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A cointegration and causality analysis of Scandinavian stock markets

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Preface

It has been a great privilege to spend the two years of my master degree at the Department of Economics at NTNU, and its members and classmates will always remain dear to me.

My first debt of gratitude must go to my supervisor, Arnt Ove Hopland. He patiently provided the vision, encouragement and advice necessary for me to proceed through the program and complete my thesis.

I also wish to thank my husband and cousin Majna for their encouragement, constructive criticism and countless hours of proof-reading.

Finally, I would like to dedicate this work to my loving parents for their unconditional love and support even from 3000 km away. This work is a small symbol of my gratitude and I hope it makes you proud.

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1. Introduction

The degree of interdependence between stock markets has been examined in many empirical studies in the last few decades [Kasa (1992), Richards (1995), Chen, Firth and Meng Rui (2002), Jeon and Chiang (1991)]. This interest is mainly because of the increase in capital flow across countries, opportunities for portfolio diversification and potential predictability of stock data. One aspect of such interdependence is cointegration. Cointegration between stock markets has become a topic of interest and states that markets tend to move together over the long-run (Engle and Granger, 1987). The mentioned studies have all showed that stock markets around the world are not as independent anymore. It has become quite plausible to expect that they share a common trend. This implies that stock indices are linked closely and that movements in one market affect other stock markets immediately (Lee and Jeon, 1995)

Cointegration has many implications both for financial theory and for portfolio management of the individual investor. Cointegration is important in theory of finance due to the fact that if the efficient market hypothesis holds, it should not be possible to predict stock indices using indices from other stock markets. However, if markets move together in the long-run, this hypothesis will not hold (Shleifer, 2000). Cointegration has also implications on the individual investor – in order to hedge risk, investors diversify their portfolios by investing in assets traded in different stock markets. If cointegration between markets is present, their indices will behave in a similar way in the long-run and give similar returns, leading to the potential reduction of gains from international diversification [Kasa (1992), French and Poterba (1991), Richards (1995)].

The purpose of this research is to examine whether there is evidence for cointegration among stock markets in Scandinavia. Stock markets of Norway, Sweden, Denmark and Finland are included in this analysis. The main reason for choosing Scandinavian stock markets is because of their historical, political and regional close relation in addition to the small amount of attention that these developing markets have received in previous cointegration research. The United States market was included mostly because of the global significance of the US economy and empirical findings the US market is an international source of common stochastic trends [Masih and Masih (2001), Hassan and Naka (1996)]. Data was gathered using a sample period from February 1993 to February 2013. This research is unique because of the recent sample period it uses, as many empirical studies use data from the 1980s and 1990s only. In addition, Scandinavian stock markets have not been in the focus of many cointegration studies. Most studies about cointegration in Scandinavia are based only on pairwise analysis and usually performed before 2000s.

Both the long-run and short-run linkages between stock markets are examined in this research, with a focus on the long-run concept of cointegration. For the long-run relationship, we test whether the stock markets are pairwise cointegrated over the sample period by using the Engle–Granger test as well as the Johansen method. The Johansen method is also used to examine cointegration among stock markets as a system. In terms of short-run relations, the Granger causality test is performed. For every test the full 20-year sample period is divided into two equal subsamples to check if the results are stable. The result suggest no strong or stable evidence for cointegration among these stock markets over this sample period, which is consistent with results of many similar research in Scandinavia [Booth, Martikainen and Tse (1997), Malkamäki, Martikainen, Perttunen and Puttonen (1993), Pynnönen and Knif (1998)]. Causality tests showed some short-run pairwise relations between the analyzed stock markets.

This thesis is divided into seven chapters. Chapter 1 is the introduction. Chapter 2 contains a theoretical introduction to cointegration and discusses its importance. Chapter 3describes the empirical background with focus on the concept of stationarity. A description of the data used in this thesis is given in Chapter 4. Chapter 5 presents the various econometric tests and methods used to examine cointegration. The results of these tests are presented in Chapter 6. Chapter 7 concludes this research.

1.1 Previous empirical work

Many studies around possible cointegration between international stock markets have been performed earlier. However, the results are quite conflicting and show no consensus on cointegration, even between the major international markets.

Corhay, Rad and Urbain (1993) examine the largest stock markets of Europe from 1975 to1991 and find evidence for cointegration between them. The same conclusion is found for stock markets in Latin America by Chen, Firth and Lui (2002), using the indices of six major stock markets in Latin America and data from 1995 to 2000. Kasa (1992) gives the strongest rejection of no cointegration hypothesis. In this research, testing for cointegration is performed between the major stock markets of USA, Japan, England, Germany and Canada using both monthly and quarterly data from 1974 to 1990. Strong evidence for one single cointegrating vector is found for these markets. This conclusion is partially at odds with other work in this area which suggests little or no cointegration between stock markets.

Richards (1995) criticizes the work of Kasa (1992) and finds little empirical evidence for cointegration of stock market indices using data for 16 international stock markets. Kanas (1998) tests for pairwise cointegration between the US stock market and six major European markets using daily data from 1983 to 1986. The results suggest that the US market is not pairwise cointegrated with any of the European markets.

The major, leading stock markets which include USA, UK, Japan, Germany etc., have received most attention in earlier cointegration analyses. However, empirical evidence for cointegration in Scandinavia is various. Booth et.al (1997) find no evidence for cointegration in Scandinavian markets using a sample period from 1988 to 1994. Some evidence for price and volatility spillovers was found. Pynnönen and Knif (1998) focus on the Finnish and the Swedish stock market in their research, covering a very large sample period from 1920 to 1994. No pairwise cointegration or fractional cointegration was found in this research. A similar analysis was performed by Malkamäki et.al (1993), where the lead-lag causality relationships between the stock markets in Sweden, Denmark, Finland and Norway were examined. Even with this research there is little or no evidence for cointegration among these markets, although some causality relations were detected and the Swedish market was found to be the leading one in the region. However, Knif and Pynnönen (1999) in their later research manage to find fractional cointegration between Scandinavian markets. One of the few recent studies performed by Zhang (2012) also suggests two cointegrating vectors among Scandinavian stock markets in the last decade.

The results from previous work about cointegration among Scandinavian markets are obviously inconsistent and mixed. In general, cointegration results depend widely on the choice of stock markets, the chosen sample period, frequency of the data and the model specification.

2. Theoretical background

The empirical concept of cointegration will be presented and discussed in chapter 3.2 but for understanding the implications of cointegration, it is important to introduce the essence of the concept. The main idea behind cointegration is that variables have a tendency to move together in the long run – there is an equilibrium relationship between them. Short-term deviations from the equilibrium are possible, but in the long-run the variables will return back to equilibrium relation due to the error or equilibrium correction model (Engle and Granger, 1987).

2.1 Factors contributing to stronger interdependence

Trading and investing across different countries and markets has increased in the past few decades. One of the reasons is certainly liberalisation of the markets. Another reason is the globalisation of world economy which has made it much easier to instantly make investments in any stock market of the world (Corhay et al. 1993).

One of the many motives behind investing abroad is diversifying the portfolio to hedge risk and increase expected return from stocks. Increased international trading has in great extent led to stronger dependence among stock markets. From the point of view of involved countries, stronger interdependence has also resulted in increased competition within the markets, positive capital flow across borders etc. This flow of capital can especially be noticed from the developed to developing countries (Bessler and Yang, 2003).

The process of globalisation is a relevant factor that contributed to a more interdependent world. Globalisation in the economic perspective means increased interdependence among national economies, which led to opening of the national economies to foreign trading, liberalization of the markets and increased capital flow across countries. Most of the developed countries removed restrictions about foreign trading during the 1980s and 1990s (Henry, 2000).

Factors that have the strongest impact on this process are deregulation of the economies, multinational corporations and their activities over the globe and coordination of national policies. These are economic growth factors that not only increase the economic interdependence among countries, but also between their stock markets (Phengpis and Apilado, 2004).

One of the most important factors to strengthen the linkages between stock markets, is the development of communications technology and computerized systems. It is impossible to imagine the stock markets today without advanced technology that shortens the time between trades being initiated and trades being completed. More relevant for our discussion about globalisation is the information that has become more available and allowed institutions, as well as individuals, over the world to buy or sell stocks rather quickly at lower transaction costs. These factors have as well had a significant impact on increased capital flow among countries and a more interdependent financial world (Blackman, Holden and Thomas, 1994).

Phengpis and Apilado (2004) analyzed in their work how stronger economic interdependence among the countries contributes to cointegration among them. The five largest stock markets in Economic and Monetary Union (EMU) were considered using a sample period from 1979 to 2002. EMU is a good example in this case, as the union promotes strong economic interdependence and harmonization of the economic policies of the members. The results indicated strong cointegration over the full sample for EMU-members. The same analysis for five non-EMU countries showed no cointegration among them. In their work the conclusion is that strong economic interdependence between countries is crucial for cointegration and common stochastic trends between stock markets.

The findings from Phengis and Apilado's work suggest that cointegration could theoretically be found between the Scandinavian stock markets, as their economic interdependence has certainly increased in the past decade. Although the process of their integration started earlier, the NASDAQ OMX[1] group was formed in May 25, 2007 containing Stockholm, Helsinki, Copenhagen and four other stock markets. This was a significant step towards stronger interdependence among the Scandinavian markets.

[1] NASDAQ OMX merger press release
http://www.nasdaqomx.com/newsroom/pressreleases/pressrelease/?messageId=760059&displayLanguage=en

2.2 Economic implications of cointegration

The cointegration results have significant implications in the world of economics. The degree of international stock market cointegration is important for investor's investment strategy and stock market portfolio. We will discuss these implications in detail.

2.2.1 Investment strategy - Diversification

The cointegration results can be helpful towards decisions about the investment strategy. Aside from the positive impacts on the capital flows, stronger interdependence among stock markets leads to diversification problems for the individual investor. In order to reduce the risk and achieve higher returns, investors often tend to invest in foreign stock markets (French and Poterba, 1991). This technique is called international diversification of the portfolio. The analogy behind this is that loss in one market is compensated with the gain in another market, but these benefits will hold only if the stock markets are not perfectly correlated. Therefore investors are constantly seeking for stocks that do not correlate with each other and hence provide better opportunities for hedging the risk. Analogously, if international stock markets are strongly correlated in the long-run, the positive effects of diversification will be diminished or excluded (Brooks, 2008).

If the cointegration analysis of stock markets shows that they follow their own different patterns, investors can fully achieve the benefits of international diversification. However, if cointegration between markets is detected, it will imply that a common trend brings these stock markets together. Any market by itself will represent the behavior of the whole group of markets gathered around a common trend. The problem is that this could reduce or even remove the gains from international diversification. Loss in one stock market will mean loss in another market as well, since they move together over time. Investing in a group of cointegrated markets at the same time will not hedge the risk of investment. However, it does not mean that short-run profits and gains are excluded.

When cointegration is present between stock markets, it indicates that fewer assets are available for diversification of the portfolio. Therefore, cointegration may force investors to reconsider allocation of their capital when investing in foreign stock markets. It is advisable to invest in stock markets that are not cointegrated to maximize the benefits of diversification (Kasa, 1992).

2.2.2 Market efficiency

The efficient market hypothesis (EMH) is one of the central hypotheses in financial theory. In efficient markets, all relevant information about stocks is free and available for all rational investors. Therefore, the stock prices already contain and fully reflect all available and relevant information (Shleifer, 2000). There are different forms of market efficiency based on the degree of information that is available. The mainly observed and examined form is the weak form of market efficiency, which claims that all past, historical information about prices is reflected in today's price [Fama (1991), Gilson and Kraakman (1984)].

The EMH excludes the possibility for investors to outperform the market and earn extra profit since the same information is available for all investors. This way of earning excess profit is known in economic theory as arbitrage opportunity. Arbitrage is a way of making a profit by simultaneously buying and selling same or *similar* assets at different prices (Shleifer and Vishny, 1997). This is possible only if markets are inefficient as the prices of same or similar asset deviate from each other and this difference can be exploited.

How is the EMH linked to cointegration? A simple example of a plausible cointegrating relation is between the spot and future price of an asset. The only difference between these two prices is in the timing of the payment and delivery, but they are both prices for the same asset. If these prices start to differ from each other due to new information in the market, an arbitrage opportunity would occur. Rational investors will exploit this opportunity to earn extra profit and this will briefly bring the prices back to equilibrium again. Hence markets where arbitrage is possible could be cointegrated (Dwyer and Wallace, 1992).

Due to this, testing for cointegration is in many studies performed in order to test the efficient market hypothesis. Hakkio and Rush (1989) for instance, use cointegration methods to test for market efficiency between spot and future rates in Germany and United Kingdom.

Moreover, the definition of efficient markets in weak form is that, based on available information, it is not possible to predict future price movements. Price movements do not follow any trend or pattern. This unpredictable pattern of the price movement can be called a 'random walk'. However, cointegration implies that stock market indices follow the *same* common pattern in the long run (Richards, 1995). Thus any known fact about one stock price index should provide valuable information about the common trend between them. This will make it possible to predict the behavior of the stock prices in other countries (Hakkio and Rush, 1989).

In summary, stock market cointegration could *contradict* the weak-form market efficiency as the movements in one market can be used to predict movements in another market.

2.2.3 Arbitrage

As the stock markets are becoming more approachable for all investors over the world due to factors mentioned in 2.1, it can be easier to exploit mispricings in different markets. Due to increased integration of markets, investors now have better opportunities to simultaneously buy and sell assets if they believe that one market is underpricing the asset. This means that when the stock markets are closely linked, arbitrage opportunities could be more available and more easily exploited.

The concept of statistical arbitrage is based on cointegration. If prices of two assets move largely together (are cointegrated), it does not mean that they move in the s*ame* direction every trading day. The general idea is that the spread between the prices is mean-reverting – in the long-run manner, the spread always returns back to its mean value. Let us illustrate this with an example, where the prices of stock A and stock B cointegrate over the long-run. When the price of stock A increases relatively to the price of stock B, the strategy is to short-sell stock A and buy stock B. This is a typical example of statistical arbitrage based on cointegrated stock prices. When investors are then exploiting this chance, the deviating prices are pushed back to their equilibrium relation. When the price spread again returns to equilibrium, this strategy results in an excess profit. Every time the spread between the prices of stocks widens, an arbitrage opportunity occurs as investors can predict how the spread will behave in the long-run [Shleifer and Vishny (1997), Alexander (2001)].

An important distinction between correlated and cointegrated stock prices can be drawn here. If the prices constantly move in the same direction even in short periods as days, we say that they are correlated. There may never be a widening in the spread between them. Even if a spread occurs in some way, it will not return to its mean value as the stocks are not cointegrated in the long-run, but correlated. Thus there will be no arbitrage opportunity to exploit and no chance to earn extra profit.

