



## **School of Economics and Management**

# **Testing Granger causality with application to Exchange rates for Swedish kronor with GB pound and US dollar.**

## **MASTER THESIS**

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# Abstract

This thesis undertakes the Causality study with application to exchange rates for Swedish kronor (SEK) with GB pound (£) and US dollar (\$) in the frame work of vector Autoregressive (VAR) model. We present the theory behind the Granger Causality, unit roots and vector auto-regression. The Augmented Dickey-Fuller test for unit roots is performed. Our data consist of three time series of daily foreign exchange rates, starting from 23<sup>rd</sup> November, 2007 to 21<sup>st</sup> May, 2008. Granger causality is a technique for determining whether one time series is useful in forecasting another. By applying this technique, we try to observe the casual relationship which exists between the three currencies of our study.

**Key words:** Granger Causality, Unit Root, VAR Model.

# **Chapter 1.**

## **Introduction**

Many years ago the value of the currencies in the world were determined by how much it is worth by a piece of gold. This means that a currency at that time represents a real amount of gold. For instance in the 1930s, the United States set a standard of valuing the United States dollar as: 1 ounce of gold equivalent to \$35. After the world war two, other countries used the USD as a way of determining the value of their currencies. Since it was well known about how much a USD was worth in gold, the value of any other currency against the dollar could be based on its value in gold.

As time went on, this system of valuing a currency was surpassed by the modern world of economics. Inflation affected the USD, while the value of the other currencies went up. This led to a reduction of the value of the USD as 1 ounce of gold was now worth \$70. Eventually in 1971, the US cancelled the gold standard of measurement. The value of the USD was then determined by market driven forces. This has led to the idea of exchange rates which is now seen as one of the customary indicators or predictors of the economy. Currencies in this world play a major role in modern economies. They help in determining value of goods across different countries. There is the need for exchange rates since one country's currency is not generally accepted in another.

In simple terms, an exchange rate can be defined as “the current market price for which one currency can be exchanged for another”.

Statistical definition of exchange rate is “the price of one country's currency in relation to another”.

It can also be defined in economics as “home currency per foreign”.

A particular currency exchange rate is determined by two systems, namely the floating system and the pegged system:

In floating system, market determines the rate of exchange. That is the rate of a currency, is determined by supply and demand and other economic factors like imports & exports, inflation, interest rates etc.

The pegged system is more or less a fixed system and here is the country's government that sets the exchange rate of its currency. The rate is normally pegged to another currency, commonly the USD.

Since the strength of exchange rates has effect on trade balances, capital inflows, growth rates, profits, inflation rates, interest rates. The recent crises across different assets and markets in global level show the importance of the causality effect between the international markets. Three currencies in the world's economy are considered in this thesis and these are the SEK, USD (\$) and GBP (£).

This thesis examines the causality effects with application to exchange rates for SEK to GBP, SEK to USD and USD to GBP. The main objective of this research is to observe the casual relationships which exist between the currencies of our consideration. We approach it through the method Time Series Analysis by application of Granger-Causality.

In the next chapter, we introduce the statistical theory. In chapter 3, we present the data and methodology. Chapter 4 is about graphical presentation of data and application of unit roots and Granger-Causality. Finally in chapter 5, we present the summary and conclusions.

## **Chapter 2.**

### **Theory**

#### **2.1. Granger Causality**

**Granger causality** is a technique for determining whether one time series is useful in forecasting another. Ordinarily, regressions reflect "mere" correlations.

Granger (1969) defined causality as follows:

A variable  $Y$  is causal for another variable  $X$  if knowledge of the past history of  $Y$  is useful for predicting the future state of  $X$  over and above knowledge of the past history of  $X$  itself.

So if the prediction of  $X$  is improved by including  $Y$  as a predictor, then  $Y$  is said to be Granger causal for  $X$ .

Granger Causality takes into account prediction rather than the name it suggests, that is causation. This is because it creates the impression that while the past can cause or predict the

future, the future cannot cause or predict the past. From what Granger deduced, ‘X’ causes ‘Y’ if the past values of ‘X’ can be used to predict ‘Y’ better than the past values of ‘Y’ itself.

Granger-causality test can be applied in three different types of situations:

1. In a simple Granger-causality test there are two variables and their lags.
2. In a multivariate Granger-causality test more than two variables are included, because it is supposed that more than one variable can influence the results.
3. Granger-causality can also be tested in a VAR framework; in this case, the multivariate model is extended in order to test for the simultaneity of all included variables.

Granger presented a clear time series approach for testing for such causality that has since been used in many econometric studies. Relationship between two variables can be unidirectional, bidirectional (or feedback) and neither bilateral nor unilateral (i.e. independence means no Granger-causality in any direction). Granger causality testing applies only to statistically stationary time series. If the time series are non-stationary, then the time series model should be applied to temporally differenced data rather than the original data.

Consider a Vector Autoregressive model of two-equation as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} A_{10} \\ A_{20} \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

Where,

$A_{i0}$  = the parameters representing intercept terms

$A_{ij}(L)$  = the polynomials in the lag\* operator  $L$

$\varepsilon_{it}$  = white-noise disturbances

In the two-equation model with  $p$  lags,  $y_{1t}$  does not Granger cause  $y_{2t}$  if and only if all of the coefficients of  $A_{21}(L)$  are equal to zero. Again, if all variables in the VAR are stationary, Granger Causality can be tested by using a standard F-test of the restriction:

$$a_{21}(1) = a_{21}(2) = a_{21}(3) = \dots = a_{21}(p) = 0$$

Where,  $a_{21}(1), a_{21}(2), \dots$  are the individual coefficients of  $A_{21}(L)$ .

