UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Exchange rates and stock markets

A cointegrated vector autoregressive approach to model the dynamics of the U.S exchange rate and the Swedish stock market

Magister Thesis in Financial Economics, (15 ECTS credits)
The School of Business, Economics and Law

Authors: Christian Staf
Adam Fathi
Supervisor: Alexander Herbertsson

Spring 2013

Abstract

The study employs a vector error correction model, cointegration analysis and Granger causality test to examine the short- and long-run dynamic relationship between the USD/SEK exchange rate and the OMXS30. In the short-run we found statistical evidence of OMXS30 granger causing the USD/SEK currency exchange rate positively but no statistical evidence that the USD/SEK exchange rate granger cause OMXS30. In the long-run we found statistically significant evidence of the USD/SEK exchange rate and OMXS30 being cointegrated. The effect of a shock to the USD/SEK currency exchange has a long-run positive effect on the OMXS30. While the effect of a shock to the OMXS30 has a long-run negative effect on the USD/SEK exchange rate.

Table of content

List of tables **Page**

List of Figures

1. Introduction

The relationship between exchange rates and stock markets have received considerable attention by economists. Both exchanges rates and stock prices play an important and influencing role in the development of a country's economy (Nieh & Lee, 2001).

According to the goods market theory the causality goes from the exchange rates to the stock market. Changes in the exchange rates affect the stock market due to international competitiveness (Dornbusch & Fischer, 1980). Theoretically, it is argued that a change in the exchange rate could affect the stock market since the change in the exchange rate will affect the firms profit and this in turn will affect the stock prices (Aggarwal, 1981).

In the portfolio balance theory the causality goes from the stock market to the exchanges rate. Theoretically, it is argued that increased stock prices will increase domestic currency due to the fact that aggregate welfare will increase as a result from increased stock prices. Aggregate welfare will affect the interest rate which will lead to a higher demand for local currency and this in turn will appreciate the local exchange rate (Dornbusch & Fischer, 1980).

From a practical view, most investors believe that both stock prices and exchange rates could serve as instruments to predict the future path of each other (Nieh & Lee, 2001). Foreign investors will benefit from an appreciation in the domestic currency due to higher stock returns. On the other hand a depreciation of the local currency will lead to lower stock returns for foreign investors. This may lead foreign investors to seek other investment opportunities abroad and this in turn may reduce domestic stock prices.

On the Stockholm stock exchange there are export oriented companies listed that may suffer a loss or a profit from domestic currency changes. The loss or the profit will be reflected in the firm’s balance sheet that could result from foreign liabilities and debts. Changes in the exchange rate will affect future cash flows and thus the firm value. The change of the firm’s balance sheet and future cash flows as a result from changes in the domestic exchange rate could alter the stock prices of the firm (Allayannis & Ofek, 2001).

The relationship between exchange rates and stock markets is an important issue to analyze. Foreign investors and domestic companies may suffer a loss or a profit from changes in exchange rates that may affect stock returns or the other way around. The dynamic relationship between exchange rates and stock markets may be different in the short-run and long-run and it may not be in line with the theory.

The purpose of this thesis is to model the dynamic relationship between the USD/SEK exchange rate and the Swedish stock market. We look at the short-run and long-run dynamic relationship between these variables and try to apply economic theory to explain the estimated parameters. Since we try to stay away from defining what "short-run" really means we simply interpret the signs of the short-run parameters in the model. The long-run effect is analysed by creating an impulse response function which tracks the effect on the variables to shocks in the system.

The question formulation of the thesis can simply be formulated as:

- What is the short-run and long-run effect of the USD/SEK exchange rate on the Swedish stock market and vice versa?
- What economic theories, if any, explain the short-run and long-run relationship between the USD/SEK exchange rate and the Swedish stock market?

The rest of this thesis is organized as following. In Section 2 we analyse the two theories explaining the causality between the domestic currency exchange rate and stock market. We describe the goods market theory and the portfolio balance theory. In this section we also review different researchers results from various countries and time periods that have used dissimilar methodologies in determining the effect between exchange rates and stock markets. Furthermore we also discuss how they interpret their results in terms of the goods market and portfolio balance theory. In Section 3 we discuss the sample used in modelling the dynamic relationship and also explain the econometric methodology applied to model and make inference on the data**.** In Section 4 we present the results from the statistical tests conducted on the data. Furthermore in Section 5 we interpret the results from Section 4 with the economic theory covered in Section 2. Finally in Section 6 we present a brief conclusion of the thesis.

2. Theory and literature review

In previous research, there are mainly two theories that researchers take into account when modeling the relationship between stock markets and exchange rates. In the following section we will define the two theories, in Subsection 2.1 we describe the goods market theory and in Subsection 2.2 we describe the second theory which is known as the portfolio balance theory.

2.1 Goods market theory

Dornbusch & Fischer (1980) studied the relationship between stock markets and exchange rates. They developed a model that takes into account and integrates the dynamic of relative prices (exchange rates), expectations and the stock markets. The relationship between the behavior of the exchange rate and the current account is also emphasized in their research.

The goods market theory advocate that changes in the exchange rate will affect the stock market due to the impact on international competitiveness. The causality goes from the exchange rate to the stock market. In an open economy changes in exchange rates will affect the profitability of an exporter due to the relative prices which will be reflected in stock prices. Incomes and expenses for a company with significant exports and import activities will be affected by changes in the exchange rates which will have an impact on the company's stock prices. The real effect from changes in exchange rates on the company's stock prices, and hence the stock market index, depends on if the company hedges against changes in the exchange rates and if they own foreign subsidiaries and whether it is an exporter or an importer.

For example, an appreciation of the local currency will decrease the sales for the exporter and reduce the cost for the importer, while a depreciation will increase the sales for the exporter and increase the cost for the importer. Furthermore a change in the local exchange rate has a significant impact on a company's transaction exposure, which will affect the value of its future receivables and liabilities if and only if they are designated in foreign exchange rate. In other words a local company will benefit from an appreciation in the local currency if the future liabilities are designated in foreign currency and suffer a loss if the future receivables are designated in foreign currency. The conclusion is that an appreciation of the exchange rate will have a negative effect on the local stock market for an export dominated economy and a positive effect on the local stock market for the import dominated economy. Where by a depreciation in the exchange rate will lead to a positive effect on the local stock market for the export dominated economy and a negative effect on the local stock market for an import dominated economy.

Aggarwal(1981) studied the relationship between exchange rates and U.S. stock prices. He only analysed the relationship when the causality goes from exchange rates to stock prices. By modeling the monthly U.S. exchange rates and stock prices from 1974 to 1978 he found that trade-weighted exchange rate measured in dollar and stock prices had a significant positive correlation. He argued that an increase in the value of the U.S. currency was correlated with an increase in the stock prices and the other way around as well, this is true since changes in exchange rates can contribute to a loss or a profit in the balance sheet of multinational companies which will affect their stock prices. Since Aggarwal(1981) used an aggregate index of stock prices (NYSE, S&P 500 and DC 500) his result will hold for both domestic and multinational firm's stock prices. Soenen & Hennigar(1988) considered a different period (1980-1986) in the U.S. market and found a significant negative relationship by modeling stock prices on exchange rates. In other words, their result states that an increase in the U.S. currency was correlated with a decrease in the stock prices and depreciation in the U.S. currency will contribute to an increase in the stock prices.

2.2 Portfolio balance theory

Portfolio balance theory advocate that changes in the stock market will affect the exchange rates through portfolio adjustments. The stock market will affect the exchange rate through changes in stock prices. This theory states that rising stock prices in the local market will attract foreign investors to invest in local stock market which will lead to capital inflow. Capital inflow will increase the demand for the local currency which in turn will appreciate the local exchange rate. Then it is true that decreasing stock prices will decrease the local currency value due to decreased demand on the local stock market which will lead to capital outflow. The causality for the portfolio balance theory goes from the stock market to the exchange rate. A rising stock market as a result from increased stock prices will lead to an increase in aggregate welfare which affects the local interest rates this will result in a higher demand for the local currency which will appreciate the local exchange rate (Dornbusch & Fischer, 1980).