Arbitrage opportunities are thus possible to find and exploit in cointegrated markets, but arbitrage is not unlimited. The definition of arbitrage does not take into account that such an opportunity is highly risky and requires capital. Economists believe that identical assets must be traded at identical prices because of the effects of arbitrage pushing them back to equilibrium. However, this is not the case when irrational investors are present in the market. A good example of differing prices is the case of American Depositary Receipts (ADR). They represent securities of a foreign stock trading in the US stock market, so they are actually identical assets. Still, the ADR have different prices in the USA than the original stocks have in their local markets (Shleifer, 2000).

The theory of limits of arbitrage could explain why prices of equal or similar assets differ. The model consists of rational investors (arbitrageurs) and irrational investors (noise traders). A rational investor is faced with additional risk when irrational investors are present in the market - the non-fundamental, noise trader risk. It is the risk that irrational noise traders will become more extreme, making the difference between prices even worse. In that case, the spread between the prices will not return to equilibrium and rational investors will loose on their investment (De Long et al. 1990).

The risk of this happening makes the rational investors more careful when it comes to exploiting arbitrage. Therefore the very important effects of arbitrage in pushing the prices back to equilibrium are limited and prolonged. A direct consequence is that prices of equal assets may differ and not be cointegrated as we would expect them to be.

Based on our discussion about arbitrage and investment strategies, examining cointegration between stocks and stock markets can be useful for the international investor in many ways. Yet, the very general idea is that existing cointegration between stock markets will imply that arbitrage opportunities are available by strategically investing in these markets. On the other hand, non-cointegration between stock markets will mean opportunities for international diversification of portfolios and possibilities for risk hedging.

3. Empirical background

3.1 Stationarity/Non-stationarity

It is important to distinguish between stationary and non-stationary time series, as well as weak and strict stationarity. This is relevant for cointegration analysis between stock markets, as we expect stock prices to be non-stationary (Richards, 1995).

A time series is considered strictly stationary if the probability distribution of its values does not change over time (Brooks, 2008):

$$f(y_t, y_{t+1}, ..., y_T) = f(y_{t+k}, y_{t+1+k}, ..., y_{T+k}) \quad (0.1)$$

The concept of strict stationarity implies that all higher-order moments are constant, including mean and variance. However, strict stationary time series are rarely found in practice. Therefore we will focus on *weakly stationary processes* in our further analysis. Conditions and assumptions of weakly stationary processes are sufficient to be regarded as stationary. A time series is considered weakly stationary when mean, variance and autocovariance are constant over time (Enders, 2008).

On the other hand, the properties of non-stationary time series change over time. For this type of time series, mean and variance have different values at different time-points. Its variance will increase as sample size goes toward infinity (Harris and Sollis, 2003).

There are several reasons why it is important to distinguish between stationary and non-stationary series. We will show this by using a simple autoregressive (AR) process:

$$y_t = \mu + \rho y_{t-1} + u_t \quad (0.2)$$

where the current value of variable *y* depends on the constant term μ, value of the variable y from last period *t-1* and an error term u_t. It is the value of ρ that we are particularly interested in, because it will indicate whether the process is stationary or non-stationary. There are three possible cases that could occur, or three possible values of ρ (Brooks, 2008):

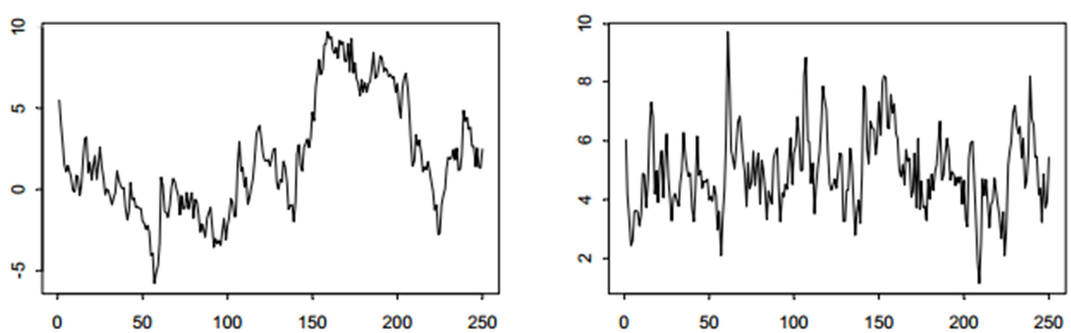
1. $|\rho| < 1$; a shock to the system in current time period t is temporary; it will die away over time and this series is **stationary** – it has constant mean, variance and autocovariance. A stationary time series will return to its mean value in the long run ('Mean reversion').

2. $\rho = 1$; a shock in time period t will not die away over time, it will be permanent. Its variance will approach infinity over time. This time series is regarded **non-stationary**, better known as the unit root case – the variable y contains a unit root.

3. $\rho > 1$; a shock in time period t will explode over time and this sort of time series is also **non-stationary.** There is no mean reversion to its true value over time.

The best way to understand this concept is to show it graphically. Figure 1a) plots a non-stationary I(1) process with non-zero mean ($\rho = 1$) and Figure 1b) shows a stationary process where $|\rho| < 1$.

<u>Figure 1</u>: Stationary / Non-stationary process[2]



a) Non-stationary I(1) process b) Stationary I(0) process

Using a model with non-stationary variables can lead to false interpretation of the results. The standard ordinary least squares[3] (OLS) estimation method of a model with non-stationary variables will give misleading results, also known as spurious regression results (Granger and Newbold, 1984). Spurious regression results show a relation between two independent,

[2] Brooks (2008)
[3] OLS is a method used for estimation of unknown coefficients in a regression model. It minimizes the sum of squared residuals to fit a function of data (Brooks, 2008).

random variables, based on high value of the coefficient of determination[4] R^2. In reality there is no meaningful economic relationship between these variables, while the coefficient R^2 shows otherwise. The t-ratios do not follow the t-distribution, meaning that standard theory of inference cannot be used.

A stationary variable is integrated of order 0, denoted $y_t \sim I(0)$, while non-stationary variables are integrated of order d, where $d \geq 1$: $y_t \sim I(d)$. In the rest of the thesis, only values d = 0 and d = 1 will be considered.

Non-stationary variables can be transformed into stationary variables by taking the difference one or more times[5]. If a time series contains one unit root (the time series is integrated of order one) then taking the difference once will make the time series variable stationary. Analogous to that, taking the difference d-times from a non-stationary variable that contains *d* unit roots (integrated of order d), will transform this variable to a stationary variable.

3.2 Concept of cointegration

The concept of cointegration has its roots in the work of Engle and Granger (1987). Two variables are cointegrated if they share a common stochastic trend in the long-run.

The general rule when combining two integrated variables is that their combination will always be integrated at the higher of the two orders of integration. The most common order of integration in time series is either zero or one (Brooks, 2008);

1.) if $y_t \sim I(0)$, and $x_t \sim I(0)$, then their combination ($ax_t + by_t$) will also be I(0),
2.) if $y_t \sim I(0)$, and $x_t \sim I(1)$, then their combination ($ax_t + by_t$) will now be I(1), because I(1) is higher order of integration and dominates the lower order of integration I(0),
3.) if $y_t \sim I(1)$, and $x_t \sim I(1)$, then their combination ($ax_t + by_t$) will also be I(1), in the general case.

However, if there exists such linear combination of non-stationary variables I(1) that is stationary, I(0), cointegration between those variables exists .

[4] Coefficient of determination shows the goodness of fit of a regression. It shows how much of the variation in the dependent variable is explained by the independent variable(s) (Enders, 2008)
[5] The proof can be found in Enders, 2008.

The following regression model includes two I(1) non-stationary variables y_t and x_t:

$$y_t = \mu + \beta x_t + u_t \tag{0.3}$$

If the OLS estimate β is such that the linear combination of y_t and x_t stationary, these two variables are cointegrated. The error term between them is then constant over time (stationary):

$$u_t = y_t - \beta x_t \tag{0.4}$$

In order for two variables to be cointegrated they need to be integrated of the same order. For example if one variable is I(0) and the other one is I(1), they cannot be cointegrated. The highest order of integration of the two variables will dominate and cointegration will not exist.

Stock market indices, which are the focus of this research are usually characterized as non-stationary I(1) variables (Bollerslev, Chou and Kroner, 1992) However, if there is a linear combination of the stock indices that is stationary, cointegration between them exists.

4. Data

This chapter describes the data that is used for tests for stationarity, cointegration and other econometric methods. In this thesis the focus is on five stock markets: USA, Norway, Sweden, Denmark and Finland. The time period of the analysis is from February 1993 to February 2013. Monthly data is used, creating 240 observations. This sample period is divided into two subsamples to check the consistency of the results and methods. The national stock price indices are collected for each of these stock markets using the Thomson Reuters DataStream database. By using price indices, dividends are excluded from this analysis. All series are expressed in terms of local currencies. For level series, all stock indices are converted into natural logarithms to smooth the financial data. In order to get monthly returns, first differences of log stock indices are taken.

The original thought was to take an even longer sample period to examine cointegration, since it is a long-run concept. By increasing the length of the sample period, tests would be more powerful and provide better discrimination among hypotheses. However, increasing the frequency by choosing weekly or daily observations in comparison to monthly observations in the same sample period would not contribute to more exact results. A large number of observations due to a longer time period rather than high frequency of data captures the cointegrating relation more efficiently (Hakkio and Rush, 1991).

The sample period of twenty years is chosen mostly because of restricted access to data further back in time. Another contribution for choosing this time period in this thesis is because it is well-known from literature that deregulations and liberalizations of stock market, as well as the informational boom that influenced comovement of stock markets, did not happen before the middle of the 1980s. The stock markets could also previously have been cointegrated, but these circumstances made a significant contribution to the cointegration between them [Corhay et al. (1993), Phengpis and Apilado (2004)].

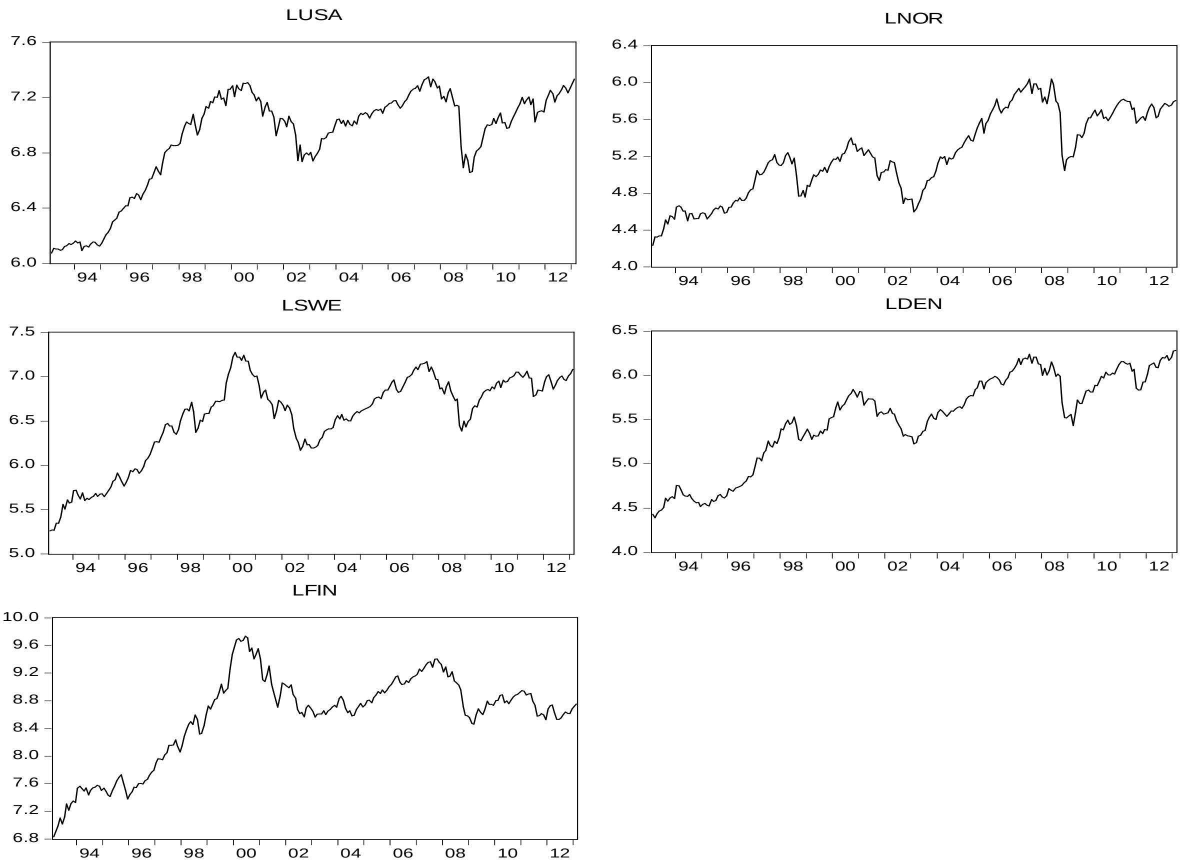
The following national price indices present the stock market data used in our analysis:

- the S&P 500 index for the U.S. market
- the OBX Price Index for Norway
- the OMX Stockholm 30 Index (OMXS30) for Sweden

