CHAPTER FOUR

METHODLOGY

4.1 Introduction

In this chapter, the core econometric methods that will be used in estimating the effect of fiscal policy on the real exchange rates and trade balance will be discussed. These methods include the unit root tests, which is used to examine if a variable is stationary or non-stationary. The cointegration technique on the other hand will be applied to estimate the long – run relationship between fiscal policy, real exchange rates and the trade balance. This technique would be using the Engle – Granger approach.

4.1.1 Unit root tests

A time series data can be thought of as being generated by a stochastic or random process. A stochastic process is said to be stationary if its mean and variance are constant overtime and the value of covariance between two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed. If we assume Y_t to be a stochastic time series it will therefore have the following time series properties.

Mean: $E(Y_t) = \mu$ ---------------------- (4.1)

Variance: $var(Y_t) = E(Y_t - \mu)^2 = \sigma^2$ ---------------------- (4.2)

Covariance: $\gamma_k = E((Y_t - \mu)(Y_{t+k} - \mu))$ ---------------------- (4.3)

Where γ_k, the covariance (or autocovariance) at lag k, is the covariance between the values of Y_t and Y_{t+k}, that is between two Y values k periods apart. If $k = 0$, we obtain γ_0, which is simply the variance of $Y(= \sigma^2)$, if $k = 1$, γ_1 is the covariance between two adjacent values of Y.

If we shift the origin of Y from Y_t to Y_{t+m}, now if Y_t is said to be stationary, the mean, the variance and autocovariances of Y_{t+m} must be the same as those of Y_t. In short if a time series is stationary, its mean variance and autocovariances (at various lags) remain the same no matter at what time it is measured. If a time series is not stationary, it is called a nonstationary time series. At times this nonstationary could be due to a shift in the mean. In order to see if a time series is stationary or nonstationary, a unit root test is applied.

Using a simple model as below:

$$Y_t = Y_{t-1} + \mu_t \quad \text{--} \quad (4.4)$$

Where μ_t is the stochastic term that follows the classical assumptions, namely it has zero mean, constant variance σ^2, and is non autocorrelated. Such an error term is also known as a white noise error term. Equation (4.4) can also be considered as an first order or autoregressive regression in that the value of Y at time t is regressed against the values of Y at time $(t-1)$. If the coefficient of Y_{t-1} is in fact equal to 1, therefore a unit root problem exist, or in other words a nonstationary situation exist or in otherwords the null hyphothesis. Therefore the following regression is run:

$$Y_t = pY_{t-1} + \mu_t \qquad \text{-----------------------------------} \qquad (4.5)$$

If in equation (4.5), the regression that is run, obtains a value of p = 1, therefore it can be considered that variable Y_t has a unit root. In time series econometrics, a time series that has a unit root is known as a random walk time series, and a random walk is an example of a nonstationary time series. Equation (4.5) is often expressed in an alternative form as:

$$\blacktriangle Y_t = (p-1)\, Y_{t-1} + \mu_t$$
$$= \delta Y_{t-1} + \mu_t \qquad \text{-----------------------------------} \qquad (4.6)$$

Where $\delta = (p-1)$ and where ▲ is the first difference operator or in otherwords
$\blacktriangle Y_t = (Y_t - Y_{t-1})$.

Making use of this definition, the null hyphothesis is $\delta = 0$ while the alternative hyphothesis is δ # 0. If it is in fact 0, therefore equation (4.6) can be written as:

$$\blacktriangle Y_t = (Y_t - Y_{t-1}) = \mu_t \qquad \text{---------------------------} \qquad (4.7)$$

Equation (4.7) says that the first difference of a random walk time series (= μ_t) are a stationary time series because by assumption μ_t is purely random. If a time series is differenced once and the differenced series is stationary, therefore the original (random walk) series is integrated of order 1, denoted by I(1). Similarly if the original series has to be differenced twice (i.e. take first difference of the first difference), before it becomes stationary, the original series is integrated of order 2 or I(2). In general, if a time series has to be differenced 'd' times, it is integrated of order 'd' or I(d).