Gavins(1989) study was one of the studies who contributed to the development of the portfolio balance theory. He studied the relationship between stock markets, capital flows, interest rates and exchange rates and analyzed how stock markets affect capital inflows, interest rate and exchange rate. He argue that large effects from the stock market could theoretically lead to an appreciation in the real exchange rate through an expansionary monetary policy.

Solnik (1987) used monthly and quarterly data on eight countries (USA, UK, Canada, France, Germany, Japan, Netherlands and Switzerland) from 1973 to 1983 to consider the relationship between real stock return and real exchange rate. He argues that the relationship between real stock return differentials and real exchange rates to be positively weak. The result is interesting since the stock markets of the eight observed countries together represented ninety percent of the world market capitalization during the observed period.

Bahmani-Oskooee & Sohrabian (1992) analyzed the causality between stock prices and exchange rates in the U.S. They wanted to test the portfolio balance theory as well as study the dual causal relationship between the exchange rate and stock market. They observed the causality and cointegration, which we describe in Subsection 3.2, between stock prices and exchange rates in the U.S economy by using monthly observations between July 1973 and December 1988. In their paper the authors used the S&P 500 as a proxy for the US stock prices and the monthly data was taken from Standard and Poor's security price index record and the effective exchange rate was monthly data measured in US dollar. The author applied Granger concept of causality to predict the dual causal relationship. They concluded that there is a short-run dual causal relationship between stock prices and effective exchange rate. The implication of this is that the causality goes from the exchange rate to the stock market and that the causality goes from the stock prices to the exchange rate as well, at least in the short-run. So the conclusion is that they found evidence for both the goods markets theory and for the portfolio balance theory. Unfortunately the test for a long-run cointegration relationship between the stock prices and effective exchange rates indicated no long-run relationship.

Ratner (1993) studied the relationship between U.S. exchange rates and U.S. stock prices by using monthly data from March 1973 to December 1989. He's result was similar to Bahmani-Oskooee & Sohrabian (1992). He states that the underlying long-term stochastic properties of the U.S. stock index prices are not related to foreign exchange rates according to the cointegration analysis since the test for no cointegration could not be rejected.

However, Ajayi & Mougoue (1996) used daily closing stock market index and exchange rates for eight advance economies (Canada, France, Germany, Italy, Japan, The Netherlands, United Kingdom and United States) between 1985 and 1991 to analyze the relationship between stock prices and exchange rates. Their study is different from previous research since they used more developed time-series analysis. They looked for stationarity using Unit root and find that their sample are nonstationary in the levels but are first-difference stationary.

The author argues that there is a cointegration between stock prices and exchange rate which was a result from the cointegration test. By implementing an error correction model the authors found significant short-run and long-run feedback relations between the two variables. This can be interpreted as due to inflation expectations and bullish stock market an increase in aggregate domestic stock prices has a negative effect on domestic currency in the short-run. However, in the long-run domestic currency will appreciate if the stock prices keep increasing continuously, which can be explained by the willingness to hold assets in the particular currency. In the short-run the inflationary effects of a decreased value of the domestic currency may impact the stock market in a diminishing way. The "bad" effects of currency depreciation on imports and on asset prices may cause stock prices to decrease and create pessimism among investors. This could be true since the authors find that currency depreciation had a negative effect on the stock market both in the short-run and in the long-run.

Batori et al. (2010) studied the effects of exchange rates on the stock markets indexes by using cointegration analysis, vector error correction, vector autoregressive modeling and a Granger causality tests. Their sample was quite consistent due to the use of daily data on stock market index returns and exchange rates for seven European economies (Czech Republic, Denmark, Hungary, Poland, Romania, Sweden and United Kingdom). The observed period was between 1999 and 2009 except for Denmark (2000 to 2009) and Sweden (2001 to 2009). The authors argue that a decrease in the domestic currency will increase the value of the domestic stock market index, since a positive shock to the difference in exchange rates increased the difference on stock market index. The result was similar for all countries except for United Kingdom and Poland. In Poland, the authors found different result where the domestic stock market index decreased when increasing the exchange rate difference. For seven countries the authors found that a decrease in the local currency value will lead to a decrease in the domestic stock market index. In the short-run authors conclude that for Sweden and Romania the exchange rates will not affect the stock market index but exchange rates will be affected from changes in the stock market index.

3. Data and methodology

In this section we describe the data and statistical methods used to model the dynamic relationship between the USD/SEK currency exchange rate and OMXS30. In Subsection 3.1 we describe the data we use in the modelling of the relationship between the currency exchange rate and OMXS30. In Subsection 3.2 we describe the statistical methods used to create the model as well as several statistical tests for model adequacy.

3.1 Data description

There are several variables of interest we use to determine the dynamic relationship between the USD/SEK currency exchange rate and the Swedish stock market. We use the OMX Stockholm 30(OMXS30) as the proxy for the Swedish stock market. The OMXS30 index contains the 30 stocks with the largest volume of transactions on the Swedish stock market and is generally considered an adequate proxy for the stock market as a whole. To try to minimize the effect of omitted variable bias we include the exchange rates of the pound sterling, EURO and the interest-rate spread of three months government bonds yield in Sweden and the US as was suggested by Oben et al. (2010). For simplicity we label the variables in the model as displayed in Table 1.

Table 1: The name of the variables in the model

Variable	Description
OMXS30	OMX Stockholm 30
USD	Cost of USD in SEK
UK	Cost of pound sterling in SEK
EURO	Cost of EURO in SEK
INDIFF30	Swedish government bond yield(30d) - US government bond yield(30d)

The data consists of four years of weekly data of the variables of interest with a total of 195 observations each. The sampling period is from 2003 to 2006. We decided not to include the sampling period 2007-2013 due to the instability of the financial crisis of 2008 caused the financial markets. The reason why we use weekly data, as apposed to daily data, is due to the problems of the excess amount of noise daily data can produce (Yang, 2003)(Obben et al, 2010). The summarized statistics of the five variables are displayed in Table 2.

Table 2: Summarized statistics of the five variables displayed in Table 1

Variable	Mean	Standard deviation	Minimum	Maximum
OMXS30	358.54	88.87	192,12	585.03
USD	7.49	0.39	6.60	8.54
UK	13.42	0.36	12.60	14.23
EURO	9.19	0.14	8.89	9.63
INDIFF90	-0.41	1.79	-2.99	2.52

However, these are only the summarized statistics of the sample and not a representative of the population. Since we have not yet verified that the variables are integrated of order zero (I(0)), which will be described in Subsection 3.2.1, we cannot interpret the statistics that are based on the stationary assumptions, such as the mean and standard deviation other than features of the sample.

3.2 Methodology

In this subsection we describe the methodology implemented in estimating the model and tests conducted for checking the model adequacy. The model estimation and statistical tests are done in five steps. The first step, which is in Subsection 3.2.1, is to test all variables for their order of integration. If the data is not integrated of order zero the data is non-stationary in its raw form and can therefore not be used without risking spurious results.

In the second step, which is in Subsection 3.2.2, we test for signs of a long-run relationship between the variables. This will be conducted by doing a Johansen's test for cointegration as was suggested by Johansen (1991) which is an generally accepted method of detecting cointegration between multiple variables (Brooks, 2008). The test tests for r number of vectors that generates a long-run stationary relationship between the variables. Where r is less than the number of variables in the model and is generally called the rank of the cointegration matrix.