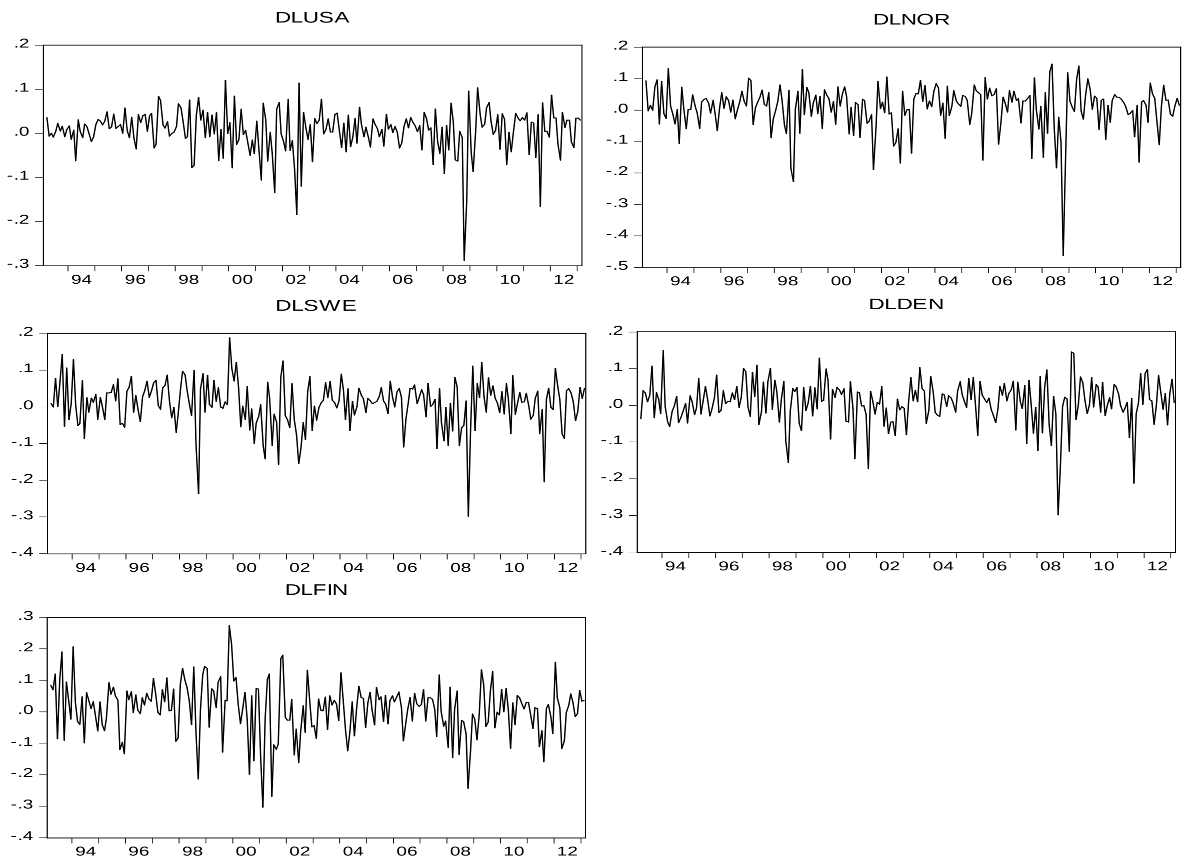
- the OMX Copenhagen 20 Index (OMXC20) for Denmark
- the OMX Helsinki 25 Index (OMXH25) for Finland

Stock market indices are generally good examples of *I(1)* series (Bollerslev et.al, 1992). Although only statistical tests can provide proof, a graphical representation can give some indication about the time series properties of the stock market indices. Figure 2 represents the levels of the stock market indices for each market, while the first differences of the logs (monthly returns) are presented in Figure 3.

<u>Figure 2:</u> Stock markets in log-levels



<u>Figure 3:</u> Stock markets in first differences (returns)



Visual inspection of Figure 2 indicates non-stationarity of the series in levels, with a tendency to drift upwards over time. Stock indices for Norway and Denmark seem to have similar behavior during the sample period, but it is not unusual that visual inspection of figures is completely misleading when it comes to cointegration analysis. A solid drop can be noticed in all figures around year 2008 and 2009, referring to the global financial crisis during these years which obviously had an impact on the analyzed stock markets as well. By looking at Figure 3, returns seem to be oscillating around the zero mean. ‘Mean reversion’ is common to return series which entails that they eventually tend to move back towards their mean. The strongest oscillations can be noticed around year 2008 in this figure as well.

The return series from Figure 3 indicate zero mean without any upward or downward trend, suggesting that they could be stationary. The stock indices in levels from Figure 2 indicate non-stationarity.

The suggestion is that stationarity can possibly be achieved when taking first differences of the logs of these indices. This is a visual indication that stock market indices in levels could be non-stationary *I(1)* processes, while taking the first differences transforms them into stationary variables. However, formal statistic tests for stationarity need to be performed.

Table 1 contains basic descriptive statistics for the first difference in log levels of these five indices. Highest average return in the sample period is detected in the Finnish stock market, while the lowest is in the US market. According to the standard deviation values, Finland has also the most volatile return, followed by Norway. By looking at Figure 2 that shows the price index from Oslo Stock Exchange, strong oscillations can be noticed for the Finnish stock market which indicates a high volatility. From excess kurtosis values, we notice that first differences in log price indices have a highly non-normal distribution. The negative numbers of skewness show that stock index returns have a left-skewed distribution, indicating that there are relatively few low values. Mass of the distribution is on the right side of the distribution figure.

Table 1: Descriptive statistics for monthly returns (Feb 1993 – Feb 2013)

	DLUSA	DLNOR	DLSWE	DLDEN	DLFIN
Mean	0,005250	0,006560	0,007610	0,007714	0,008006
Median	0,011307	0,018500	0,013656	0,011037	0,020273
Maximum	0,119906	0,146680	0,188461	0,148999	0,274402
Minimum	-0,288490	-0,462991	-0,297831	-0,298270	-0,303907
Std.Dev.	0,049173	0,070779	0,063057	0,058803	0,083116
Skewness	-1,5666	-1,8755	-0,982184	-1,064026	-0,44763
Kurtosis	6,1197	11,01215	5,9057	6,64699	4,25246

Note: DLUSA is a variable name which shows that the first difference has been taken of the logs, in order to get monthly returns. This is true for DLNOR, DLSWE, DLDEN and DLFIN as well.

Table 2 shows simple correlation coefficients between returns from these five stock markets. Generally, the correlation coefficient can have values from -1 to +1. A coefficient more close to 1 means relatively strong correlation between variables. All coefficient values from Table 2 show mostly strong, positive correlation between national stock indices, where the correlation with value of 77,59% between Sweden and Finland appears to be the strongest one. The weakest correlation among these markets is between Denmark and Finland, only 58,1%. However, all of the markets indicate high mutual interdependence.

Table 2: Correlation matrix, monthly returns

	DLUSA	DLNOR	DLSWE	DLDEN	DLFIN
DLUSA	1,0000	-	-	-	-
DLNOR	0,742606	1,0000	-	-	-
DLSWE	0,729137	0,764841	1,0000	-	-
DLDEN	0,653075	0,770528	0,716926	1,0000	-
DLFIN	0,605948	0,606462	0,775859	0,580999	1,0000

Note: All correlations are statistically significant at the 5% and 1% level.

5. Methodology

5.1 Testing for stationarity

After discussing the concept of stationarity, the next step is to show how stationarity can be tested. Many empirical papers concerning cointegration start with using either DF test or Phillips-Perron test[6] for stationarity of the original stock market data [Kasa (1992), Richards (1995), Chen et al. (2002)].

We test whether there are one or more unit roots in the data - whether the individual series are *I(1).* As stated earlier, performing such tests at the beginning of any analysis is necessary because of the possibility of getting misleading results if non-stationary variables are included. There are various ways to test for stationarity, but the most commonly used test is the Dickey-Fuller test (DF) (Dickey and Fuller, 1979). To show how this test works, we start with the simplest case, using an AR(1) model, which was introduced in chapter 3.1:

$$y_t = \beta y_{t-1} + u_t \tag{2.1}$$

where u_t is the error term - a white noise process.[7]
By differentiating the equation above once, we obtain:

$$y_t - y_{t-1} = \beta y_{t-1} - y_{t-1} + u_t \tag{2.2}$$

or

$$\Delta y_t = \rho y_{t-1} + u_t \tag{2.3}$$

where $\rho = (\beta\text{-}1)$. The DF test tests the value of ρ; if $|\rho| < 1$, variable y is stationary. Since $\rho = (\beta\text{-}1)$, the restriction on ρ being less than 1 implies that also β, the coefficient at the lagged value of variable y, is less than 1. In this case, the time series will be stationary.

[6] Phillips–Perron (PP) test is similar to the DF test, but here a correction is implemented to the DF procedure allowing for autocorrelated residuals. The DF tests perform better than the PP tests in small samples (Davidson and MacKinnon, 2001).
[7] The error term is a white noise process if it has a zero mean, constant variance and zero autocovariances (Brooks, 2008).

The hypotheses that we want to test with a Dickey-Fuller test are:

$$\begin{aligned} &H_0 : \rho = 0 \qquad\qquad (\beta = 1) \\ &H_A : |\rho| < 1 \qquad\qquad (\beta < 0) \end{aligned} \tag{2.4}$$

The null hypothesis H_0 claims that the time series is non-stationary and contains at least one unit root. Performing the DF test on levels reveals whether the time series is stationary or not; whether *at least* one unit root is included or not. Performing the same test on first differences will help us to determine the order of integration. In order to test for cointegration, as previously stated in chapter 3.2, variables have to be integrated of the same order.

The null hypothesis is tested against the alternative hypothesis H_A, which states that the time series is stationary. An OLS procedure has to be performed on the equation (4.3) in order to get the estimated value for coefficient ρ.

The test statistics used in a DF test for stationarity is (Brooks, 2008):

$$test\ statistic = \frac{\hat{\rho}}{SE(\hat{\rho})} \tag{2.5}$$

where $\hat{\rho}$ is the OLS estimated coefficient, and $SE(\hat{\rho})$is the standard error of $\hat{\rho}$. The test statistics does not follow a normal distribution, neither the usual t-distribution, but rather a non-standard 'Dickey-Fuller' distribution, skewed to the left (Dickey and Fuller, 1979). Therefore, the critical values used for comparison with the computed test statistics are special DF critical values. These values are much larger in absolute values than the standard critical values from t-distribution. This implies that the null hypothesis in a DF test is harder to reject, than for a standard *t*-test. The null hypothesis is rejected whenever the test statistic is higher in absolute terms than the DF critical value.

There are several practical issues that have to be considered before performing the DF test for stationarity. One of them is whether to include deterministic terms as intercept and linear trend into the basic equation (4.3). This decision is important since it implies different critical values, depending on which deterministic terms are included. There are three possible options to model the equation (4.3) (Enders, 2008):

1. A model with no intercept and no trend
2. A model with an intercept, but no trend
3. A model with an intercept and a linear trend

The test procedure is the same regardless of the chosen model, but the DF critical values are different for each model. Tables can be found in Davidson and Mackinnon (2001).

It is important to determine which model to use before proceeding with testing, because adding irrelevant terms into the equation will increase the DF critical values in absolute terms and make the null hypothesis harder to reject. Harris and Sollis (2003) suggest examining the figures of the series. A constant should be included if the plot of the data does not start from zero, as can be observed in Figure 2. A trend should be added if the plot of the data shows an upward or downward trend.

Another practical issue is that the DF test presented above is valid only if the error term u_t is a white noise process; $u_t \sim IID\ (0,\sigma^2)$, but in most financial series this is not the case. When there is autocorrelation in the dependent variable Δy_t, the error term will also be autocorrelated, because the omitted lags of Δy_t will be a part of it. To control for the possible autocorrelation, the basic equation for this test (4.3) has to be expanded with p lags of the dependent variable Δy_t (Enders, 2008):

$$\Delta y_t = \rho y_{t-1} + \sum\nolimits_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \tag{2.6}$$

By including lags of the dependent variable, its potential autocorrelation is absorbed, the error term is a white noise process and usual DF test statistics and critical values can be used. This test is known as the Augmented Dickey-Fuller (ADF) test and will be used further in the cointegration analysis of the included stock markets, to ensure that the error terms are white noise processes. The hypotheses, test statistics and DF critical values are exactly the same as for the simple DF test.

Expanding the basic equation with lags of the dependent variable also leads to the issue of the number of lags to include. Including too few lags can result in some of the autocorrelation to remain in the model. On the other hand, choosing too many lags will unnecessarily use up degrees of freedom and thus reduce the power of the test (Cheung and Lai, 1995). There are various methods to choose the optimal number of lags. Such methods include different information criterion which will be discussed later. For the ADF test, the Akaike information criterion (AIC) will be used. The number of lags that minimizes the AIC value is the optimal lag length, where AIC is:

$$AIC = \log\left|\hat{\Sigma}\right| + \frac{2k}{T} \tag{2.7}$$

where $\widehat{\sum}$ is the variance-covariance matrix of residuals, T is the number observations and k is the number of coefficients in equation (Davidson and MacKinnon, 2001).

5.2 Testing for cointegration

Cointegration tests should reveal whether the stock markets move together over a longer time period. There are several methods to test for cointegration between two or more variables (Engle and Granger, 1987). First it is important to distinguish between the univariate and the multivariate approach:

The univariate approach to cointegration implies a pairwise analysis of the five stock market indices. The Engle-Granger single-equation method is applied to perform pairwise analysis of the stock indices presented in chapter 4. It allows only for one endogenous and one exogenous variable. We will also apply the Johansen method for pairwise cointegration to check the consistency of the results achieved with the Engle-Granger method (Kühl, 2010).

The multivariate approach to cointegration tests whether there is cointegration in a system of more than two variables. The Johansen method is widely used to perform this analysis (Juselius, 2006). It improves some of the drawbacks with the Engle-Granger method (Brooks, 2008), which will be discussed later. The Johansen method allows for all variables to be endogenous and makes it possible to determine all cointegrating relationships between the stock markets. Both methods will be explained in details in this chapter.

5.2.1 The Engle-Granger test

The Engle-Granger test is a single-equation method used to determine whether there is a cointegrating relationship between two variables (Engle and Granger, 1987). The precondition to examine cointegration is that the variables are both non-stationary and integrated of the same order. The Engle-Granger (EG) method can be performed by following the next four-step procedure:

Step 1: Perform the ADF test as explained in chapter 5.1 to pretest for the order of integration. If the variables are both I(1), cointegration is theoretically possible and we can proceed to step 2. If the variables are of different order, the conclusion is that cointegration is not possible as explained in chapter 3.2.

Step 2: Estimate the long-run, static relationship or equilibrium by running the OLS regression on the general equation:

$$y_t = \beta x_t + u_t \tag{2.8}$$

This equation can be expanded with a constant term or a constant term and a time trend, but this issue will be discussed later. If the variables are cointegrated, an OLS regression will give a "super-consistent" estimator, denoted as $\hat{\beta}$, implying that the coefficient β will converge faster to its true value than using OLS on stationary variables, *I(0)* (Dolado et al, 1990). If there is a linear combination of variables y_t and x_t that is stationary, the variables are said to be cointegrated. This linear combination of the variables can then be presented with the estimated error term $\hat{u}_t$:

$$\hat{u}_t = y_t - \hat{\beta} x_t \tag{2.9}$$

Step 3: Store the residuals $\hat{u}_t$ and examine whether they are stationary or not. Here an ADF test, as explained earlier, is performed on the saved residuals from every regression [equation (2.3)]. The hypotheses for the EG test for cointegration are:

$$\begin{aligned} &\mathrm{H}_0 : \hat{u}_t \sim I(1) \quad \text{- non-stationary residual and no cointegration between variables} \\ &\mathrm{H}_\mathrm{A} : \hat{u}_t \sim I(0) \quad \text{- stationary residual and cointegration between variables} \end{aligned} \tag{2.10}$$

If the null hypothesis is rejected, the variables from the model are cointegrated. The test statistics is the same as the one used for the ADF test, but the critical values are different. Since the Engle-Granger method includes testing on estimated residuals $\hat{u}_t$ instead of the actual values, the estimation error will change the distribution of the test statistics. Therefore the critical values used in an Engle-Granger approach will be larger in absolute value, or more negative compared to those used in a DF or ADF test. This means that the magnitude of the test statistics must be much larger in order to reject the null hypothesis, compared to the usual DF critical values. Davidson and Mackinnon (2001) provide appropriate critical values for residual-based cointegration testing, depending on whether and which deterministic terms are included in the model.