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\* In time series analysis, the lag operator, operates on an element of a time series to produce the previous element.

## 2.2. Stationarity

Stationarity can be defined as:

A time series  $y_t$  is covariance (or weakly) stationary if, and only if, its mean and variance are both finite and independent of time, and the auto-covariance does not grow over time, for all  $t$  and  $t-s$ ,

1. Finite mean

$$E(y_t) = E(y_{t-s}) = \mu$$

2. Finite variance

$$\text{var}(y_t) = E[(y_t - \mu)^2] = E[(y_{t-s} - \mu)^2] = \sigma_y^2$$

3. Finite auto-covariance

$$\text{cov}(y_t, y_{t-s}) = E[(y_t - \mu)(y_{t-s} - \mu)] = \gamma_s$$

i.e. auto-covariance between  $y_t, y_{t-s} = \rho_s = \frac{\gamma_s}{\gamma_0}$

### 2.2.1. Non-Stationarity

The variance is time dependent and goes to infinity as time approaches to infinity. A time series which is not stationary with respect to the mean can be made stationary by differencing. Differencing is a popular and effective method of removing a stochastic trend from a series.

### 2.2.2. Testing of Stationarity

If a time series has a unit root, the series is said to be non-stationary. Tests which can be used to check the stationarity are:

1. Partial autocorrelation function and Ljung and Box statistics.
2. Unit root tests.\*

To check the stationarity and if there is presence of unit root in the series, the most famous of the unit root tests are the ones derived by Dickey and Fuller and described in Fuller (1976), also Augmented Dickey-Fuller (ADF) or said-Dickey test has been mostly used.

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\*A test designed to determine whether a time series is stable around its level (trend-stationary) or stable around the differences in its levels (difference-stationary).

### Dickey-Fuller (DF) test:

Dickey and Fuller (DF) considered the estimation of the parameter  $\alpha$  from the models:

1. A simple AR (1) model is:  $y_t = \alpha y_{t-1} + \varepsilon_t$

2.  $y_t = \mu + \alpha y_{t-1} + \varepsilon_t$

3.  $y_t = \mu + \beta t + \alpha y_{t-1} + \varepsilon_t$

It is assumed that  $y_0 = 0$  and  $\varepsilon_t \sim$  independent identically distributed, i.i.d  $(0, \sigma^2)$

The hypotheses are:

$$H_0: \alpha = 1$$

$$H_1: |\alpha| < 1$$

Alternative three versions of the Dickey-Fuller test of the parameter  $\alpha$  from the models:

1. Pure random walk model.

$$y_t = \alpha y_{t-1} + \varepsilon_t$$

$$\Rightarrow y_t - y_{t-1} = \alpha y_{t-1} - y_{t-1} + \varepsilon_t$$

$$\Rightarrow \Delta y_t = (\alpha - 1) y_{t-1} + \varepsilon_t$$

So,  $\Delta y_t = \gamma y_{t-1} + \varepsilon_t$

Null hypothesis is:  $H_0: \gamma = 0$

Similarly, we have

2. Drift +random walk.

$$\Delta y_t = \mu + \gamma y_{t-1} + \varepsilon_t$$

Null hypothesis is:  $H_0: \mu = 0; \gamma = 0$

3. Drift +linear time trend.

$$\Delta y_t = \mu + \gamma y_{t-1} + \beta t + \varepsilon_t$$

Null hypothesis is:  $H_0: \beta = 0; \gamma = 0$

Where,  $\mu$  is a drift or constant term,  $\beta t$  is a time trend, and  $\Delta y_t$  is the first-order difference of the series  $y_t$ .

### Augmented Dickey-Fuller (ADF) or Said-Dickey test:

Augmented Dickey-Fuller test is an augmented version of the Dickey-Fuller test to accommodate some forms of serial correlation and used for a larger and more complicated set of time series models.



If there is higher order correlation then ADF test is used but DF is used for AR (1) process. The testing procedure for the ADF test is the same as for the Dickey-Fuller test but we consider the AR (p) equation:

$$y_t = \alpha + \gamma t + \sum_{i=1}^p \beta_i y_{t-i} + \varepsilon_t$$

Assume that there is at most one unit root, thus the process is unit root non-stationary. After reparameterize this equation, we get equation for AR (p):

$$\Delta y_t = \mu + \gamma t + \alpha y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-i} + \varepsilon_t$$

Each version of the test has its own critical value which depends on the size of the sample. In each case, the null hypothesis is that there is a unit root,  $\gamma = 0$ . In both tests, critical values are calculated by Dickey and Fuller and depends on whether there is an intercept and, or deterministic trend, whether it is a DF or ADF test.

### 2.3. Vector Auto-regression (VAR)

Vector Auto-regression (VAR) is an econometric model has been used primarily in macroeconomics to capture the relationship and independencies between important economic variables. They do not rely heavily on economic theory except for selecting variables to be included in the VARs. The VAR can be considered as a means of conducting causality tests, or more specifically Granger causality tests.

VAR can be used to test the Causality as; Granger-Causality requires that lagged values of variable 'X' are related to subsequent values in variable 'Y', keeping constant the lagged values of variable 'Y' and any other explanatory variables.

In connection with Granger causality, VAR model provides a natural framework to test the Granger causality between each set of variables. VAR model estimates and describe the relationships and dynamics of a set of endogenous variables.

For a set of 'n' time series variables  $y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ , a VAR model of order p (VAR (p)) can be written as:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + \varepsilon_t$$

Where,

p = the number of lags to be considered in the system.

n = the number of variables to be considered in the system.

