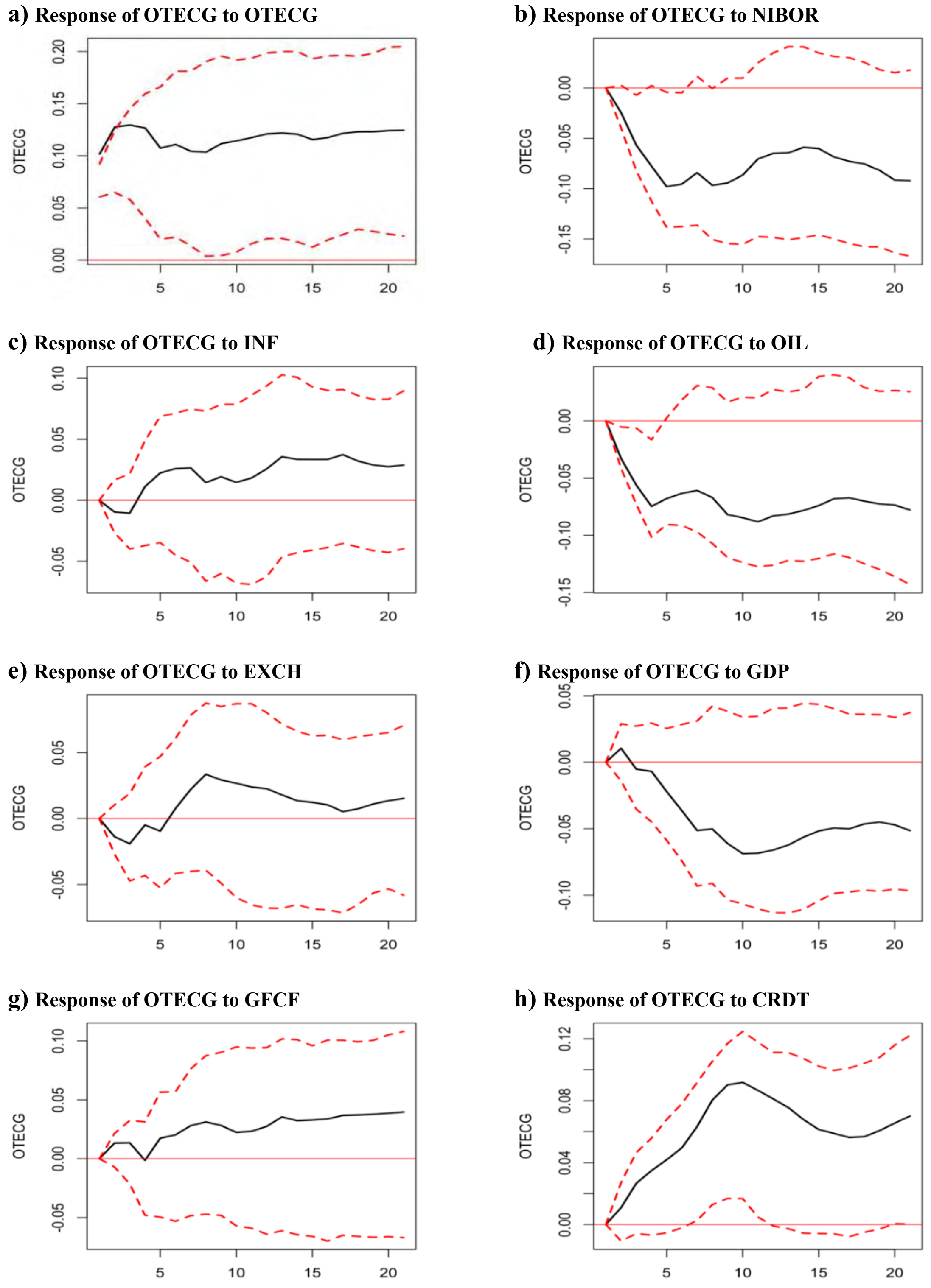


Figure 12: The impulse response functions show how OTECG will respond to a one-unit standard deviation (SD) shock in the macroeconomic variables. For numbers, see appendix IV, (Table 16).

Figure 13 (a) to (h) reveal the response of each of the macroeconomic variables to a one-unit standard deviation shock in OTECG. Again, for almost all the analyzed relationships, the confidence intervals are large and include zero. This means that the estimated effect to a variable may or may not materialize after a shock in OTECG.

In figures (b) and (c), it appears that the NIBOR rate has an immediate negative response before it changes and the response turns permanently positive. On the other hand inflation has a significant negative response to a shock in OTECG. The two macroeconomic variables respond immediately to a shock. However, the effect of inflation is transitory as it fades away over time. The finding supports the findings of the VECM, as changes in technology stock prices do not seem to signal changes in inflation.

The oil price has a positive and permanent response to a shock in OTECG. We learn from figure (d) that a shock in OTECG leads to an immediate increase in the oil price before a fall is observed. In figure (e), the exchange rate appreciates (i.e., the response is negative) with immediate effect to a shock in OTECG. The shock seems transitory as it fades away after approximately eight quarters (i.e., two years).

As for GDP, figure (f) shows no significant response to a one-unit standard deviation shock in OTECG. The finding is supported by the marginal explanatory power from the variance decomposition (see section 5.5.2). There is no influence from technology stock prices to the level of GDP.

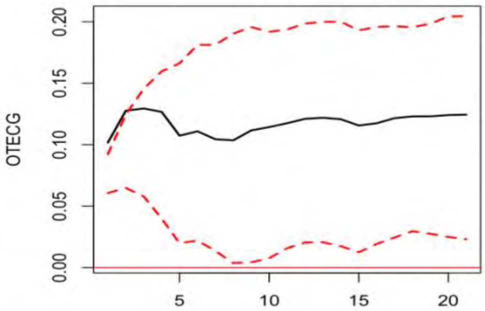
From figure (g), we see a slightly positive immediate effect in GFCF to a shock in OTECG. However, the effect seems to be transitory based on the insignificant values of the impulse responses. Lastly, figure (h) exhibits a negative response of credit to the private sector to a shock in OTECG. CRDT immediately reacts negatively, and after five quarters, the effect stabilizes. This suggests that the negative effect is permanent. A reasonable explanation could be that when stock prices increase, people get wealthier and, as a result, reduce their debt. The economic theory suggesting that a rise in stock prices increases the supply and demand for loans does not seem to hold for the Norwegian technology stocks.[21]

[21] The relation is investigated in Sun Bae, K., & Moreno, R. (1994). Stock prices and bank lending behavior in Japan. *Economic review (San Francisco)*(1), 31. This is the most relevant study we have found regarding the relationship between loans and stock prices.

