Is there a long-run relationship between stock prices and economic activity and are stock returns a leading indicator for economic growth?

Evidence from the Scandinavian countries: Sweden, Norway and Denmark

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Abstract

The purpose of this paper is twofold. First, the Johansen cointegration framework is applied to analyze the long-run relationship between stock prices and economic activity, using GDP as a proxy. In consideration of a long-run relationship a vector error correction model (VECM) is estimated to analyze the parameters of cointegration. Secondly, the paper proceeds by estimating a vector autoregressive model (VAR) in order to analyse the relationship between stock returns and economic growth, measured as GDP-growth, and its dynamics. Further, a Granger-causality framework is adopted along with a recursive forecast framework to investigate if stock returns improve the forecast of economic growth. These analyses are carried out for Sweden, Norway and Denmark using a time period ranging from 1996Q1 to 2020Q1.

Evidence from the Johansen cointegration framework verifies a long-run relationship between stock prices and economic activity in Sweden, which supports that dividends, on average, grow with economic activity over time. However, results provide no evidence of a long-run relationship in Norway and Denmark. Furthermore, results from the Granger-causality framework verifies that stock returns are a significant explanatory variable for economic growth in all countries. Despite this, the recursive forecast framework shows that the VAR-model, which in addition to GDP-growth also includes stock returns, does not improve the forecast of economic growth in comparison to an AR(1)-benchmark model including only GDP-growth. Further, the trivariate VAR-model, which incorporates not only GDP-growth and stock returns but also yield spread, shows similar results, hence it cannot outperform the benchmark model.
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1. Introduction

The fact that stock prices are assumed to be determined by the present value of future expected cash flows generated by the company makes the stock market a potential leading indicator of economic activity.\(^1\) Consequently, macroeconomic variables such as GDP are important since these variables affect a company’s earnings and thus affect stock prices today.

The stock market is considered a vital factor in economic analysis and is monitored by many central banks in order to understand the effect monetary policy has on the real economy (Fransson & Tysklind 2017). It also provides policy makers with information of the market’s expectation about inflation and economic growth which are useful when conducting stabilization policy in order to promote a stable financial system.\(^2\) Hence, it is an important part of a country’s economic well-being since it also contributes capital to companies, promotes competition and enables individuals and households to invest and save money (Gottfries 2013). A collapse of prices on the financial markets can cause severe economic consequences in a country. For example, in the US, the stock market crash in 1929 played an important role in the great depression that struck the country in the 1930s (Gottfries 2013). Another example is the stock market crash in 1987. According to Harvey (1989), some forecasters were able to use the stock market crash to predict the upcoming recession in 1988.

More recent examples that shine light on how the stock market is related to economic activity is the financial crisis of 2008 and the corona pandemic. The financial crisis of 2008 started on the financial markets, particularly on the derivatives market for mortgages bonds, and later struck the US economy and spread further internationally. While the general economy around the world was in recovery for many years after the crisis, stock markets started to rise already in 2009, before the real economic recovery occurred. A similar type of situation occurred during 2020, when covid-19 paralyzed the world. In the spring of 2020, when covid-19 started spreading across Europe and the US, stock markets crashed world-wide since investors became concerned how the health crisis would affect the general global economy. A couple of months later, GDP-numbers across the western countries showed a significant decline in economic activity, a result of the major shutdowns and restrictions that were introduced to reduce the

\(^1\) Using expectations of future cash flows to value stocks is a well-known procedure for valuing stocks, see for example Alexius and Spång (2018); Bodie, Kane and Marcus (2018); Alsterlind, Lindskog and von Brömsen (2020); Berk and DeMarzo (2019); Estrella and Mishkin (1998).
\(^2\) See for example Andersson and D’Agostino (2008).
spread of the virus. However, while countries around the globe were on its way into a recession, stock prices started to rise again. The fact that stock prices increase while the real economy is still in recovery highlights the question how the stock market in a country is related to economic activity.

In light of how stock prices are related to economic activity, this paper aims to examine if there is a long-run relationship between stock prices and economic activity, measured as GDP, and if stock returns help improve the forecast of economic growth, using GDP-growth as a proxy, in Denmark, Norway and Sweden, with a time period ranging from 1996Q1 to 2020Q1.

In the field of financial literature, multiple papers have analyzed the stock market as a leading indicator for economic growth, where the results have been mixed. However, similar research have not been found for the Scandinavian countries. Further, there are only a handful of papers that have analyzed the long-run relationship between stock prices and economic activity and research specifically targeting Norway and Denmark have not been found. Hence, this paper contributes to the existing literature in two ways: First, the Johansen cointegration framework provides insights how stock prices are related to economic activity in the long-run and secondly, the paper provides evidence whether stock returns improve the forecast of economic growth in the Scandinavian countries.

1.1 Method and result
The Johansen cointegration framework is applied to test whether there exists cointegration between stock prices and economic activity, measured as GDP, in Sweden, Norway and Denmark. If there exists cointegration, the analysis proceeds by estimating a vector error correction model (VECM) to analyze the key parameters. Furthermore, a vector autoregressive (VAR) model for each country is estimated to examine the dynamics between stock returns and economic growth, measured as GDP-growth. This is then followed by Granger-causality tests and impulse response functions (IRF). Finally, a recursive-forecast framework is applied to assess whether stock returns improve the forecast of economic growth, compared to an AR(1)-

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3 For example, in quarter 2 of 2020, the US GDP fell by 31.4 percent (CNBC 2020), GDP in the Euro area fell by 11.8 percent (Eurostat 2020) and in United Kingdom, GDP decreased by 20.4 percent (CNBC 2020a).
4 See for example Harvey (1989); Schwert (1990); Estrella and Mishkin (1998); Andersson and D’Agostino (2008); Espinoza, Fomari and Lombardi (2011).
5 Example of research that have analyzed the long run relationship can be found in Yin-Wong and Lilian (1998); Österholm (2016); Alexius and Spång (2018).
benchmark model. The root mean squared error (RMSE), mean absolute error (MAE) and Diebold-Marino test is used to examine the relative forecast accuracy.

Results from the cointegration analysis verifies the existence of a long-run relationship in Sweden, though it cannot be verified for Norway and Denmark. Additionally, although stock returns have an explanatory power for economic growth in all countries, the results from the recursive-forecast framework shows that stock returns cannot improve the forecast of economic growth, at least not compared to an AR(1)-benchmark model.

1.2 Disposition
The paper is distributed as follows: Chapter 2 provides a background on how the stock market, as a part of the financial channels, is related to economic activity along with a brief description of the Scandinavian economies. Chapter 3 provides a literature review of previous relevant research. The theoretical framework is presented in Chapter 4 and provides an explanation of the constant growth dividend discount model, which intends to provide insights regarding how stock valuation is related to economic activity. Chapter 5 contains a description of the data followed by an explanation of how the variables have been processed. Further, Chapter 6 presents the methodological framework followed by Chapter 7 which presents the results. The paper then proceeds with a discussion in Chapter 8 and finalizes with a conclusion in Chapter 9.
2. Background
The background intends to provide an understanding of how financial stability enables central banks to conduct an efficient monetary policy, which highlights the importance between financial conditions and the real economy. Furthermore, a brief overview regarding the Scandinavian economies is presented to provide the reader knowledge of the difference between the countries in regard to the key drivers in the economy.

As previously mentioned, policy makers such as the central bank follow the conditions on the financial markets in order to analyze the economic activity in the country. When the central bank conducts monetary policy, for example by increasing the liquidity on the financial markets, it will affect interest rates, risk premiums and the access to credit in the economy. This will in turn affect asset prices due to changing discount rates, risk appetite and changing interest rates for borrowing and lending money which leads to changes in economic activity (Alsterlind, Lindskog & von Brömsen 2020).

Hence, since monetary policy mainly affects the economy through the financial markets, it is important for central banks to understand its relationship with the rest of the economy (Fransson & Tysklind 2017). However, as Alsterlind, Lindskog and von Brömsen (2020) points out, monetary policy is just one of the factors that affect the financial conditions in a country. Expectations of future economic growth is another factor that leads to changes in stock prices, as well as exogenous factors like lower risk-appetite from investors (Alsterlind, Lindskog and von Brömsen 2020).

Further, in line with previous discussion, the Swedish National institute of economic research argues that stock prices should be related to GDP; the value of the stock market should reflect the production which in turn is connected to the whole economy (Konjunkturinstitutet 2016). However, as Andersson, D’Agostino, de Bondt and Roma (2011) argues, some industries may be more related to future economic activity than others. The authors found that the financial sector, which includes banks, insurance, real estate and financial services, has better

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6 The corona pandemic provides an example of this; in order to increase credit and limit the impact of the pandemic on the economy, the Central Bank of Sweden has purchased bonds for billions of SEK and kept the repo rate at zero percent (Sveriges Riksbank 2020). The Central Bank of Norway took measures such as lowering the repo rate from 1.5 to zero percent and provided loans with different maturities to the banks in order to increase the liquidity in the economy (Olsen 2020). The government of Denmark increased their spending, liquidity measures, etcetera (IMF 2020).
predictability for economic growth than the 15 other examined sectors; some examples of sectors with less predictability are industrial goods and services, personal and household goods, oil and gas and the retail industry. This result was more apparent in the euro area than in the US (Andersson et al. 2011).

A similar discussion is brought by European Central Bank (2012), who states that although the stock market is important for economic activity there exists mixed empirical results whether this actually holds true. The high volatility of stock prices and the fact that stock prices can deviate from their underlying economic fundamentals is highlighted by the authors as possible explanations for these mixed results. Further, as the author states, although empirical evidence has verified improvements in forecasting economic activity by implementing stock prices as a variable, there is also empirical evidence that indicates the weakening of this relationship due to occasions when stock prices have not been driven by economic fundamental factors.

