CHAPTER IV

METHODOLOGY

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4.1 Introduction

In this section, we will look into the methodology and statistics used in this study. We will discuss the stationarity test, cointegration and finally VAR estimation. To test if the time series data is stationary, we will apply the stationarity test. When the stationary test data is not stationary, spurious regression occurs. So, cointegration analysis is considered a pre test to avoid the problem of spurious regression. Meanwhile, the cointegration test that we applied is the Johansen Test and then we will proceed to VAR.

4.2 Scope of the Study

The data of each variable used for the period of 1999:1 to 2003:7. in the study, several statistical tests are used to provide consistent estimates of the parameters. This study employ monthly series over the period of 1991:1 to 2003:7.Three types of variables namely, nominal interest rate, inflation expectations and real interest rate (please refer appendix for details). This study examines the impact of the monetary shock on the variables as stated above. The impact is limited on the financial market view.

4.3 Sources of Data

Data on financial markets and CPI are extracted from various of issues of the Monthly Bulletin published by BNM (Bank Negara Malaysia) and from web site itself.

4.4 Use of Software Package.

Econometric Views (Eviews) will be used to analyze and test the functional relationship for the above model such a the Augmented Dickey Fuller(ADF) unit root test, the Johansen and Juselius (1990) rest for cointegration and Vector Auto Regression (VAR) model.

4.5 A Stationarity Test

A number of statistical tests may be used to test for the stationarity. Time series may not be stationary and in fact there may be situation that exemplifies the problem of spurious regression whereby the time series involved exhibit strong trends trend, and not to be true between the time series. Below is the stationary test for time series which uses the using unit root test.

4.5.1 Unit Root Test

This study uses the unit root test to test presence of unit root. The most popular class of unit root test was developed by Fuller (1976) and Dickey Fuller (1979), and hence they were called Dickey-Fuller (DF) Test. When the series indicates the presence of unit roots, it means that the time series of the observation indicates non stationarity. If a series must be different d times before it become stationary then it contains d unit roots and is said to integrated of order d, denoted as I (d). By obtaining stationarity, a variable is understood that its mean, variance and covariance are all invariant with respect to time period.

The DF test applies to a model as follows;

$$\text{Suppose } Yt = \rho Y_{t-1} + U_t \qquad (4.1)$$

If $|\rho| < 1$, Y_t is I (0) ; if $\rho = 1$, Y_t is I (1). Therefore, test for stationarity is to test for $\rho = 1$.

Based on econometric theory, a time series with a unit root is known as a non stationary time series and for economic term as a random walk.

$$\Delta Y_t = (\rho-1)\, Y_{t-1} \quad + U_t$$

$$= \delta Y_{t-1} \quad + U_t \qquad (4.2)$$

the null hypotheses will be H: $\delta<0$.

Rewrite equation (2) if $\delta = 0$

$$\Delta Y_t = (Y_t - Y_{t-1}) = U_t \qquad (4.3)$$

From equation (3) explain that the first differences of a random walk time series are stationary time series because by assumption Ut is purely random. So, a time series is differenced once, and the differenced series is stationary, the random walk series is integrated of order 1{I (1)}. In a general form, if a time series has to be differenced d times, it is integrated of order d {I (d)} as above stated.

4.6 Cointegration

Using the definition of Engle and Granger (1987), two series, both I(d), are said to be cointegrated if there exists a linear combination of the series which is I (d-b), where b is an integer less than or equal to d. if the case d=b=1, the linear combination of the series is stationary or I(0) but if the time series are integrated of different order, then further testing for cointegration can be considered, as the two series will not be related in the long run. We can proceed to test for cointegration if we can establish that the series are integrated of the same order.

As Engle and Granger definition, if a series Y is I(1) and at the same time another series Z is also I(1) they are cointegrated if we can prove that the error term (U_t) or residuals obtained from regression show it is stationary. So if the U_t is stationary, the series will be the same wave length. It is because the trends (U_t) in the variables are cancelled out.

But for this study purpose, we will look into long run cointegration for all the series in equation, since we will estimate for VAR analysis.

4.6.1 Johansen Methodology

Due to several shortcomings (Ender, 1995) of using Engle Granger, Johansen (1988) and Johansen and Juselius (1990) have introduced the Johansen methodology. By using this methodology, we do not need to specify endogenous and exogenous variables. The Johansen methodology is based on a maximum likelihood procedure that determines the number of cointegrating vectors in a VAR process to be estimated. In addition, Johansen methodology can be extended to multivariate time series analysis and it has a great advantage of using a unified framework to determine the dimension of cointegrating space.

There are two steps. First is for all the variables to be integrated to be of the same order and second is to determine the appropriate lag length to be used in the VAR model. These procedures will yield to time length provided that the initial choice of the length includes the time length (depends on AIC and BIC)

4.6.2 Test of Cointegration (Johansen Methodology)

A brief discussion of the Johansen methodology in testing of cointegration is shown below:

Given that the vector of n variables, X = (X_t... Xnt) is generated from the following VAR process of order k

$$X_t = a_0 + \Sigma \prod X_{t-1} \quad +U_t \qquad (4.4)$$

Where:

X_t = an n-dimentional vector of I (1) variables.