The third step, which is covered in Subsection 3.2.4, is estimating the long-run relationship using the cointegration matrix and the short-run relationship using an underlying vector autoregressive(VAR) model. This kind of model is called an vector error correction (VEC) model. In the fourth step, which is in Subsection 3.2.5, we conduct various diagnostics tests on the models residuals. The tests are for multivariate autocorrelation, normality, heteroskedasticity and model stability as is suggested by Lütkepohl et al. (2009). The final step, which is covered in Subsection 3.2.7, is implementing the impulse response function to determine the short-run and long-run effect of an isolated shock to USD/SEK and OMXS30 in the system.

When constructing an impulse response function based on a VAR/VEC model the function tracks the effect of one standard deviation shock to one variable on another. However, since the goal is to shock the USD/SEK exchange rate and observe the effect on OMXS30 and vice versa it would be more appropriate to shock a percentage change in the USD/SEK exchange rate and OMXS30 instead of a unit change. By transforming all variables except the interest rate spread to their natural logarithm their estimates can be interpreted as elasticities or percentages (Obben et al, 2010).

3.2.1 Unit root tests

A stationary time series is defined as a process with a constant mean, constant variance and constant autocovariance for any given lag. If the time series has a unit root the process never reverts to a mean and therefore it is non-stationary. If a non-stationary time series must be differentiated d times to be made stationary it is said to be integrated of order d denoted by I(d) and if a process x_t is I(d) we write $x_t \sim I(d)$. If a variable $y_t \sim I(d)$ then $(y_t - y_{t-d}) \sim I(0)$ i.e. a process without a unit root, where $(y_t - y_{t-d})$ mean that we have differentiated d times (Brooks, 2008).

A lot of financial data tend to be I(1), that is, first difference stationary (Brooks, 2008). If we do not check and correct for this we run the risk of getting spurious results. Therefore the order of integration will determine whether we can model the dynamic relationship in VAR model in it's raw form or if we need to differentiate the data to implement it in a VAR. However, by differencing you may lose some long-run information (Johansen & Juselius, 1990) and therefore it is preferred for that the data being I(0). In the following equation variable y_t is a unit root process if ϕ=1

$$y_t = \phi y_{t-1} + u_t \tag{3.1}$$

where ϕ is the regression coefficient with the first lag and u_t is an i.i.d white noise process. However, instead of using (3.1) in practice the following form is used

$$\Delta y_t = \psi y_{t-1} + u_t \tag{3.2}$$

where Δy_t is the first difference of y_t, i.e. Δy_t= y_t-y_{t-}1, and ψ= ϕ-1. To test if the process y_t is stationary, and thus to test if $y_t \sim$ I(0), we use equation (3.2) together with the normal Dickey-Fuller test, where the null hypothesis is ψ=0 versus ψ<0. Thus, the null hypothesis is that y_t is non-stationary. However, the test conducted on (3.2) is under the assumption that u_t is not autocorrelated but if the dependant variable, Δy_t, is autocorrelated this assumption does not hold. Therefore we control for this autocorrelation by transforming it into an augmented form where lagged values of the first differences of y_t is included. This test is called the augmented Dickey-Fuller (ADF) test and is performed on the following equation

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \tag{3.3}$$

where α_i is the regression coefficient of first difference of y_t at lag i (Brooks, 2008). The null hypothesis of the augmented Dickey-Fuller test is that y_t is non-stationary. As in the normal Dickey-Fuller test the null hypothesis ψ is zero versus the alternative hypothesis of $\Psi<0$. The test statistic for the ADF test is given by

$$\frac{\hat{\psi}}{SE(\hat{\psi})} \tag{3.4}$$

where $\hat{\psi}$ is the estimate for ψ in (3.3) and $SE(\hat{\psi})$ is the standard error of $\hat{\psi}$. The test statistic follows a non-standard distribution where the critical values for the test is supplied by e.g. Brooks (2008).

The number of lags to include in (3.3) is determined by Akaike's information criterion (AIC)(Akaike, 1974). The AIC is a standardized goodness-of-fit measure that can be used to compare different models. It compares the likelihood of the estimated parameters in the different models with a standardized penalization of the amount of variables included in the model. The number of lags to include in the model is the model is determined by minimizing the following function

$$AIC = -2\ln(L(\psi,\alpha_1,\alpha_2\ldots\alpha_p) + \frac{2k}{n} \tag{3.5}$$

where k is the number of parameters in the model, n is the sample size and $L(\psi,\alpha_1,\alpha_2\ldots\alpha_p)$ is the likelihood function for the parameters $\alpha_1,\alpha_2\ldots\ \alpha_p$ in (3.3) (Enders, 2010).

3.2.2 Cointegration

As mentioned in Subsection 3.2.1, by differencing your data you may lose some long-run information (Johansen & Juselius, 1990). However, if the variables, in their levels, share a long-run relationship you may find a vector of linear combinations of these variables that is stationary. We say that a k x 1 vector is integrated of order (d,b) if $y_{t,1}$, $y_{t,2}\ldots y_{t,k}$ are I(d) and there is at least one vector of coefficients, $\boldsymbol{\alpha}$, that $\boldsymbol{\alpha}'\mathbf{y_t} \sim$ I(d-b) (Engle & Granger, 1987). Here b is the so called cointegration order. So despite the individual variable not being stationary in and by itself we may find a long-run equilibrium between I(d) variables that can help make inference about long-term effects to changes in the variables. To test the number of vectors of $\boldsymbol{\alpha}$ we perform Johansen's test of cointegration, which we specify the methodology of in Subsection 3.2.4.

3.2.3 Vector autoregressive model

In this subsection we will discuss the methodology used in estimating a VAR model. Since we want to make a dynamic system where all variables are endogenous we estimate a system of g number of variables. A VAR representation containing g number of endogenous variables is given by (Brooks, 2008)

$$\mathbf{y}_t = \boldsymbol{\beta}_{\mathbf{p}}\mathbf{y}_{t-1} + \boldsymbol{\beta}_2\mathbf{y}_{t-1} \ldots + \boldsymbol{\beta}_p\mathbf{y}_{t-p} + \boldsymbol{u}_t \tag{3.6}$$

where:
- $\mathbf{y_t}$: is a g x 1 vector with endogenous variables
- $\boldsymbol{\beta}_{\mathbf{p}}$: is a g x g matrix of regression coefficients of time t-p
- $\mathbf{u_t}$: is a g x 1 vector of i.i.d. white noise
- p: the number of lags of each variable

Each variable is regressed on its own lag as well as the lags of the other variables in the system. They key problem is determine what variables to include to minimize the omitted variable bias and the lag length. The goal is to use a sufficiently large size of the lag length so that the residuals in the system are not serially correlated. There are several measures that can be used to choose the optimal length of the size of the lag. This thesis will optimize the dynamic model through using the AIC criterion, which is the same criterion we used in the ADF test in Subsection 3.2.1, to determine the optimal lag size. The downside of using a VAR is that since the right hand side of all equations is equal for all variables the number of parameters to be estimated increases swiftly as one adds more variables or lags. The number of parameters to be estimated is $g+pg^2$ and therefore the numbers of degrees of freedom is used up rapidly which decreases the precision of the estimates.