Although the relationship has been debated, the global financial crisis of 2008 highlights the fact that it was possible to note negative signals on the financial markets, before the real economy started to decline. For example, in Norway the stock market started to decline in the beginning of 2008 while the real economy started to decline in late 2008.7 Norway was not an exception, indeed stock markets around the world preceded a decline in economic growth.8 However, the magnitude of the decline in stock returns and economic growth varied from country to country, even in Scandinavia (see Figure 1-3).

In Scandinavia the Norwegian economy experienced a greater drop in both stock prices and GDP compared to its neighboring countries. Since the Norwegian economy is considered a “oil dependent economy”, driven by its export of oil and gas (IMF 2019), it is sensitive to global changes in the demand for oil.9 Indeed, in 2008 the Norwegian export of crude oil declined by 43 percent (Bloomberg n.d.a) which is one of the explanations for the large drop in the broad market index OSEAX and GDP.10 According to IMF (2019), oil and gas investments are key

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7 At the end of 2008, stock prices had plummeted with 51 percent (see Figure 2).
8 For example, S&P 500 started to decline in late 2007 while US GDP did not start to decline until quarter 4, 2008; FTSE 100 also began to drop in late 2007 while the British GDP began to drop in 2008; DAX reached the top in late December of 2007 and then started to fall, while German GDP dropped in mid 2008 (Bloomberg n.d.).
9 The Norwegian export of oil and gas accounted for approximately 62 percent and stood for 18 percent of the Norwegian GDP in the year of 2018 (European Commission n.d.).
10 The oil and gas industry accounts for roughly 32 percent of the Norwegian market index, OSEAX (Avanza n.d.).
drivers in the Norwegian economy and contribute to positive spillover-effects to other industries, which clarifies the fact that Norway, through its dependency of the global oil market, reacts strongly to changes in supply and demand for oil.\textsuperscript{11}

Further, the Swedish and Danish economy is not considered to be “oil dependent economies”, whereas the Swedish economy mainly relies on its production of industrial goods, medical and pharmaceutical products and technical products, which accounts for 70 percent of total export (SCB n.d.), while Denmark’s meat industry and medicine and pharmaceutical industry make up a large part of their economy (OEC n.d.).

\textsuperscript{11} For example, during 2008 between July and December, the price of brent oil decreased with around 74 percent (Market Insider n.d.).
3. Previous literature

The relationship between economic activity and the stock market have been subject to extensive research where the use of the stock market as a leading indicator of economic activity has caught multiple researchers’ interest. Results have been mixed and it seems to exist different perceptions whether the stock market improves the forecast of economic growth. Additionally, whether there exists a long-run relationship between the variables have also been examined, hence this section presents a selection of previous research that have investigated these issues.

In the context of analyzing if the stock market improves the forecast accuracy of economic growth, Estrella and Mishkin (1998) studied if financial variables can be used as a predictor of future recessions. Results suggest that incorporating stock prices and yield spread into macroeconomic models increases the accuracy of forecasting future economic activity. Additionally, the authors found that stock prices improved the prediction with 2 or 3 quarters ahead. Moreover, Stock and Watson (2003) found that the stock market and the yield spread provided some indication of an economic slowdown during 2001 in the US, however this was not the case for the 1980s and 1990s economic slowdowns. Likewise, Harvey (1989) evaluated the accuracy of using the yield curve and the stock market to forecast economic growth. By comparing the root mean squared error (RMSE) between different out-of-sample forecasts, results showed that the yield spread performed better than the stock market. Further, Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010) found that financial condition indices, especially a broad stock market index, help predict future economic activity. Moreover, Hassapis and Kalyvitis (2001) found, by using a bivariate VAR-model, that stock prices are related to economic growth in the G-7 countries. Another study was carried out by Espinoza, Fornari and Lombardi (2011), who incorporated stock market indices, dividend yields, 10-year and 3-month bond yields in a VAR framework to examine if the forecast of economic activity could be improved in Europe and the US. Although the authors showed that shocks to these variables influence economic activity, the authors found weak evidence that financial variables could help produce more accurate forecasts of economic activity.

Further, Andersson and D´Agostino (2008) examined if sectoral stock prices could predict economic growth in the Euro area, using a time period from 1973 to 2006. The authors found that sectoral stock prices improved the forecasting accuracy of economic growth from the year
1999 and onwards. Similarly, Andersson et al. (2011) examined the predictive power of sectoral stock prices for real GDP, investment and consumption using out-of-sample forecasts for the US and Europe, during the time period 1973 to 2009. By also controlling for the yield spread and corporate bond spread, the authors found that stocks in the US real estate and financial sector, and stocks in the banking sector of the euro area provided strong predictive power for future economic activity. The result from the out-of-sample forecasts showed that, in line with Andersson and D’Agostino (2008), sectorial stock prices outperformed the yield spread and corporate bond spread. Moreover, Schwert (1990) found that US stock prices provide useful information about future economic growth, which corresponds with the findings of Switson (2008) who showed that equity returns have a positive influence on GDP growth. Moreover, Beber, Brandt and Kavajecz (2011) showed that information regarding order flow movements, which is defined as the act of starting a purchase or a sale of a security, among stock sectors is linked to economic activity while Levine and Zervos (1998) found that liquidity on the stock market can predict economic growth. Other examples of research that have found support for the stock market as a leading indicator for real economic activity in the United States can be found in Stock and Watson (2003a); Fama (1990).

Furthermore, Adrian, Boyarchenko and Giannone (2019) examined the distribution of GDP growth, conditional on financial conditions. The authors found that future downside risk of GDP growth increases as financial conditions worsens. By using industrial production instead of GDP as a proxy for economic activity, Kanas and Ioannidis (2008) found that stock returns Granger-cause industrial production in the UK, but only when market volatility was low. In line with Kanas and Ioannidis (2008), Gallinger (1994) examined the relationship between stock returns and real economic activity using Granger-causality. The result showed a linkage between the movement in financial wealth, which in turn affects the demand of future consumption and investments. Further, Fama (1981) found support that real stock returns are positively related to variables such as capital expenditure, return on capital and economic activity.

Furthermore, several studies have examined how stock prices are related to consumption, which is a part of economic activity. For example, Funke (2004) studied 16 emerging markets during a time span ranging from 1985 to 2000 and found a link between private consumption growth and stock returns. On the contrary, Case, Quigley and Shiller (2001) found a weak effect on consumption with respect to changes in the stock market which also corresponds with
the findings of Star-Maccluer (2002). However, Jansen and Nahuis (2003), who examined eleven European countries throughout the period 1986 to 2001, found a short-run link between stock returns and consumption. Instead of examining consumption, Barro (1990) looked at investments and found that stock price fluctuations in the US have explanatory power for investments in the economy, especially when using a longer time span.

Regarding the long-run relationship, several studies have employed the Johansen cointegration framework along with a VECM to examine if stock prices follow the same long-run stochastic trend as economic activity. Consequently, Yin-Wong and Lilian (1998) were able to verify this relationship in Canada, Germany, Italy, Japan and the US. Likewise, Österholm (2016) found a long-run relationship between the stock market and GDP in Sweden while Chaudhuri and Smiles (2004) reports evidence of this relationship in Australia. Humpe and Macmillan (2009) found corresponding results, however, the authors examined stock prices and industrial production in the US and Japan. Similarly, Mukherjee and Naka (1995) found cointegration between the Japanese stock market and multiple macroeconomic variables. Finally, Alexius and Spång (2018) showed that stock price indices are cointegrated with both domestic and foreign GDP in the G7 countries, except the US.
4. Theoretical framework

According to Fransson and Tysklind (2017) it is well-established in the field of finance that investors are forward looking. This makes the dividend discount model an intuitive method for valuing stocks since it is based on a company’s future expected cash flows, discounted to a present value.\textsuperscript{12} Another well-known assumption is that only systematic risk affects risk premiums on the stock market.\textsuperscript{13} Based on these assumptions, systematic risk will affect investors’ expectations of future cash flows. Thus, future economic activity will be a priced factor in current stock prices.

When an investor buys a stock, the investor buys the expected price at a future date, along with the dividends that will be paid out during that time (Gordon 1959). Thus, a stock has two possible cash flows, the future dividend payments and the capital gain from selling the stock (Berk & DeMarzo 2019).

Consider an investor who owns a stock for $N$ years. The price of the stock today will be the sum of future dividends and the price at year $N$, discounted at the expected return (required rate of return) for that specific company. This is formulated as follows:

$$S_0 = \frac{D_1}{1+E[r]} + \frac{D_2}{(1+E[r])^2} + \cdots + \frac{D_N + S_N}{(1+E[r])^N}$$  \hspace{1cm} (1)$$

where, $S_0$ is the current stock price, $D$ is the dividend, $S_N$ is the price of the stock at year $N$ and $E[r]$ is the expected return (required rate of return). This is referred to as the multi-period dividend-discount model (Gordon 1959) and holds for any horizon $N$. However, the model is not as desirable for stock valuation since one needs to forecast the dividends every period to year $N$ (Bodie, Kane & Marcus 2018). Instead, this model is simplified by assuming that dividends grow at a constant rate. Thus, if dividends increase by a growth factor $g$ in perpetuity, the dividend-discount model can be expressed as:

$$S_0 = \frac{D_1}{(E[r] - g)}$$  \hspace{1cm} (2)$$

\textsuperscript{12} See for example Gordon (1959); Berk and DeMarzo (2019); Bodie, Kane and Marcus (2018).