A_0 = a constant term

$\prod_i$ = is a (n x n) matrix of long run coefficients whose rank determinants the number of distinct cointegrating vectors which exists between the variables in X

n_t = is a (nxn) vector of residual terms

Expressing the VAR model in the E-C form

$$\Delta X_t = a_0 \;+\; r_i \, \Delta X_{t-1} - \prod X_{t-k} + U_t$$

where

$\prod$ = the long run impact matrix

$\prod X_{t-k}$ = is included to correct for the long run deviations of the relationship

Johansen & Juselius (1990) estimated the rank, r, and $\prod$ matrix in order to detect the number of cointegrating vectors. Let say, $\prod$ matrix,

The rank may take the following forms

r = n, the matrix $\prod$ has full rank implying that the X is stationary

$r=0$, the matrix $\prod$ is zero and a first difference VAR is appropriate.

$0<r<$means that there are (n x n) matrices of α and β such that $\Pi=\alpha\beta$, α is a (n x r) matrix of error correction coefficients and β is a (n x r) matrix of cointegrating vector.

The number of cointegration vectors r is determined by likelihood ratio test. Johansen was derived two likelihood ratio statistics for testing the number of cointegrating vectors, r.

The first statistic is labeled the trace test. It is used to test the null hypotheses that there are at most r cointegrating vectors against the alternative hypothesis of r or more such vectors. The second statistic is known as the maximal Eigenvalues Test. It is employed to test the null hypothesis of at most r cointegrating vector against the alternative hypothesis of r+1 cointegrating vector.

a) Test of the null hypothesis for the trace statistic

$$H_0 : r \leq r_0$$

$$H_a : r \geq r_0$$

$$Trace = -T \sum_{i=t+1}^{\rho} \ln(1-\lambda_i)$$

b) Test of the null hypothesis for maximal eigenvalue

$$H_0 : r = r_0$$

$$H_a : r = r_0 + 1$$

$$\lambda - \max = T \ln(1 - \lambda_{i+1})$$

In establishing the number of cointegrating vectors, the result of the Trace and Maximal Eigenvalue Test can be coefficient. Johansen and Juselius (1990) provide the critical values of two ratio tests which are obtained using simulation studies. In that conflict, Maximal Eigenvalue Test is preferred as this was a sharper alternative hypothesis. Follows Enders (1995), it is preferred in determining the final number of cointegrating vectors.

4.7 VAR Analysis

In Sims work, with no prior information on lag variables, he uses only a set of unconstrained reduced form and equations to forecast* the joint movement of

* Sims (1980) describes his models as "unrestricted reduced forms" that treat all variables as endogenous. It appears that since the VAR contains as much equilibrium as it has variables, it should b interpreted as the reduced form of a complete system.

related macro economic variables[†], Sims described this unrestricted reduced form as a "VAR".

Accordingly to Engle and Granger (1987), noted for the long run constraints are satisfied asymptotically a level VAR or an unrestricted VAR model. This means that, for the case of cointegrated series, we may use the level of VAR.

In the VAR analysis in this section, we consider the simple bivariate system:

$$y_t = b_{10} - b_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \varepsilon y_t \qquad (4.5)$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{21}z_{t-1} + \varepsilon z_t \qquad (4.6)$$

where

With assumptions:

- Both y_t and z_t are stationary
- ε_{yt} and ε_{zt} are white noise disturbances with standard deviation of σ_y and σ_z

respectively. ME

- $\{\varepsilon_{yt}\}$ and $\{\varepsilon_{zt}\}$ are uncorrelated white noise disturbances. $-b_{12}$ is the

contemporaneous effect of an unit changes of z_t on y_t and γ_{21} the effect of an unit changes in y_{t-1} on z_t

† In Sims estimation with VAR, the variables of seasonally adjusted quarterly in the vector autoregressive model for the US and West Germany.

Rewrite the above equation to the compact form:

$$\begin{bmatrix} 1 & b_{12} \\ b21 & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma 12 \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \qquad (4.7)$$

or

$$B_{xt} = r_0 + r_1 x_{t-1} + \varepsilon_t \qquad (4.8)$$

where

$$\mathrm{B} = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}, x_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}, r_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$$

$$r_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix}$$

VAR model in the standard form (premultiplication by β^{-1})

$$x_t = A_0 + A_1 x_{t-1} + e_t \qquad (4.9)$$

Where

$$A_0 = B^{-1} r_0$$

$$A_1 = B^{-1} r_1$$

$$e_t = B^{-1} \varepsilon_t$$

VAR in standard form:

$$y_t = a_{10} + a_{11} y_{t-1} + a_{12} z_{t-1} + e_{1t} \qquad (4.10)$$

$$z_t = a_{20} + a_{21} y_{t-1} + a_{22} z_{t-1} + e_{2t} \qquad (4.11)$$

4.6.1 Impulse Response Function

The impulse response function is available for VAR estimation.

Let say VAR (1) of y_t and z_t

$$y_t = a_{10} + a_{11} y_{t-1} + a_{12} z_{t-1} + e_{1t}$$

$$z_t = a_{20} + a_{21} y_{t-1} + a_{22} z_{t-1} + e_{2t}$$

where:

y_t	= dependent variable
z_t	= dependent variables
a_{10}	= intercept
a_{11}, a_{21}	= constant parameters
t	= time or trend of variables
e_t	= disturbance term

The impulse response function traces out the response of all the dependent variables in the VAR system to shocks in e_{1t} and e_{2t}. An increase of one standard deviation as shock in e_{1t} will cause a change in y_t in the current periods through a_{21}, this change will impact y in future periods. Through a_{21}, this change has impact on z_t. Further, through, a_{22} the future values of z will change. So the impulse response function traces out the impact of such shocks for several periods into future.

4.7 Conclusion

This chapter explained the methodology that applied in this study.