Step 4: If cointegration is found between the variables, estimate an error-correction model. However, this will not be part of our analysis, since we are interested only in detecting cointegration.

Drawbacks with the Engle-Granger method

The Engle-Granger cointegration test is very popular mostly because it is easy to estimate the regression using OLS and the error correction model provides valuable information about the speed of adjustment to equilibrium. Therefore it is often used when testing for pairwise cointegration [Richards (1995), Jang and Sul (2003)].

However, there are several problems with this method. One of the drawbacks with using OLS regression in general is that it can identify *only one* cointegrating vector even when there are many variables in the system (Dolado et al., 1991). On the other hand, the Johansen method makes it possible to detect *all* cointegrating relationship in a system of variables.

Other problems with the EG tests are linked to the usual small sample problems and unit root testing (Harris and Sollis, 2003):

- Lack of power in stationarity tests, which is a typical ADF test problem
- Standard inference cannot be used, as the included variables are non-stationary
- Potentially biased results, which usually occurs if a variable that belongs to the model is omitted from the regression

Also, a challenge that usually arises is whether to include deterministic terms into the model. Including unnecessary terms can lower the power of the test (Harris and Sollis, 2003). Generally, including a time trend in the ADF test on residuals, will result in loss of power or to be more specific, will lead to under-rejecting the null hypothesis of no cointegration when it is false.

5.2.2 The Johansen method

There could be more than one cointegrating vector in a system of variables and the Johansen method can discover all such cointegrating relations [Juselius (2006), Johansen and Juselius (1990), Kasa (1992)]. The Johansen method relies on a vector autoregression (VAR) model. A VAR is a system regression model which includes more than one dependent variable. Every variable is regressed on a combination of its own lagged values and lagged values of other variables from the system. Here, the simplest form is presented, where *k* denotes the number of lags included (Brooks, 2008):

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_k y_{t-k} + u_t \tag{2.11}$$

To use the Johansen test, the VAR model needs to be transformed into a vector error correction model (VECM), by differentiating:

$$\Delta y_t = \prod y_{t-k} + \Gamma_1 + \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + ... + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \tag{2.12}$$

where there are *g* variables in the model and *k-1* lags of the dependent variables. Γ is the coefficient matrix for every lagged variable and Π is the long-run coefficient matrix.

This VECM is estimated by Maximum Likelihood[8] estimation process, not OLS estimation as for the Engle-Granger method. The Johansen test is a multivariate case of an ADF test for unit root. The focus in this method is on the Π matrix - we test the rank (r) of this matrix. The rank is equal to the number of characteristic roots (eigenvalues, denoted λ), that are significantly different from zero. That means that the rank (r) will give us the number of cointegrating vectors in a system of variables.

There are three possible cases, based on the rank of the Π matrix (Johansen and Juselius, 1990):

- *full rank (r = g)* - all eigenvalues are significantly different from zero, implying that the original variables are stationary and therefore cointegration is not possible.

[8] Explanation of the maximum likelihood estimation procedure can be found in Johansen and Juselius (1990).

- *rank is zero (r = 0)* – none of the eigenvalues are significantly different from zero, implying that there are no linear combinations of variables that are I(0), and thus no cointegration.

- *reduced rank* (0 < r < g) – there are *r* linear combinations of variables that are I(0), meaning that cointegration exists in this system, with *r* cointegrating vectors.

For example, if g > 2 and resulting $r = 2$, there are two linear combinations of non-stationary variables that are stationary, or two cointegrating vectors in the model.

In the Johansen method, two tests are used to detect cointegration and the number of cointegrating vectors *r* (Enders, 2008):

1. The Trace test:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g} \ln(1-\hat{\lambda}_i) \qquad (2.13)$$

The null hypothesis of *r* or less than *r* cointegrating vectors is tested against the alternative of more than *r* cointegrating vectors.

2. The Maximum eigenvalue test (the Max test):

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \qquad (2.14)$$

The null hypothesis of exactly *r* cointegrating vectors is tested against the alternative of *r+1* cointegrating vectors.

r is the number of cointegrating vectors, $\hat{\lambda}_{\mathrm{i}}$ is the estimated eigenvalue of order *i* from the Π matrix, and T is the number of observations. The distribution of the two test statistics is not standard and the critical values depend on the value of ($g - r$) and the deterministic terms included (Johansen and Juselius, 1990). If the test statistics is larger than the appropriate critical value, the null hypothesis of no cointegration is rejected.

If we detect a reduced rank and we find cointegration with *r* cointegrating vectors, the Π matrix can be defined as a product of two matrices:

$$\prod = \alpha\beta' \qquad (2.15)$$

where α is a *(g x r)* matrix and β is a *(r x g)* matrix. The β matrix shows the cointegrating vectors while the matrix α shows the amount of each cointegrating vector in the VECM, or the adjustment coefficients.

The critical values of the Johansen method are sensitive to the lag length and the number of deterministic terms in the VECM. Therefore it is important to choose the optimal lag length and whether a constant term and/or a time trend should be included. This will be discussed in the model specification in chapter 6.3.

5.3 Granger causality test

Cointegration indicates existence of a long-run relationship between variables. Even when the variables are not cointegrated in the long-run, they might still be related in the short-run. In order to understand short-run interdependence among stock markets, Granger causality tests will be performed.

Granger causality test is based on a standard F-test which seeks to determine if changes in one variable cause changes in another variable. A variable X is said to 'Granger cause' variable Y, if the previous values of X could predict the current value of Y. Let us start with a simple VAR model:

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_k y_{t-k} + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_q x_{t-q} + u_t \qquad (2.16)$$

If all α - coefficients on lagged values of X are significant in this equation, then 'X Granger causes Y'. If X Granger causes Y and not vice versa, it is called unidirectional causality. If the causality goes both ways from X to Y and from Y to X, then this is called bidirectional causality (Brooks, 2008).

After estimating the VAR, restrictions are imposed and the following hypotheses are tested in a Granger causality test:

$$\begin{array}{ll} H_0: \alpha_1 = \alpha_2 = \ldots = \alpha_p = 0 & (\text{"X does not Granger cause Y"}) \\ H_A: \text{at least one of } \alpha\text{-coefficients} \neq 0 & (\text{"X does Granger cause Y"}) \end{array} \qquad (2.17)$$

The test statistic follows a χ^2 distribution, with p degrees of freedom under the null hypothesis. p is the optimal number of lags.

The term 'causality' should not be wrongly interpreted – it does not mean that changes in one variable cause changes in the other variable. It simply means that there is a correlation between the current value of one variable and the previous values of another variable.
We will use Granger causality tests to examine the lead-lag relationships among stock markets.

However, these tests can only provide information of whether a significant impact exists between stock markets, but nothing about the sign of the impact or how long it will last. An impulse response analysis could give us answers regarding this, but as cointegration between the stock markets is the focus of this thesis, we will leave this as a suggestion for further research.

6. Empirical results

6.1 ADF stationarity tests

A requirement for cointegration is that the stock markets are integrated of the same order. The visual impression from the figures in chapter 4 is that the stock markets are all integrated of order one, since their first differences appear to be integrated of order zero. However, the ADF test, described in 5.1 will be used to formally test for stationarity and order of integration.

The optimal lag length must be selected for each stock market index. This is a precondition for performing the ADF test. The Akaike information criteria (AIC) will be used to select the lagged terms by using a regular t-test. As suggested by Brooks (2008), we start with 12 lags since the data is monthly. The optimal number of lags is the one that minimizes the value of the Akaike information criterion.

The null hypothesis is non-stationarity in series, while the alternative hypothesis is stationarity. The null hypothesis of non-stationarity is rejected in favor of the alternative hypothesis, if the test statistics is more negative than the critical values. The optimal lag lengths as well as the ADF test results obtained from the software package EViews are presented in Table 3:

Table 3: ADF test results (log-levels, Feb 1993 – Feb 2013)

Stock market	Number of lags	Test statistics ADF (constant)	Test statistics ADF (constant + trend)
LUSA	0	-2,024	-1,907
LNOR	1	-1,784	-2,820
LSWE	1	-2,436	-2,394
LDEN	5	-1,533	-2,820
LFIN	1	-2,603	-2,012

Note: A constant term and/or a trend are included, as some of the series indicated a trend but this is not absolutely obvious from the figures in chapter 4. A constant should be included anyways, as the plots of data do not begin from the origin. Hence, the ADF test was performed for these two cases.

When only a constant is included, the critical Dickey-Fuller (DF) values are -3,46 and -2,88 at 1% and 5% significance level, respectively (Davidson and Mackinnon, 2001). When a constant and trend are included, the critical DF values are -3,99 (1%) and -3,42 (5%). The table shows that none of the test statistics are larger than the critical values in absolute value in order to reject the null hypothesis. Therefore, the null hypothesis of non-stationarity cannot be rejected. The stock market indices contain a unit root and are considered non-stationary.

As the ADF test is sensitive to the chosen lag length, a sensitivity analysis was performed for different lag lengths. The test results showed no sensitivity to the chosen, optimal lag length. If we increase or reduce the lag length, the results will still show non-stationarity of stock markets.

An ADF test on first differences is additionally performed to determine the order of integration of the stock markets as they have to be integrated of the same order to perform cointegration tests. If the ADF results show stationarity, *I(0)*, for the first differences, this will imply that stock market indices in levels are integrated of order one, *I(1).* Again, the null-hypothesis of non-stationarity (unit root) is tested against the alternative hypothesis of stationarity. The results are presented in Table 4.

Table 4: ADF test results (first differences, Feb 1993 – Feb 2013)

Stock market	**Number of lags**	**Test statistics ADF (constant)**
DLUSA	0	-15,961 **
DLNOR	0	-13,467 **
DLSWE	0	-13,425 **
DLDEN	0	-14,285 **
DLFIN	0	-12,641**

Note: Only a constant term is included, as the plots of data for returns (Figure 3) do not show an upward or downward trend. (*) denotes rejection of the null hypothesis at 5% significance level, and (**) at 1% significance level.

The critical values are the same: -3,46 and -2,88 at 1% and 5% significance level respectively. All of these test statistics are also larger in absolute value than the critical values, and the null-hypothesis of non-stationarity is rejected at all significance levels. The first differences of stock market indices seem therefore to be stationary, *I(0).* The same results are obtained for two sub-samples and the results are shown in Appendix A.

Since differentiating the stock indices once converts them into stationary variables, the conclusion is that stock markets are initially integrated of order one, *I(1).*This finding confirms the results of many other studies. Although there is little consensus concerning the cointegration between stock markets, almost every study confirms that stock markets are non-stationary I(1) variables, including Kasa (1992), Richards (1995) and Pynnönen and Knif (1998) for the Scandinavian markets. Cointegration is hence theoretically possible and we can perform the cointegration tests.

6.2 The Engle–Granger pairwise test

Using the Engle-Granger test for cointegration, a pairwise analysis of the five stock markets can be performed as described in chapter 5.2.1. We will test whether a linear combination of two stock market indices is stationary. If it is found to be stationary, the two stock markets are cointegrated. Table 5 presents the results from this test obtained by using EViews.
The equation (2.8) is formulated for every pair of stock markets. As an example, the first pair from the table LNOR – LUSA can be used. A constant term is included in the regression and OLS is used for its estimation:

$$LNOR_t = \beta_0 + \beta_1 LUSA_t + u_t \tag{3.1}$$

Ten possible pairs of stock markets are formulated. From the table, the first variable in every pair is the dependent one, while the second is the independent variable. In the pair LNOR – LUSA for example, the Norwegian stock market index is the dependent variable (*Y*), while the US market is the independent variable (*X*). Table 5 shows the estimated values of the constant term β_0 and the coefficient on the independent variable β_1 for each market pair.

An ADF test is performed on the saved residuals from every regression, where the hypotheses for the Engle-Granger cointegration test are:

$$
\begin{aligned}
&H_0 : \hat{u}_t \sim I(1) \quad -\text{non-stationary residual; no cointegration between stock markets} \\
&H_A : \hat{u}_t \sim I(0) \quad -\text{stationary residual; cointegration between stock markets}
\end{aligned} \tag{3.2}
$$

The optimal lag lengths chosen by the AIC as well as test results are shown in Table 5 for every pair of market.

<u>Table 5:</u> Regressions and Engle-Granger test for cointegration (Feb 1993 – Feb 2013)

Pair	Constant β_0	Coefficient β_1	Number of lags	ADF test statistics (on residuals)
LNOR – LUSA	-1,898031	1,029637	4	-1,356464
LSWE – LUSA	-2,417344	1,296199	3	**-3,223982 +**
LDEN – LUSA	-3,611066	1,320097	3	-1,346232
LFIN – LUSA	-2,834791	1,649799	0	-2,094409
LSWE – LNOR	1,630582	0,940994	1	-2,280216
LDEN – LNOR	-0,141671	1,083538	0	-2,132605
LFIN – LNOR	3,094888	1,048671	1	-1,607205
LFIN – LSWE	0,537029	1,227686	2	-0,744119
LDEN – LFIN	-0,452743	0,696251	11	-0,979091
LDEN - LSWE	-1,074423	1,007010	0	-1,911824

Note: Only constant is included, in ADF tests on residuals, as the plots of the residuals showed no trend.
+ rejection of the null hypothesis at 10% significance level

When only a constant is included, the EG critical values are -4,00, -3,37 and -3,07 at 1%, 5% and 10% significance level, respectively (Davidson and Mackinnon, 2001).

Based on the regression coefficients, in order to have cointegration, the constant term β_0 needs to be close to 0, while the coefficient β_1 should be close to 1. It is easy to notice that none of the coefficients from the table have these required values, except of the pair Denmark – Norway.

The results from Table 5 indicate cointegration between Sweden and USA at 10% significance level. The ADF test statistics of -3,224 is larger in absolute value than the critical value of -3,04. The coefficient estimate β_1 indicates that if the US stock market increase by 1%, then the Swedish stock market will increase by 1,29%. However, the null hypothesis of no cointegration is rejected only at 10% significance level, which is not a very strong proof of cointegration. At more strict significance levels like 5% or 1%, no cointegration is found between Sweden and USA. This result is not sensitive to the chosen lag length. Random lag lengths from 1 to 12 were tested and cointegration between Sweden and USA is still found at 10% significance level.