To find out if a time series Y_t is nonstationary, firstly regression of equation (4.5) must be run, in order to find out if 'p' is statistically equal to 1 or, equivalently estimate equation (4.6) if $\delta = 0$. Using the Dickey – Fuller test (tau test) the null hyphotesis, of $p = 1$ and $\delta = 0$ is rejected if the variable is non-stationary.

In its simplest form, a regression equation (4.5) is estimated, divide the estimated "p" coefficient by its standard error to compute the Dickey - Fuller tau statistics and later refer it to the Dickey - Fuller tables to see if the null hyphothesis $p = 1$ is rejected. If the computed absolute value of the tau statistics (i.e.$|T|$) exceeds the critical value in the Dickey - Fuller critical values, then we reject the hyphothesis that the given time series is non-stationary. If on the other hand, if it is less than the critical value, the time series is non-stationary and we accept the alternative hyphothesis that the given time series is non-stationary. The Dickey-Fuller test is applied to regressions run in the following form:

$$\blacktriangle Y_t = \delta Y_{t-1} + \mu_t \qquad \text{---} \qquad (4.8)$$

$$\blacktriangle Y_t = \beta 1 + \delta Y_{t-1} + \mu_t \qquad \text{---} \qquad (4.9)$$

$$\blacktriangle Y_t = \beta 1 + \beta 2_t + \delta Y_{t-1} + \mu_t \text{ ---------------------------------- } (4.10)$$

Equation (4.8) excludes the constant and time trend variable, while equation (4.9) excludes the time trend variable only, on the other hand equation (4.10) includes both the time trend and and constant variable. In each case the null hyphothesis is that $\delta = 0$, that is there is a unit root. However, if the error term (μ_t) is autocorrelated, therefore equation (4.10) would have to be modified as follows:

$$\blacktriangle Y_t = \beta 1 + \beta 2Trend + \delta Y_{t-1} + \alpha_i \sum \blacktriangle Y_{t-i} + \varepsilon_t \text{ ------------ } (4.11)$$

Where $\blacktriangle Yt - 1 = (Yt{-}1 - Yt - 2)$ and $\blacktriangle Yt - 2 = (Yt - 2 - Yt - 3)$ and so forth, that is one uses lagged difference terms. The number of lagged difference terms to include is often determined empirically, the idea being to include enough terms so that the error term in equation (4.11) is serially independent. The null hyphothesis is still that $\delta = 0$ or $p = 1$ that is a unit root exists in Y (i.e. Y is nonstationary). When the Dickey – Fuller test is applied to models like equation (4.11) it is called as Augmented Dickey – Fuller (ADF) test.

4.2 Testing for Cointegration: The Engle – Granger method.

Suppose that two variables such as Y_t and Z_t are believed to be integrated of order one and if we want to determine there exists an equilibirium relationship between the two. Engle and Granger (1987) propose a straightforward test whether the two I(1) variables are cointegrated of order CI(1, 1).

Step 1: Pretest the variables for their order of integration. By definition, cointegration necessitates that the variables be integrated of the same order. Thus the first step in the analysis is to pretest each variable to determine its order of integration. The Dickey – Fuller tests can be used to infer the number of unit roots (if any) in each of the variables. If both variables are stationary, it is not necessary to proceed since standard time series methods apply to stationary variables. If the variables are integrated of different orders, it is possible to conclude that they are not cointegrated.

Step 2 : Estimate the long – run equilibirium relationship. If the results of step 1 indicate that both Y_t and Z_t are I(1), the next step is to estimate the long – run equilibirium relationship in the form:

$$Y_t = \beta 0 + \beta 1 \, Z_t + \epsilon_t \quad (4.12)$$

If the variables are cointegrated, an OLS regression would provide a super consistent estimator of the cointegrating parameters of β0 and β1. According to Stock (1987), OLS models estimates of β0 and β1 would converge if the variables are stationary. In order to determine if the variables are actually cointegrated denote the residual sequence by $|\epsilon_t|$. Thus $|\epsilon_t|$, is the series of the estimated residuals of the long – run relationship. If these deviations from long – run equilibirium are found to be stationary, the Y_t and Z_t sequences are cointegrated of order (1 , 1). It would be convenient if a Dickey – Fuller test is performed on these residuals to determine their order of integration.