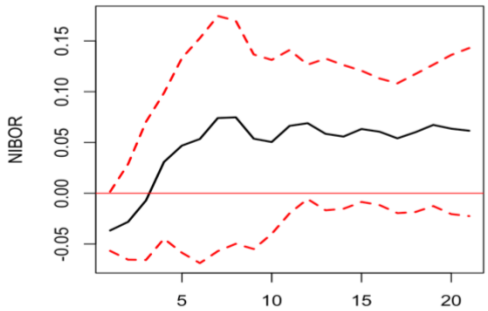
Interestingly, from the impulse response analysis, we find that the interest rate, oil price and credit to the private sector have a permanent effect to a shock in OTECG. From the VECM analysis (see section 5.4), we were unable to find a causal relationship from OTECG to any of these variables. However, the large confidence intervals imply that we cannot conclude that the expected outcome actually will occur. The effect from OTECG to NIBOR and OIL is supported by a reasonable explanatory power in the variance decomposition, while the explanatory power from OTECG to CRDT is lower.

Figure 13. Impulse Response Functions for the Macroeconomic Variables.

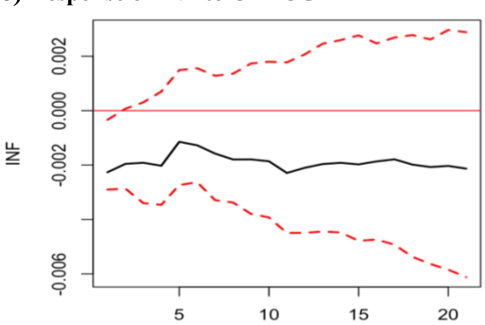
a) Response of OTECG to OTECG



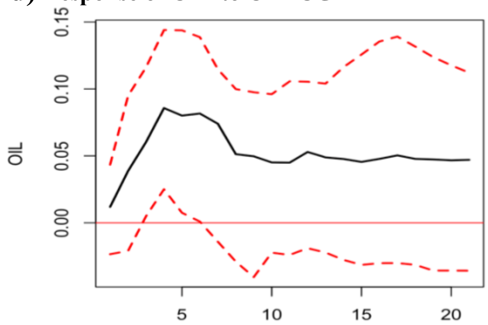
b) Response of NIBOR to OTECG



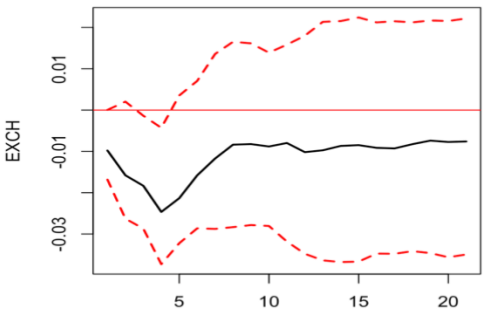
c) Response of INF to OTECG



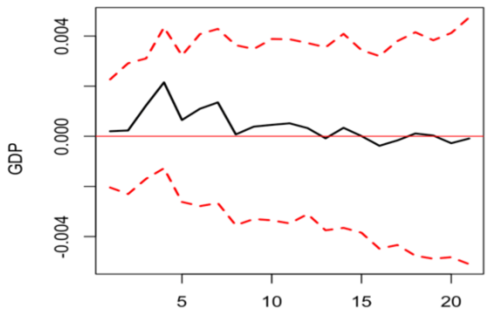
d) Response of OIL to OTECG



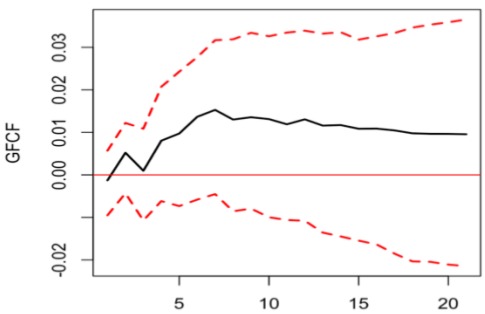
e) Response of EXCH to OTECG



f) Response of GDP to OTECG



g) Response of GFCF to OTECG



h) Response of CRDT to OTECG

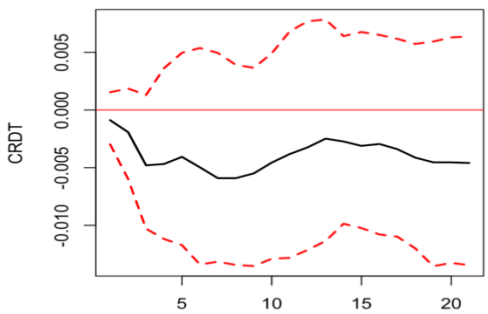


Figure 13: The impulse response functions show how the macroeconomic variables will respond to a one-unit standard deviation (SD) shock in OTECG. For numbers, see appendix IV, (Table 17).

5.5.2 Forecast Error Variance Decomposition

The impulse response analysis revealed that shocks in some of the macroeconomic variables cause permanent changes to the technology index. The forecast error variance decomposition has been analyzed to further examine the findings of the vector error correction model and to elaborate on the results of the impulse response functions. The variance decomposition is performed to identify the driving forces of business cycles in the Norwegian technology market, as mentioned in section 4.5. The model enables us to determine how much of the variation in each variable that is caused by another variable over time. A variable might explain an insignificant part of the variation in the short run but a significant part in the long run, or vice versa. In this section, we will examine the magnitude of the changes in the technology index explained by the included macroeconomic variables. The latter part will cover the magnitude of the changes in each independent variable caused by the technology index.

The decomposed error variance of our dependent variable (OTECG) is presented in Table 12 and shows to which degree the variations in the technology index could be explained by movements in the macroeconomic variables. Table 13 exhibits the forecasted error variance decomposition of the macroeconomic variables, which can be linked to one standard deviation shock in the Norwegian technology index. We present the results from the variance decomposition for the first, 4th, 8th, 12th, 16th and 20th quarter.