$y_t$  is an  $(n,1)$  vector containing each of the ‘ $n$ ’ variables included in the VAR.

$A_0$  is an  $(n,1)$  vector of intercept terms.

$A_i$  is an  $(n,n)$  matrix of coefficients.

$\varepsilon_t$  is an  $(n,1)$  vector of error terms.

Consider a two-variable VAR ( $I$ ):

$$(1) \quad y_{1t} = a_{10} + a_{11} y_{1t-1} + a_{12} y_{2t-1} + \varepsilon_{1t}$$

$$(2) \quad y_{2t} = a_{20} + a_{21} y_{1t-1} + a_{22} y_{2t-1} + \varepsilon_{2t}$$

In matrix form a two-variable VAR ( $I$ ) can be written as:

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

More simply, VAR in standard form (unstructured VAR) is:

$$y_t = A_0 + A_1 y_{t-1} + \varepsilon_t$$

### 2.3.1. Determination of Lag-Length for VAR model

A critical element in the specification of VAR models is the determination of the lag length of the VAR. Various lag length selection criteria are defined by different authors like, Akaike’s (1969) final prediction error (FPE), Akaike Information Criterion (AIC) suggested by Akaike (1974), Schwarz Criterion (SC) (1978) and Hannan-Quinn Information Criterion (HQ) (1979).

These criteria mainly indicate the goodness of fit of alternatives (models) so they should be used as complements to the LR test. The LR test (Sequential modified LR test statistic) should be used as a primary determinant of how many lags to include.

### 2.3.2. LR test

$$LR = (T - m)(\ln |\Sigma_r| - \ln |\Sigma_u|) \sim \chi^2(q)$$

Where,

$T$  = number of usable observations.

$m$  = number of parameters estimated in each equation of the unrestricted system, including the constant.

$\ln|\Sigma_r|$  = natural logarithm of the determinant of the covariance matrix of residuals of the restricted system.

$\ln|\Sigma_u|$  = natural logarithm of the determinant of the covariance matrix of residuals of the unrestricted system.

To compare the test statistic:

$$(T - m)(\ln |\Sigma_r| - \ln |\Sigma_u|) \text{ to a } \chi^2 \text{ distribution}$$

Where:

$q$  = total number of restrictions in the system (equal to number of lags times  $n^2$ ) and  $n$  is the number of variables (or equations).

If the LR statistics < critical value, reject the null hypothesis of the restricted system.

The likelihood ratio test may not be very useful in the small samples. When the model is restricted version of the other, the likelihood ratio test is only applicable in situation. Multivariate generalizations of the AIC and SC are the alternative test criteria.

### 2.3.3. Information Criteria

$$AIC = T \ln |\Sigma| + 2N$$

$$SC = T \ln |\Sigma| + N \ln T$$

$$HQIC = T \ln |\Sigma| + 2N \ln \ln T$$

Where,

$|\Sigma|$  = determinant of the variance/covariance matrix of the residuals.

$N$  = total number of parameters estimated in all equations.

$T$  = number of usable observations.

### 2.3.4. Stability of the Stationary VAR system

The  $P$ th-order VAR model  $y_t = a_0 + a_1 y_{t-1} + \dots + a_p y_{t-p} + \varepsilon_t$  can be written by using

lag operators as:  $(1 - a_1 L - a_2 L^2 - \dots - a_p L^p) y_t = a_0 + \varepsilon_t$

Or more briefly:  $A(L) y_t = a_0 + \varepsilon_t$

Where,  $A(L)$  is the polynomial  $(1 - a_1 L - a_2 L^2 - \dots - a_p L^p)$  in the lag operator. The roots of the polynomial must lie outside the unit circle.

Similarly, in the first-order autoregressive model  $y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$ , the stability condition is  $|a_1| < 1$ .

So, the necessary and sufficient condition for stability of stationary VAR is that all characteristic roots must lie outside the unit circle.

## **Chapter 3.**

### **Data and Methodology**

#### **Data**

The data of our thesis consist of three time series of foreign exchange rates, namely Swedish kronor (SEK), GB pound (£) and US dollar (\$). The data is daily which means, we observe the currency exchange rates five days in a week (Monday to Friday) and for the other two days (Saturday and Sunday) the values remains same because of no trading.

The data has 181 observations, starting from 23<sup>rd</sup> November, 2007 to 21<sup>st</sup> May, 2008, obtained from internet (<http://www.exchange-rates.org>).

#### **Methodology**

Our task is to analyze the data to determine the causality between SEK and USD (categorized as SEKUSD), SEK and GBP (categorized as SEKGPB), and finally USD and GBP (categorized as USDGBP).

Before analyzing the causal relationship between exchange rates, data has been transformed to natural logarithms, and then we examine the possible existence of unit roots in the data to ensure that the model constructed later is stationary in terms of the variables used. If a time series has a unit root, the first difference of the series is stationary and should be used.

The stationarity of each series is investigated by employing Augmented Dickey-Fuller unit root test. The test consists of regress each series on its lagged value and lagged difference terms. The number of lagged differences included is determined by the Schwarz Information Criterion (SIC). The equation used for conducting Augmented Dickey Fuller test has the following structure:

$$\Delta y_t = \mu + \gamma t + \alpha y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-i} + \varepsilon_t$$

We further proceed with the VAR lag order selection criteria to choose the best lag length for the VAR time series model to examine the Granger causality and we perform the pair wise Granger Causality test for all the series.