Considering the autoregression of the residuals;

$$\Delta \epsilon_t = \alpha 1 \epsilon_{t-1} + \psi_t \quad (4.13)$$

Since the $|\epsilon t|$ value is a residual from a regression equation, there is no need to include an intercept term. The parameter of interest in the equation above is $\alpha 1$. If we cannot reject the null hyphothesis $\alpha 1 = 0$, therefore we can conclude that the residual series contains a unit root. Hence we conclude that the Y_t and Z_t variables are not cointegrated. The more precise wording is not appropriate because of a triple negative, but to be technically correct, if it is not possible to reject the null hyphothesis $|\alpha_1| = 0$, we cannot reject the hyphothesis that the variables are not co-integrated. Instead, the rejection of the null hyphothesis implies that the residual sequence is stationary. Given that both Y_t and Z_t were found to be I(1) and the residuals are stationary, we can conclude that the series are cointegrated of order (1 , 1). If the residuals from equation (4.13) do not appear to be white noise, an augmented Dickey – Fuller test can be used instead of (4.13). Suppose that diagnostic checks indicate that ψ_t sequence of (4.13) exhibits serial correlation. Instead of using the results from (4.13), estimate the autoregression (4.14) in order to conclude that the residual sequence is stationary and Y_t and Z_t are cointegrated in the order (1, 1):

$$\blacktriangle \epsilon_t = \alpha 1 \ \epsilon_{t-1} + \sum \alpha_{i-1} \blacktriangle \epsilon_{t-1} + \psi_t \quad \text{-------------------------} \quad (4.14)$$

Step 3: Estimate the error-correction model. If the variables are cointegrated (i.e. if the null hyphothesis of no cointegration is rejected), the residuals from the equilibrium regression can be used to estimate the error-correction model. The value of the residuals ϵ_{t-1} estimates the deviation from long-run equilibrim in period (t-1). Hence it is possible to use the saved residuals (ϵ_{t-1}) obtained in Step 2 as an instrument to estimate the following error-correction models.

$$\blacktriangle Y_t = \alpha_1 + \alpha_2 \epsilon_{t-1} + \sum_{i=1} \alpha_3 \blacktriangle Y_{t-i} \sum_{i=1} \alpha_4 \blacktriangle Z_{t-i} + L_t \quad \text{---------------} \quad (4.15)$$

$$\blacktriangle Z_t = \beta_1 + \beta_2 \epsilon_{t-1} + \sum_{i=1} \beta_3 \blacktriangle Y_{t-i} + \sum_{i=1} \beta_4 \blacktriangle Z_{t-i} + K_t \quad \text{-------------} \quad (4.16)$$

where: ϵ_{t-1} = Error-correction term

$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \beta_1, \beta_2, \beta_3, \beta_4$ = parameter

L_t = random disturbance

K_t = random disturbance

t-i = lagged quarters

The speed of adjustment coefficients α_2 and β_2 are of particular interest in that they have important implications for the dynamics of the system. From equation (4.16), it is clear that for any given value of ϵ_{t-1}, a large value of β_2 is associated with a large value of ΔZ_t. If β_2 is zero, the change in Z_t does not at all respond to the deviation from long-run equilibrium in (t-1). If β_2 is zero and $\beta_3 = 0$, then it can be said that ΔY_t does not Granger cause ΔZ_t. One or both of these coefficients should be significantly different from zero if the variables are cointegrated. After all if both α_2 and β_2 are zero, there is no error-correction and equation (4.15) and (4.16) comprise nothing more than a Vector Autoregressive in first differences. Moreover, the absolute values of these speed of adjustment coefficients must not be too large. The point estimates should imply that $\blacktriangle Y_t$ and $\blacktriangle Z_t$ converge to the long-run equilibrium relationship.