Table 12. Forecast Error Variance Decomposition for OTECG

Step	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
1	100.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
4	71.96 %	11.93 %	0.40 %	11.88 %	0.70 %	0.22 %	0.44 %	2.47 %
8	50.44 %	21.63 %	1.16 %	12.80 %	1.12 %	3.44 %	1.36 %	8.04 %
12	42.80 %	19.01 %	1.08 %	14.87 %	1.35 %	6.65 %	1.46 %	12.77 %
16	42.56 %	17.09 %	1.70 %	15.42 %	1.14 %	7.29 %	1.96 %	12.83 %
20	42.69 %	17.42 %	1.95 %	15.20 %	0.95 %	7.88 %	2.42 %	12.27 %

Table 12: The variance decomposition of OTECG, attributed to its own innovation (column 2), and innovations in other macroeconomic variables (column 3-9) for a period of 1 to 20 quarters (i.e., five years).

From the impulse response analysis, we observed that movements in the technology index could be explained by shocks in some of the macroeconomic variables. The variance decomposition in Table 12 supports these findings. We observe that movements in the tech index are 100% explained by its own innovations in the first quarter. The variability of OTECG declines over the five-year forecast horizon, indicating that long-run movements in OTECG could be caused by some of the other macroeconomic variables included in our analysis.

A significant fraction of the variation in OTECG can be accounted for by the NIBOR rate after five years, implying that the development of the Norwegian technology index, is largely driven by changes in the interest rate. These findings are supported by the previous study of Bernanke and Kuttner (2005). In addition, a standard deviation shock in OTECG on the variance in NIBOR, seen in Table 13, supports our findings from the impulse response analysis that changes in the technology index cause changes in the NIBOR rate. The forecast variance decomposition reveals that innovations in the oil price explain 15.20% of the variation in OTECG after five years, supporting the findings of VECM. From Table 13 we observe that innovations in OTECG explain 13.49% of the variance in the oil price over the forecasted period. These findings are in line with the findings from the impulse response function. Throughout the forecast horizon, credit to the private sector and GDP increases its explanatory power, indicating a delayed response in OTECG caused by innovation in CRDT and GDP. Additionally, the innovation of OTECG affects the variations in CRDT and GDP to a smaller degree, as presented in Table 13 with 4.31% and 0.70% explanatory power, respectively.

For the variables INF, EXCH and GFCF, we found the variables have an insignificant explanatory power on variations in OTECG. These results are consistent with findings from the impulse response analysis. However, it contradicts the unidirectional causality running from ΔINF to ΔOTECG and ΔEXCH to ΔOTECG (equation a in Table 10).

Table 13. Forecast error variance decomposition of a shock in OTECG on the variables

Step	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
1	100.00 %	6.47 %	16.25 %	0.59 %	6.66 %	0.05 %	0.17 %	0.78 %
4	71.96 %	2.20 %	17.70 %	12.59 %	16.23 %	2.78 %	2.32 %	3.62 %
8	50.44 %	5.23 %	13.87 %	17.91 %	15.18 %	1.68 %	6.03 %	4.17 %
12	42.80 %	7.31 %	12.50 %	17.07 %	10.18 %	1.15 %	5.59 %	4.58 %
16	42.56 %	9.48 %	10.09 %	15.14 %	7.26 %	0.89 %	4.88 %	4.41 %
20	42.69 %	10.84 %	8.00 %	13.49 %	6.01 %	0.70 %	4.27 %	4.31 %

Table 13: The variance decomposition of OTECG (column 2) and all macroeconomic variables (column 3-9), attributed to innovation in OTECG for a period of 1 to 20 quarters (i.e., five years).

The VECM analysis in section 5.4 found no significant short-run relationship from ΔOTECG to any of the variables. In contrast, the impulse response analysis suggested that a shock in OTECG would have a long-run effect on NIBOR, OIL and CRDT. The forecast error variance decomposition of a shock in OTECG and its effect to the other variables are exhibited in Table 13. The results indicate that a significant proportion of the variation in NIBOR, INF, OIL and EXCH can be explained by OTECG over the forecast horizon. The variation in INF and EXCH is declining throughout the forecast horizon, while the variation in interest rates yields a delayed response to changes in the Norwegian technology index.

The findings of the forecast variance decomposition are in accordance with the results from the impulse response analysis, indicating that shocks in the technology index cause movements in some of the macroeconomic variables. However, when assessing the results of the forecast error variance decomposition, one should bear in mind that for a longer forecast period, the standard deviations are increasing, causing inefficient estimates.

6. Conclusion

This thesis investigated the macroeconomic determinants of Norwegian technology stock prices, represented by the Oslo Stock Exchange technology index, for the 2000-2021 period. Our thesis is a contribution to the existing literature on the relationship between macroeconomic factors and stock returns. Also, it provides knowledge on how technology stock prices are exposed differently to certain macroeconomic variables compared to the overall stock market. In addition, we studied how an unexpected change in each variable would affect the technology index. By using the methodological framework of a cointegration analysis, an autoregressive distributed lag model and a vector error correction model, this thesis attempted to answer the following research question:

How do macroeconomic determinants affect the development of the Norwegian technology index?

To answer the research question, we first investigated the existence of a relationship between the technology index and macroeconomic variables. The results of Table 4 and Table 8 identified an equilibrium relationship between Norwegian technology stock prices and the chosen macroeconomic factors, which is significant at a 1% and 5% confidence level, respectively. This challenges the conclusions drawn by the efficient market hypothesis (EMH) that economic indicators are unable to influence stock returns. We conclude that information about leading macroeconomic indicators can help predict future technology stock prices and give insight into when it may be favorable to invest in the technology index.

The second part of the research examined how a change to each macroeconomic variable would impact the value of the Norwegian technology index. Consistent with findings from the US, the 3-month interest rate had a significant impact on the Norwegian technology stock market. We found that when interest rates increased, on average, the price of technology stocks would decrease. This was expected because technology stocks, valued on uncertain future earnings, are vulnerable to changes in interest rates through the discount factor. However, compared to the findings of Rigobon and Sack (2004), our findings suggest that the Norwegian technology index is less sensitive to changes in interest rates than the US NASDAQ technology index.