\textsuperscript{13} For a thorough reading of determinants of stock returns, see for example Sharpe (1964) and Ross (1976).
Equation (2) is known as the constant growth dividend discount model. This formula shows that a high stock price today is a result of a high dividend in the upcoming period, a low expected return or a high growth in dividends.\(^\text{14}\)

Further, Berk and DeMarzo (2019) states that the growth in dividends will equal the growth in company earnings. Consequently, the growth rate in dividends will depend on the product of the company’s retention rate and the return on new investments (ROI) (Berk & DeMarzo 2019).\(^\text{15}\) This implies that a company can increase its growth rate by reinvesting more of its earnings. However, as Berk and DeMarzo (2019) points out, if the retention rate goes up, current dividends will decrease.\(^\text{16}\) Hence, whether or not an increased retention rate will increase the company’s share price and stimulate growth will depend on the return on investments being larger than expected return (required rate of return). Thus, the risk premiums on the stock market will affect a company’s profitability of new investments, which ultimately will impact the cash flows and the stock price. If returns on the stock market increase it means that stock prices also increase, which indicate a lower market risk premium. An increase in the stock market implies that excepted future profits and dividends will be higher, which gives companies incentives to increase their capital stock (Gottfries 2013). This is referred to as Tobin’s q which is expressed as the ratio between the market value of a company’s capital stock and the replacement value of the existing capital stock. A high Tobins’s q indicates a high market value relative to the existing capital stock. Following this, stock prices and investments should be closely related, since a low market risk premium and a high market value of a company’s capital stock, caused by an increase in stock prices, stimulates investments (Andersson & D’Agostino 2011). Following this, lower risk premiums will decrease expected returns (required rate of returns) and lead to an increase in investments since more investments will have a positive net present value.\(^\text{17}\) Further, an increase in new investments will increase the company’s growth rate which in turn will increase the stock price, in accordance with equation (2).

\(^{14}\) Note that this formula only holds for \(E[r] > g\).

\(^{15}\) A company’s retention rate shows how much of the earnings that are reinvested in the company and not paid out as dividends.

\(^{16}\) If a company reinvests more of its earnings dividends will fall since less earnings is used to pay dividends to shareholders (Berk & DeMarzo 2019).

\(^{17}\) A positive net present value is a result of return on investment (ROI) > \(E[r]\).
Rangvid (2006) states that it is reasonable to expect that economic activity, company earnings and dividends follow the same growth trend over long horizons. The author also states that company earnings and dividends should mean-revert towards GDP. This is also mentioned by Rozeff (1984), who argues that the growth rate of dividends should be related to the economy’s growth in output. Following this, it could be argued that the growth rate in a company’s dividends should be related to the long-run growth of the economy.\textsuperscript{18} Thus, if economic growth is expected to decrease, future dividends will also be expected to decrease as investors expect lower future earnings. Additionally, investors will also demand a higher rate of return due to the increase of future uncertainty which reduces the value of these cash flows today, lowering prices and holding back investments.\textsuperscript{19} Consequently, it can be argued that the growth rate approximately should equal the long-run growth of the economy, thus the growth in a company’s dividends is dependent on how the real economy will develop.

\textsuperscript{18} See for example Diamond (1999) who states that the growth in prices and dividends should approximately equal the growth in GDP.

\textsuperscript{19} A higher required rate of return means that future cash flows are discounted at a higher rate which reduces the present of these cash flows, hence higher expected return means lower prices today (Berk & DeMarzo 2019).
5. Data
This chapter is organized as follows: The first section provides a brief description on how data regarding stock prices and GDP have been retrieved and handled; this is followed by a description of the yield spread which is used as a control variable. The chapter ends with a graphical representation of the variables in first difference, together with descriptive statistics.

5.1 Variables
This paper uses quarterly data between 1996Q1 and 2020Q1 for all variables. The time period is motivated by the fact that stock data for the Danish and Norwegian broad stock indices were only available from January 1996.

Daily data on stock prices for Denmark, Norway and Sweden were collected from Bloomberg (n.d.b). The indices used are OMX Copenhagen Index (KAX), OMX Stockholm All-Share Index (OMXSPI) and Oslo All-Share Index (OSEAX). All three indices are market capitalization weighted indices and attempt to track all shares listed on the stock exchange (Bloomberg n.d.b.). Daily closing prices were transformed into quarterly prices by taking an arithmetic average over the daily prices for each quarter. Quarterly stock returns were calculated by taking the first difference of the average quarterly prices, which are transformed into logarithmic values.

Seasonally adjusted nominal GDP from the user-side were gathered from the national statistical agency for each country (SCB 2020; SSB 2020; DST 2020). The observations, originally measured in millions of the local currency, were transformed into logarithmic values. In order to get quarterly percentage growth, the first difference was employed to the logarithmic values.

5.2 Control variable
The yield spread is represented by the difference between the yield of a 10-year government bond and the yield of a 3-month treasury bill. Daily observations for Sweden were gathered from the Swedish Central Bank (Riksbanken n.d.) and daily observations were retrieved from Macrobond (n.d.) for Norway and Denmark. The daily yields were transformed into quarterly yields by taking an arithmetic average of the daily values for each quarter.

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20 The method of taking an arithmetic average over daily prices for each quarter are used by the Swedish National institute of economic research in their forecasting model (Konjunkturinstitutet 2016).
Further, a country’s yield curve shows yields of government bonds with different maturities (Berk & DeMarzo 2019). The yield curve can indicate changes in economic activity since changes in yields for different maturities reflect investors’ expectations of future interest rates. According to the expectation hypothesis, long-term interest rates are determined by investors’ expectations of future short-term interest rates, plus a risk premium for holding longer maturity bonds (Berk & DeMarzo 2019; Bodie, Kane & Marcus 2018; Fransson & Tysklind 2017). This means that if long-term interest falls, investors expect lower short-term rates in the future, which indicate an economic slowdown (Fransson & Tysklind 2017). Thus, if investors suspect worsening economic conditions, they will buy long-term bonds and sell short-term bonds which increases the price of long-term bonds and decreases the price of short-term bonds (Harvey 1989). This will increase the yield of short-term bonds and decrease the yield of long-term bonds, something that can lead to an inverted yield curve, which is often interpreted as a signal of an upcoming recession (Berk & DeMarzo 2019). Indeed, as Harvey (1989) points out, the spread between long-term interest rates and short-term interest rates have helped predict multiple recessions in the US during the 1960s to the 1980s.

Given the fact that differences in yields between long-term and short-term bonds (i.e., the yield curve spread) can indicate future macroeconomic conditions, it is relevant to control for this variable when examining the predictability of the stock market. Another reason for including the yield spread is that the government bond market is related to the valuation of all private bonds, which means that the yield spread shows expectations not only for government bonds but for the whole bond market (Alsterlind, Lindskog & von Brömsen 2020).

5.3 Descriptive statistics
A graphical representation of the raw data for all countries is provided in the appendix (see Figure A.1-A.3). In Figure 1-3, stock returns and GDP-growth are shown. A large drop in stock returns and GDP-growth are seen for all countries during the financial crisis of 2008. Note that Norway experienced a substantially larger drop. Further, all countries had a decline in stock returns during the late 1990s, but Sweden experienced a larger increase in returns around the millennium shift, during the IT-boom. Moreover, GDP-growth is clearly more volatile for Norway, though increases and decreases in growth seems to occur at the same time periods for all countries.
**Figure 1.** Quarterly stock returns and GDP-growth – Denmark.

Note: The graph to the left shows quarterly stock returns and the graph to the right shows quarterly GDP-growth. The y-axis shows the percentage, and the x-axis shows the time in years. Source: Bloomberg (n.d.b) and DST (2020).

**Figure 2.** Quarterly stock returns and GDP-growth – Norway.

Note: The graph to the left shows quarterly stock returns and the graph to the right shows quarterly GDP-growth. The y-axis shows the percentage, and the x-axis shows the time in years. Source: Bloomberg (n.d.b) and SSB (2020).

**Figure 3.** Quarterly stock returns and GDP-growth – Sweden.

Note: The graph to the left shows quarterly stock returns and the graph to the right shows quarterly GDP-growth. The y-axis shows the percentage, and the x-axis shows the time in years. Source: Bloomberg (n.d.b) and SCB (2020).
Table 1. Descriptive statistics for stock returns \((r)\), GDP-growth \((g)\) and yield spread \((i)\).

<table>
<thead>
<tr>
<th>Country</th>
<th>Var.</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
<td>(r)</td>
<td>96</td>
<td>2.271</td>
<td>3.726</td>
<td>8.163</td>
<td>-38.699</td>
<td>15.356</td>
</tr>
<tr>
<td></td>
<td>(g)</td>
<td>96</td>
<td>0.826</td>
<td>1.014</td>
<td>0.997</td>
<td>-2.62</td>
<td>3.071</td>
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<tr>
<td></td>
<td>(i)</td>
<td>96</td>
<td>1.054</td>
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<td>0.945</td>
<td>-1.803</td>
<td>3.485</td>
</tr>
<tr>
<td>Norway</td>
<td>(r)</td>
<td>96</td>
<td>2.291</td>
<td>3.703</td>
<td>10.021</td>
<td>-50.57</td>
<td>19.768</td>
</tr>
<tr>
<td></td>
<td>(g)</td>
<td>96</td>
<td>1.291</td>
<td>1.447</td>
<td>2.201</td>
<td>-8.558</td>
<td>6.391</td>
</tr>
<tr>
<td></td>
<td>(i)</td>
<td>96</td>
<td>0.826</td>
<td>0.922</td>
<td>1.105</td>
<td>-2.239</td>
<td>2.919</td>
</tr>
<tr>
<td>Sweden</td>
<td>(r)</td>
<td>96</td>
<td>1.907</td>
<td>2.726</td>
<td>8.971</td>
<td>-28.838</td>
<td>29.896</td>
</tr>
<tr>
<td></td>
<td>(g)</td>
<td>96</td>
<td>0.993</td>
<td>1.05</td>
<td>0.984</td>
<td>-1.778</td>
<td>2.976</td>
</tr>
<tr>
<td></td>
<td>(i)</td>
<td>96</td>
<td>1.368</td>
<td>1.3</td>
<td>0.788</td>
<td>-0.28</td>
<td>3.24</td>
</tr>
</tbody>
</table>

Note: Stock returns \((r)\) and GDP-growth \((g)\) is the first difference of the logarithmic values expressed in percent. Yield spread \((i)\) is the difference in yield between the 10-year government bond and the 3-month treasury bill. The quarterly observations cover a time period between 1996Q1 and 2020Q1.