To carry out the analysis of the data, we use the statistical package, E-views<sup>®</sup> version 6 which is used mainly for economic and statistical analysis.

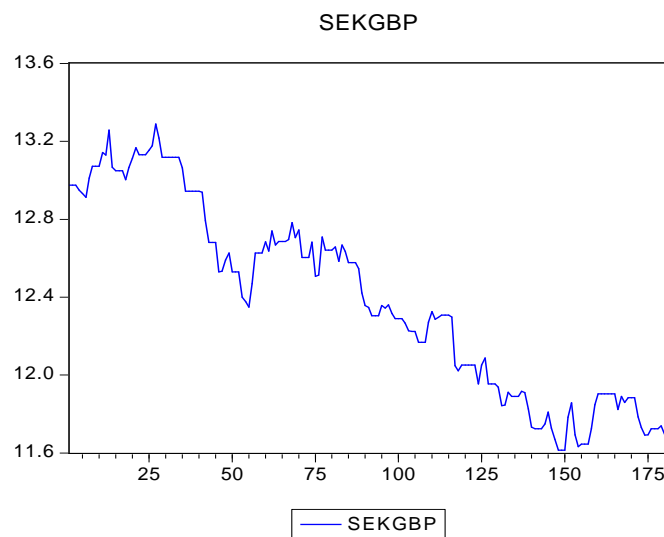
## Chapter 4.

### Graphical Presentation & Application

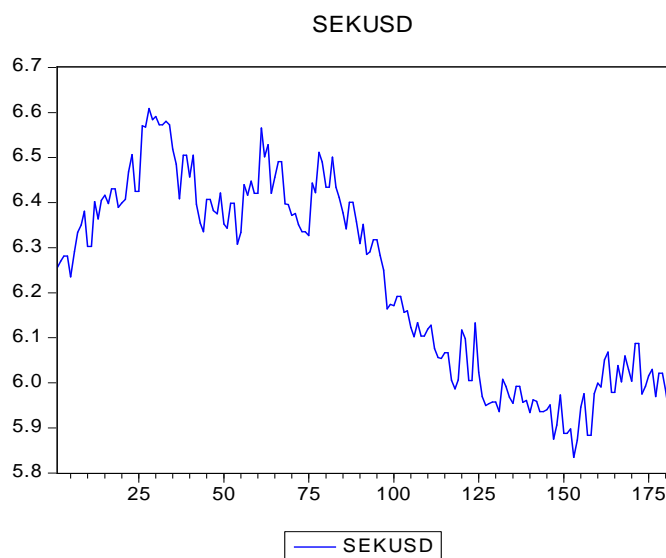
This chapter consists of graphical presentation of data and applications of unit root test, VAR lag order selection criteria and pair-wise Granger Causality.

The research starts by showing the graphs of the raw data, which comprises the series SEKGBP, SEKUSD and USDGBP in order to know how they behave in their natural state. The (Fig. 1, Fig. 2 and Fig. 3) are shown below.