Our short-run analysis detected several significant relationships between external factors and the technology index. According to our study, both the VECM and the ARDL model found a significant relationship from the NOK/USD exchange rate, the oil price and inflation to the technology index. Thus, they appear to be vital factors influencing the Norwegian technology stock prices.

The relationship from the exchange rate to technology stock prices suggests that tech stocks are profitable when the home currency appreciates. Further, our results indicated that an increase in the oil price reduces the technology stock prices while rising inflation contributes to an increase in the stock prices. This is contrary to the previous findings by Gjerde and Sættem (1999) from the Norwegian stock market. However, these previous findings are limited to the composite market index and did not investigate the technology-specific indexes. Although we observed an unexpected relationship between technology stock returns and the oil price, our research demonstrates that the significant results from the US technology sector are also valid in the Norwegian technology market. The fact growth opportunities are important to keep up with technological development and increase the company's future earnings, also makes the finding of inflation causing higher stock prices reasonable for the technology sector.

The above findings thereby suggest that some of the economic determinants of technology stock prices differ from the broad market. By exploiting these differences, there is a possibility of making abnormal returns. We recommend investors to be aware of the development in the above-mentioned macroeconomic factors in order to implement an appropriate trading strategy for technology stocks. We conclude that investing in the technology sector is favorable when inflation rises, and the oil price decreases since the technology index then performs better than the overall market.

Moreover, this thesis examined if the development of the technology index caused changes in any of the macroeconomic variables. The analysis failed to find evidence for any such relationships. Based upon this, we conclude that the relationship is asymmetric, meaning the return of technology stocks is a bad indicator for predicting the development of the chosen macroeconomic determinants.

Lastly, the impulse response functions and variance decomposition supplemented our primary analysis and showed that most innovations from the macroeconomic variables explained movements in the technology stock market and that the technology index was less able to signal movements in the macroeconomic determinants. As observed in Table 12, almost 60% of the variation in stock prices was accounted for by changes in macroeconomic variables, suggesting the technology stock price variability is fundamentally connected to changes in these variables. However, some of the variables only explained a small part of the variation in the technology index, and hence the prediction must be done with caution.

6.1 Limitations

This thesis is a comprehensive study of technology stock prices in Norway. Although the study contributes to understanding the relationship between the technology market and macroeconomic determinants, there are still some limitations that could be considered in future research. Firstly, as only seven explanatory variables were included, the econometric models might only capture some of the macroeconomic relationships. On the other hand, too many variables included in a model could lead to it being over-specified, and thus, the results could be biased. More relevant is perhaps which variables to include when studying the technology stock market. Some explanatory variables omitted from the analysis could possibly have captured macroeconomic relationships more relevant for the technology sector. As discussed in section 3.2, additional variables such as industrial production and money supply could have been included. Other relevant variables could be savings rate and consumption, as well as other stock indexes. Lastly, we observed issues regarding normality in some of our models that could affect the estimates such that they are consistent but not efficient.

Another point that may be relevant to address is that the technology index is composed of companies with different characteristics. For example, the companies may have different capital structure, profitability and market capitalization. Some of these companies have suffered firm-specific events throughout the period from 2000 to 2021. This may have led to a decline in the company's stock price even though there were no significant changes in the macroeconomic variables. Particularly, this can be relevant for the technology index as this is a relatively small index regarding the number of listed companies. Thus, events specific to a company will have greater significance to the index's total value. Consequently, the results we get from the analysis may have been somewhat disturbed due to company-specific factors. This is particularly relevant for firms that form much of the sector in terms of market capitalization.

6.2 Suggestions for Further Studies

Our analysis only aims to study the effect of macroeconomic determinants on technology stock prices in Norway. We do not examine how macroeconomic variables affect the return of technology stocks in other countries. The thesis also does not consider the effect of foreign stock markets on the Norwegian technology index. For example, it could be interesting to study how the American NASDAQ technology index affects the return of the Norwegian technology index. Moreover, it could be exciting to perform the ARDL and VECM on data from other countries to examine how macroeconomic determinants affect technology stock prices in different economies and whether the relationships we find in Norway also apply to other markets. The American and British economies, as well as the other Nordic countries are natural candidates for further research and comparison.

Furthermore, this thesis restricts itself to only studying one index/industry. A possible extension to this research is therefor to study how other industry-related indexes are affected by changes in macroeconomic variables. For example, energy, industrials and utilities are sectors it could be interesting to examine. If the relevant industries react differently to changes in a macroeconomic variable, diversification benefits could exist. On the other hand, if the returns from different sectors are cointegrated, the diversification benefits could decrease. Examining the relationships between macroeconomic factors and various industries might be important to better understand the advantages of industry diversification. It would also expand the literature regarding macroeconomic factors and the Norwegian market. In extension, a comprehensive study including several countries could explain the potential for international diversification.

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Appendix

I. Descriptive Statistics

Table 14. Descriptive statistics, logarithmic first difference

Variable	Abbreviation	Mean	Standard deviation	Min	Max
Oslo Stock Exchange Technology Index	OTECG	0.0094	0.1518	-0.3682	0.3661
NIBOR 3-month interest rate	NIBOR	-0.0241	0.2356	-1.2667	0.8518
Inflation	INF	0.0052	0.0084	-0.0178	0.0348
The price of Crude Oil	OIL	0.0136	0.2424	-1.2421	0.8555
Exchange rate NOK/USD	EXCH	0.0006	0.0589	-0.1423	0.2360
Gross Domestic Product per capita	GDP	0.0017	0.0128	-0.0498	0.0437
Government Fixed Capital Formation	GFCF	0.0134	0.0485	-0.1780	0.1798
Credit to Private sector	CRDT	0.0045	0.0193	-0.0719	0.0510

Table 14: Descriptive statistics of the variables in logarithmic first difference for the period Q1 2000 – Q4 2021.