From Table 1, it is observed that the data set includes a large drop in economic growth, given by the minimum value for each country. Further, the remarkable drop of 50.57 percent for the stock market in Norway is a result of the financial crisis in 2008. During the same period, economic growth also dropped substantially in Norway, more than 8 percent – which is larger than Sweden and Denmark who only experienced a decrease of 1.78 and 2.62 percent. As with Norway, Sweden and Denmark also experienced major drops in stock returns during the crisis, 28.84 percent and 38.70 percent respectively. Further, by observing the standard deviation for all countries it is also observed that Norway experienced larger volatility during 1996 to 2020, both in stocks and economic growth. Regarding the yield spread, all the countries show a similar evolution (see Figure A.3). For example, the spread was small during the financial crisis in 2008 but started to increase after the crisis. However, since around 2009 it has shown a decreasing trend again.
6. Method

This chapter provides a description of the methodology and is constructed as follows: To start with, the Augmented Dickey-Fuller (ADF) test is presented, which is conducted in order to test for stationarity. The chapter proceeds by explaining the VAR-model, the Granger-causality test and the IRF:s, followed by a description of the recursive forecast framework. Finally, the chapter ends with explaining the Johansen cointegration framework and VEC-model which are used to evaluate the long-run relationship.

6.1 Testing for stationarity

Augmented Dickey-Fuller (ADF) test is used to test for unit roots. The lag-length is based on Schwarz information criterion (SIC) (Schwarz 1978), which are considered to result in a more parsimonious model specification, see for example Koehler and Murphee (1988).

The ADF-test is applied to test the variables for unit roots in levels. The test is based on the following equation:

\[ \Delta y_t = \mu_0 + \zeta y_{t-1} + \mu_1 t + \phi_1 \Delta y_{t-1} + \cdots + \phi_p \Delta y_{t-p} + \epsilon_t \] (3)

where \( \mu_0 \) is an intercept and \( \mu_1 t \) is a time trend. Further, the dependent variable and the first difference for each lag are summed up on the right-hand side of the test equation. To test whether the AR(\(p\))-process is stationary in level the coefficient \( \zeta \) is tested under the null hypothesis: \( \zeta = 0 \), which states that the AR(\(p\))-process is non-stationary. This is tested against the alternative hypothesis: \( \zeta < 0 \), meaning that the AR(\(p\))-process is stationary (Dickey & Fuller 1979).

A question that has received attention in the literature is whether GDP is trend-stationary, meaning that the variable is stationary around a deterministic trend. In order to account for the possibility of trend-stationarity, both an intercept and a time trend is included for GDP, in accordance with equation (3). Regarding stock prices, it is established empirically that the time

---

21 Indeed, Stock and Watson (2015) points out that if too many lags are included it can introduce additional estimation error in the model.

22 For example, Beechy and Österholm (2008) could verify trend-stationarity in US GDP while Nelson and Possner (1982) found no evidence of trend-stationarity in 13 out of 14 examined macroeconomic variables.
series follow a stochastic trend, thus $\mu_1 t$ is excluded from equation (3). Further, testing for a unit root in yield spread is carried out in a similar way as with stock prices.

6.2 VAR-model
The VAR-model was proposed by Sims (1980) and is an $n$-equation, $n$-variable linear multivariate model where the dependent variables are explained by its own lagged values, together with lagged values of the remaining $n-1$ variables (Hamilton 1994). SIC is used to determine the lag-length for all the estimated VAR-models. All the variables in the VAR-model are considered to be endogenous and observed over the same time period, hence the model is considered to be an extension of an AR($p$)-process. Becketti (2013) points out that since a VAR-model provides information about the dynamics of the jointly endogenous variables, it makes the model able to account for how shocks to one variable impact other variables in the system. According to Switson (2008), this feature is important when dealing with financial variables since there is a theoretical connection in how financial variables are related to other economic variables ex ante.

A VAR($p$)-model is written in matrix form as follows:

$$
\begin{bmatrix}
Y_{1,t} \\
\vdots \\
Y_{n,t}
\end{bmatrix}
= 
\begin{bmatrix}
\mu_1 \\
\vdots \\
\mu_n
\end{bmatrix}
+ 
\begin{bmatrix}
\theta_{11}^{(1)} & \cdots & \theta_{1n}^{(1)} \\
\vdots & \ddots & \vdots \\
\theta_{n1}^{(1)} & \cdots & \theta_{nn}^{(1)}
\end{bmatrix}
\begin{bmatrix}
Y_{1,t-1} \\
\vdots \\
Y_{n,t-1}
\end{bmatrix}
+ 
\cdots 
+ 
\begin{bmatrix}
\theta_{11}^{(p)} & \cdots & \theta_{1n}^{(p)} \\
\vdots & \ddots & \vdots \\
\theta_{n1}^{(p)} & \cdots & \theta_{nn}^{(p)}
\end{bmatrix}
\begin{bmatrix}
Y_{1,t-p} \\
\vdots \\
Y_{n,t-p}
\end{bmatrix}
+ 
\begin{bmatrix}
\varepsilon_{1t} \\
\vdots \\
\varepsilon_{nt}
\end{bmatrix}
$$

(4)

A more compact way to express equation (4) is to write it in vector form:

$$
y_t = \mu + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \varepsilon_t
$$

(5)

where $y_t$ is a $n \times 1$ vector with all the endogenous dependent variables observed in time $t$; $\mu$ is a $n \times 1$ vector with intercepts; $\theta$ is a $n \times n$ matrix of coefficients; $y_{t-p}$ is a $n \times 1$ vector of the lagged values of the $n$-variables and $\varepsilon_t$ is a $n \times 1$ vector of identically and independently distributed

---

23 See for example Samuelson (2015); Fama (1965) and Narayan and Smyth (2007).
24 The VAR framework has also been applied to previous similar studies, see for example Switson (2008); Espinoza, Fornari and Lombardi (2011); Kanas and Ionnaidis (2008); Gallinger (1994).
25 For example, this paper applies the constant dividend discount model to describe how the stock market is related to economic growth, see Chapter 4.
error terms, where the covariance matrix is positive definite, independent of time $t$ and with an expected value of zero.

6.3 Granger-causality test
Granger-causality, proposed by Granger (1969), tests whether one variable helps predict another variable. In this paper, the Granger-causality framework examines if lagged values of stock returns improve the prediction of GDP-growth, when also controlling for lagged values of GDP-growth. It is important to note that the Granger-causality test does not test the true causality; it has more to do with the prediction or precedence of multiple variables (Granger 1969). Given that a VAR-model is an extension of an AR-model, the results from the Granger-causality tests provides an unbiased way to assess whether a model with multiple variables improves the prediction of the dependent variable (Øystein & Sættem, 1999; Stock & Watson 2001). Additionally, Granger-causality tests are made with stationary time series to avoid the risk of spurious results (Green 2001).

Following this, Granger-causality generates a $F$-statistic in order to test the null hypothesis which states that the coefficients of lagged values of stock returns have no predictive content of GDP-growth, meaning that the coefficients of the lagged values of stock returns are equal to zero (Stock & Watson 2015).

Thus, consider the following equation:

$$g_t = \mu_1 + \delta_1 g_{t-1} + \cdots + \delta_p g_{t-p} + \omega_1 r_{t-1} + \cdots + \omega_p r_{t-p} + \epsilon_{1,t} \quad (6)$$

where GDP-growth ($g_t$) in time $t$ is explained by an intercept $\mu_1$; the coefficient $\delta_1$ in front of GDP-growth ($g_{t-1}$) in time $t-1$; the coefficient $\delta_p$ in front of GDP-growth ($g_{t-p}$) observed in time $t-p$; the coefficient $\omega_1$ in front of stock returns ($r_{t-1}$) in time $t-1$; the coefficient $\omega_p$ which corresponds to stock returns ($r_{t-p}$) observed in time $t-p$, and lastly an error term $\epsilon_{1,t}$.

In order to examine whether stock returns help predict economic growth, the Granger-causality tests if the coefficient $\omega_p$ from equation (6) is significantly different from zero.
Granger-causality therefore tests the following hypotheses:

\[ H_0: \omega_1 = \cdots = \omega_p = 0 \]

\[ H_A: \omega_p \neq 0 \]

If the reported test statistic from the F-distribution is larger than the critical value on the 5 percent level, \( H_0 \) is rejected; thus, lagged values of a stock returns help predict the current value of GDP-growth.

6.4 Impulse response function
As a complement to the Granger-causality test, the impulse response function (IRF) is conducted to analyze the dynamic properties from the estimated VAR-model. The impulse response describes the reaction of a dynamic system at current and future points in time, in response to a positive shock in one variable (Stock & Watson 2001). When analyzing the impulse response function, it is assumed that the error terms from respective regressions in the VAR-model are uncorrelated. However, if this assumption is violated then it implies that the covariance matrix of the error terms is not diagonal. To correct for this, the Cholesky decomposition with a recursive structure is conducted, which produces a lower triangular matrix that makes the error terms uncorrelated with a covariance equal to zero (Hamilton 1994).

The ordering matters when using the Cholesky decomposition. This is because the variables in the model are ordered in relation to their sluggishness or exogeneity (Sims 1980). The variable ordered first in the system has a contemporaneous effect on the subsequent variables. The second variable has no contemporaneous effect on the first variable but has an effect on the following variables, etcetera. The variable ordered last affects the other variables with its lagged values (Hamilton 1994). In this paper, GDP-growth is ordered first in the system followed by stock returns. This is in line with Switson (2008) who ordered GDP first followed by the financial conditions index (FCI) with the argument that the GDP is more sluggish and does not react in the current period.