3.2.4 Vector error correction model

As explained in Subsection 3.2.2, by differencing data we may lose some long-run information. However, if the variables order of integration is larger than zero we cannot model the relationship in its levels without risking spurious results. By using a VEC model we can still model the short-term dynamic relationship between the variables using their differences but adjusting it in the long-run towards their long-run equilibrium. In order to estimate the VEC model and perform the Johansen test for cointegration we transform (3.6) into a VEC form given by (Lütkepohl et al, 2009)

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{y}_{t-p} + \boldsymbol{\Gamma}_1\Delta\mathbf{y}_{t-1} + \boldsymbol{\Gamma}_2\Delta\mathbf{y}_{t-2}\ldots\boldsymbol{\Gamma}_{p-1}\Delta\mathbf{y}_{t-(p+1)} + \mathbf{u}_t \quad (3.7)$$

where: $\Delta\mathbf{y}_t$: is a g x 1 vector with differentiated endogenous variables

$\boldsymbol{\alpha}$: is a g x 1 vector with the re-adjustment speed to the equilibrium

$\boldsymbol{\beta}$: is a g x 1cointegration matrix

$\boldsymbol{\Gamma}_p$: is a g x g matrix of regression coefficients at lag p

The alpha vector is a vector of the variables re-adjustment speeds to the long-term equilibrium. While the beta vector contains estimates of the strength of the long-term relationship. There can be at most g-1 long-run linear relationships that are stationary. And the number of independent long-run relationships is known as the cointegration matrix's rank. To determine the rank of the co-integration matrix we employed the test proposed by Johansen (1991). One can detect the rank of the matrix by the number of characteristic roots, or eigenvalues, that are different from zero. There are two tests for co-integration proposed by Johansen (1991). To do this first consider the VEC form given by

$$\Delta \mathbf{y}_t = \Pi\mathbf{y}_{t-k} + \Gamma_1\Delta\mathbf{y}_{t-1} + \Gamma_2\Delta\mathbf{y}_{t-2}\ldots\Gamma_{p-1}\Delta\mathbf{y}_{t-(p+1)} + \mathbf{u}_t \quad (3.8)$$

where $\boldsymbol{\Pi}$= $\left(\sum_{i=1}^{p}\beta_i\right) - I_g$. In Johansen (1991) the author proposed analysing the eigenvalues of the matrix **Π.** The **Π** can be interpreted as the long-run coefficient matrix because in equilibrium all $\Delta \mathbf{y}_{t-i}$ will be zero. And since $\mathbf{u}_t$ is a white noise process with an expected value of zero the $\Pi \mathbf{y}_{t-p}$ will be zero (Brooks, 2008). Johansen (1991) formed two tests that tests the number of eigenvalues, or characteristic roots, that are different from zero. The two test statisticas he proposed are given by

$$\begin{aligned} \lambda_{trace}(r) &= -n \sum_{i=r+1}^{g} \ln(1-\hat{\lambda}_i) \\ \lambda_{\max}(r, r+1) &= -n \ln(1-\hat{\lambda}_{r+1}) \end{aligned} \tag{3.9}$$

where r is the number of cointegrating vectors under the null hypothesis and $\hat{\lambda}_i$ is the ith ordered eigenvalue from the co-integration matrix.

Both statisticas in (3.9) tests different hypothesis. The trace statistic tests the null hypothesis of the rank being less than or equal to r against the rank being greater than r. While the max statistic tests the null hypothesis of the rank being r against it being r+1. Johansen & Juselius (1990) provides the critical values for the two tests. Since the two tests do not always give a unanimous test result we use both tests in determining the rank of the co-integration matrix.

3.2.5 Model diagnostics

In this subsection we discuss the statistical tests we conduct on the VEC model to verify that it represents the data generating process (DGP) adequately. First we discuss the multivariate test for autocorrelation. Secondly we review the multivariate test for normality. Finally we discuss the multivariate test for heteroskedasticity and stability test.

3.2.5.1 Lagrange multiplier test for multivariate autocorrelation

The Lagrange multiplier(LM) test tests for residual autocorrelation. If there is presence of autocorrelation in the system the estimates in the underlying VAR system will be inefficient. The test on the VEC model form is as proposed by Lütkepohl et al (2009)

$$\hat{u}_t = \boldsymbol{\alpha\beta}'\mathbf{y}_{t-p} + \boldsymbol{\Gamma}_1\Delta\mathbf{y}_{t-1} + \boldsymbol{\Gamma}_2\Delta\mathbf{y}_{t-2}\ldots\boldsymbol{\Gamma}_{k-1}\Delta\mathbf{y}_{t-(p+1)} + \mathbf{B}_1\hat{u}_{t-1} + \mathbf{B}_2\hat{u}_{t-2}\ldots\mathbf{B}_h\hat{u}_{t-h} + \boldsymbol{e}_t \tag{3.10}$$

where $\hat{u}_t$ is the estimated residuals of the VEC model in (3.7), $\mathbf{B_i}$: is a g x g matrix of regression coefficients at lag I and $\mathbf{e}_t$ is a g x 1 vector of residuals.

From this auxiliary model one computes the LM test statistic for the hypothesis

$$H_0 : \boldsymbol{B}_1 = \boldsymbol{B}_1 \ldots \boldsymbol{B}_h = 0$$
$$H_1 : \boldsymbol{B}_j \neq 0 \text{ for at least one j } \in (1,2\ldots\text{h})$$

The LM test statistic can be computed by the following equation

$$Q_{LM} = n\left(k - tr(\hat{\Sigma}_u^{-1}\hat{\Sigma}_e\right) \sim \chi^2\left(kg^2\right) \tag{3.11}$$

where k is the number of estimated parameters in (3.10), $\hat{\Sigma}_u$ is the variance covariance matrix of $\hat{u}_t$ and $\hat{\Sigma}_e$ is the variance covariance matrix of e_t.

The LM statistic has a chi-square distribution with hg^2 degrees of freedom. Under the null hypothesis the system is not affected by autocorrelation at lag h.

3.2.5.2 Test for multivariate normality

The second test is a test for normality of the residuals. The test tests whether the residuals distributions third and fourth moment is significantly different from a normal distribution. In a Jarque & Bera test for normality under the null hypothesis the distribution of the variable is akin to a normal distribution. However, even though normality is not a necessary condition to make inference of the model it could indicate that the model could be improved (Lütkepohl et al, 2009). The test will be conducted as proposed by Lütkepohl (2005) who suggests a multivariate case of normality which is an extension of Jarque & Bera (1987) test for univariate normality. The actual mathematics for the test is beyond the scope of this thesis.

3.2.5.3 Test for multivariate heteroskedasticity

In this subsection we describe the methodology behind multivariate heteroskedasticity testing. To test for heteroskedasticity in the system we perform a multivariate autoregressive conditional heteroskedasticity(ARCH) test. An multivariate ARCH model of order h is given by

$$vech(\Sigma_{t|t-1}) = \boldsymbol{\beta}_0 + \mathbf{B}_1 vech(u_{t-1}u_{t-1}^{'}) + \mathbf{B}_2 vech(u_{t-2}u_{t-2}^{'}) \ldots + \mathbf{B}_h vech(u_{t-h}u_{t-h}^{'}) \quad (3.12)$$

where vech is the column stacking operator which stacks the columns from the diagonal downwards and $\Sigma_{t|t-1}$ is the covariance matrix (Lütkepohl et al, 2009). To test for multivariate ARCH effects we simply test the null hypothesis of all elements of B_1, $B_{2...}$ B_h being zero against it not being zero. If we cannot reject the null hypothesis we have no statistical evidence of the system being affected by multivariate heteroskedasticity at order h. In this thesis we will test for heteroskedasticity up to order 3.

3.2.5.4 Stability test

The final diagnostic test of the VEC model is to test its stability. By performing a stability test we check whether the cointegration equation is misspecified or it is not stationary. The cointegration matrix, which maps the cointegration relationships, should have g-r number of eigenvalues, meaning its absolute values, smaller than one for the VEC to be stable (Lütkepohl, 2005). This is due to the restriction we impose on the cointegration relationship. If the model is stable there should be g-r eigenvalues within the unit circle.

3.2.6 Granger causality

When discussing causality between two or more variables we usually mean how the cause and effect relates to the relationship between variables. One test for causality is whether the lags of $y_{t,2}$ adds any information to help predict $y_{t+i,1}$. This does not necessary mean that $y_{t,2}$ causes $y_{t+i,1}$ but it is a useful predictor. This is called Granger causality. We say that $y_{t,2}$ granger causes $y_{t+i,1}$ if we have statistical support of the lags of $y_{t,2}$ can help predict $y_{t,1}$. Obben et al (2010) suggest performing a block-granger causality test. Consider a simple bivariate VAR system with two lags.

$$\begin{bmatrix} y_{t,1} \\ y_{t,2} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} y_{t-1,1} \\ y_{t-1,2} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} y_{t-2,1} \\ y_{t-2,2} \end{bmatrix} + \begin{bmatrix} e_{t,1} \\ e_{t,2} \end{bmatrix} \tag{3.13}$$

The block granger causality test for $y_{t,2}$ causing $y_{t,1}$ is simply testing the null hypothesis $\alpha_{12} = \beta_{12} = 0$.