II. Supplementing stationarity tests

Figure 14. Stationarity properties of the variables – logarithmic

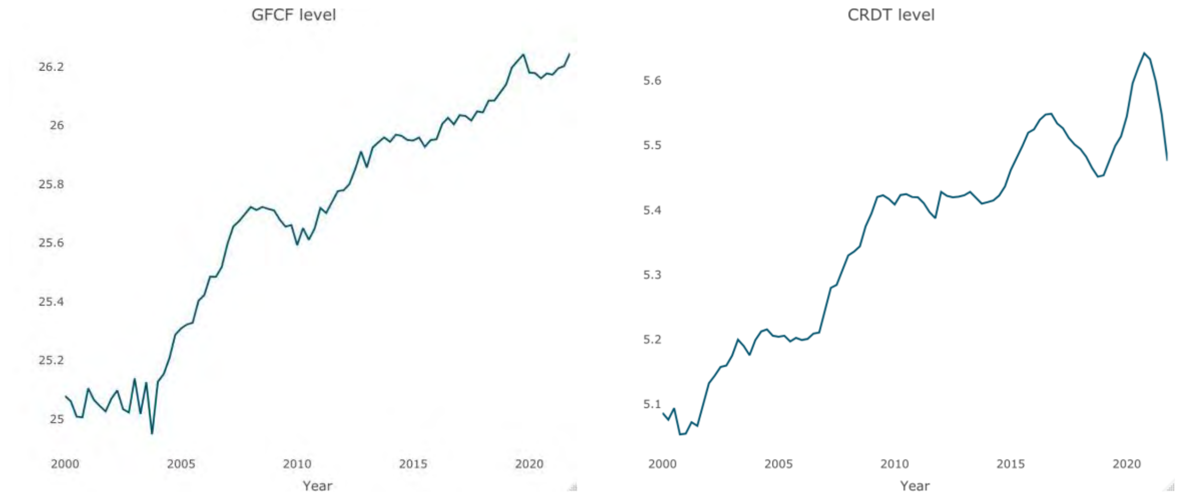

Figure 14: Time series plots of variables used in the analysis. Logarithmic returns in level. The figure shows that all the macroeconomic series contain a unit root and are non-stationary processes.

Figure 15. Stationarity properties of the variables – logarithmic first difference

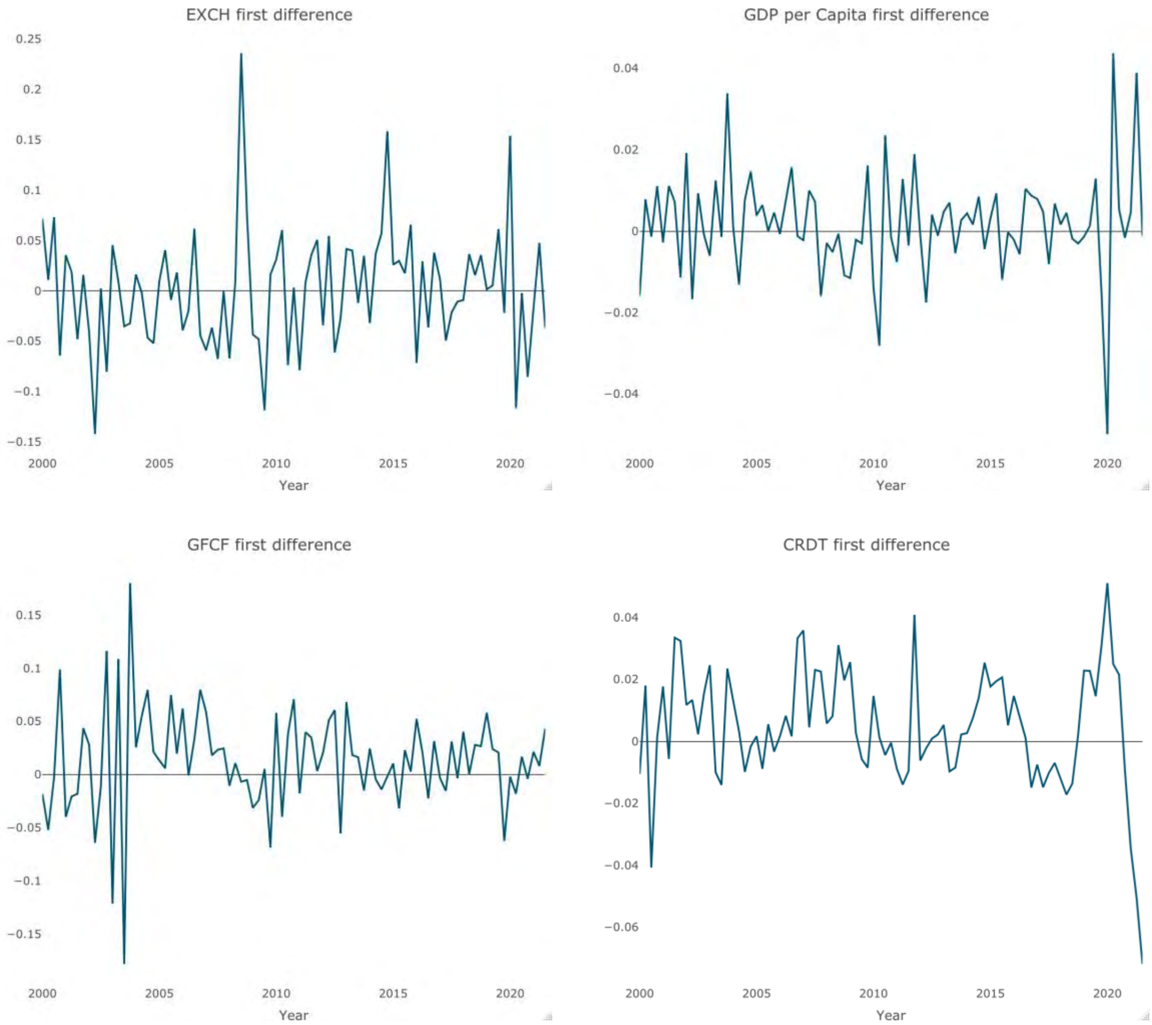

Figure 15: Time series plots for variables used in the analysis. Logarithmic returns in first difference. The figure shows that the first difference of all the macroeconomic variables is stationary.