6.5 Recursive out-of-sample forecast
The recursive forecast framework is used to examine if stock returns improve the forecast of economic growth. The chosen forecast horizon is 4 quarters, which is in line with Andersson and D’Agostino (2008) and Andersson et. al (2011). The forecast is estimated on a restricted
subsample known as an estimation window, which is used to forecast the growth rate 4 steps ahead outside the estimation window. By expanding the estimation window with 1 quarter, the equation is re-estimated recursively as the forecast proceeds in time. Thus, the first estimation window covers the period from 1996Q1 to 2009Q4 and forecast 2010Q1 to 2010Q4. The last estimation window starts at the same period but ends in 2019Q1 and forecasts 2019Q2 to 2020Q1.

The forecasts are based on a VAR($p$)-model, where the number of lagged values is based on SIC. Forecasts are carried out using two types of VAR-models, one bivariate model including stock returns and GDP-growth and one trivariate model including stock returns, yield spread and GDP-growth. As a benchmark forecast-model, an AR(1)-model is used, which is in line with the Swedish National Institute of economic research (Konjunkturinstitutet 2016a). Moreover, using multiple lags in a benchmark AR-model might impose misleading results since it often results in high autocorrelation (Konjunkturinstitutet 2016a), suggesting that an AR(1)-model is preferable.

In order to evaluate the forecasts, the root mean squared error (RMSE) and mean absolute error (MAE) is calculated where a smaller error indicates a more accurate forecast. RMSE is based on the square root of the squared forecasting errors and is calculated as follows:

$$RMSE_h = \left( \frac{1}{T} \sum_{t=1}^{T} \varepsilon_{t+h|t}^2 \right) * 100$$  \hspace{1cm} (7)

where $\varepsilon_{t+h|t} = y_{t+h} - \hat{y}_{t+h|t}$. Hence, $y_{t+h}$ is the actual value observed and $\hat{y}_{t+h|t}$ is the $h$ step ahead forecasted value at time $t$, and $T$ is the number of forecasts.

Further, mean absolute error (MAE) is based on the absolute values of the forecast errors and is calculated as follows:

$$MAE_h = \left( \frac{1}{T} \sum_{t=1}^{T} |\varepsilon_{t+h|t}| \right) * 100$$  \hspace{1cm} (8)

The calculated RMSE and MAE are used to evaluate which of the models that provides the smallest forecasting error. However, in order to compare different forecast models, the
difference between the errors needs to be analyzed. In order to do that, the Diebold-Mariano test is carried out.

The Diebold-Mariano test (see Diebold & Mariano 2002) examines whether there is a statistically significant improvement in the forecast ability between the different forecast models. This is done by testing whether there is a significant loss-differential between the forecast errors (Diebold 2015). The Diebold-Mariano test is carried out by first taking the differences between the squared errors of the benchmark and the selected VAR($p$)-model (see Diebold & Mariano 2002). These differences are then regressed on a constant. Since the forecasts are overlapping for forecast horizons longer than 1 quarter, Newey-West standard errors are used in order to correct for autocorrelation in the error terms (see Newey & West 1986). The regression is estimated using ordinary least squares (OLS) and is carried out for each forecast horizon. Under the null hypothesis, the constant in the regression is equal to zero. If the null hypothesis is rejected, meaning that the constant is significantly different from zero, there is a difference in how well the forecasts perform. Further, if the constant is significantly positive, the benchmark model AR(1) performs better and if the constant is significantly negative, the VAR($p$)-model outperforms the benchmark model. If the null hypothesis cannot be rejected, the two forecasts perform equally good/bad.

6.6 Johansen cointegration test and VECM

According to Engle and Granger (1987), two variables are cointegrated if there exists a linear combination that is integrated by order zero, I(0), which means that the variables possess a long-run relationship and share a common stochastic trend over time. Cointegration requires that the variables are stationary in their first difference, I(1), and non-stationary in level, hence two variables $Y_t$ and $X_t$ are cointegrated if both of them are I(1) and there exists a linear combination of the variables that is I(0) (Tsay 2002). Based on this, $Y$ and $X$ will share a common stochastic trend if there exists some parameter value $\beta$ such that, when multiplied with for example $Y$, causes $Y$ to follow a similar path through time as $X$. Hence, consider the following equation:

$$Z = X - \beta Y$$  \hspace{1cm} (9)

If there exists a relationship between $X$ and $Y$ that is constant through time, then $Z$ is I(0), meaning that the difference between the two non-stationary time series $X$ and $Y$ is a constant,
stationary process. The number of cointegrating factors will equal the number of linear combinations, and these linear combinations are referred to as cointegrating vectors (Tsay 2002). For example, in equation (9) there is one linear combination, hence one cointegrating relationship.

Following this, there can be a maximum of $n-1$ cointegrating vectors, where $n$ is the number of I(1) variables (Becketti 2013). To analyze cointegration between stock prices and GDP, the Johansen cointegration test is applied (Johansen 1988, 1991), which is based on maximum likelihood estimation. SIC is used to determine the number of lags and is set to $p-1$, where $p$ is the lag-length suggested by SIC. In order to retrieve the number of lags, the variables are tested in a VAR-model, where the series are in log-level.

Further, testing for cointegration is based on the following model:

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \theta_i \Delta y_{t-i} + \varepsilon_t \hspace{1cm} (10)$$

where $y_t$ is a $n \times 1$ vector of I(1) endogenous variables in time $t$, $\mu$ is a $n \times 1$ vector of intercepts; the term $\Pi$ is an error correction term and is written as $\Pi = \alpha \beta'$ where $\beta$ is the cointegrating vectors while $\alpha$ is the speed of adjustment coefficient; $y_{t-i}$ is the endogenous variables in level; $\theta_i$ is a $n \times n$ matrix of the coefficient of the differenced lagged variables $y_{t-i}$, and $\varepsilon_t$ is a $n \times 1$ vector of error terms that are assumed to be independent and identically distributed with a finite covariance independent of time and an expected mean of zero.\textsuperscript{26} Given that $y_t$ is I(1), $\Delta y_t$ is an I(0) process. Hence, this model accounts for how cointegration between the variables affects the dependent variable (Tsay 2002).

The number of linearly independent cointegrated relations of the vector $y_t$ is equal to the rank of the matrix $\Pi$ (Lütkepohl, Saikkonen & Trenkler 2002; Engle & Granger 1987). Hence, according to Granger’s representation theorem (see Johansen 1991; Engle & Granger 1987), if the coefficient matrix $\Pi$ has reduced rank, meaning that the rank is less than the number of

\textsuperscript{26} As observed in equation (10), the difference from a regular VAR-model is the error correction term $\Pi$ which accounts for the cointegrating relationship.
columns in the matrix $\Pi$, there exists a matrix $\alpha$ and a matrix $\beta$ such that $\Pi = \alpha\beta'$ (EViews 2015).

In order to determine the rank of $\Pi$, the paper applies the method developed by Johansen (1988; 1991), which involves estimating $\Pi$ from an unrestricted VAR and then testing if the restrictions implied by the reduced rank of $\Pi$ can be rejected (EViews 2015). To do this, Johansen’s (1988; 1991) Trace statistic and maximum eigenvalue statistic are used (EViews 2015). If the value of the Trace statistic and maximum eigenvalue statistic indicates that $\Pi$ has reduced rank, it indicates cointegration between the variables.

The Trace statistic is based on a log-likelihood ratio (EViews 2015). The test will set $n$ equal to two which means that it can exist at most one $(n-1)$ cointegrating relations. Thus, two null hypotheses are evaluated in the test, where the first is $H_0$: no cointegrating relations, and the second is $H_0$: at most one cointegrating relations. The Trace statistic is calculated as follows (see EViews 2015):

$$L_{R_{tr}}(r|n) = -T \sum_{t=r+1}^{n} \log(1 - \lambda_t)$$  \hspace{1cm} (11)

where $T$ is the sample size; $n$ is the number of endogenous variables; $r = 0, 1, \ldots, n-1$ and is the number of cointegrating relations; $\lambda_t$ is the $t^{th}$ largest eigenvalue of the matrix $\Pi$. The null hypothesis is rejected if the log-likelihood ratio is larger than the critical value of 0.05. Furthermore, the maximum eigenvalue statistic tests the same null hypotheses as the Trace test. It is written as follows (see EViews 2015):

$$L_{R_{max}}(r|r+1) = -T\log(1 - \lambda_{r+1}) = L_{R_{tr}}(r|n) - L_{R_{tr}}(r+1|n)$$  \hspace{1cm} (12)

Since both the Trace statistic and the maximum eigenvalue are reported in the statistical software, while it is also common to consider both in empirical studies, the paper applies both test statistics.\(^{27}\)

\(^{27}\) See for example Lütkepohl, Saikkonen & Trenkler 2002 who found that the power of the tests is similar and Österholm (2016), who reports both statistics.
If cointegration is present, a VECM (see equation 10) is estimated in order to evaluate the long-run relationship between the variables. The vector error correction framework is based upon the model in equation (10) and is a restricted VAR that incorporates cointegrating relations in the framework (Lütkepohl 2005).

The VECM set restrictions on the long-run behavior of the endogenous variables so that they converge to their long-run relationship, while simultaneously allowing for the dynamic of the short-run behavior (EViews 2015). Hence, Lütkepohl (2005) and Becketti (2013) argue that a VECM is appropriate to use when analyzing the long-run relationship between cointegrated variables; a VAR-model might distort interesting features of the cointegration when differencing each variable individually. By differencing the variables, the cointegration term gets eliminated which is not desirable for an analysis aimed to understand the long-run behavior (see Tsay 2002; Engle & Granger 1987). Further, recall the error correction term $\Pi = \alpha \beta'$ from equation (10), where $\alpha$ and $\beta$ are nxn matrices. The matrix $\Pi$ can be expressed as followed:

$$\Pi = \alpha \beta' = \begin{pmatrix}
\alpha_{11} & \cdots & \alpha_{1n} \\
\vdots & \ddots & \vdots \\
\alpha_{n1} & \cdots & \alpha_{nn}
\end{pmatrix}
\begin{pmatrix}
\beta_{11} & \cdots & \beta_{1n} \\
\vdots & \ddots & \vdots \\
\beta_{n1} & \cdots & \beta_{nn}
\end{pmatrix}$$

where $\alpha$ is the speed of adjustment coefficients and $\beta$ is the coefficients of cointegration, i.e., the cointegrating vectors. Thus, $\beta$ shows the effect on the dependent variable from last periods deviation from the long-run relationship, and $\alpha$ measures the speed at which the dependent variable returns to its equilibrium after last periods change. If $\alpha$ is non-zero and statistically significant then, according to Diebold (2007), the model becomes different from a VAR in first difference since it also incorporates the effect of the deviation from the long-run relationship.