3.2.7 The impulse response function

While we can conduct a Granger causality test on the variables to determine the predictive power of the variables it does not explain the sign and power of the relationship. To do that we create a impulse response function(IRF) on the VEC system. Through the application of the IRF we can trace out the effect of an isolated unit, or a percentage, shock to one variable to the other variables in the system.

4. Statistical results

In the following section we will present the results of the statistical tests. In Subsection 4.1, 4.2 and 4.3 we present the result of the pre-modelling statistical tests. The pre-modelling statistical tests are the unit root test, the test for number of lags in the underlying VAR model and the test for cointegration. We have used Stata and SAS to perform these statistical tests.

4.1 Unit root tests

Following the methodology outlined in the previous section the unit root tests are done by conducting an augmented Dickey-Fuller test. The number of lagged differences included in the tests is decided by the AIC.

Table 3: Unit root test for OMXS30, USD, UK, EURO and INDIFF30

	I(0)		I(1)	
Variable	**Test statistic**	**P-value**	**Test statistic**	**P-value**
OMXS30	-2,237	0,4693	-9,371	**<0,001**
USD	-2,342	0,1587	-12,876	**<0,001**
UK	-2,631	0,0868	-13,944	**<0,001**
EURO	-2,033	0,2725	-11,071	**<0,001**
INDIFF30	-1,282	0,6373	-5,498	**<0,001**

As can be seen in Table 3 none of the variables are I(0). Therefore we cannot use a simple VAR to model the dynamic relationship between the variables without risking spurious results. However, they are I(1) and can therefore be modelled by their first differences.

4.2 Vector autoregressive order

To decide the number of lags in the underlying VAR model to determine the cointegration rank we use the AIC as suggested in section 3.2.3.

Table 4: AIC values for number of lags in the underlying VAR model

Lag order	AIC
0	-23,2132
1	-36,7874
2	-36,8229*
3	-36,7408
4	-36,6072

According to Table 4 the AIC recommends using two lags in the underlying VAR model. Since the variables are not I(0) but I(1) we will use their first differences. Hence the model will use two lagged difference in the VEC model in addition to the cointegration variable. However, even though the AIC recommends this lag level to be used in the final model it could be increased due to persistence of autocorrelation in the system.

4.3 Test for cointegration

In this subsection we display the results of the test for cointegration between the variables.

Table 5: Johansen's test for cointegration in the VEC system

Maximum rank	eigenvalue(λ)	Trace statistic	5% critical value for Trace	Max statistic	5% critical value for max
0		68,7993	68,52	28,1957	33,46
1	0,13592	**40,6036***	47,21	26,2224	27,07
2	0,12704	14,3812	29,68	9,1653	20,97
3	0,04638	5,2159	15,41	3,9339	14,07
4	0,02018	1,2820	3,76	1,2820	3,76
5	0,00662				

The two results of the tests presented in Table 5 gives conflicting results. The trace statistic tests, which tests the null hypothesis of rank<=r versus rank>r, indicates that there is one cointegrated vector. While the max statistic, which tests the null hypothesis of rank=r against rank=r+1, indicates that there is not cointegrated vector. Patterson (2000) suggests in such a situation to do further analysis on the higher rank but making sure the model can correctly identify all the cointegration vectors in the VEM model.

4.4 The vector error correction model and block Granger causality test

From the pre-modelling tests we know that the variables are reliable. They are I(1) and we have found one long-term relationship vector. Therefore, they can be used to model the dynamic short-term and long-term relationship in a VEC model. The number of lags to include in the model is the same as when we tested for cointegration rank, which are two. Table 6 displays the cointegration vector normalized on OMXS30, which is also called the VEC models beta vector.

Table 6: Beta vector estimates in the vector error correction model normalized on OMXS30

	OMXS30	USD	UK	EURO	INDIFF30	CONSTANT
Estimated parameters	1	2.62	-3.90	-2.14	7.22	3.88
P-value		**<0.001**	**<0.001**	0.447	**<0.001**	

These estimates are the estimated parameters of the beta vector in (3.7) in Subsection 3.2.4. Since we use logs of the variables these can be interpreted as long-term elasticities (Mukherjee & Naka, 1995). What is noteworthy are the signs of the currencies. All the long-term relationships are statistically significant except the EURO exchange rate. What is interesting is that the two statistically significant currencies have different signs. The USD/SEK has a long-term positive relationship with OMXS30 while UK/SEK has a negative. For more detailed information of the long-term cointegration matrix estimates see Table 15 in Appendix. This result is similar to Obben et al (2010) results who found that different currencies affecting the New Zealand stock market differently.

Table 7: Estimated parameters in the vector error correction model (with p-values in the parenthesis)

Variables	ΔOMXS30	ΔUSD	ΔUK	ΔEURO	ΔINDIFF30
α_{t-1}	0.036 (0.067)	**-0.0490** **(<0.001)**	-0.0015 (0.857)	-0.0062 (0.180)	0.0004 (0.635)
$\Delta OMXS30_{t-1}$	**-0.2133** **(0.015)**	**0.1217** **(0.019)**	0.0281 (0.468)	0.0128 (0.537)	0.0015 (0.694)
$\Delta OMXS30_{t-2}$	-0.0654 (0.448)	0.0957 (0.060)	0.0726 (0.056)	**0.0495** **(0.015)**	0.0045 (0.230)
ΔUSD_{t-1}	0.0599 (0.711)	-0.0137 (0.886)	**-0.2046** **(0.004**	-0.0655 (0.086)	0.0032 (0.644)
ΔUSD_{t-2}	-0.1075 (0.500)	0.0434 (0.644)	0.0427 (0.542)	0.0654 (0.081)	-0.0087 (0.209)
ΔUK_{t-1}	-0.1979 (0.385)	0.0734 (0.585)	0.1811 (0.070)	**0.1247** **(0.020)**	0.0131 (0.184)
ΔUK_{t-2}	0.0001 (1.000)	0.1331 (0.317)	0.0010 (0.992)	0.0287 (0.589)	0.0085 (0.383)
$\Delta EURO_{t-1}$	0.6194 (0.123)	0.1271 (0.591)	-0048 (0.784)	**-0.2003** **(0.034)**	-0.0266 (0.126)
$\Delta EURO_{t-2}$	**0.8096** **(0.046)**	-0.1794 (0.454)	0.0685 (0.701)	-0.0865 (0.366)	-0.0208 (0.239)
$\Delta INDIFF30_{t-1}$	-1.2957 (0.444)	0.0082 (0.993)	-0.8296 (0.784)	-0.0098 (0.980)	**0.2888** **(<0.001)**
$\Delta INDIFF30_{t-2}$	1.6906 (0.322)	1.1549 (0.251)	0.0685 (0.701)	-0.1714 (0.670)	-0.0835 (0.260)
Constant	0.0037 (0.139)	0.0027 (0.066)	-0.0008 (0.509)	0.0001 (0.835)	**-0.0002** **(0.022)**

In Table 7 we have the estimated parameters in the VEC model with the p-values in the parenthesis. The estimated parameters of α_{t-1} are the estimated elements of the alpha vector in (3.7) in Subsection 3.2.4. There are quite a few non-significantly different from zero estimates. However, the individual short-run estimates significance is not of great important in a VAR system since they are rarely interpreted other than the sign; what is more important is the block significance of the variables.