For the other pairs, the ADF test statistics are below the critical values, so we fail to reject the null hypothesis of a unit root in the residuals. The residuals are *I(1)*.The graphs for the residuals are presented in Appendix B, indicating that they are non-stationary processes.

This pairwise analysis shows no cointegration between the other pairs of stock markets in the full sample from February 1993 to February 2013. There is no long-run relationship between stock markets and equation (3.1) is spurious, without any economic meaning. This is quite surprising, as the stock index figures showed similar patterns, for instance between Denmark and Norway.

However, when deterministic terms are excluded from the regressions, the conclusions about cointegration are quite different. For several pairs, the null hypothesis of no cointegration is rejected at 5% and 10% significance level. Since it is essential for the outcome of the tests whether deterministic terms are included in the model or not, a standard t-test is used to test the statistical significance of the constant in every regression. The test statistics were various but in every case statistically significant. This means that constant terms need to be included in the ADF equations.

We will now look at the Engle–Granger test results from two subsamples, before making a conclusion about pairwise cointegration.

6.2.1 Test for cointegration in subsamples

The full sample period from February 1993 to February 2013 is divided into two subsamples to check the consistency and stability of the results:

- Subsample 1; from February 1993 to February 2002
- Subsample 2; from March 2002 to February 2013

The results for the two subsample periods are presented in Table 6 and 7. The test procedure is identical; the only difference with regards to the full sample test is that the critical values are slightly higher in absolute values as the number of observations is smaller.

Table 6: Regressions and Engle-Granger test for cointegration (Feb 1993 – Feb 2002)

Pair	Constant $\hat{\beta}_0$	Coefficient $\hat{\beta}_1$	Number of lags	ADF test on residuals
LNOR – LUSA	0,741700	0,616270	9	**-3,4483 ***
LSWE – LUSA	-2,21598	1,264128	3	**-3,3176 +**
LDEN – LUSA	-1,63746	1,003960	8	**-3,0793 +**
LFIN – LUSA	0,67125	0,213261	0	-1,9101
LSWE – LNOR	-2,44878	1,787256	0	-2,1093
LDEN – LNOR	-1,97671	1,451046	0	-2,3239
LFIN – LNOR	-3,53932	2,412186	0	-1,5906
LFIN – LSWE	-0,60223	1,408294	11	-1,2989
LDEN – LFIN	0,70037	0,535002	6	-2,6428
LDEN - LSWE	0,18419	0,784353	0	-1,6449

**rejection of the null hypothesis at 1% significance level
* rejection of the null hypothesis at 5% significance level
\+ rejection of the null hypothesis at 10% significance level
Critical values: -4,01 (1%), -3,39 (5%) and -3,04 (10%).

Table 7: Regressions and Engle-Granger test for cointegration (Mar 2002 – Feb 2013)

Pair	Constant β_0	Coefficient β_1	Number of lags	ADF test on residuals
LNOR – LUSA	-7,63509	1,85705	0	-2,0197
LSWE – LUSA	-2,60316	1,32412	0	-1,7887
LDEN – LUSA	-4,59262	1,47643	3	-1,8309
LFIN – LUSA	2,30733	0,92389	0	-1,0537
LSWE – LNOR	2,96787	0,68990	0	**-3,2741 +**
LDEN – LNOR	1,81473	0,73367	0	-1,9580
LFIN – LNOR	6,58123	0,41099	0	-1,8454
LFIN – LSWE	5,33359	0,51872	0	-1,3566
LDEN – LFIN	-0,02072	0,663702	0	-2,3647
LDEN - LSWE	-1,10250	1,02809	5	**-3,1687 +**

Note: Only a constant is included in every ADF equation, as the plots of the saved residuals did not indicate a trend.
**rejection of the null hypothesis at 1% significance level
* rejection of the null hypothesis at 5% significance level
\+ rejection of the null hypothesis at 10% significance level
Critical values: -4,01 (1%), -3,39 (5%) and -3,04 (10%).

Dividing the full sample into two subsamples, the results become more various. In subsample 1, we find proof for cointegration between Norway and USA at 5% significance level. Also, USA seems to be cointegrated with Denmark and Sweden at 10% significance level. At the downside, the results are extremely sensitive to the lag length, probably because this is a small sample with only 109 observations. The ADF test has a tendency to under-reject the null hypothesis when it is false and to over-reject it when it is true in small samples (Harris and Sollis, 2003). The AIC chosen lag length for Denmark – USA is 8. If we try to select the lag length of 7 or 9 lags in the ADF regression, we find no cointegration between Denmark and USA. A similar outcome is detected for the pair Sweden – USA. The pair Norway – USA shows cointegration for higher lags as well and it is in some degree robust to different lag lengths, probably because cointegration is found at a higher significance level. This cointegrating relationship appears to be more stable. For the rest of the pairs in subsample 1, the null hypothesis of no cointegration cannot be rejected.

In subsample 2, Sweden – Norway and Denmark – Sweden seem to be cointegrated at 10% significance level. No cointegration is detected at 5% level. However, these pairs show strong sensitivity to the chosen lag length. The reason is once again probably the small sample size of 132 observations, which will strengthen the negative sides of an ADF test.

The results from 1990s show stronger cointegration of the Nordic countries with USA which is not detected in the past 10 years. In 2000s, Sweden indicates some cointegration to Norway and Denmark, but the evidence for this is neither strong nor stable over time.

The general conclusion based on Engle - Granger cointegration test is that Sweden and USA show a weak cointegration relationship at 10% significance level. This was stronger in the 1990s than in the 2000s. This is consistent with the findings by Knif and Pynnönen (1999), who also detected cointegration between the US and Swedish stock market using data from 1990s. However, before taking any strong conclusion, we have to keep in mind that this detected cointegrating relationship is weak and not stable over the two subsamples. We will verify these results using a Johansen pairwise cointegration test.

6.3 Formulating the VAR model for the Johansen test

The test results of the Johansen method are affected by the selected lag length in the model and the included deterministic terms. We will now show how to formulate a VAR model and determine this before performing the Johansen test.

6.3.1 The optimal lag length

Two common procedures can be used to determine the optimal lag length (Enders, 2008):

1. Likelihood ratio (LR) test
2. Using an information criterion

A likelihood ratio test implies estimating an unrestricted VAR. One should begin with the longest lag length that seems reasonable and then test if it can be shortened. The null hypothesis is that the coefficients on this highest lag are jointly zero. If rejected, that lag is the optimal one. If we fail to reject, we continue to the next lag length, until the null hypothesis is rejected. Enders (2008) provides the test statistic for every lag length:

$$LR = (T - c)(\log|\Sigma r| - \log|\Sigma u|) \tag{3.3}$$

where $\sum$ denotes the variance–covariance matrix of residuals for the restricted model (r) and for the unrestricted model (u), T is the sample size and c is the number of parameters in the unrestricted model. The test statistics has a χ^2 distribution with degrees of freedom equal to the number of coefficient restrictions.

The LR test requires that the errors from each equation are normally distributed (Brooks, 2008). However, this is not likely to hold for stock market data, as the descriptive statistics in Table 1 showed. Therefore, a suggestion is to concentrate on an information criterion when selecting the lag length.

We are familiar with the information criterion process, as it was used to determine the lag length for the ADF stationarity test. The Akaike information criterion was presented in chapter 5.1, but since this is an important matter for the Johansen test, the other information criteria will also be presented here (Brooks, 2008):

1. Schwarz - Bayesian criterion (SC): $$SC = \log|\hat{\Sigma}| + \frac{k}{T}\log T \tag{3.4}$$
2. Hannan – Quinn criterion (HQ): $$HQ = \log|\hat{\Sigma}| + \frac{2k}{T}\log(\log T) \tag{3.5}$$
3. Akaike criterion (AIC): $$AIC = \log|\hat{\Sigma}| + \frac{2k}{T} \tag{3.6}$$

where $\hat{\sum}$ is the variance – covariance matrix of residuals, T is the number of observations and k is the number of parameters in all equations.

The values of the criteria are calculated for different lags from 0 to k lags, and the optimal number of lags is the one that minimizes the value of the information criteria.
Monte Carlo studies showed that the Schwarz–Bayesian (SC) criterion could be the better selection criterion to use than the AIC when dealing with small samples (Koehler and Murphree, 1988). We will therefore focus on this criterion when selecting lag length for the Johansen test.

6.3.2 Deterministic terms – the Pantula principle

After choosing the appropriate lag length, the next step is to specify which deterministic terms will be included in the VECM or in the cointegrating relation; a constant term and/or a trend. Based on the deterministic terms included in the model, Harris and Sollis (2003) suggest the following models:

- **Model 1**: There are no deterministic terms in the data or in the cointegrating relations. There is little or almost no possibility that this model is the optimal one, as the constant term is usually necessary to account for different units of measurement of the variables.
- **Model 2:** Only a restricted constant term is included in the cointegrating relation, implying that the equilibrium mean is not zero. There are no linear trends in the levels of data, which implies that the returns as first-differenced data have zero means.
- **Model 3**: Two constant terms are included; in the short-run model and in the cointegrating relation, which are combined to form only an unrestricted constant term in the short-run model. There are no linear trends included. This model should be used if all trends seem to be stochastic (Juselius, 2006).
- **Model 4**: There is a linear trend (restricted) in the cointegrating relation, but no trend in the VECM. This model should be chosen if we believe some of the variables are trend-stationary in levels.
- **Model 5:** Linear trends are present both in the cointegrating relation and in the model. Similar as for model 1, this case occurs rarely in practice.

Since models 1 and 5 are not likely to occur often in practice, we will consider only models 2 – 4 as possible (Juselius, 2006). It is not easy to decide which model to use in the Johansen method and this must be done carefully. Critical values and the asymptotic distribution of the cointegration test will depend on the chosen model. If the model is not specified well, the results can be misleading and biased.

One possibility is to look at the figures of stock indices in levels and in returns, but this will only provide an indication. Juselius (2006) suggests the Pantula principle to choose the appropriate model. The idea behind this principle is to first estimate the VAR model for the three plausible cases. The results should be ordered from the most restrictive case (model 2), to the least restrictive case (model 4). Starting from the most restrictive model, we compare the test statistics for that model with the critical values. If we fail to reject the null hypothesis of a unit root, we can stop the process there. If we reject the null hypothesis, we move on to the next most restrictive model and so on until the null hypothesis is not rejected. First non-rejection of the null hypothesis indicates the appropriate model for the data. It is possible to use the Pantula principle in EViews and let the software package determine which of the five models is appropriate to use and which deterministic terms should enter the model.

Enders (2008) suggests the use of an intercept term outside the cointegrating relation to capture the effects of an increasing or decreasing tendency of variables. A suggestion is also to avoid including a trend term unless there is a good reason to do so.

6.4 Testing pairwise cointegration using the Johansen method

Although the Johansen method is best known as a multivariate approach to cointegration testing, it can also be used to test for cointegration between a pair of variables (Johansen, 1991). The results can also be used to check the consistency with the Engle - Granger test results. All variables are in log-levels. The pairs of stock markets are the same as in the Engle-Granger procedure. A VAR model is formulated for every pair of markets.

The optimal lag length for each pair will be determined first. Table 8 shows the Schwarz – Bayesian lag length criterion considering up to 5 lags and estimating a VAR for each lag length.

Table 8: The selection of lag length for pairwise analysis using SC

Pair	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
LNOR - LUSA	**-6,3296 ***	-6,3019	-6,2256	-6,1769	-6,1328
LSWE – LUSA	**-6,5796 ***	-6,5517	-6,4720	-6,4079	-6,3397
LDEN - LUSA	**-6,4897 ***	-6,4619	-6,4173	-6,3653	-6,2894
LFIN – LUSA	-5,7307	**-5,7345 ***	-5,6482	-5,5648	-5,4786
LSWE – LNOR	**-5,9273 ***	-5,9103	-5,8218	-5,7520	-5,6619
LDEN – LNOR	**-6,0957 ***	-6,0288	-5,9474	-5,8687	-5,7850

LFIN – LNOR	-4,9499	**-4,9637 ***	-4,8831	-4,8055	-4,7179
LFIN – LSWE	**-5,6719 ***	-5,6429	-5,5769	-5,5058	-5,4342
LDEN – LFIN	**-5,2786 ***	-5,2653	-5,1820	-5,1191	-5,0334
LDEN – LSWE	**-6,1791 ***	-6,1293	-6,0612	-6,0011	-5,9111

*indicated lag order selection by SC information criterion

SC clearly indicates the use of 1 lag for most of the pairs of stock markets. Exceptions are Finland – USA and Finland - Norway with 2 as the optimal lag length. The other information criteria such as the Akaike and Hannan – Quinn criterion were evaluated as well. HQ did not seem to differ much from the SC chosen lag length, but AIC suggested higher lags than 1 and 2. As mentioned earlier, this information criterion tends to overfit the model, so the SC suggested lag length will be used.

The deterministic terms that will be included in the VECM are specified by applying the Pantula principle, which performs a joint test for cointegration and deterministic terms. A VAR with the chosen lag length is estimated for model 2, 3 and 4. The testing starts with the most restrictive model, which is model 2, and move rightwards to the least restrictive model; model 4. Using EViews, Trace and Max test statistics are obtained for model 2 and we compare them to the given critical values. The first time we reject the null hypothesis indicates the correct model to use. This test will show us which model fits the data best, but also which model detects cointegration.

The results from this joint test are presented in Table 9, with the test statistics for every model and the critical values in brackets. The results show no cointegration between any of the pairs. For every pair the test statistics is lower than the critical value so the null hypothesis of no cointegration cannot be rejected. This is valid both for the Trace and Max test.