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28 Support for using this model is found in for example Swedish National institute of economic research who used a VECM in their method for forecasting GDP and stock prices (Konjunkturinstitutet 2016).

29 Deviations from the long-run relationship indicate a disequilibrium that cannot go on indefinitely (Becketti 2013).
7. Results

This section starts with a presentation of the long-run relationship between stock prices and economic activity by interpreting the results from the Johansen cointegration test, which is followed by the estimated VECM, where the estimated parameters are interpreted. The section progresses by presenting the dynamic relationship between stock returns and economic growth, applying the Granger-causality test and IRF for respective countries. This is followed by results from the out-of-sample forecast, which are presented for two different VAR-models. Finally, the results from the Diebold-Mariano test are shown, for each country.

7.1 Johansen cointegration

The notion of the variables being I(1) is supported by the ADF-test where the null hypothesis of a unit root for stock prices and GDP cannot be rejected in log level but is rejected in first difference (see Table A.1). The Johansen cointegration test is carried out using $p-1$ lags, where $p = 2$ in accordance with SIC. The test statistics from Johansen cointegration test shows that the null hypothesis of no cointegration vector cannot be rejected for Denmark and Norway (see Table 2). However, the result for Sweden shows that the null hypothesis of no cointegrating relations is rejected while the null hypothesis of at most one cointegrating relations cannot be rejected (see Table 2). This implies that there exists one cointegrating vector between GDP and stock prices at 1 percent significance level and this holds for both the Johansen’s Trace test and maximum eigenvalue. Thus, results show that the matrix $\Pi$ has a rank equal to one.\(^{30}\)

\[\text{Table 2. Test statistics from Johansen cointegration test.}\]

<table>
<thead>
<tr>
<th></th>
<th>Denmark</th>
<th>Norway</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Johansen Trace Statistic</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>13.05</td>
<td>11.38</td>
<td>19.788***</td>
</tr>
<tr>
<td>At most 1</td>
<td>2.722</td>
<td>4.481</td>
<td>1.193</td>
</tr>
<tr>
<td><strong>Johansen Maximum Eigenvalue</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>10.327</td>
<td>6.898</td>
<td>18.595***</td>
</tr>
<tr>
<td>At most 1</td>
<td>2.722</td>
<td>4.481</td>
<td>1.93</td>
</tr>
</tbody>
</table>

Note: *** indicates the rejection of $H_0$ at 1 percent significance level. None indicates no cointegration vector, suggesting that the matrix $\Pi$ has full rank. At most 1 suggests that there are no more than 1 cointegrating vector, hence there exists 1 linearly dependent column in the matrix $\Pi$.

\(^{30}\)If the matrix $\Pi$ has a rank of zero it implies no cointegration, meanwhile if the matrix $\Pi$ has full rank it means that both series are stationary.
Further, given these results, this paper progresses by interpreting the output from the VECM for Sweden in the next section.

7.2 VECM

The key parameters from the estimated VECM for Sweden can be observed in Table 3. The VECM incorporates two variables, GDP and stock prices, which results in two equations being estimated in the system with each variable being the dependent variable in the respective equation. The number of lags in the VECM is based on SIC and is set to \( p-1 \), where \( p = 2 \). Based on the Johansen cointegration test, one cointegration equation is estimated in the VECM. The cointegrating vector is \( \beta = (1, -0.678)' \), where the coefficient in front of \( \ln(GDP_{t-1}) \) is normalized to unity. The coefficient in front of \( \ln(S_{t-1}) \), which is statistically significant, is interpreted as follows: if the stock market has increased by 1 percent in the previous period, it will lead to a change in GDP of around 0.68 percent on average. However, this is not a sign of a causal relationship, it aims only to describe how the long-run relationship connects the variables with each other.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>( \hat{\alpha}_1 )</th>
<th>( \hat{\alpha}_2 )</th>
<th>( \hat{\mu}_0 )</th>
<th>( \hat{\beta}_1 )</th>
<th>( \hat{\beta}_2 )</th>
<th>( H_0: \beta = (1, -1)' )</th>
</tr>
</thead>
<tbody>
<tr>
<td>(-0.020***)</td>
<td>0.181**</td>
<td>-9.718</td>
<td>1</td>
<td>(-0.678***)</td>
<td>6.110**</td>
<td></td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.063)</td>
<td></td>
<td>(0.0686)</td>
<td></td>
<td>([-9.883])</td>
<td></td>
</tr>
<tr>
<td>[-3.101]</td>
<td>[2.873]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: \( \hat{\alpha} \) is the speed of adjustment parameters, \( \hat{\beta} \) is the cointegrating coefficients, \( \hat{\mu}_0 \) is the intercept and \( \beta = (1, -1)' \) is a maximum likelihood test for mean-reversion between the variables. *** indicates that the coefficient is statistically significant at 1 percent significance level, whereas ** indicates statistical significance at the 5 percent level. The values in parentheses are standard errors while the values in square brackets are t-statistics.

Further, it is observed in Table 3 that the speed of adjustment parameters \( \hat{\alpha}_1 \) and \( \hat{\alpha}_2 \) are statistically significant. \( \hat{\alpha}_1 = -0.020 \) relates to the equation where GDP is the dependent variable while \( \hat{\alpha}_2 = 0.181 \) relates to the equation where stock prices is the dependent variable. Since both parameters are significant it implies that GDP and stock prices adjust back to their long-run relationship when a deviation occurs from equilibrium. Additionally, it is observed that \( \hat{\alpha}_2 \) is larger than \( \hat{\alpha}_1 \). This means that a deviation resulting in a disequilibrium is
adjusted mainly through stock prices since the speed of adjustment parameter related to the equation where stock prices is the dependent variable is larger.

Further, based on the VECM, the paper evaluates whether or not the ratio between the variables is mean-reverting (see Rangvid 2006; Österholm 2016). This is carried out by testing the imposed restriction $\beta = (1, -1)'$ with a likelihood ratio test. According to Rangvid (2006), if the price-to-GDP ratio is mean-reverting, it suggests that future stock returns are expected to be low if current stock prices are high, relative to GDP, and vice versa. The notion of mean-reversion implies that fluctuations in one of the variables matters for the other variable (Rangvid 2006). By testing this imposed restriction, it is observed in Table 3 that the null hypothesis is rejected at 5 percent significance level, which supports the notion of mean-reversion. This result indicates that it is appropriate to account for a long-run relationship between the variables and not impose the restriction in the model.

Summarizing the results from the cointegration analysis, Sweden shows a long-run relationship between stock prices and economic activity, which is in line with Österholm (2016). This is why a VECM only is estimated for Sweden and not the other countries. The results for Denmark and Norway suggest that there is no long-run relationship with economic activity, at least not for the examined time interval using the Johansen cointegration framework.

7.3 In-sample analysis

The results from the ADF-test (see Table A.1) shows that stock prices and GDP are I(1) while yield spread is I(0). Hence, all the VAR-models are estimated with stationary variables.

In Table 4 all the estimated VAR-models are presented, where GDP-growth is the dependent variable for all models. All the models include one lag as suggested by SIC. It is observed that the previous quarter of stock returns provides a significant explanation for GDP-growth for all the estimated models. For example, looking at the second estimated model for Denmark, the coefficient in front of $r_{t-1}$ can be interpreted as follows: Given a 10 percent increase in stock returns 1 quarter ago, GDP-growth will increase by 0.47 percent this quarter on average, holding everything else constant. This interpretation holds for all the estimated coefficients. It is observed in Table 4 that all the coefficients in front of lagged values of GDP-growth and yield spread are insignificant, suggesting that it does not provide any explanation for current GDP-growth. The fact that yield spread does little to improve the model is also confirmed by
looking at the change in $R^2$ when yield spread is added to the model. For example, for Denmark $R^2$ only changes from 0.229 to 0.24 when the yield spread is incorporated in the model.

**Table 4. Estimation output from the estimated VAR(1)-models.**

<table>
<thead>
<tr>
<th></th>
<th>$g_t$(DEN)</th>
<th>$g_t$(DEN)</th>
<th>$g_t$(NO)</th>
<th>$g_t$(NO)</th>
<th>$g_t$(SWE)</th>
<th>$g_t$(SWE)</th>
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<tbody>
<tr>
<td>C</td>
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<td>0.005***</td>
<td>0.009***</td>
<td>0.0117***</td>
<td>0.010***</td>
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<td>(-0.001)</td>
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<td>(-0.003)</td>
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<td>(-0.002)</td>
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<td></td>
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<td>[4.103]</td>
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<td>[3.845]</td>
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<td>$g_{t-1}$</td>
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<td>0.076</td>
<td>0.0962</td>
<td>0.071</td>
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<td>-0.122</td>
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<tr>
<td></td>
<td>(-0.095)</td>
<td>(-0.096)</td>
<td>(-0.101)</td>
<td>(-0.102)</td>
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<td>[1.018]</td>
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<td>[0.957]</td>
<td>[0.701]</td>
<td>[-1.168]</td>
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<tr>
<td>$r_{t-1}$</td>
<td>0.053***</td>
<td>0.047***</td>
<td>0.098***</td>
<td>0.111***</td>
<td>0.047***</td>
<td>0.0387***</td>
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<td>[1.670]</td>
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<tr>
<td>$R^2$</td>
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<td>0.24</td>
<td>0.24</td>
<td>0.26</td>
<td>0.195</td>
<td>0.219</td>
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<tr>
<td>$\overline{R^2}$</td>
<td>0.212</td>
<td>0.214</td>
<td>0.223</td>
<td>0.231</td>
<td>0.178</td>
<td>0.193</td>
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<tr>
<td>SE</td>
<td>0.009</td>
<td>0.009</td>
<td>0.02</td>
<td>0.019</td>
<td>0.009</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Note: The values in parentheses shows the standard errors and the values in square brackets is the t-statistics. SE indicates the residual standard error for each of the estimated models. $R^2$ and $\overline{R^2}$ are measures of the goodness of fit. *** represent the statistical significance of the estimated coefficients at the 1 percent significance level. There are two estimated equations for each country, one with the first lag of GDP-growth ($g$) and stock returns ($r$) and one that also includes the first lag of yield spread ($i$). GDP-growth is the dependent variable for all the equations.