III. VECM output, excl. cointegrating equations

Equation (23) represents the VECM model

$$\Delta \mathrm{OTECG} = \pi_0 + \sum_{i=1}^{5} \pi_1 \Delta \mathrm{OTECG}_{t-1} + \sum_{i=1}^{5} \pi_2 \Delta \mathrm{NIBOR}_{t-1} + \sum_{i=1}^{5} \pi_3 \Delta \mathrm{INF}_{t-1} + \sum_{i=1}^{5} \pi_4 \Delta \mathrm{OIL}_{t-1} + \sum_{i=1}^{5} \pi_5 \Delta \mathrm{EXCH}_{t-1} + \sum_{i=1}^{5} \pi_6 \Delta \mathrm{GDP}_{t-1} + \sum_{i=1}^{5} \pi_7 \Delta \mathrm{GFCF}_{t-1} + \sum_{i=1}^{5} \pi_8 \Delta \mathrm{CRDT}_{t-1} + \delta ECT1_{t-1} + \delta ECT2_{t-1} + \varepsilon_{1t} \quad (23)$$

Table 15. Complete list of VECM outputs, excluding cointegration equations

Explanatory variables	ΔOTECG	ΔNIBOR	ΔINF	ΔOIL	ΔEXCH	ΔGDP	ΔGFCF	ΔCRDT
δ_1	-0.195***	-0.017	0.008**	0.124	-0.006	0.000	0.027	-0.004
δ_2	-0.204***	-0.029	-0.001	0.103	-0.041*	0.002	-0.018	-0.002
$\Delta OTECG_{t-1}$	0.016	0.264	0.006	0.105	-0.056	-0.012	0.012	-0.018
$\Delta OTECG_{t-2}$	-0.156	-0.167	-0.003	-0.116	0.079	-0.004	-0.061	-0.003
$\Delta OTECG_{t-3}$	0.161	0.359	-0.004	0.297	-0.039	0.017	0.019	0.015
$\Delta OTECG_{t-4}$	-0.034	0.025	0.004	0.336	-0.082	0.011	0.056	0.017
$\Delta OTECG_{t-5}$	0.160	-0.021	0.015*	-0.128	0.015	0.009	-0.067	-0.015
$\Delta NIBOR_{t-1}$	0.062	0.204	0.002	-0.159	-0.003	-0.011	0.044	0.010
$\Delta NIBOR_{t-2}$	-0.148	-0.119	-0.019***	-0.053	0.049	-0.025**	-0,013	0.026*
$\Delta NIBOR_{t-3}$	0.035	0.147	0.004	-0.383*	0.032	0.000	-0.063	-0.003
$\Delta NIBOR_{t-4}$	-0.140	0.269	0.011	0.054	-0.049	-0.015	0.008	0.000
$\Delta NIBOR_{t-5}$	-0.140	-0.248	0.001	-0.192	0.011	-0.011	-0.014	0.004
ΔINF_{t-1}	-2.675	2-596	-0.601***	2.573	1.471	-0.131	1.376	-0.186
ΔINF_{t-2}	0.935	2.588	-0.656***	-1.035	2.977**	0.038	1.810	-0.189
ΔINF_{t-3}	7.163**	2.257	-0.618***	-0.766	3.446**	0.179	0.781	-0.025
ΔINF_{t-4}	10.052***	2.188	-0.356*	4.348	0.6000	0.634*	2.262*	0.168
ΔINF_{t-5}	8.172***	-0.522	-0.319*	3.287	0.317	0.771**	1.261	0.103
ΔOIL_{t-1}	-0.439**	-0.003	0.023**	-0.933***	0.046	-0.018	-0.167***	-0.011
ΔOIL_{t-2}	-0.368*	0.298	0.010	-0.850**	-0.010	-0.017	-0.107	-0.019
ΔOIL_{t-3}	-0.360*	-0.128	0.011	-0.456	0.046	-0.024	-0.014	-0.010
ΔOIL_{t-4}	-0.209	-0.248	0.001	-0.450	0.025	-0.026	-0.016	0.018
ΔOIL_{t-5}	-0.030	0.388	0.001	0.111	-0.088	-0.011	-0.018	-0.003
$\Delta EXCH_{t-1}$	-0.938*	-0.418	0.040	-1.955**	0.047	-0.031	-0.372**	-0.035
$\Delta EXCH_{t-2}$	-1.368**	-1.563*	0.023	-2.813***	0.100	-0.124**	-0.447*	-0.007
$\Delta EXCH_{t-3}$	-0.803	-0.203	0.057*	0.258	-0.152	-0.035	0.096	-0.071
$\Delta EXCH_{t-4}$	-0.895*	-0.642	-0.025	-2.178**	0.164	-0.079	-0.065	0.057
$\Delta EXCH_{t-5}$	-0.373	1.624*	0.049*	-0.383	-0.043	-0.042	-0.129	-0.015
ΔGDP_{t-1}	1.122	2.278	-0.039	-0.607	0.022	-0.276	0.793	-0.010
ΔGDP_{t-2}	0.262	-0.216	-0.265**	-3.060	1.384*	-0.263	0.535	-0.033
ΔGDP_{t-3}	0.639	-0.959	-0.171	2.415	-0.755	0.079	2.455***	-0.241
ΔGDP_{t-4}	-3.218	2.886	-0.244*	3.639	1.708*	-0.018	1.227*	0.041
ΔGDP_{t-5}	-3.400	2.749	0.120	-0.918	1.214	-0.045	0.896	0.165
$\Delta GFCF_{t-1}$	0.207	1.731**	-0.033	3.388***	-0.636***	0.071	-0.151	-0.100
$\Delta GFCF_{t-2}$	0.478	-0.259	-0.102***	2.337**	-0.408*	0.113*	0.235	-0.094
$\Delta GFCF_{t-3}$	-0.608	-0.850	-0.078**	0.078	0.233	0.040	0.078	-0.056
$\Delta GFCF_{t-4}$	0.009	-0.155	-0.058	0.752	0.014	0.042	0.337*	0.070
$\Delta GFCF_{t-5}$	-0.390	-0.110	0.034	0.833	0.118	0.057	0.188	0.053
$\Delta CRDT_{t-1}$	0.917	-4.252	-0.140	-8.245***	2.232***	-0.340**	0.280	0.479**
$\Delta CRDT_{t-2}$	1.721	3.627	-0.076	1.489	-0.186	0.062	0.534	0.147
$\Delta CRDT_{t-3}$	1.042	-2.048	0.037	1.166	-0.659	-0.048	0.381	0.216
$\Delta CRDT_{t-4}$	0.056	-1.532	0.117	-3.931	-0.104	-0.125	-0.822*	-0.226
$\Delta CRDT_{t-5}$	-1.640	-0.005	0.203**	1.862	-0.757	-0.102	-0.651	-0.122
Constant	-19.023***	-2.616	-0.151	9.749	-3.461*	0.126	-1.212	-0.211

Table 15: ***significant at 1% level, **significant at 5% level, *significant at 10% level.