Table 8: Block granger causality test of OMXS30 and USD/SEK currency exchange

Variable	Block variables	χ2 test statistic	p-value
ΔOMXS30	ΔUSD	0.52	0.77
ΔUSD	ΔOMXS30	7.92	0.01

In Table 8 we display the block Granger causality test discussed in Subsection 3.2.6. The table displays the Granger causality between OMXS30 and the USD/SEK currency exchange rate, for a complete granger causality test on all variables see Table 16 in Appendix. The test shows that in the short-run the OMXS30 granger causes the USD/SEK currency exchange rate but not vice versa at 1% significance level.

The estimates important for the long-term relationship, other than the estimates to the beta vector in Table 6, are the estimates to the error correction term(ECT). The ECT measures the speed of the re-adjustment to the long-term equilibrium. These variables are the α_{t-1} estimates in table 7 which are the elements in the alpha vector. The alpha vector is displayed in Table 9.

Table 9: Alpha vector estimates in the vector error correction model

	OMXS30	USD	UK	EURO	INDIFF30	CONSTANT
Estimated parameters	0.036	-0.049	-0.001	-0.006	-0.006	3.88
P-value	0.067	<0.01	0.857	0.857	0.180	

The ECT for USD is significant at any relevant significance level while the ECT for OMXS30 has a p-value of 0.067, which although not statistically significant at the 5% level is sufficiently low to not disregard an relationship. Enders (2010) suggests performing a test for significance of all parameters in the alpha vector. Since the alpha vector measures the re-adjustment speed a non-significant joint test indicates there is no error correction and the VEC model is simply an VAR model in first differences as can be seen in equation (3.7) in Subsection 3.2.4.

Table 10: Chi-square test for all error correction parameters being zero

χ2 test statistic(5)	P-value
28.38	**<0,001**

From Table 10 we can see that we have strong statistical support of at least one of the error correction parameters not being zero. This result indicates that at least one of the variables adjusts in the long-term to the long-run equilibrium.

4.5 The diagnostics of the vector error correction model

In this subsection we will present the results of the diagnostic tests of the VEC model that was discussed in Subsection 3.2.5. We test the residuals for multivariate autocorrelation, heteroskedasticity , normality and model stability. In Table 11 is the results of testing for the presence of autocorrelation in the system up to lag six.

Table 11: Lagrange multiplier test for autocorrelation

Lag order	$\chi 2$ test statistic	degrees of freedom	P-value
1	24.5060	25	0.49031
2	26.2339	25	0.39520
3	15.0667	25	0.93981
4	30.5683	25	0.20371
5	27.6821	25	0.32269
6	26.0928	25	0.40266

Since the null hypothesis in a Lagrange multiplier test for autocorrelation is that there is no presence of autocorrelation up to lag h we can conclude that the model does not suffer from autocorrelation in the system.

The next diagnostic test is to test the whether the residuals of the model share the same third and fourth moment as a normal distribution. The result of the test can be seen in Table 12 where we test the joint test of the two moments.

Table 12: Jarque-Bera test for nomality

Equation	χ2 test statistic	degrees of freedom	P-value
ΔOMXS30	46.232	2	**<0.001**
ΔUSD	0.393	2	0.8216
ΔUK	0.673	2	0.7141
ΔEURO	5.090	2	0.0784
ΔINDIFF30	66.184	2	**<0.001**
All	118.573	10	**<0.001**

Since under the null hypothesis the distribution of the residuals shares the third and fourth moment with a normal distribution we can reject it for OMXS30, INDIFF30 and all residuals combined. As we discussed in the methodology section, though normality is not a necessary condition it could point to possible improvements could be made to the model. For a more detailed test where we test for the third and fourth moment separately, to see what moment each variable fails see Table 17 in Appendix.

The next diagnostic to test for is multivariate heteroskedasticity. This, as mentioned in Subsection 3.2.5, is checked by testing for multivariate ARCH effects. The results of these tests is displayed in Table 13.

Table 13: Test for multivariate ARCH effects in the vector error correction model

Order	χ2 test statistic	Degrees of freedom	P-value
1	21.75	25	0.6499
2	53	50	0.3592
3	78.31	75	0.3743

Since under the null hypothesis the elements of the matrices are jointly non-significant up to order three we have statistical evidence of the system being free of heteroskedasticity.

The final diagnostic test of the VEC model is the stability test. We perform this to determine the stability of the estimated parameters and to check for stationarity.

Table 14: Eigenvalues of the vector error correction model

Eigenvalue	
1	.478872
1	.432757
1	.42097
1	.403767
.906246	.403767
.496683	.196888
.496683	.196888
.478872	

In Table 14 we display the eigenvalues of the system. Since we have five variables and one cointegration matrix we can at most have four eigenvalues outside or on the unit circle. And since we have four eigenvalues on the unit circle the model is not unstable or non-stationary. For a graphically representation of the eigenvalues in the unit circle see Figure 3 in Appendix.

4.6 The impulse response function

With the impulse response function we implement a shock at week zero and observe the effect on OMXS30 and the USD/SEK exchange rates as time increases. Since we have used the natural logs of the variables the shock will be a one percentage shock to USD and the response to OMXS30 will be in percentages. The result of a shock to USD on OMXS30 is presented graphically in Figure 1.

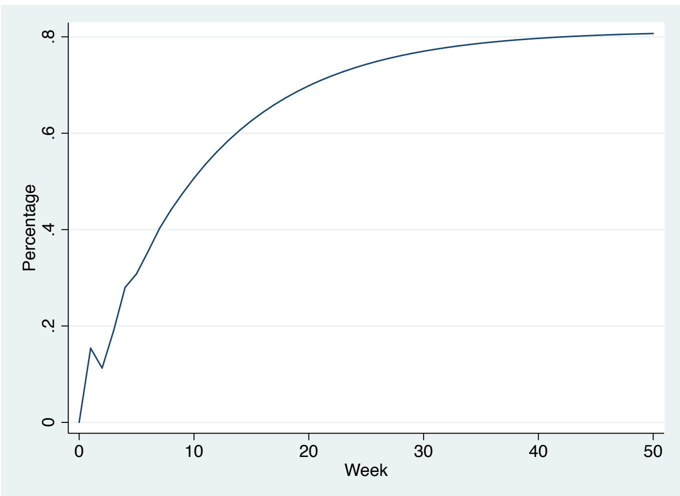

Figure 1: OMXS30 response in percentage to 1% shock to USD/SEK currency exchange rate

As can be seen in Figure 1 the effect of the shock converges to the long-run equilibrium as time increases. The effect of 1% shock on OMXS30 is roughly 0.8% increase of SEK/USD over the long-run. For more detailed information of the exact values for each week see Table 18 in Appendix. In Figure 2 we show graphically the effect on the USD/SEK currency exchange when OMXS30 is exposed to an isolated 1% shock.

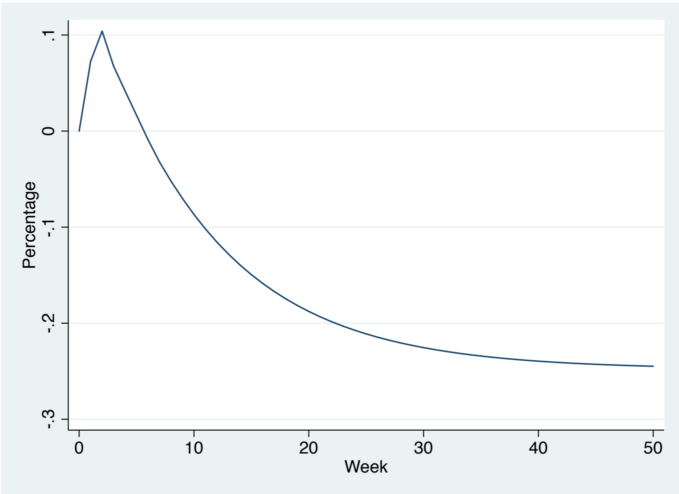

Figure 2: USD/SEK currency exchange rate response in percentage to 1% shock to OMXS30

The effect of a percentage shock to the OMXS30 has a long-run negative effect on the USD/SEK currency exchange rate. What is interesting is that the short-term effect is positive, and as can be seen in Table 7's estimated short-run parameters of OMXS30 is statistically significant, while the long-term is negative.