The results from the Granger-causality test for each country are found in Table 5 where the null hypothesis specifies that stock returns do not Granger-cause GDP-growth. Thus, from the F-statistic it is seen that the null hypothesis is rejected at 1 percent significance level for all countries, supporting the idea that stock returns help improve economic growth. However, it is important to be aware that the results from Granger-causality tests and the estimated VAR-model only explain the quarterly fluctuations in economic growth and does not explain economic growth in the long-run.
Further, no evidence of a reverse relationship, meaning that GDP-growth Granger-cause stock returns, is found for Denmark, Norway and Sweden, which is not surprising since stock returns are assumed to follow a random walk and if it was possible to forecast stock returns, investors could make unlimited money (see Table A.2).

Table 5. Granger-causality test from the estimated VAR(1)-model including stock returns (r) and GDP-growth (g).

<table>
<thead>
<tr>
<th>Country</th>
<th>Obs</th>
<th>F-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denmark</td>
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<td>21.976***</td>
</tr>
<tr>
<td>Norway</td>
<td>95</td>
<td>19.878***</td>
</tr>
<tr>
<td>Sweden</td>
<td>95</td>
<td>22.097***</td>
</tr>
</tbody>
</table>

Note: *** represent the rejection of $H_0$ at 1 percent significance level.

The result from the Granger-causality tests is carried out in IRFs, where a positive shock in stock returns affects GDP-growth (see Figure 4). By using the Cholesky decomposition, it becomes possible to isolate the response of the dependent variable to a shock of the system’s residuals, holding all else equal (Diebold 2007).

As expected, it is seen that a positive shock in stock returns has a positive significant effect on GDP-growth for all countries. It can be seen for all the generated impulse response functions that a positive shock in stock returns with one standard deviation leads to a positive response in GDP-growth in quarter 1 where the effect starts to diminish in quarter 2 and eventually dies out around quarter 4.

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31 All the IRF:s generated from the estimated VAR-model are found in appendix, see figure A.4 – A.6.
Figure 4. Response of GDP-growth from a shock in stock returns: Denmark (left), Norway (right) and Sweden (bottom).

Note: The IRF are carried from the bivariate VAR-model including GDP and stock returns for each country. The X-axis shows the number of periods, ranging from 1 to 10 quarters. The y-axis shows the response of GDP-growth in percentage points to one standard deviation shock to stock returns.

Following this, stock returns have a positive significant effect on GDP-growth for all countries which makes it a potential predictor of GDP-growth. Thus, fluctuations in quarterly stock returns contain information about future fluctuations in GDP-growth and it is therefore relevant to examine if the dynamics improve the forecast and are able to perform better than an ordinary AR(1)-process. This will be presented in the following section.

7.4 Forecast evaluation
The calculated RMSE and MAE (see table A.3.) shows that the VAR(1)-model for Sweden gives slightly smaller RMSE and MAE than the AR(1)-model. Hence, VAR(1) seems to perform better over the 4 horizons. However, the Diebold-Mariano test provides no evidence of this since the null hypothesis cannot be rejected at any horizon (see Table A.4.). As for the VAR(1)-model including both stock returns and yield spread, the model provides smaller errors than the AR(1) (see Table A.3.). Despite this, there are no significant differences between the models (see Table A.4.).

For Norway, the results are not convincing either. AR(1) gives smaller RMSE and MAE than the VAR(1), except for the fourth horizon (see Table A.3.). Despite this, results from the
Diebold-Mariano test provides no significant evidence that one of the forecasts is better than the other (see Table A.4.). The same results are found for VAR(1) including yield spread and stock returns, except for the third horizon where the Diebold-Mariano test indicates that AR(1) might even be better; the coefficient is significantly positive at 10 percent (see Table A.4.).

Finally, results from Denmark also show that RMSE and MAE is lower for AR(1) in horizon 1, 2 and 3, but not in horizon 4 (see Table A.3.). The Diebold-Mariano test for Denmark provides evidence that AR(1) actually performs better in horizon 1 and 2 (see Table A.4.). However, in horizon 3 and 4, AR(1) seems to lose its advantage and the two models perform equally as good/bad (see Table A.4.). Similar results are found for VAR(1) including both stock returns and yield curve spread (see Table A.3.); AR(1) has smaller errors for all horizons except horizon 4 and the Diebold-Mariano test indicates that AR(1) is relatively better at horizons 1 and 2 while both models is equally as good/bad at horizon 3 and 4 (see Table A.4.).
8. Discussion

Evidence of the long-run relationship between stock prices and economic activity in Sweden suggests that stock prices evolve in accordance with economic activity. The fact that there exists cointegration between these variables is in line with previous research (see for example Yin-Wing & Lilian 1998; Chaudhuri & Smiles 2004; Österholm 2016; Humpe & Macmillan 2009). Further, results from the mean-reverting test supports this finding, where movements in stock prices and GDP will converge to their long-run relationship. An implication of mean-reversion is that high current stock prices in relation to GDP should indicate lower expected returns (Rangvid 2006). These results are consistent with the assumptions from the constant growth dividend discount model, namely that dividends on average grow in correspondence with economic growth, at a constant rate. This suggests that prices on the stock market reflect the development of the real economy since the variables are driven by the same underlying stochastic trend. This line of reasoning suggests that all the variables in the dividend discount model share a common attribute since they are all affected by the same underlying economic factors. To illustrate the connection between the model and the real economy, consider investments which are one of the key drivers of economic activity. If investments increase it implies positive NPV-investments, suggesting that $\text{ROI} > \text{E}[r]$, which, according to the constant dividend discount model, will stimulate growth in dividends and stock prices. Further, the implication of the long-run relationship is also connected to the expected rate of return, which incorporates a risk premium. This risk premium is based on current market conditions which is solely based on systematic risk (Berk & DeMarzo 2019), suggesting that the development of the real economy will be an important determinant of risk premiums.

The notion that dividends approximately grow at the same rate as economic activity in the long-run makes it intuitive to think that there is a long-run relationship between stock prices and GDP. In contrast to Sweden, evidence for Denmark and Norway cannot verify a cointegrated relationship between the variables, given the time period examined. However, this does not necessarily imply that there exist no cointegration. The Johansen cointegration test is sensitive to the chosen time period. If it was possible to carry out the analysis using a longer time span, for example 100 years, it could provide more robust results of the true relationship. However, this paper is limited to the time period starting in 1996 due to the lack of historical data for the Danish- and Norwegian stock indices. Despite this limitation, it is reasonable to assume that stock prices and economic activity should share a common stochastic trend in the long-run,
which opens up for further analysis. Hence, analyzing the absence of cointegration in these countries may require a more thorough analysis including other factors that are related to the long-run stochastic trend. For example, as mentioned in section 2, the Norwegian economy and the Oslo All-Share Index is heavily influenced by fluctuations in oil prices and can therefore be a factor to include in the cointegration analysis. Regarding Denmark, the fact that the Danish crown is pegged to the euro, making the monetary policy ineffective since the Central Bank is unable to adjust interest rates, might be a factor to include in order to enable a deeper analysis.

Turning to the results from the in-sample analysis, it confirms that fluctuations in stock returns have an explanatory power for fluctuations in economic growth and that stock returns Granger-cause economic growth for all countries (see Table 5). These findings are in line with previous research (see for example Schwert 1990; Switson 2008; Stock & Watson 2003a; Kanas & Ioannidis 2008; Hatzius et al. 2010). Hence, fluctuations in the stock market might provide an early signal of future economic activity. Furthermore, since an increase in stock returns implies an increase in economic growth, it supports the notion that a lower market risk premium and a high Tobin’s q stimulates investments, where investments make up a large part of economic growth. Further, it corresponds with the theory of stock prices being based on expectations of future cash flows.

Regarding the results from the recursive forecast framework, it is possible to distinguish lower average RMSE and MAE for the VAR-models compared to the benchmark model in Sweden, though this is not the case for Denmark and Norway (see table A.3.). By only considering the forecast errors, it seems like stock returns in Sweden increases the accuracy of the forecast and therefore could be considered a leading indicator of economic growth. However, the conclusion from the Diebold-Mariano test implies that there is no significant difference between the VAR-models and the benchmark-model for Sweden, which also is seen in Norway. Regarding the results for Denmark, it shows that the benchmark model outperforms the VAR-models in horizon 1 and 2 (see table A.4.). These results are in contrast to the findings of Estrella and Mishkin (1998); Andersson and D’Agostino (2008) and Andersson et al. (2011) but are in line with previous research such as Espinoza, Fornari and Lombardi (2011) and European Central Bank (2012) who also found mixed evidence of the ability for stock returns to improve the forecast of economic growth. Hence, the result from this paper supports the difficulty in empirically validating the theoretical argument of stock returns being a leading indicator for economic growth. Moreover, the inclusion of the yield spread did not improve the forecasting
ability which is in contrast to previous findings such as Harvey (1989) and Estrella and Miskin (1998).