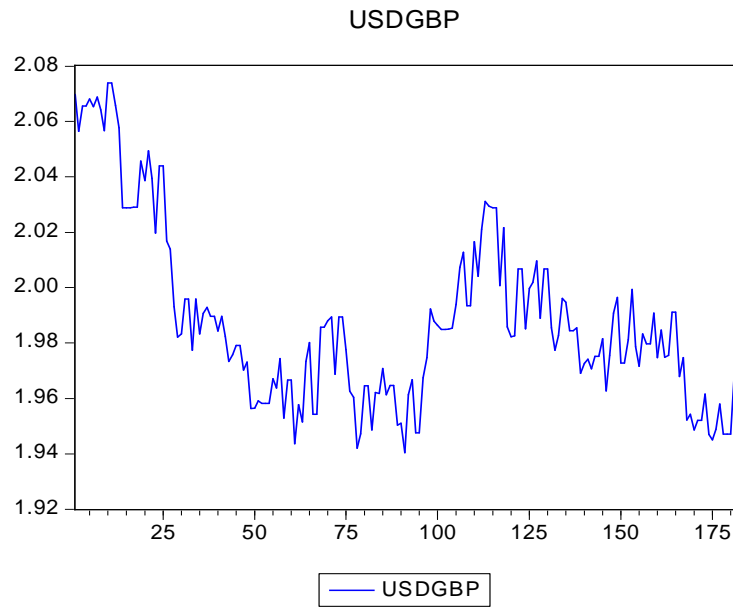
**Figure. 1 (Graph of SEKGBP)**



**Figure. 2 (Graph of SEKUSD)**



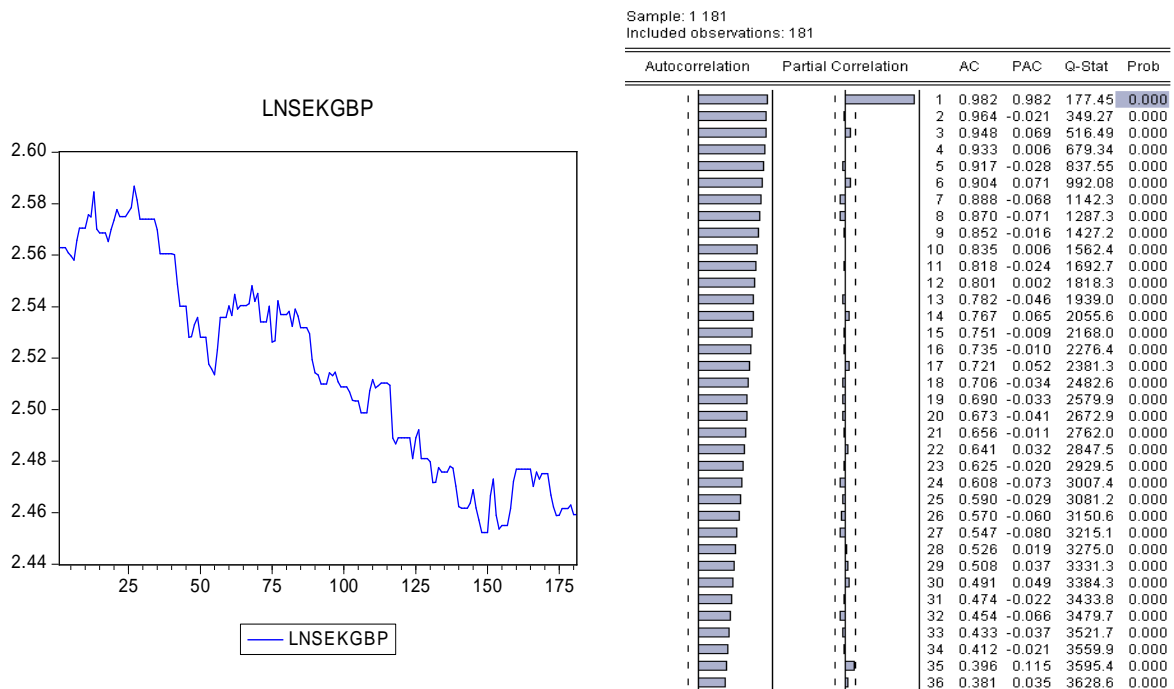
**Figure. 3 (Graph of USDGBP)**



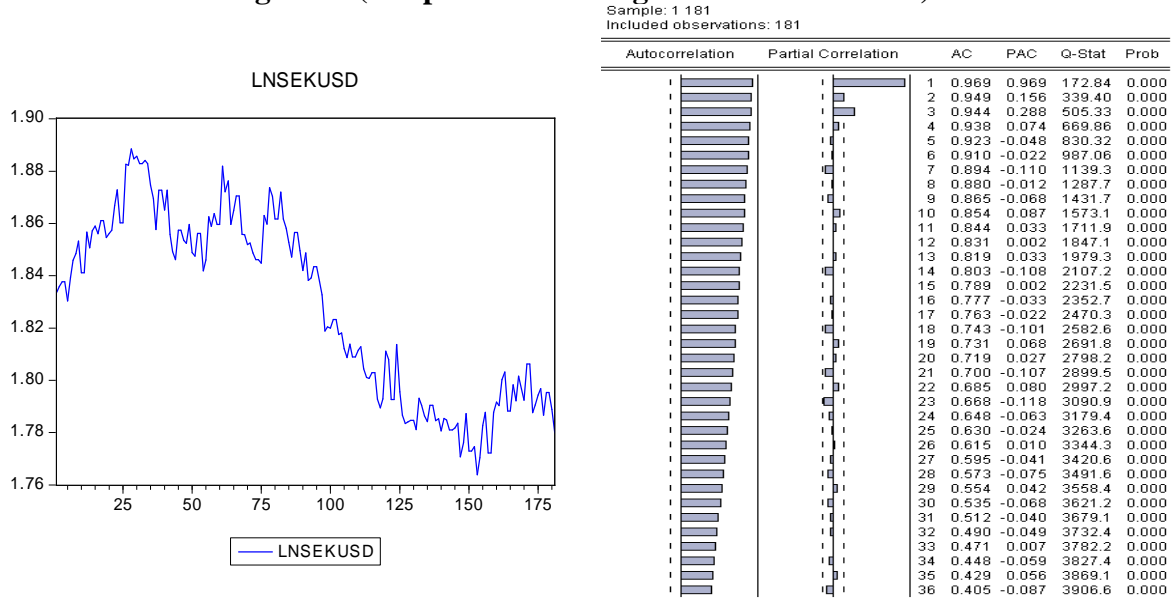
From the above three figures, the impression is that the series are not stationary.

Our next step is to make the series linear. We take the logarithms of the original series: SEKUSD, SEKGBP, and USDGBP and produce their graphs. To conclude that the series are stationary or not, we also produce the correlograms of the three logarithmic series: LNSEKGBP, LNSEKUSD, and LNUSDGBP (Fig. 4, Fig. 5 and Fig. 6).

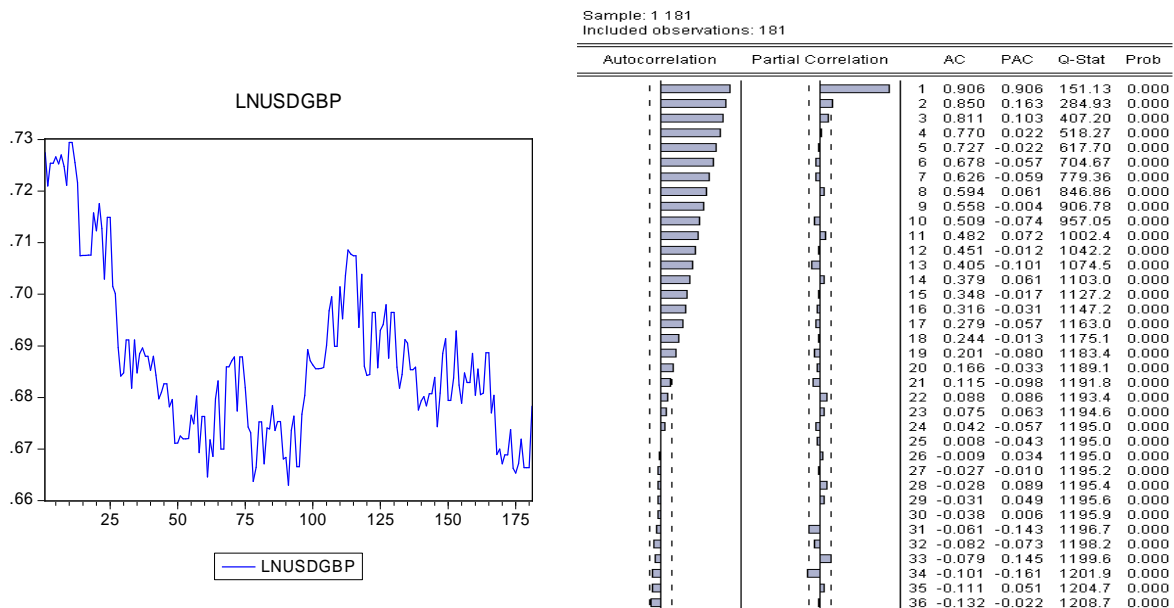
**Figure. 4 (Graph and Correlogram of LNSEKGBP)**