5. Discussion

In this section we will discuss the short-run and long-run dynamic relationship between OMXS30 and the USD/SEK exchange rate. The discussion will be made from two perspectives; the goods market and the portfolio balance theory perspective. As far as we know there has been only one study that analysed short- and long-term relationship between exchange rates and stock markets in Sweden. The study was conducted 2010 by Batori et al. (2010) who studied various countries for this relationship.

According to the goods market theory the causality goes from the exchange rate to the stock market. To determine the Granger causality in the short-run we analysed the short-run parameters in the VEC model. As can be seen in Table 7 the short-run parameters ΔUSD_{t-1} and ΔUSD_{t-2} correlation to $\Delta OMXS30_t$ are not statistically significant at any relevant significance level. That is, we do not have any statistically evidence of short-run causality from USD/SEK to OMXS30. In the short-run our result is in line with Batori et al. (2010) who found no evidence that the domestic exchange rate affected the domestic stock market for Sweden.

However, unlike Batori et al. (2010) we found a long-run cointegrated relationship between the USD/SEK and OMXS30. There are two criterion that have to be satisfied for there to be a long-run cointegrated relationship in the VEC model. The first criteria is that the parameters in the alpha vector, which measures the speed of the re-adjustment to the long-run equilibrium, is statistically significant. The second criteria is that the beta vector, which measures the strength of the long-run relationship, is statistically significant. As can be seen in Table 9 both re-adjustment parameters for USD/SEK and OMXS30 is statistically significant at 6,7% significance level. When normalizing the beta vector to OMXS30 the USD/SEK is statistically significant at any relevant significance level. The estimated error correction for OMXS30 is 0,036 and USD/SEK is -0,049. The interpretation of these parameters are that OMXS30 re-adjusts 3,6% and USD/SEK 4,9% of the disequilibrium per week.

When exposing the USD/SEK exchange rate to a one percentage shock to the OMXS30 the long-run affect over 50 weeks is roughly 0,8%. This is in accordance with the goods market theory. This result conflicts with the result from Batori et al. (2010) whose result for the test of cointegration in Sweden was rejected. The result of this shock to the cost of USD effect on the OMXS30 is expected. According to economic theory an depreciation in the domestic currency increases the global competitiveness of the domestic firms. Hence, the value of their stocks increases as a result. This indicates that the firms listed on the OMXS30 tend to be export oriented. This can be explained by the fact that Sweden is an export dominated economy and therefore their stock market should reflect that.

According to the portfolio balance theory the causality goes from the stock market to the exchange rate. The estimated parameter of $\Delta OMXS30_{t-1}$ is 0,1217 and is statistically significant at 1,9% significance level. We also found that the estimated parameter for $\Delta OMXS30_{t-2}$ is 0,0957 and is statistically significant 6,0% significance level. This result indicates that in the short-run the increased value of the OMXS30 depreciates the SEK relative to the USD. In the short-run our result is in line with Ajayi & Mougoue (1996). Ajayi & Mougoue (1996) argued that an increase in the domestic stock markets will depreciate the domestic currency, this is due to inflation expectations.

When increasing OMXS30 with one percentage point the long-run effect on the USD/SEK is negative. The cumulative effect of this change on USD/SEK is roughly -0,25%. That is, an increase in the OMXS30 will in the long-run appreciate the SEK relative to the USD. Our result is in accordance whit the conclusion made by Ajayi & Mougoue (1996). Who concluded that in the long-run the domestic currency will appreciate if the stock market increases due to the willingness of investors to hold assets in the domestic currency increases.

This can be interpreted as due to inflation expectations and bullish stock market an increase in aggregate domestic stock prices has a negative effect on domestic currency in the short-run. However, in the long-run the domestic currency will appreciate if the stock prices increases, which can be explained by the willingness to hold assets in the particular currency.

6. Conclusion

In this thesis we have investigated the dynamic relationship between the USD/SEK exchange rate and OMXS30. Since the variables were I(1) we used the method of vector error correction model to detect a short-run and long-run relationship between the variables. In the short-run we found no statistical evidence of the USD/SEK exchange rate granger causing OMXS30. However, in the long-run we found statistical evidence of the USD/SEK exchange rate and OMXS30 being cointegrated. The effect of a shock to the USD/SEK currency exchange has a long-run positive effect on the OMXS30. This we explained by the economic theory of increased global competitiveness for the export-driven companies on the stock market due to a depreciated local currency.

In the short-run we found statistical evidence of OMXS30 granger causing the USD/SEK currency exchange rates positively. We explained this result as inflation expectations increases in the short-run and therefore the exchange rate is depreciated to incorporate these new expectations. However, in the long-run the effect of an increased value of the stock market appreciates the exchange rate. That could be due to the increased willingness of investors to hold domestic assets in the long-run.

7. Appendix

In this section we present more detailed figures and tables relevant to the thesis. In Table 15 we display a more detailed information about the long-term cointegration matrix covered in Subsection 4.4. Furthermore in Table 16 the block Granger causality test of all variables are presented which is an complement to the block Granger causality in Subsection 4.4. In Table 17 we display detailed information of the third and fourth moments of the residuals in the VEC model covered in Subsection 3.2.5. Additional to the table of eigenvalues in Table 14 Subsection 4.5 we present a graphical representation of the eigenvalues in Figure 3. Finally in Table 18 we display the exact values of the impulse response function which is graphically presented in Figure 1 and 2 in Subsection 4.6.

Table 15: The long-term cointegration matrix normalized on OMXS30

Variable	Coefficient	Std.error	Z	P<Z	95% confidens interval	
OMXS30	1	.	.	.	.	.
USD	2.62	0.53	4.90	<0.001	1.57	3.67
UK	-3.90	1.01	-3.84	<0.001	-5.89	-1.90
EURO	-2.14	2.82	-0.76	0.447	-7.66	3.37
INDIFF30	7.22	1.67	0.00	<0.001	3.94	10.49
CONSTANT	3.88	.	.	.	.	.

Table 16: Block Granger causality test of all endogenous variables

Variable	Block variables	χ2 test statistic	p-value
ΔOMXS30	ΔUSD	0.52	0.7702
	ΔUK	0.76	0.6851
	ΔEURO	5.44	0.0659
	ΔINDIFF30	1.27	0.5295
ΔUSD	ΔOMXS30	7.92	0.0190
	ΔUK	1.36	0.5055
	ΔEURO	1.02	0.5999
	ΔINDIFF30	1.41	0.4948
ΔUK	ΔOMXS30	3.86	0.1450
	ΔUSD	8.30	0.0157
	ΔEURO	0.27	0.8751
	ΔINDIFF30	1.67	0.4336
ΔEURO	ΔOMXS30	6.00	0.0498
	ΔUSD	5.12	0.0773
	ΔUK	5.85	0.0537
	ΔINDIFF30	0.20	0.9052
ΔINDIFF30	ΔOMXS30	1.49	0.4742
	ΔUSD	1.64	0.4397
	ΔUK	2.66	0.2645
	ΔEURO	3.19	0.2031

Table 17: Normality test of skewness and kurtosis of the residuals

		Skewness			Kurtosis	
	Skewness	χ2 test statistic	p-value	Kurtosis	χ2 test statistic	p-value
ΔOMXS30	-0.622	12.382	<0.001	5.057	33.850	<0.001
ΔUSD	-0.057	0.106	0.745	2.810	0.287	0.591
ΔUK	-0.132	0.560	0.454	2.880	0.113	0.736
ΔEURO	-0.098	0.310	0.577	3.773	4.781	0.028
ΔINDIFF30	0.318	3.247	0.071	5.804	62.937	<0.001
All		16.605	<0.001		101.969	<0.001