Further, with regards to the insignificant difference between the benchmark model and the VAR-models for Sweden and Norway, the recommendation to forecasters is that the stock market does not work as a leading indicator for the economy when considering 1 to 4 quarters ahead. Thus, forecasters and policymakers should think closely about including stock returns in the model as it may yield higher estimation errors due to more coefficient being estimated. This argues for using the AR(1)-model which is considered more parsimonious, and as it has been shown, performs equally as good/bad. Considering Denmark, forecasters and policymakers should not include stock returns as a variable when forecasting economic growth, hence the AR(1)-model is the preferable choice between the models.
9. Conclusion
The purpose of this paper has been twofold. First, the paper aimed to test if there is a long-run relationship between stock prices and economic activity, using GDP as a proxy, for Denmark, Norway and Sweden, during a time period from 1996Q1 to 2020Q1. Second, this paper preceded by examining if stock returns are a leading indicator for economic growth, measured as GDP-growth.

Evidence provided from the Johansen cointegration framework, which is a well-known method for analysing how I(1) variables are related in the long-run (see Chapter 3), verified a long-run relationship between stock prices and economic activity in Sweden. Hence, this supports the notion that dividends grow with the growth of the economy over time, on average. Given the existence of cointegration, deviations from the long-run equilibrium should eventually converge, which is also supported from the test of mean-reversion. For example, if the development of the general economy has been weak while the stock market has been bullish, this may indicate an increase in economic activity, or that stock prices are being valued too high in relation to economic development.

Considering the results for Norway and Denmark, no evidence for cointegration is found. The absence of cointegration in these countries is a subject for further research by including other relevant variables and testing for other proxies of economic activity. As addressed by Alexius and Spång (2018), there are only a handful of papers that have examined how stock prices and GDP are related in the long run. Hence, additional evidence could strengthen the hypothesis of a long-run relationship.

The Granger-causality framework confirms that stock returns help improve the prediction of economic growth for all countries. These results are in line with the notion that stock markets are forward looking, hence fluctuations in stock returns today incorporate information of the fluctuations in economic growth. This corresponds with how the constant dividend discount model values stocks since this model implies that stocks are values based on expectations of future cash flows. Despite these findings, evidence from the recursive forecast framework do not support the notion of stock returns as a leading indicator for economic growth. Moreover, including yield spread in the model did not improve the forecasts (see table A.4.). The recommendations for policymakers and forecasters are the following: Since stock returns do
not improve the forecast of economic growth compared to the benchmark, it may be more preferable to use the AR(1)-model for Sweden and Norway, since it is a more parsimonious model. However, since the benchmark is significantly outperforming the VAR-models in quarter 1 and 2 for Denmark, a strong recommendation is to use the benchmark instead of the VAR-models when forecasting the 1 and 2 quarter of economic growth.

For further research, this paper can be extended by examining certain sector indices within the Scandinavian all-share stock market indices in order to evaluate if some sectors are closer related to economic activity than others. This approach has been done for the euro area and the US, see for example Andersson and D’Agostino (2008); Andersson et.al (2011). Additionally, as previously mentioned, the fact that no long-run relationship was found in Denmark and Norway opens up for further analysis, for example by including other factors that influence the long-run relationship.
10. Bibliography


Avanza (n.d.). *Aktielistan.*


11. Appendix

*Figure A.1. Sweden stock market index (left), Norway stock market index (right) and Denmark stock market index (bottom).*

![Stock Market Index Graphs](image1)

Note: The OMXSPI index is used for Sweden, Oslo all-share index (OSEAX) is used for Norway and OMX Copenhagen (KAX) is used for Denmark. All the graphs show quarterly average prices, calculated from daily closing prices, between the time period 1996Q1 and 2020Q1. Source: Bloomberg (n.d.).

*Figure A.2. Sweden GDP (left), Norway GDP (right) and Denmark GDP (bottom).*

![GDP Graphs](image2)

Note: Seasonally adjusted quarterly nominal GDP from the user-side, measured in millions of the local currency, is used for all countries. Sources: Sweden GDP (SCB 2020); Norway GDP (SSB 2020); Denmark GDP (DST 2020).
Figure A.3. Sweden yield spread (left), Norway yield spread (right) and Denmark yield spread (bottom).

Note: For all countries the yield spread is the difference in yield between the 10-year government bond and the 3-month treasury bill. The quarterly yields are the arithmetic average of the daily yields for each quarter. Sources: Sweden yield spread (Riksbanken n.d.); Norway and Denmark yield spread (Macrobond n.d.).

Figure A.4. Impulse response functions Denmark. Response to one standard deviation of innovations using Cholesky (d.f. adjusted), +/- 2 standard errors.

Note: The X-axis shows the number of periods, ranging from 1 to 10 quarters. The y-axis shows the response in percentage points to one standard deviation shock. The line in the middle shows the response to the disturbance and the two utmost lines show +/- 2 standard errors.
Figure A.5. Impulse response functions Norway. Response to one standard deviation of innovations using Cholesky (d.f. adjusted), +/- 2 standard errors.

Note: The X-axis shows the number of periods, ranging from 1 to 10 quarters. The y-axis shows the response in percentage points to one standard deviation shock. The line in the middle shows the response to the disturbance and the two utmost lines show +/- 2 standard errors.

Figure A.6. Impulse response functions Sweden. Response to one standard deviation of innovations using Cholesky (d.f. adjusted), +/- 2 standard errors.

Note: The X-axis shows the number of periods, ranging from 1 to 10 quarters. The y-axis shows the response in percentage points to one standard deviation shock. The line in the middle shows the response to the disturbance and the two utmost lines show +/- 2 standard errors.
Table A.1. Result from Augmented Dickey-Fuller test.

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<td>t-statistic</td>
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<td>$i$</td>
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<td>-6.761***</td>
</tr>
</tbody>
</table>

Note: Stock prices ($S$), GDP ($g$) and yield spread ($i$). In level stock prices and GDP are in logarithmic values and in the first difference the variables are interpreted as stock returns and GDP-growth. GDP is tested with both an intercept and a time trend while stock prices and yield spread is tested with only an intercept. *** represents significance on 1 percent level.

Table A.2. Granger-causality from GDP-growth to stock returns.

$H_0$: GDP-growth does not Granger-cause stock returns

<table>
<thead>
<tr>
<th>Country</th>
<th>Obs</th>
<th>F-statistic</th>
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Note: $H_0$ cannot be rejected for any country.
Table A.3. RMSE and MAE for the benchmark model and the two VAR(1)-models, for each country.

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<td>VAR(1)-model, GDP-growth, stock returns and yield curve spread</td>
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<td>Benchmark model: AR(1), GDP-growth</td>
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</table>

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Benchmark model: AR(1), GDP-growth</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.8618</td>
</tr>
<tr>
<td>2</td>
<td>0.7950</td>
</tr>
<tr>
<td>3</td>
<td>0.7962</td>
</tr>
<tr>
<td>4</td>
<td>0.7879</td>
</tr>
<tr>
<td>Average</td>
<td>0.8102</td>
</tr>
</tbody>
</table>

Note: The first sub-sample is 1996Q1 to 2009Q4 which forecasts 1, 2, 3 and 4 quarters ahead. The sample is then expanded with 1 quarter each time, always forecasting the 1, 2, 3 and 4 quarter ahead. Thus, each horizon consists of 38 forecast errors, for every model. RMSE and MAE have been calculated using equation (7) and (8). The average value for each forecast error and model is the arithmetic mean over the 4 horizons.
Table A.4. Diebold-Mariano test: Denmark (first), Norway (second) and Sweden (third).

Diebold-Mariano test: VAR(1) vs. AR(1)

<table>
<thead>
<tr>
<th>Forecast differential</th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
<th>Horizon 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-value</td>
<td>0.0164**</td>
<td>0.0032***</td>
<td>0.4271</td>
<td>0.616</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.000022</td>
<td>0.000015</td>
<td>0.000018</td>
<td>0.00000244</td>
</tr>
</tbody>
</table>

Diebold-Mariano test: VAR(1) (including yield curve spread) vs. AR(1)

<table>
<thead>
<tr>
<th>Forecast differential</th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
<th>Horizon 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-value</td>
<td>0.0181**</td>
<td>0.0348**</td>
<td>0.9074</td>
<td>0.9093</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.0000213</td>
<td>0.000013</td>
<td>-0.000004</td>
<td>-0.00000305</td>
</tr>
</tbody>
</table>

Diebold-Mariano test: VAR(1) vs. AR(1)

<table>
<thead>
<tr>
<th>Forecast differential</th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
<th>Horizon 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-value</td>
<td>0.5022</td>
<td>0.2078</td>
<td>0.1565</td>
<td>0.6313</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.0000166</td>
<td>0.000022</td>
<td>0.000019</td>
<td>-0.00000932</td>
</tr>
</tbody>
</table>

Diebold-Mariano test: VAR(1) (including yield curve spread) vs. AR(1)

<table>
<thead>
<tr>
<th>Forecast differential</th>
<th>Horizon 1</th>
<th>Horizon 2</th>
<th>Horizon 3</th>
<th>Horizon 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-value</td>
<td>0.5703</td>
<td>0.1615</td>
<td>0.0999*</td>
<td>0.7912</td>
</tr>
<tr>
<td>Coefficient</td>
<td>0.0000157</td>
<td>0.0000207</td>
<td>0.0000130</td>
<td>0.0000195</td>
</tr>
</tbody>
</table>

Note: *, ** and *** indicates the rejection of $H_0$ at 1, 5 and 10 percent significance level, respectively. The Diebold-Mariano test examines the difference between the squared forecast errors of the benchmark model and the VAR-models. This is done for all 4 horizons. The difference is then regressed on a constant using Newey-west standard errors and ordinary least squares (OLS). $H_0$ states that the constant is equal to zero which indicates no difference in forecast accuracy of the benchmark model and the VAR-model. If $H_0$ is rejected and the coefficient is positive, the benchmark model outperforms the VAR-model and if $H_0$ is rejected while the coefficient is negative, the opposite holds.