**Figure. 5 (Graph and Correlogram of LNSEKUSD)**



**Figure. 6 (Graph and Correlogram of LNUSDGBP)**



From the above graphs, we conclude that all the three series are not stationary also the above correlograms do not show stationarity. It is clear from correlograms that the non-decaying behavior of the sample Autocorrelation Function (ACF) is due to lack of stationarity because ACFs are suffered from linear decline but the Partial Autocorrelation Function (PACFs) decaying very quickly and there is only one significant spike of PACFs.

To make the above conclusion more confirm, we perform a unit root test (Augmented Dickey-Fuller) to observe whether the series are stationary or not.

**Table. 1 (Augmented Dickey-Fuller Test on LNSEKGBP, LNSEKUSD, LNUSDGBP)**

**Null Hypotheses: LNSEKGBP, LNSEKUSD, LNUSDGBP has a unit root**

LNSEKGBP	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 0 (Automatic based on SIC, MAXLAG = 13)
			-0.685041	0.8466	
	Test critical values	1% level	-3.466786		
		5% level	-2.877453		
		10% level	-2.575332		
LNSEKUSD	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 2 (Automatic based on SIC, MAXLAG = 13)
			-0.483526	0.8903	
	Test critical values	1% level	-3.467205		
		5% level	-2.877636		
		10% level	-2.575430		
LNUSDGBP	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 2 (Automatic based on SIC, MAXLAG = 13)
			-2.565420	0.1022	
	Test critical values	1% level	-3.467205		
		5% level	-2.877636		
		10% level	-2.575430		

\*MacKinnon (1996) one-sided p-values.

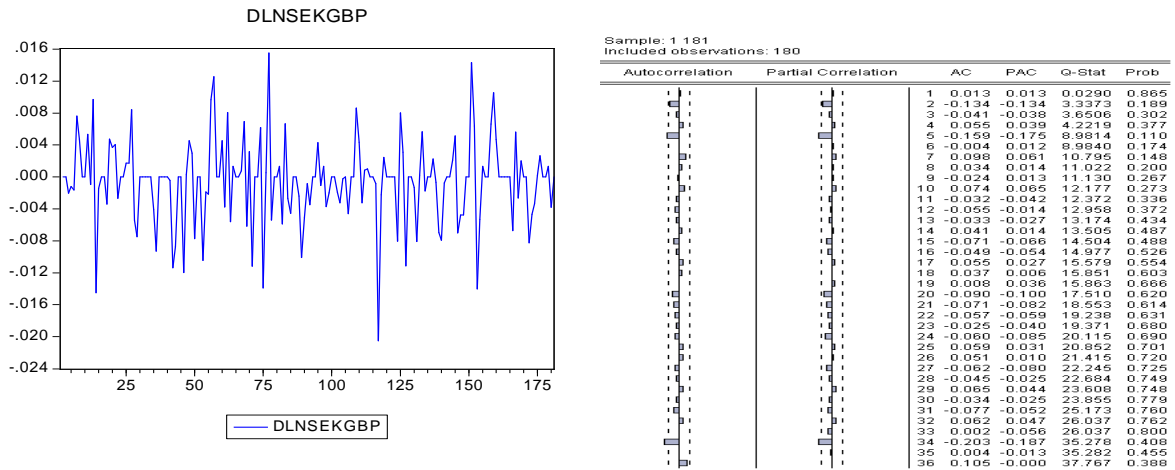
Above table is the summary of results of Augmented Dickey-Fuller test. According to (Table.1), we conclude that there is presence of unit root according to the P-values of all the three series as the P-values are insignificant. Since the values of computed ADF test-statistic of the three series are greater than the critical values at 1%, 5% and 10% levels of significance, respectively with different lag lengths (based on Schwarz Information Criterion). So, the null hypotheses cannot be rejected that means all the three series have a unit root.