<u>Table 9:</u> Joint test for pairwise cointegration and deterministic terms (full sample)

Pairs	No. of coint. vector	Model 2		Model 3		Model 4	
		Trace statistics (critical value)	Max statistics (critical value)	Trace statistics (critical value)	Max statistics (critical value)	Trace statistics (critical value)	Max statistics (critical value)
LNOR - LUSA	None	**8,89**(20,3)	**6,97**(15,9)	**6,18**(15,5)	**4,28**(14,3)	**11,15**(25,9)	**8,23**(19,4)
	At most 1	**1,91**(9,16)	**1,91**(9,16)	**1,91**(3,8)	**1,91**(3,84)	**2,93**(12,5)	**2,93**(12,5)
LSWE – LUSA	None	**15,2**(20,3)	**9,80**(15,9)	**12,3**(15,5)	**8,67**(14,3)	**14,17**(25,9)	**10,40**(19,4)
	At most 1	**5,46**(9,16)	**5,46**(9,16)	**3,70**(3,8)	**3,70**(3,84)	**3,77**(12,5)	**3,77**(12,5)
LDEN - LUSA	None	**11,4**(20,3)	**7,49**(15,9)	**7,66**(15,5)	**4,41**(14,3)	**17,38**(25,9)	**13,33**(19,4)
	At most 1	**3,87**(9,16)	**3,87**(9,16)	**3,24(**3,8)	**3,24**(3,84)	**4,05(**12,5)	**4,05**(12,5)
LFIN – LUSA	None	**16,7**(20,3)	**14,7**(15,9)	**13,9**(15,5)	**12,7**(14,3)	**18,7** (25,9)	**13,74**(19,4)
	At most 1	**1,98**(9,16)	**1,98**(9,16)	**1,25**(3,8)	**1,25**(3,84)	**4,96**(12,5)	**4,96**(12,5)
LSWE – LNOR	None	**13,6**(20,3)	**9,92**(15,9)	**10,9**(15,5)	**7,49**(14,3)	**15,61**(25,9)	**9,26**(19,4)
	At most 1	**3,71**(9,16)	**3,71**(9,16)	**3,36**(3,8)	**3,36**(3,84)	**6,36**(12,5)	**6,36(**12,5)
LDEN – LNOR	None	**13,8**(20,3)	**8,77**(15,9)	**9,79**(15,5)	**7,24**(14,3)	**14,35**(25,9)	**9,28**(19,4)
	At most 1	**5,05**(9,16)	**5,05**(9,16)	**2,55**(3,8)	**2,55**(3,84)	**5,07**(12,5)	**5,07**(12,5)
LFIN – LNOR	None	**9,66**(20,3)	**8,07**(15,9)	**7,90**(15,5)	**6,57**(14,3)	**15,7** (25,9)	**9,08** (19,4)
	At most 1	**1,59**(9,16)	**1,59**(9,16)	**1,33**(3,84)	**1,33**(3,84)	**6,57**(12,5)	**6,57**(12,5)
LFIN – LSWE	None	**13,1**(20,3)	**11,5**(15,9)	**10,5**(15,5)	**9,22**(14,3)	**18,27**(25,9)	**9,33**(19,4)
	At most 1	**1,66**(9,16)	**1,66**(9,16)	**1,25**(3,8)	**1,25**(3,8)	**8,94**(12,5)	**8,94**(12,5)
LDEN – LFIN	None	**10,9**(20,3)	**8,56**(15,9)	**7,25**(15,5)	**6,74**(14,3)	**16,5**(25,9)	**10,8**(19,4)
	At most 1	**2,34**(9,16)	**2,34**(9,16)	**0,51**(3,8)	**0,51**(3,8)	**5,70**(12,5)	**5,70**(12,5)

LDEN – LSWE	None	**18,6**(20,3)	**11,2**(15,9)	**14,7**(15,5)	**11,2**(14,3)	**22,83**(25,9)	**11,67**(19,4)
	At most 1	**7,39**(9,16)	**7,39**(9,16)	**3,55**(3,84)	**3,55**(3,84)	**11,17**(12,5)	**11,17**(12,5)

*denotes rejection of the hypothesis at 5% significance level

The results from Table 9 indicate that model 2 fits the stock market data best. Let us demonstrate this for the first pair, Norway – USA. The Pantula principle suggests starting with model 2. The test statistics is 8,89 which is less than the critical value 20,3 at 5% significance level. The null hypothesis of no cointegration cannot be rejected and this is the first non-rejection of the null. Therefore we do not continue to the next model, but rather conclude that model 2 is appropriate for the Johansen test. The same thing can be concluded for every pair.

The Johansen test results in Table 9 from the full sample do not detect the cointegrating relation found between Sweden and USA in Engle–Granger testing. However, the Johansen test in EViews uses 5% significance level and these values are valid at that level. We remember that Sweden and USA showed cointegration at 10% significance level in the Engle – Granger testing, but not at 5%. It was also detected that this relation was no consistent over the two subsample periods.

There is no strong evidence of cointegration between any of the pairs of stock markets, when the full sample from Feb 1993 to Feb 2013 is considered. The investors could theoretically diversify their portfolios and achieve gains from diversification by investing in these pairs of stock markets.

Subsamples

We will now test for cointegration in the two subsamples. The EG results indicated cointegration between some pairs of markets in the subsamples and we will see whether the Johansen method will detect the same cointegrating relations. The lag lengths and the appropriate model used for the full sample in the previous section are valid for the subsamples as well. The results of the Johansen test for subsample 1 are presented in Table 10.

<u>Table 10:</u> Pairwise cointegration using Johansen method (subsample 1)

Pair	Number of cointegrating vectors	Trace	Max
LNOR – LUSA	None *	**20,36** (20,26) *****	**15,98** (15,89) *****
	At most 1	**4,44** (9,16)	**4,44** (9,16)
LSWE – LUSA	None	**19,55** (20,26)	**16,05** (15,89) *
	At most 1	**3,50** (9,16)	**3,50** (9,16)
LDEN – LUSA	None *	**20,66** (20,26) *	**18,89** (15,89) *****
	At most 1	**1,77** (3,84)	**1,77** (3,84)
LFIN – LUSA	None	**19,70** (20,26)	**18,28** (15,89)*
	At most 1	**1,42** (9,16)	**1,42** (9,16)
LSWE – LNOR	None	**13,31** (20,26)	**8,81** (15,89)
	At most 1	**4,50** (9,16)	**4,50** (9,16)
LDEN – LNOR	None *	**23,31** (20,26) *****	**18,22** (15,89) *****
	At most 1	**5,10** (9,16)	**5,10** (9,16)
LFIN – LNOR	None	**9,74** (20,26)	**6,37** (15,89)
	At most 1	**3,37** (9,16)	**3,37** (9,16)
LFIN – LSWE	None	**11,23** (20,26)	**7,77** (15,89)
	At most 1	**3,47** (9,16)	**3,47** (9,16)
LDEN – LFIN	None	**11,39** (20,26)	**7,22** (15,89)
	At most 1	**4,17** (9,16)	**4,17** (9,16)
LDEN – LSWE	None	**19,46** (20,26)	**13,87** (15,89)
	At most 1	**5,59** (9,16)	**5,59** (9,16)

***** denotes rejection of the null hypothesis at 5% significance level
Model 2 is used for all pairs. Number of observations is 109.

Cointegration is suggested for several pairs of markets. In subsample 1, which includes the period from February 1993 to February 2002, cointegration is detected for:

- Norway – USA
- Denmark – USA
- Denmark – Norway

The indication is that there is one cointegrating vector in each of these 4 pairs at 5% significance level. Both Trace and Max test confirm this conclusion. Denmark is pairwise cointegrated with USA and Norway, while Norway is also pairwise cointegrated with USA. The null hypothesis was not rejected for any of these pairs. If this happened, it would indicate two cointegrating vectors (full rank), and the original stock market variables would be stationary.

Comparing the results from subsample 1 to the ones from EG testing, similar cointegrating pairs are found. Cointegration between Norway and USA at 5% significance level is confirmed by both methods. It is interesting that the pair Sweden – USA seems to be cointegrated according to the Max test, but not to the Trace test. In small samples, it is not rare to get different conclusions for these two tests. However, Juselius (2006) claims that the power of the Trace test is larger than the one for the Max test, which means the Trace test results could be more reliable. With the EG method, we found cointegration between Sweden and USA, but only at 10% significance level. Although the results for 10% level are not reported here, the Johansen method shows cointegration between them at 10% level as well.

Denmark and USA are cointegrated at 10% significance level according to the EG method, but the Johansen test shows that this cointegrating relation is more stable (5%).

<u>Table 11:</u> Pairwise cointegration using Johansen method (subsample 2)

Pair	Number of cointegrating vectors	Trace	Max
LNOR – LUSA	None	**6,07** (20,26)	**4,25** (15,89)
	At most 1	**2,82** (9,16)	**2,82** (9,16)
LSWE – LUSA	None	**7,40** (20,26)	**4,90** (15,89)
	At most 1	**2,50** (9,16)	**2,50** (9,16)
LDEN – LUSA	None	**10,71** (20,26)	**8,43** (15,89)
	At most 1	**2,28** (9,16)	**2,28** (9,16)
LFIN – LUSA	None	**7,08** (20,26)	**5,68** (15,89)
	At most 1	**1,40** (9,16)	**1,40** (9,16)

LSWE – LNOR	None	**12,94** (20,26)	**8,69** (15,89)
	At most 1	**4,24** (9,16)	**4,24** (9,16)
LDEN – LNOR	None	**7,08** (20,26)	**4,85** (15,89)
	At most 1	**2,23** (9,16)	**2,23** (9,16)
LFIN – LNOR	None	**7,50** (20,26)	**5,04** (15,89)
	At most 1	**2,46** (9,16)	**2,46** (9,16)
LFIN – LSWE	None	**10,16** (20,26)	**8,57** (15,89)
	At most 1	**1,59** (9,16)	**1,59** (9,16)
LDEN – LFIN	None	**9,42** (20,26)	**7,53** (15,89)
	At most 1	**1,89** (9,16)	**1,89** (9,16)
LDEN – LSWE	None *	**21,08** (20,26) *	**16,32** (15,89) *
	At most 1	**2,07** (9,16)	**2,07** (9,16)

*denotes rejection of the null hypothesis at 5% significance level.
Note: Model 2 is used. Number of observations is 132.

In subsample 2 (period March 2002 – February 2013) the only cointegrating pair we find at 5% significance level is Denmark – Sweden, which confirms the same result from EG testing. However, at the same level, no cointegration is detected between Sweden and Norway, while EG test found this relation. We will now examine cointegration for these two pairs as EG test suggested, but only at 10% significance level. The results are shown in Table 12.

<u>Table 12:</u> Pairwise cointegration at 10% significance level (subsample 2)

Pair	**Number of cointegrating vectors**	**Trace**	**Max**
LSWE – LNOR	None *	**15,31** (13,43) *	**13,75** (12,30) *
	At most 1	**1,55** (2,71)	**1,55** (2,71)
LDEN – LSWE	None *	**18,09** (13,43) *	**16,32** (12,30) *
	At most 1	**1,77** (2,71)	**1,77** (2,71)

* denotes rejection of the null hypothesis at 10% significance level

We see that both Trace and Max test confirm cointegration between Sweden – Norway and Denmark – Sweden at 10% significance level during the 2000s. These are the same results as in the EG tests. The null hypothesis of at most one cointegrating vector is rejected for all pairs. This suggests one cointegrating relation in every pair. Again, this is confirmed by both Trace and Max test at 10% significance level. The other pairs do not show cointegration in subsample 2 at 5% or 10% level.

Cointegration between Sweden - Norway and Denmark – Sweden was detected in period 2002 – 2013, but not before that or in the full sample. This could suggest that these pairs have become cointegrated over the past 10 years. Subsample 2 gives us some interesting results. It makes sense that the Scandinavian stock markets show more cointegration in the 2000s, as their financial interdependence deepened during these years, when they became a part of OMX Group. For both subsamples, the Johansen method confirms most of the results of the EG results at least at 10% level of significance. This indicates consistency of the used methods to some degree.

However, a downside is that all these potential cointegrating pairs are extremely sensitive to the chosen lag length, except Denmark – USA in the first subsample. This is not unusual when dealing with small samples. When interpreting these results, we have to keep in mind that the samples are very small, only 109 and 132 observations, respectively. Choosing higher frequency of data (daily or weekly) is not very helpful, as we discussed earlier in chapter 4.

The general conclusion about pairwise cointegration between these stock markets is that no stable cointegrating relation is found. Neither method managed to detect a stable cointegrating relation over the full sample period. However, there are some indications about pairwise cointegration between the mentioned Nordic stock markets in the past 10 years. This finding confirms the results of Zhang (2012) where using a short sample period from 2001 to 2011 showed that Scandinavian stock markets are cointegrated to some extent in 2000s, but not before.

6.5 The Johansen multivariate test

6.5.1 Lag length selection

After performing the pairwise analysis of stock markets, we will now consider the markets of USA, Norway, Sweden, Denmark and Finland as a system. We will examine whether there is cointegration between these five stock markets together using the Johansen method once again.

A VAR model will be formulated with all five markets together. We will determine the optimal lag length of the model, as the Johansen test is sensitive to this. Since there are many restrictions on LR test, only the information criteria used to choose the lag length will be presented here. A VAR model was estimated for every lag from 1 to 6. Three different information criteria are reported for each VAR. Table 13 presents the results.

Table 13: **Lag length selection (full sample)**

	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)	VAR(6)
AIC	-17,065	**-17,099***	-17,087	-17,065	-16,967	-16,888
HQ	**-16,886***	-16,773	-16,612	-16,442	-16,196	-15,968
SC	**-16,623***	-16,289	-15,909	-15,519	-15,053	-14,606

*denotes indicated lag order by different information criteria

In the multivariate approach, the AIC suggests two lags, while the HQ and SC suggest only one lag. In general, Juselius (2006) recommends the use of two lags when dealing with a system of variables. In the Juselius example, the information criteria also indicated using only one lag, but it is argued for the use of rather two lags as a starting point, because even in small samples, two lags can cover a very rich dynamic structure. We will follow this example in our analysis, and use the lag length of 2 for the system of five stock markets.

6.5.2 Deterministic terms

The same joint test for cointegration and deterministic terms as described in chapter 6.3.2 will be performed for the system of stock markets.

All three plausible models are estimated with a lag length of 2 and the results are presented in Table 14 and 15 from the most restrictive alternative (model 2) to the least restrictive (model 4). We move from model 2 to model 4, until the null hypothesis cannot be rejected. As in any test, we compare the test statistics with the critical value. There can be at most four cointegrating vectors in the model, as there are five variables (stock markets) included in the

VAR. The results for the Trace test are shown in Table 14, and those for the Max test are in Table 15. The critical values are given in brackets.

Beginning with model 2, the Trace test statistics is 63,78 which is less than the critical value 76,97 at 5% significance level. This means that we cannot reject the null hypothesis of no cointegrating vectors. This is the first time that the null hypothesis cannot be rejected and we will therefore conclude that model 2 is the best model to describe the given data. The Max test confirms this result.

Table 14: Trace test for cointegration and deterministic terms (full sample)

Number of cointegrating vectors	Model 2	Model 3	Model 4
None	**63,78** (76,97) *	**58,90** (69,82)	**80,99** (88,80)
At most 1	**35,44** (54,08)	**33,33** (47,86)	**52,19** (63,88)
At most 2	**19,53** (35,19)	**17,74** (29,80)	**29,54** (42,92)
At most 3	**7,20** (20,26)	**5,44** (15,49)	**15,51** (25,87)
At most 4	**2,19** (9,16)	**0,60** (3,84)	**3,63** (12,52)

* denotes the first time the null hypothesis cannot be rejected.
Lag length of 2 is used.
Endogenous variables are LUSA, LNOR, LSWE, LDEN and LFIN.