IV. Outputs from the Impulse Response Analysis

Table 16. The response of OTECG to shocks in the macroeconomic variables

Step	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
1	0.1017	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.1276	-0.0246	-0.0097	-0.0328	-0.0138	0.0105	0.0133	0.0109
3	0.1295	-0.0568	-0.0106	-0.0561	-0.0191	-0.0052	0.0135	0.0266
4	0.1267	-0.0776	0.0112	-0.0748	-0.0049	-0.0068	-0.0013	0.0348
5	0.1073	-0.0980	0.0223	-0.0679	-0.0095	-0.0221	0.0174	0.0418
6	0.1109	-0.0954	0.0259	-0.0633	0.0075	-0.0365	0.0203	0.0496
7	0.1044	-0.0841	0.0265	-0.0608	0.0220	-0.0513	0.0281	0.0633
8	0.1035	-0.0966	0.0145	-0.0670	0.0335	-0.0502	0.0313	0.0804
9	0.1116	-0.0943	0.0192	-0.0819	0.0293	-0.0611	0.0283	0.0902
10	0.1143	-0.0865	0.0146	-0.0846	0.0267	-0.0688	0.0224	0.0918
11	0.1174	-0.0705	0.0182	-0.0882	0.0239	-0.0685	0.0233	0.0867
12	0.1210	-0.0650	0.0257	-0.0831	0.0226	-0.0660	0.0275	0.0812
13	0.1219	-0.0644	0.0356	-0.0815	0.0179	-0.0623	0.0355	0.0755
14	0.1207	-0.0590	0.0335	-0.0783	0.0135	-0.0564	0.0323	0.0678
15	0.1156	-0.0602	0.0334	-0.0740	0.0123	-0.0517	0.0329	0.0614
16	0.1174	-0.0685	0.0335	-0.0681	0.0104	-0.0495	0.0338	0.0589
17	0.1216	-0.0728	0.0373	-0.0673	0.0052	-0.0501	0.0372	0.0562
18	0.1230	-0.0754	0.0321	-0.0701	0.0074	-0.0464	0.0372	0.0568
19	0.1230	-0.0819	0.0289	-0.0726	0.0110	-0.0450	0.0377	0.0607
20	0.1241	-0.0914	0.0275	-0.0736	0.0135	-0.0471	0.0386	0.0655

Table 16: The impulse response functions are applied to analyze the short-run dynamics of the variables. The forecasting period is 20 quarters (steps 1-20). Column 2-9 shows the effect on OTECG when there is a shock in a macroeconomic variable.

Table 17. The response of macroeconomic variables to shocks in OTECG

Step	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
1	0.1017	-0.0367	-0.0023	0.0120	-0.0098	0.0002	-0.0013	-0.0008
2	0.1276	-0.0282	-0.0020	0.0387	-0.0158	0.0002	0.0052	-0.0019
3	0.1295	-0.0071	-0.0019	0.0603	-0.0183	0.0012	0.0009	-0.0048
4	0.1267	0.0308	-0.0020	0.0857	-0.0247	0.0022	0.0080	-0.0047
5	0.1073	0.0469	-0.0011	0.0801	0.0213	0.0006	0.0097	-0.0041
6	0.1109	0.0534	-0.0013	0.0816	-0.0158	0.0011	0.0137	-0.0050
7	0.1044	0.0741	-0.0016	0.0740	-0.0117	0.0014	0.0153	-0.0059
8	0.1035	0.0748	-0.0018	0.0513	-0.0084	0.0000	0.0130	-0.0059
9	0.1116	0.0537	-0.0018	0.0497	-0.0082	0.0004	0.0136	-0.0055
10	0.1143	0.0504	-0.0019	0.0451	-0.0088	0.0005	0.0131	-0.0046
11	0.1174	0.0664	-0.0023	0.0450	-0.0080	0.0005	0.0119	-0.0038
12	0.1210	0.0690	-0.0021	0.0529	-0.0102	0.0003	0.0131	-0.0032
13	0.1219	0.0585	-0.0020	0.0489	-0.0097	-0.0000	0.0116	-0.0025
14	0.1207	0.0558	-0.0019	0.0477	-0.0087	0.0003	0.0117	-0.0027
15	0.1156	0.0633	-0.0020	0.0455	-0.0085	0.0000	0.0108	-0.0031
16	0.1174	0.0606	-0.0019	0.0478	-0.0091	-0.0003	0.0109	-0.0029
17	0.1216	0.0541	-0.0018	0.0504	-0.0093	-0.0002	0.0105	-0.0033
18	0.1230	0.0601	-0.0020	0.0477	-0.0083	0.0001	0.0098	-0.0041
19	0.1230	0.0673	-0.0021	0.0473	-0.0074	0.0000	0.0096	-0.0045
20	0.1241	0.0636	-0.0020	0.0467	-0.0077	-0.0003	0.0096	-0.0046

Table 17: The impulse response functions are applied to analyze the short-run dynamics of the variables. The forecasting period is 20 quarters (steps 1-20). Column 2-9 shows the effect to the selected macroeconomic variables of a shock in OTECG.