From the unit root test, we conclude that the three series are not stationary, so we make these three non-stationary series, stationary by taking first difference as: DLNSEKGBP,

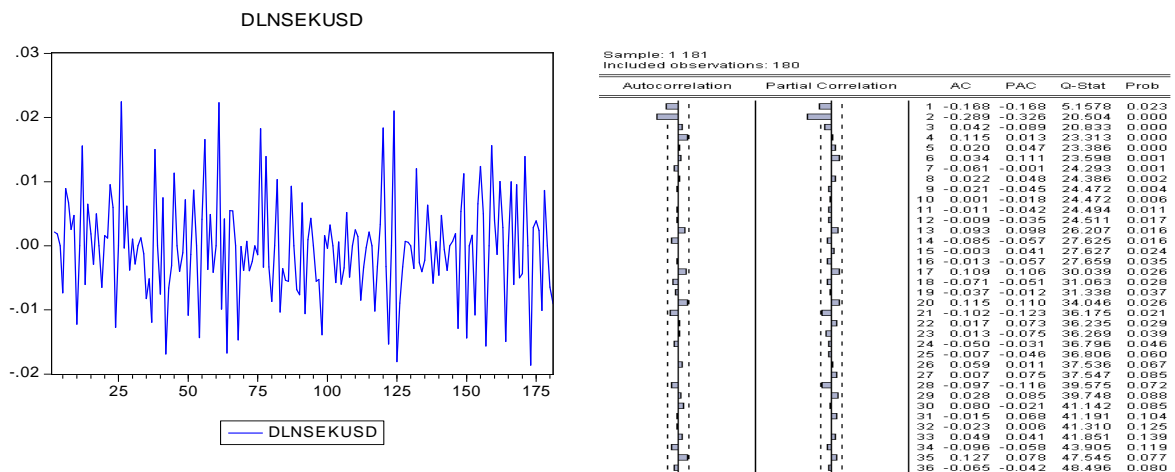


DLNSEKUSD and DLNUSDGBP. Below graphs and correlograms clearly shows the first difference of the series.

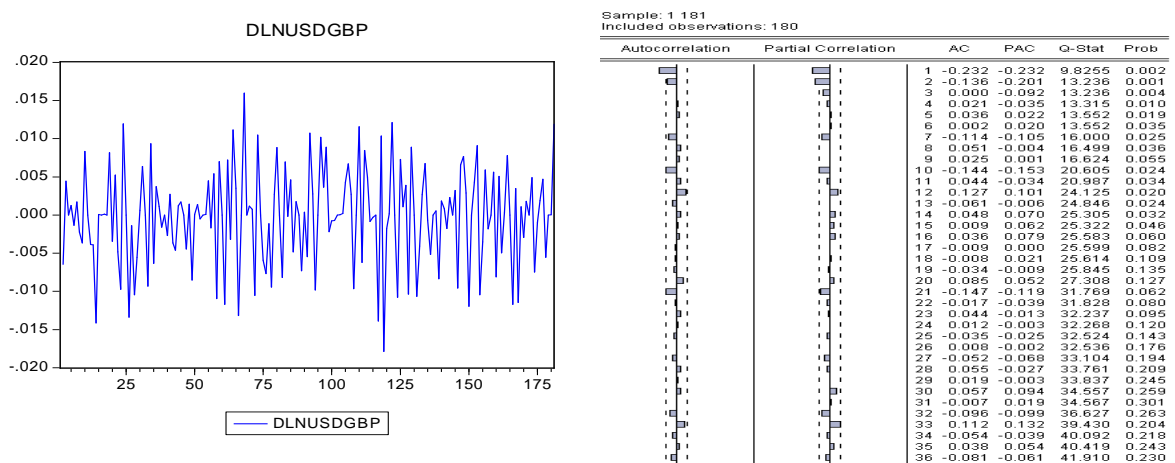
**Figure. 7 (Graph and Correlogram of DLNSEKGBP)**



**Figure. 8 (Graph and Correlogram of DLNSEKUSD)**



**Figure. 9 (Graph and Correlogram of DLNUSDGBP)**



A first difference of all the three series looks stationary and correlograms also verifies the same as we see that ACFs tend to zero rather quickly.

We apply unit root test with Augmented Dickey-Fuller after taking the first difference to check whether the series are now stationary or not.

**Table. 2 (Augmented Dickey-Fuller Test on DLNSEKGBP, DLNSEKUSD, DLNUSDGBP)**

**Null Hypotheses: DLNSEKGBP, DLNSEKUSD, DLNUSDGBP has a unit root**

DLNSEKGBP	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 0 (Automatic based on SIC, MAXLAG = 13)
			-13.13764	0.0000	
	Test critical values	1% level	-3.466994		
		5% level	-2.877544		
		10% level	-2.575381		
DLNSEKUSD	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 1 (Automatic based on SIC, MAXLAG = 13)
			-14.18079	0.0000	
	Test critical values	1% level	-3.467205		
		5% level	-2.877636		
		10% level	-2.575430		
DLNUSDGBP	Augmented Dickey-Fuller test statistic		t-Statistic	Prob.*	Lag Length: 1 (Automatic based on SIC, MAXLAG = 13)
			-12.67032	0.0000	
	Test critical values	1% level	-3.467205		
		5% level	-2.877636		
		10% level	-2.575430		

\*MacKinnon (1996) one-sided p-values.

According to the results of Augmented Dickey-Fuller test, above summary (Table. 2), we conclude that there is absence of unit root according to the P-values of all the three series as the P-values are significant. The values of computed ADF test-statistic of the three series are smaller than the critical values at 1%, 5%, and 10% levels of significance, respectively with different lag lengths (based on Schwarz Information Criterion). Therefore, we reject the null

hypotheses that mean all the three series do not have a unit root. We conclude that all the three series are stationary according to the results of Augmented Dickey-Fuller (Table. 2). Finally, we get the stationarity (there is absence of unit root in ADF test) at different levels of significance with different lag lengths.

Since the three series are stationary, so we proceed with the lag order selection criteria for testing the Granger Causality. Lag length selection criteria determines the VAR model (Table. 3). We select the best lag length for the VAR time series model on which Granger causality is based.