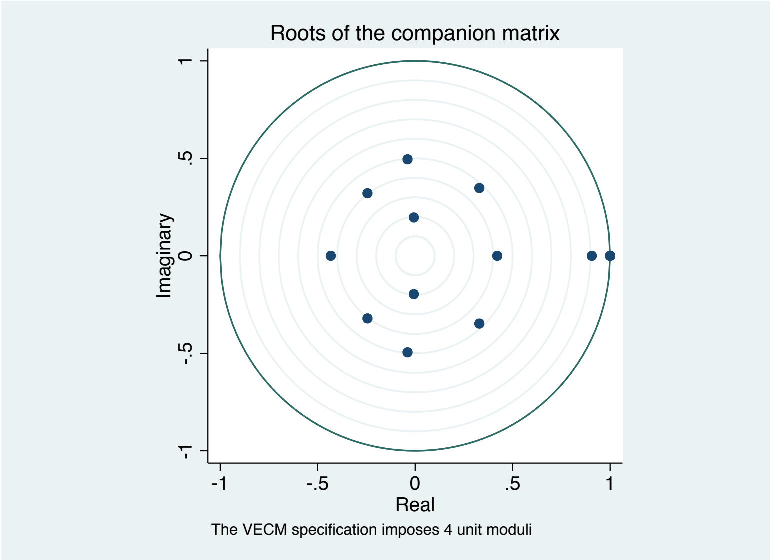

Figure 3: Graphically representation of the eigenvalues

Table 18: Impulse response function values

Impulse response function							
Impulse: ΔUSD		Response: ΔOMXS30		Impulse: ΔOMXS30		Response: ΔUSD	
Week	**IRF**	**Week**	**IRF**	**Week**	**IRF**	**Week**	**IRF**
1	.153875	**26**	.749483	**1**	.072674	**26**	-.214617
2	.112722	**27**	.755422	**2**	.104044	**27**	-.217744
3	.189857	**28**	.760805	**3**	.067558	**28**	-.220577
4	.279923	**29**	.765683	**4**	.041746	**29**	-.223145
5	.308364	**30**	.770103	**5**	.01633	**30**	-.225471
6	.354586	**31**	.77411	**6**	-.009037	**31**	-.22758
7	.402374	**32**	.77774	**7**	-.032212	**32**	-.229491
8	.440962	**33**	.78103	**8**	-.052153	**33**	-.231223
9	.47493	**34**	.784012	**9**	-.070242	**34**	-.232793
10	.506661	**35**	.786714	**10**	-.086843	**35**	-.234215
11	.535518	**36**	.789163	**11**	-.10197	**36**	-.235504
12	.561502	**37**	.791382	**12**	-.115648	**37**	-.236672
13	.585011	**38**	.793393	**13**	-.12805	**38**	-.237731
14	.606381	**39**	.795216	**14**	-.139298	**39**	-.23869
15	.625751	**40**	.796868	**15**	-.149488	**40**	-.239559
16	.643288	**41**	.798365	**16**	-.158719	**41**	-.240347
17	.659181	**42**	.799721	**17**	-.167085	**42**	-.241061
18	.673587	**43**	.80095	**18**	-.174668	**43**	-.241708
19	.686643	**44**	.802065	**19**	-.18154	**44**	-.242295
20	.698473	**45**	.803074	**20**	-.187767	**45**	-.242826
21	.709195	**46**	.803989	**21**	-.193411	**46**	-.243308
22	.718912	**47**	.804818	**22**	-.198526	**47**	-.243744
23	.727717	**48**	.80557	**23**	-.203161	**48**	-.24414
24	.735697	**49**	.806251	**24**	-.207361	**49**	-.244498
25	.742929	**50**	.806868	**25**	-.211168	**50**	-.244823

8. References

Aggarwal, R. (1981) – Exchange Rates and Stock Prices: A Study of the US Capital Markets Under Floating Exchange Rates, Akron Business Economic Review, vol. 12, pp. 7-12.

Ajayi, R.A. & Mougoue, M. (1996) – On the Dynamic Relation Between Stock Prices and Exchange Rates, Journal of Financial Research, vol. 19, pp. 193-207.

Akaike, Hirotugu (1974) - A New Look at the Statistical Model Identification, IEEE Transactions on Automatic Control 19:6: 716–723.

Allayanis, G & Ofek. (2001) – Exchange Rate Exposure, Hedging, and the use of Foreign Currency derivatives, Journal of International Money and Finance, vol. 20, pp.273-296.

Bahmani-Oskooee, M. & Sohrabian, A. (1992) – Stock Prices and the Effective Exchange Rate of the Dollar, Applied Economics, vol. 24, pp. 459-464.

Batori, O. A. Tsoukalas, D & Miranda, P. (2010) – Exchange Rates and Equity Markets: Evidence From Some European Countries, The Journal of Applied Business Research, vol. 26, No. 6.

Brooks, C (2008) – Introductory Econometrics For Finance, Cambridge university press.

Brüggemann, Ralf. Lütkepohl, Helmut & Saikkonen, Pentti (2006) – Residual Autocorrelation Testing For Vector Error Correction Model, Journal of Economics 134 (2006).

Dornbusch, R. & Fischer, S. (1980) – Exchange Rates and the Current Account, The American Economic Review, vol. 70, No. 5.

Enders, Walter (2010) – Applied Econometric Time Series, John Wiley & Sons, Ltd.

Engle, Robert. F & Granger, C.W.J (1987) – Co-Integration and Error Correction: Representation, Estimation And Testing, Econometrica 55:2 Mars 1987.

Gavin, M. (1989) – The Stock Market and Exchange Rate Dynamics, Journal of International Money and Finance, vol. 8, pp. 181-200.

Jarque, Carlos. M & Bera, Anil. K (1987) – A Test for Normality of Observations and Regression Residuals, International Statistical Review 55:2 August 1987.

Johansen, Søren & Juselius, Katarina (1990) – Maximum Likelihood Estimation and Inference on Cointegration – With Applications to the Demand For Money, Oxford Bulletin Of Economics And Statistics 52:2 (1990).

Johansen, Søren (1991) – Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, Econometrics 59:6 November 1991.

Lütkepohl, Helmut. Belsley, David A & Kontoghiorghes, Erricos John (2009) – Handbook of Computational Econometrics, John Wiley & Sons, Ltd.

Lütkepohl, Helmut (2005) - New Introduction To Multiple Time Series Analysis. Springer-Verlag, Berlin.

Mukherjee, Tarun K & Naka, Atsuyuki (1995) – Dynamic Relations Between Macroeconomic Variables and the Japanese Stock Market: an Application of a Vector Error Correction Model, The Journal of Financial research 18:2 p.223-237

Nieh, C-C & Lee, F-C. (2001) - Dynamic Relationship between Stock Prices and Exchange rates for G-7 Countries. The Quarterly Review of Economics and Finance, vol. 41, pp. 477-490.

Obben, J. Pech, A & Shakur, S (2010) - Analysis of the Relationship Between the Share Market and Exchange Rates in New Zealand: A Cointegrated VAR Approach, New Zealand economics papers, 40:2, 147-180.

Patterson, Kerry (2000) An Introduction To Applied Econometrics: A Time Series Approach, Macmillan Press Ltd, London.

Ratner, M. (1993) A Cointegration Test of the Impact of Foreign Exchange Rates on U.S. Stock Prices, Global Finance Journal, vol. 4, pp. 91-101.

Solnik, B. (1987) Financial Prices to Test Exchange Rate Models: A Note, The Journal of Finance, vol. 42, No. 1.

Yang, S-Y (2003) – Price and Volatility Spillovers Between Stock Prices and Exchange Rates: Empirical Evidence From The G-7 Countries, International journal of business and economics, 3:2, 47-56.