V. Outputs from the variance decomposition

Table 18. Complete variance decomposition of OTECG and macroeconomic variables

	Step	OTECG	NIBOR	INF	OIL	EXCH	GDP	GFCF	CRDT
OTECG	1	**100.00 %**	**0.00 %**	**0.00 %**	**0.00 %**	**0.00 %**	**0.00 %**	**0.00 %**	**0.00 %**
	4	**71.96 %**	**11.93 %**	**0.40 %**	**11.88 %**	**0.70 %**	**0.22 %**	**0.44 %**	**2.47 %**
	8	**50.44 %**	**21.63 %**	**1.16 %**	**12.80 %**	**1.12 %**	**3.44 %**	**1.36 %**	**8.04 %**
	12	**42.80 %**	**19.01 %**	**1.08 %**	**14.87 %**	**1.35 %**	**6.65 %**	**1.46 %**	**12.77 %**
	16	**42.56 %**	**17.09 %**	**1.70 %**	**15.42 %**	**1.14 %**	**7.29 %**	**1.96 %**	**12.83 %**
	20	**42.69 %**	**17.42 %**	**1.95 %**	**15.20 %**	**0.95 %**	**7.88 %**	**2.42 %**	**12.27 %**
NIBOR	1	**6.47 %**	93.53 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
	4	**2.20 %**	58.60 %	1.47 %	2.01 %	16.59 %	2.66 %	4.19 %	12.29 %
	8	**5.23 %**	31.52 %	0.66 %	2.04 %	18.38 %	16.45 %	5.24 %	20.47 %
	12	**7.31 %**	25.93 %	0.70 %	1.76 %	18.13 %	19.16 %	7.98 %	19.05 %
	16	**9.48 %**	24.12 %	0.95 %	1.75 %	17.31 %	18.49 %	10.45 %	17.45 %
	20	**10.84 %**	23.52 %	0.87 %	1.73 %	17.49 %	17.78 %	11.47 %	16.31 %
INF	1	**16.25 %**	1.27 %	82.48 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
	4	**17.70 %**	1.70 %	59.76 %	1.38 %	5.95 %	4.62 %	0.40 %	8.50 %
	8	**13.87 %**	2.01 %	59.96 %	7.11 %	5.13 %	4.58 %	1.17 %	6.17 %
	12	**12.50 %**	2.69 %	54.53 %	12.54 %	3.18 %	3.29 %	6.52 %	4.76 %
	16	**10.09 %**	5.25 %	47.94 %	13.31 %	2.08 %	2.05 %	14.15 %	5.13 %
	20	**8.00 %**	9.87 %	40.02 %	12.89 %	1.32 %	1.35 %	21.82 %	4.73 %
OIL	1	**0.59 %**	23.77 %	0.06 %	75.58 %	0.00 %	0.00 %	0.00 %	0.00 %
	4	**12.59 %**	7.63 %	0.68 %	43.31 %	12.72 %	2.50 %	11.98 %	8.60 %
	8	**17.91 %**	5.04 %	1.65 %	38.11 %	8.83 %	5.80 %	17.23 %	5.43 %
	12	**17.07 %**	4.79 %	1.96 %	39.90 %	6.64 %	4.86 %	20.59 %	4.19 %
	16	**15.14 %**	6.05 %	1.65 %	41.61 %	5.78 %	5.22 %	20.46 %	4.09 %
	20	**13.49 %**	5.57 %	1.49 %	42.87 %	5.49 %	6.65 %	19.66 %	4.77 %
EXCH	1	**6.66 %**	14.88 %	0.76 %	36.35 %	41.34 %	0.00 %	0.00 %	0.00 %
	4	**16.23 %**	8.35 %	1.85 %	18.90 %	29.71 %	7.46 %	10.63 %	6.86 %
	8	**15.18 %**	10.85 %	6.80 %	15.96 %	19.89 %	13.18 %	14.27 %	3.87 %
	12	**10.18 %**	21.09 %	6.39 %	17.67 %	14.97 %	13.79 %	12.21 %	3.69 %
	16	**7.26 %**	23.22 %	5.48 %	18.83 %	14.08 %	15.77 %	9.54 %	5.82 %
	20	**6.01 %**	22.77 %	5.87 %	19.72 %	13.40 %	17.46 %	8.46 %	6.30 %
GDP	1	**0.05 %**	7.32 %	14.48 %	0.78 %	7.38 %	69.99 %	0.00 %	0.00 %
	4	**2.78 %**	5.66 %	18.23 %	2.31 %	3.80 %	58.23 %	2.15 %	6.85 %
	8	**1.68 %**	14.99 %	15.78 %	3.03 %	2.17 %	52.03 %	5.18 %	5.13 %
	12	**1.15 %**	19.39 %	17.09 %	2.71 %	3.83 %	45.38 %	7.15 %	3.29 %
	16	**0.89 %**	17.90 %	17.17 %	3.03 %	4.62 %	44.33 %	9.26 %	2.79 %
	20	**0.70 %**	16.06 %	16.07 %	3.91 %	4.10 %	45.08 %	10.66 %	3.43 %
GFCF	1	**0.17 %**	0.22 %	1.75 %	0.11 %	1.69 %	0.12 %	95.95 %	0.00 %
	4	**2.32 %**	1.82 %	1.90 %	0.84 %	1.94 %	5.75 %	85.21 %	0.45 %
	8	**6.03 %**	4.68 %	0.85 %	0.57 %	0.80 %	8.89 %	77.62 %	0.56 %
	12	**5.59 %**	9.70 %	0.47 %	0.46 %	1.50 %	7.59 %	74.31 %	0.37 %
	16	**4.88 %**	10.34 %	0.31 %	0.35 %	2.48 %	6.24 %	74.93 %	0,48 %
	20	**4.27 %**	9.24 %	0.27 %	0.43 %	2.56 %	6.20 %	76.63 %	0.39 %
CRDT	1	**0.78 %**	4.36 %	2.97 %	23.80 %	4.82 %	2.89 %	4.93 %	55.45 %
	4	**3.62 %**	1.63 %	5.35 %	37.10 %	6.02 %	6.03 %	0.65 %	39.60 %
	8	**4.17 %**	19.95 %	2.48 %	36.88 %	4.82 %	4.98 %	0.36 %	26.36 %
	12	**4.58 %**	28.62 %	1.97 %	35.32 %	4.11 %	4.50 %	0.97 %	19.93 %
	16	**4.41 %**	24.76 %	1.85 %	40.12 %	3.75 %	4.73 %	2.80 %	17.59 %
	20	**4.31 %**	19.27 %	1.64 %	44.40 %	4.29 %	3.76 %	4.96 %	17.38 %

Table 18: Column 2 forecasts the different horizons spanning from 1-20 quarters. The first section, with OTECG as the dependent variable (Period 1, 4, 8, 12, 16, 20), reports the effect on the variance of OTECG by a shock in itself (column 3) and shocks in the remaining variables (column 4-10). The same interpretation applies to the remaining variables