Table 15: Max test for cointegration and deterministic terms (full sample)

Number of cointegrating vectors	Model 2	Model 3	Model 4
None	**28,34** (34,81)*	**25,58** (33,88)	**28,80** (38,33)
At most 1	**15,91** (28,59)	**15,59** (27,58)	**22,65** (32,12)
At most 2	**12,33** (22,30)	**12,30** (21,13)	**14,03** (25,82)
At most 3	**5,01** (15,89)	**4,84** (14,26)	**11,89** (19,39)
At most 4	**2,19** (9,16)	**0,60** (3,84)	**3,63** (12,52)

* denotes the first time the null hypothesis cannot be rejected.
Lag length of 2 is used. Endogenous variables are LUSA, LNOR, LSWE, LDEN and LFIN.

The results from Table 14 and 15 suggest that there is no cointegrating vector in the system. This assumes that we have specified the right model and used the optimal lag length. We will check how sensitive these results are to the chosen lag length and model. All five models will be considered, as well as a lag length up to 6. The maximum lag length of 6 is chosen as Enders (2008) suggests starting with a lag length of approximately $T^{1/3}$ where T is the number of observations, which is 241 in our analysis. Table 16 shows the number of cointegrating vectors in the system.

Table 16: Sensitivity analysis of cointegration results to selected lag length and model

	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length 1					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 2					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 3					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 4					
Trace	0	0	0	0	1
Max	0	0	0	0	0
Lag length 5					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 6					
Trace	0	0	0	0	1
Max	0	0	0	0	0

It is clear that no cointegration vectors are found for the system of stock markets, regardless of the assumptions made. The results are robust to the selected lag length as well as to the included deterministic terms.

Pynnönen and Knif (1998) suggest in their research to test the use of up to 12 lags in cointegration analysis. This was tested for the full system, however the results are not reported here but no cointegration was found even at very high lag lengths. Choosing the significance level of 10% did not change the results.

The conclusion is that when the stock markets of USA, Norway, Sweden, Denmark and Finland are all included in the VAR, no cointegration is detected among them in the full sample.

6.5.3 The Johansen multivariate test: Subsamples

The full sample will once again be divided into two subsamples to check the consistency of the results. So far the results did not show cointegration for the system of stock markets. The model formulation as well as the testing procedure is the same as for the full sample.

Subsample 1:

Table 17 shows the results from the Johansen multivariate test for subsample 1, containing 109 observations. Critical values are in brackets. We see that the Trace test suggests two cointegrating vectors in the system, while the Max test does not confirm this result, when lag length 2 is used. A sensitivity analysis of the model assumptions was performed and the numbers of cointegrating vectors for different models and lags are presented in Table 18.

<u>Table 17:</u> Trace and Max test for cointegration at 5% significance level (subsample 1)

Number of cointegrating vectors	Trace test statistics	Max test statistics
None*	**90,09** (76,97)*	**32,94** (34,81)
At most 1*	**57,15** (54,08)*	**23,60** (28,59)
At most 2	**33,55** (35,19)	**20,12** (22,30)
At most 3	**13,44** (20,26)	**9,85** (15,89)
At most 4	**3,58** (9,16)	**3,58** (9,16)

* rejection of the null hypothesis
Lag length of 2 is used. Endogenous variables are LUSA, LNOR, LSWE, LDEN and LFIN.

It is difficult to come to a conclusion based on this sensitivity analysis, as the numbers of cointegrating vectors are very various. This means that the results are very sensitive to chosen lag length, which is not unusual for cointegration analyses. Many cointegration studies such as those from Kasa (1991) and Ahlgren and Antell (2002) showed mixed results when concluding about the number of cointegrating vectors.

Table 18: Sensitivity analysis of cointegration results (subsample 1)

	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length 1					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 2					
Trace	1	2	3	0	0
Max	1	0	0	0	0
Lag length 3					
Trace	1	1	2	0	0
Max	1	1	0	0	0
Lag length 4					
Trace	2	3	5	2	3
Max	1	1	1	0	1
Lag length 5					
Trace	2	3	5	2	2
Max	1	2	1	0	0
Lag length 6					
Trace	2	5	5	2	2
Max	1	1	1	1	1

It is possible to observe from Table 18 that some models and lag lengths indicate no cointegrating vectors, while others indicate a full rank. Trace test for higher lag lengths suggests a full rank, meaning that the stock markets are stationary, which is not the case[9]. The results for one lag length suggest no cointegration. However, as mentioned earlier, Juselius (2006) argues against the use of only one lag in systems of variables as it cannot capture the dynamic structure well. We will therefore not pay much attention to this lag length.

Unlike the Trace test, the Max test results are quite robust to the main lag and model assumptions, indicating mostly one cointegrating relation.

From the results in Table 18, we can see that even in a small sample like this one, cointegration is found to some extent. It would probably be wrong to make a strong conclusion about two or three existing cointegrating vectors in the system, but the results

[9] This may be due to low power of cointegration tests or a misspecified VAR model.

indicate one for sure, when the optimal assumptions are considered. As stated, this is detected only for the period Feb 1993 – Feb 2002.

Subsample 2:

This subsample contains 132 observations and includes period from March 2002 to February 2013. Table 19 present the results from Johansen multivariate test in this sample period. Critical values are in brackets. There is no cointegrating relation in the system of stock markets, under the assumptions of 2 lags and model specification 2. The results from changing these assumptions are given in Table 20. Even for higher lags and different models, no evidence for cointegration is found in period 2002 – 2013.

Table 19: Trace and Max test for cointegration at 5% significance level (subsample 2)

Number of cointegrating vectors	Trace test statistics	Max test statistics
None	**50,96** (76,97)	**20,20** (34,81)
At most 1	**30,76** (54,08)	**15,80** (28,59)
At most 2	**14,95** (35,19)	**10,25** (22,30)
At most 3	**4,70** (20,26)	**3,54** (15,89)
At most 4	**1,16** (9,16)	**1,16** (9,16)

* rejection of the null hypothesis
Lag length of 2 is used. Endogenous variables are LUSA, LNOR, LSWE, LDEN and LFIN.

Table 20: Sensitivity analysis of cointegration results (subsample 2)

	Model 1	Model 2	Model 3	Model 4	Model 5
Lag length 1					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 2					
Trace	0	0	0	0	0
Max	0	0	0	0	0
Lag length 3					
Trace	0	0	0	0	0
Max	0	0	0	0	0

Lag length 4

Trace	0	0	0	0	0
Max	0	0	0	0	0

Lag length 5

Trace	0	0	0	0	0
Max	0	0	0	0	0

Lag length 6

Trace	1	1	1	2	2
Max	0	0	1	1	1

The general conclusion for the multivariate analysis of cointegration is that no stable cointegrating relation is detected between the five stock markets from Feb 1993 to Feb 2013. In other words, long – run equilibrium does not exist between them.

However, the results from the two subsamples are different – at least one cointegrating vector is found in period 1993 – 2002, while the later period shows no cointegration. The plots of the first potential cointegrating relations are shown in Appendix C for the full sample and for the two subsamples. The figures indicate non-stationarity, except the relation in subsample 1 which looks stationary to some degree.

Similar result of one cointegration vector existing among Nordic stock markets during the 1990s is found in the research of Mangeloja (2001). No cointegration was detected among the five stock markets in the recent 10 years, which is unusual concerning the constantly higher integration of stock markets around the world and in Scandinavia as well.

6.6 Granger causality analysis

In the long run, there is no cointegration between the US, Norwegian, Swedish, Danish and Finnish stock market. However, short-run relations among them could exist. We will try to detect short-term lead-lag relations among the five stock markets by using the Granger causality test. This causality test is also based on a VAR model. Since the results can be misleading when more than two variables are included, we will perform a pairwise causality analysis here. A requirement for the causality test is that the variables are stationary, so we have to use the first differenced data (monthly returns) in this test.

The general rule is that if cointegration is detected between two stock markets, then there must be Granger causality between them in at least one way. However, if there is causality in one or both ways between two stock markets, it does not have to mean that they are cointegrated (Granger, 1988). This could hopefully be a useful test for validity of our cointegration results.

Table 21 presents the results from the Granger causality test for the full sample. The decision whether to reject of not reject the null hypothesis is based on the p-values from the table.

<u>Table 21:</u> Granger causality test (Feb 1993 – Feb 2013)

Null hypothesis	**df**	**Chi-squared test statistic**	**p-value**	**Conclusion**
Norway does not Granger cause USA	5	3,7331	0,5884	
USA does not Granger cause Norway	5	7,0820	0,2146	
Sweden does not Granger cause USA	2	12,077	**0,0024***	SWE → USA
USA does not Granger cause Sweden	2	1,8545	0,3956	
Denmark does not Granger cause USA	4	3,9959	0,4066	
USA does not Granger cause Denmark	4	13,572	**0,0088***	USA → DEN
Finland does not Granger cause USA	2	10,812	**0,0045***	FIN → USA
USA does not Granger cause Finland	2	2,2833	0,3193	
Sweden does not Granger cause Norway	2	4,6899	0,0958	
Norway does not Granger cause Sweden	2	4,0507	0,1319	
Denmark does not Granger cause Norway	1	0,1662	0,6835	
Norway does not Granger cause Denmark	1	4,1056	**0,0427***	NOR → DEN
Finland does not Granger cause Norway	2	1,8527	0,3960	
Norway does not Granger cause Finland	2	4,3608	0,1130	
Finland does not Granger cause Sweden	2	5,7202	**0,0408***	FIN → SWE
Sweden does not Granger cause Finland	2	1,0660	0,5868	
Denmark does not Granger cause Finland	2	3,7983	0,1497	
Finland does not Granger cause Denmark	2	6,4241	0,3617	
Denmark does not Granger cause Sweden	2	3,5146	0,1725	
Sweden does not Granger cause Denmark	2	13,864	**0,0010***	SWE → DEN

*denotes significance at 5%. Note: The degrees of freedom are denoted df.

The conclusions from Granger causality tests at 5% significance level are:

- Finland 'Granger causes' USA and Sweden
- Sweden 'Granger causes' USA and Denmark
- Norway 'Granger causes' Denmark
- USA 'Granger causes' Denmark

No bidirectional Granger causality is found in the sample period, only unidirectional causality. As we can notice, more short-term relations are found between the analyzed stock markets than long-run. The results indicate that Finland and Sweden are the most influential markets in this sample, which is interesting given that the US market is present in the analysis.

The cointegration detected by the EG test between Sweden and USA is supported with the Granger causality test. This means that previous values of Sweden can be used to predict US stock market index. We would not expect the causality to go in the direction from, for example Finland or Sweden to USA, as it is not highly plausible that an investor from USA can predict movements in the US stock index by observing the movements in the Swedish or Finnish stock market and earn extra profit. Both markets are relatively small in order to predict changes in a large market as the US. However, causality is a purely statistical result and cannot say much about realistic economic relations.

Pynnönen and Knif (1998) surprisingly detected weak short – term causality from Finland to Sweden, which is consistent with our findings. This indicates that current value of Swedish stock market index is correlated to the past values of the Finnish stock index. However, because of the lack of cointegration between the markets, we cannot draw strong conclusions about predictability here. The predictive power of stock market returns depends on the volatility of returns as well and this has to be examined before making conclusions about predictability and violation of the weak form of market efficiency (Pesaran and Timmermann, 1995).

In the other cases, the absence of Granger causality implies that the short-run differences between the markets are sufficient for investors to achieve gains by portfolio diversification.

6.7 Misspecification tests

After estimating the VAR model, assumptions of its residuals should be checked. The assumption is that error terms are i.i.d. Gaussian random variables with zero mean and variance-covariance matrix $\sum$. Among many diagnostic tests, it is most important to check for normality, autocorrelation and heteroscedasticity (Juselius, 2006). We will also check the stability of the VAR model.

All of these diagnostic tests were performed in EViews and details about the procedures will not be explained here[10]. The summary of the performed tests is given in Table 22. The tests are performed for subsamples as well, since subsample 1 gave different results than the full sample.

Stability of the VAR model

The estimated VAR is stable if all roots have modulus smaller than 1. They will then lie inside the unit circle, and we can say that the VAR model is stable. Performing an AR roots test in EViews shows that all roots are inside the unit circle, and the VAR satisfies the stability condition. This is valid for both subsamples as well.

Normality of residuals

The null hypothesis is that the residuals are multivariate normal. We used the Jarque–Bera residual normality test (Johnston and Dinardo, 1997) and the results are presented in Table 22. The p-values in brackets indicate rejection of the null hypothesis of normality. The residuals are not normally distributed in any sample. In small samples non–normality is often a problem, as it takes a very large sample to get skewness and kurtosis asymptotically normal (Juselius, 2006). A quick look at the excess kurtosis and skewness values for the residuals indicates a left-skewed distribution with fat tails.

A possible solution to remove non-normality could be to re-specify the model; include dummy variables to account for reforms, crisis and any significant event that could affect the variables. This was also attempted by dividing the full sample in two parts, based on the global financial crisis and merging in Nordic stock markets in year 2008. The results are not reported here but the residual tests for those two subsamples did not indicate better results.

[10] Details about diagnostic tests are available in Johnston and Dinardo (1997).

Autocorrelation of residuals

The null hypothesis is no autocorrelation in residuals. Using the Portmanteau test, we can see if there is significant correlation left in the residuals. The reported Q-statistic is adjusted for small samples. Still the null is clearly rejected and autocorrelation is present in the residuals. Autocorrelation can come from a wrongly specified model or omission of some important variables (Brooks, 2008). It usually warns us that our model contains some unnecessary variables or that important variables are not included. As we are analyzing cointegration of all five stock markets, it is possible that some of them do not belong to the model. A suggestion is to use exclusion tests to check if one of the stock markets can be excluded from the model. Another possible solution to remove autocorrelation from the error term could be to add more variables to the model – include more than only 2 lags in the VAR. However, this did not seem to work for lags up to 8.

Heteroskedasticity

According to the p-values obtained from the White heteroskedasticity test, variances of the error terms are not constant. This implies that results of hypothesis tests could be wrong. To remove heteroskedasticity, Mackinnon and White (1985) suggest the use of a modified version of heteroskedasticity-consistent covariance matrix estimator - HC3, which performs well when the sample size is less than 250. As this option is not available for a cointegrating VAR model in software packages, we will not utilize this method in our research.