**Table. 3 (VAR Lag Order Selection Criteria)**

Endogenous variables: DLNSEKGBP DLNSEKUSD DLNUSDGBP

Exogenous variables: C

Included observations: 175

<b>Lag</b>	<b>LR</b>	<b>FPE</b>	<b>AIC</b>	<b>SC</b>	<b>HQ</b>
0	NA	4.85e-14	-22.14369	-22.08944	-22.12168
1	38.18044	4.30e-14	-22.26411	-22.04710	-22.17608
2	51.94239	3.50e-14	-22.47043	-22.09066*	-22.31639
3	27.38039	3.29e-14	-22.53352	-21.99098	-22.31345
4	20.52528	3.21e-14	-22.55736	-21.85206	-22.27127
5	35.62151*	2.84e-14*	-22.67854*	-21.81048	-22.32643*

\* indicates lag order selected by the criterion

According to the results of VAR lag order selection criteria (Table. 3), we decide to use lag length 5 for the Granger Causality test. This is due to the fact that LR, Akaike and Hannan-Quinn choose 5 lags but Schwarz choose 2 lags. We use the LR test [sequential modified LR test statistic (each test at 5% level)] as a primary determinant of how many lags to be include. Also Akaike and Schwarz are complements to the LR to determine the goodness of fit for the models. As the majority of the information criteria choose 5 lags so, we reach at this conclusion that 5 lags are optimal for the data.

With continuation of analysis, we proceed to perform the pair-wise Granger Causality test for all the series DLNSEKGBP, DLNSEKUSD and DLNUSDGBP (Table. 4) by using the above selected lag length 5.

**Table. 4 (Pair-wise Granger Causality Tests)**

Null hypothesis	Lags	Obs	Prob.	Decision
DLNSEKUSD does not Granger Cause DLNSEKGBP			0.0011	reject
DLNSEKGBP does not Granger Cause DLNSEKUSD	5	175	0.0004	reject
DLNUSDGBP does not Granger Cause DLNSEKGBP			0.0005	reject
DLNSEKGBP does not Granger Cause DLNUSDGBP	5	175	0.8233	Do not reject
DLNUSDGBP does not Granger Cause DLNSEKUSD			0.6437	Do not reject
DLNSEKUSD does not Granger Cause DLNUSDGBP	5	175	0.8633	Do not reject

**Consider Pair-wise comparison of series, DLNSEKUSD VS DLNSEKGBP:**

According to the results of (Table. 4), the P-value (0.0011) is significant so, we reject the null hypothesis and we conclude that DLNSEKUSD Granger Cause DLNSEKGBP. The P-value (0.0004) is also significant so, we reject the null hypothesis and we conclude that DLNSEKGBP Granger cause DLNSEKUSD. So, DLNSEKUSD affects DLNSEKGBP and the converse is also true, it means the Granger Causality is (bidirectional) between the series, running from DLNSEKUSD to DLNSEKGBP and the other way.

**Now, Pair-wise comparison of the series, DLNUSDGBP VS DLNSEKGBP:**

According to (Table. 4), the P-value (0.0005) is significant so, we reject the null hypothesis and we conclude that DLNUSDGBP Granger Cause DLNSEKGBP. But the converse is not true as P-value (0.8233) is insignificant so, we cannot reject the null hypothesis and we conclude that DLNSEKGBP does not Granger Cause DLNUSDGBP. So, DLNUSDGBP affects DLNSEKGBP but the converse is not true, it means the Granger Causality is (unidirectional) between the series, DLNUSDGBP and DLNSEKGBP, running from DLNUSDGBP to DLNSEKGBP and not the other way.

**Finally, Pair-wise comparison of series, DLNUSDGBP VS DLNSEKUSD:**

According to (Table. 4), the P-value (0.6437) is insignificant so, we cannot reject the null hypothesis and we conclude that DLNUSDGBP does not Granger Cause DLNSEKUSD. The P-value (0.8633) is also insignificant so, we cannot reject the null hypothesis and we conclude that DLNSEKUSD does not Granger Cause DLNUSDGBP. So, DLNSEKUSD does not affect DLNUSDGBP, also the converse is true, it means the Granger Causality is (non-directional) between the series.

## **Chapter 5.**

### **Summary and Conclusions**

The main objective of this master thesis is to analyze the causality effect with application to exchange rates for Swedish kronor (SEK) with GB pound (£) and US dollar (\$). We perform unit root test, VAR lag order selection criteria and pair-wise Granger-Causality test to establish the relationship which exists between the three currencies of our study.

According to the results of this research with real data, we find from the unit root test (Augmented Dickey-Fuller) on logarithmic series that the three series have a unit root which means all the series do not show stationarity. After taking first difference of the series, the results of unit root test show stationarity at the levels of significance: 1%, 5% and 10% with different lag lengths.

According to the results of pair-wise Granger Causality tests, we find bidirectional causality between SEKUSD and SEKGBP, which means both series affect each other. We observe SEKUSD is useful to forecast SEKGBP also the converse is true.

We observe unidirectional causality between USDGBP and SEKGBP which means USDGBP is useful to forecast SEKGBP but the converse is not true.

Finally, we find non-directional causality between USDGBP and SEKUSD which shows USDGBP cannot be used to forecast SEKUSD, also the converse is true.

Moreover, according to the results of Granger-Causality of our research, we observe that the casual relationship which exists between Swedish kronor, US dollar and GB pound adjust to reflect changes in the price levels of the three countries. The leading role of the US Dollar is clearly visible throughout the causality tests.

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