Table 22: Misspecification tests on residuals

	Test	Full sample	Subsample 1	Subsample 2
Stability	AR root test	Stable	Stable	Stable
Normality	Jarque – Bera	501,417 [0,0000]	42,261 [0,0000]	233,919 [0,0001]
Autocorrelation	Portmanteau	76,517 [0,0000]	73,402 [0,0000]	51,782 [0,0013]
Heteroskedasticity	White test	415,075 [0,000]	371,129 [0,0145]	385,786 [0,0006]

Juselius (2006) argues that cointegration tests are highly sensitive to autocorrelation and non-normality of residuals, as this can lead to over-rejecting the null hypothesis of no cointegration. Further, Juselius (2006) argues that heteroskedastic residuals are not such a big issue in the Johansen test. Unfortunately, diagnostic tests of our VAR model are not encouraging. None of the assumptions about the multivariate error term is fulfilled, which generally indicates a misspecified model. There is relevant information left in the residuals and we probably need to include more variables. These could be dummy variables to control for significant events during the sample period or simply including more lags on dependent variables. Selecting higher frequency of data is probably not a good solution, as the autocorrelation and non-normality tests could show even worse results. We tried to include up to 8 lags in the VAR model, which did not improve the diagnostic test results much. We will not estimate another VAR model, as it is rarely a good idea to include more lags than necessary and as two lags are usually enough to capture the dynamics. Specifying an over-parameterized VAR model is more harmful for the results than accepting autocorrelation to some degree (Juselius, 2006). However, interpretation of all cointegration results must be done with extra care.

7. Conclusion & further work

As the degree of economic interdependence deepens due to world-wide globalisation and financial liberalisation, it is important to examine the effects it has on the stock markets relations. In this research we examined long-run cointegration between the stock markets of USA, Norway, Sweden, Denmark and Finland. We also tested whether short-term relations between these markets exist.

The sample period from February 1993 to February 2013 was used. Price indices in local currencies were collected from every stock market and adjusted to fit the analysis. The figures showing the development of stock market indices indicated comovement between some countries. Before starting with cointegration testing, we pre-tested the stock market indices for stationarity using an ADF test. After confirming the indications that the stock markets are integrated of order one, long-run cointegration between pairs of stock markets was tested by using the Engle–Granger and the Johansen method. The latter method was also used to test for cointegration in a system of all five stock markets together. Further, Granger causality tests were performed to examine the short-run linkages between the markets.

As in many previous studies, the results of pairwise cointegration are mixed. The Engle-Granger test indicates cointegration between Sweden and USA. This could possibly indicate that there are reduced diversification opportunities when investing pairwise into these stock markets. The Johansen bivariate test did only confirm this for subsample 1 (Feb 1993 – Feb 2002). Therefore this detected cointegrating relation is very weak and we cannot make any strong conclusions. Other pairs of stock markets did not show cointegration over the full sample.

The full sample of 20 years was divided into two equal subsamples to check the consistency and stability of the results. Cointegration was then detected between more stock markets, but these results were very sensitive to the chosen lag length and hence weak and unstable.

The full system of all five stock markets together was also examined, but no proof for cointegration was found in the full sample. However, the Johansen test revealed at least one cointegrating vector between the five markets in the period from 1993 to 2002.

The specification of the VAR model used in the Johansen test was also examined, but the test results were not reassuring - the residuals were not i.i.d.Gaussian random error terms. This indicates that our model could be misspecified and give biased results.

In summary, although the financial integration of Scandinavian stock markets is more than obvious, there is little or no proof for cointegration between them in the past decade. The results reveal cointegration at earlier points in the sample from year 1993 to 2002, but not later. The reason for this lack of long-run relationship between them could be in some barriers remaining in the markets with regards to international investments or even behavioral-based reasons as preferring investments in the home market. Other reasons could be purely statistical, as true *economic* integration of stock markets does not mean their *statistical* integration, which we are examining in this analysis.

From the perspective of individual investors, the overall long-run analysis of cointegration implies that long-run benefits from portfolio diversification can be achieved by combining investments in the five stock markets of USA, Norway, Sweden, Denmark and Finland. The stock indices of these markets seem to move at separate patterns in the long run. As no stable cointegrating relation was detected, the weak-form market efficiency is not violated as the price movements across stock markets cannot be predicted in the long run. However, short-term analysis reveals return spillovers between several pairs of stock markets. This indicates that opportunities for diversification by investing in these pairs of market in the short run could probably be diminished.

This research could be expanded in the several ways. A longer time period could be examined for cointegration between the same stock markets. Also the stock markets could be tested for cointegration during a financial crisis as the markets usually tend to move together more closely during turbulent periods. Examining the volatility spillovers by formulating a GARCH – BEKK model can be a natural extension to our Granger causality analysis.

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Appendix A: ADF test results for subsamples

<u>Table 23:</u> ADF test results, log-levels (Feb 1993 – Feb 2002)

Stock market	Number of lags	Test statistics ADF (constant)	Test statistics ADF (constant + trend)
LUSA	0	-1,431	-0,128
LNOR	0	-2,177	-2,036
LSWE	1	-1,798	-1,018
LDEN	6	-0,993	-2,837
LFIN	2	-1,329	-2,828

<u>Table 24:</u> ADF test results, first differences (Feb 1993 – Feb 2002)

Stock market	Number of lags	Test statistics ADF (constant)
DLUSA	0	-10,728**
DLNOR	0	-9,859**
DLSWE	0	-8,697**
DLDEN	5	-4,912**
DLFIN	1	-7,305**

** rejection of the null hypothesis at 1% significance level.
Critical values constant only: -3,51 (1%) and -2,89 (5%)
Critical values constant + trend: -4,04 (1%) and -3,45 (5%)

<u>Table 25:</u> ADF test results, log-levels (Mar 2002 – Feb 2013)

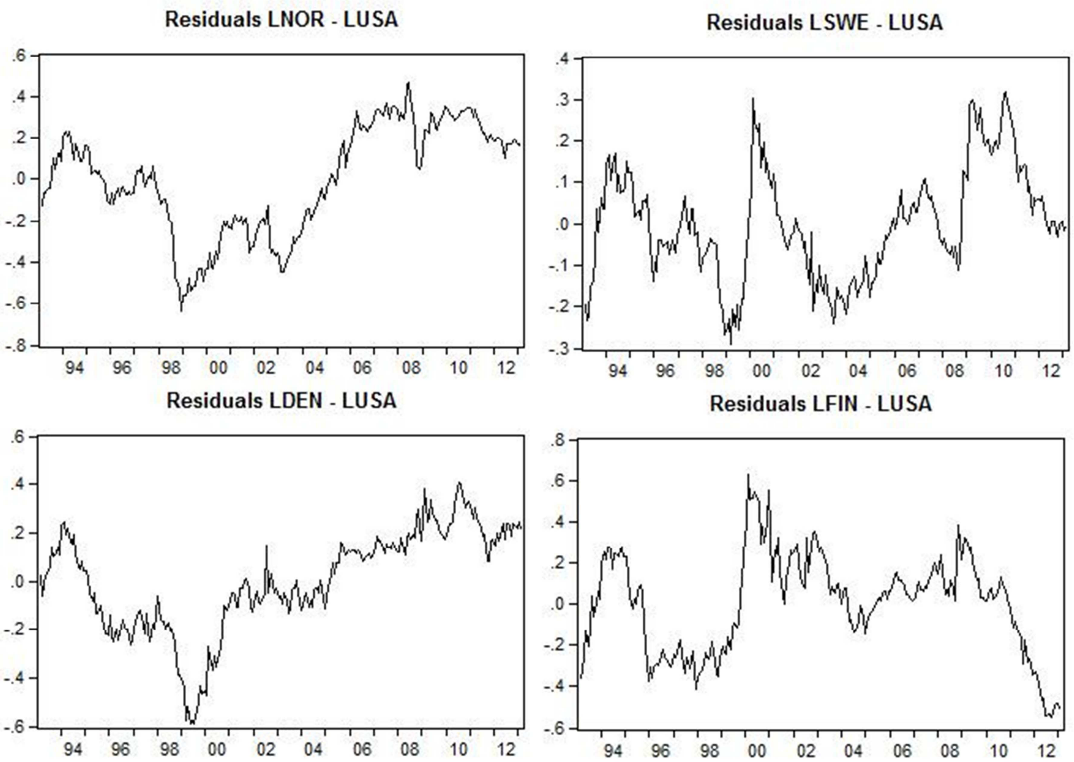
Stock market	Number of lags	Test statistics ADF (constant)	Test statistics ADF (constant + trend)
LUSA	6	-2,148	-2,233
LNOR	1	-1,519	-1,981
LSWE	0	-1,037	-2,061
LDEN	6	-1,658	-2,154
LFIN	6	-1,764	-1,804

<u>Table 26:</u> ADF test results, first differences (Mar 2002 – Feb 2013)

Stock market	Number of lags	Test statistics ADF (constant)
DLUSA	5	-5,165**
DLNOR	0	-9,394**
DLSWE	0	-10,039**
DLDEN	5	-5,122**
DLFIN	0	-5,168**

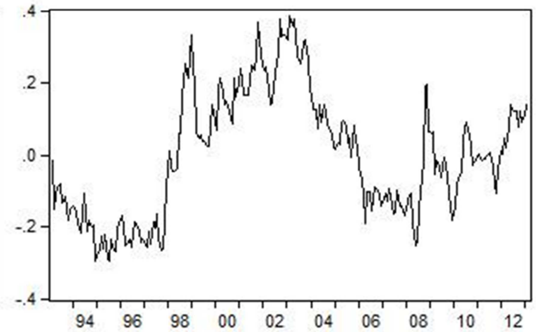
** rejection of the null hypothesis at 1% significance level.
Critical values constant only: -3,51 (1%) and -2,89 (5%)
Critical values constant + trend: -4,04 (1%) and -3,45 (5%)

Appendix B: Residuals from the Engle-Granger test for cointegration

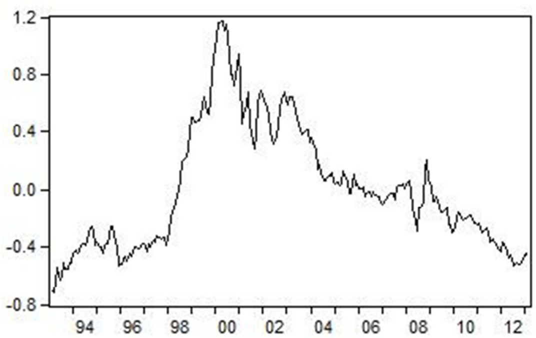


Residuals LSWE - LNOR

Residuals LDEN - LNOR

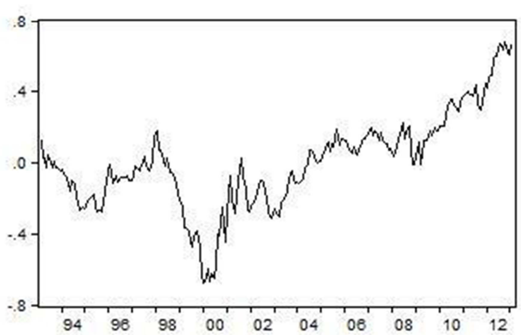


Residuals LFIN - LNOR

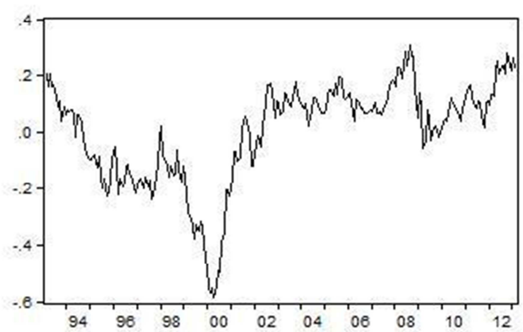


Residuals LFIN - LSWE

Residuals LDEN - LFIN

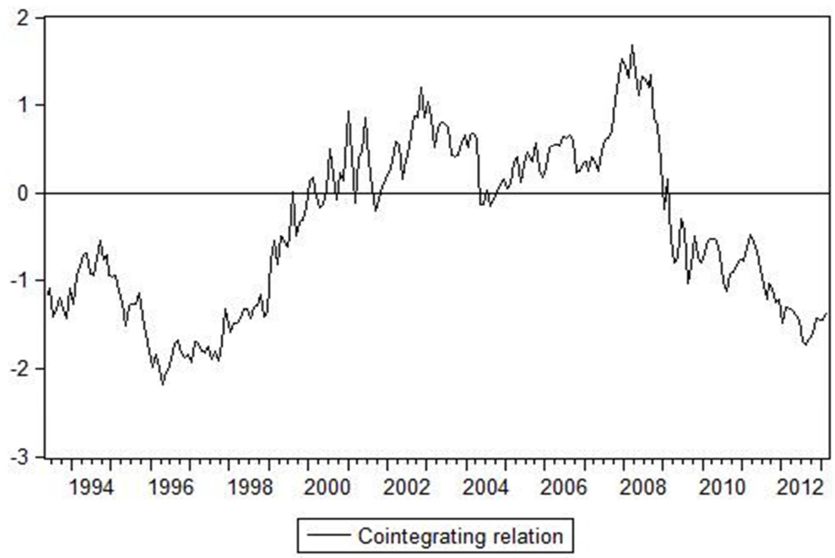


Residuals LDEN - LSWE

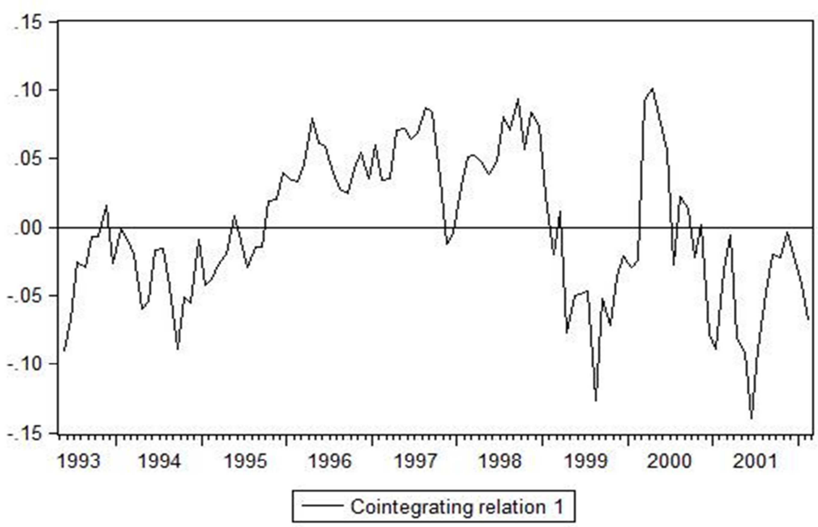


Appendix C: Potential cointegrating relations from Johansen multivariate test

Full sample (Feb 1993 – Feb 2013):



Subsample 1 (Feb 1993 – Feb 2002):



Subsample 2 (Mar 2002 – Feb 2013):