CHAPTER FOUR: RESEARCH METHODOLOGY

4.0 INTRODUCTION

Many of the previous studies[9] on the export-led growth hypothesis have used variables in (log) level form and the OLS techniques. These applications presume that the time series involved are stationary. The assumptions of the classical regression model require the variables to be stationary and the errors to have zero mean and a finite variance. However, if the variables are not stationary, there might occur what **Granger and Newbold (1974)** called a spurious regression. A spurious regression is one which has a very high coefficient of determination (R^2), t-statistics which appear to be significant, but the results are meaningless from the economic point of view **(see Gujarati, 1995)**. In addition, if the time series are not stationary, then the estimated coefficients are likely to be inconsistent and the standard statistical tests will no longer be valid[10].

In order to avoid the above-mentioned shortcomings, cointegration and error-correction modeling techniques are applied in this paper. Use of error-correction models is made to account for the dynamics of short run adjustments towards the long run equilibrium level. Before applying the cointegration and error-correction modeling methodology, the time series properties, that is the order of integration of each variable, are established.

9. studies such as Balassa (1978); Tyler (1981) and Henriques and Sadrosky (1996)
10. see Engle and Granger (1987); Enders (1995)

4.01 SOURCES OF DATA

In order to explore the co-movement between exports and economic growth, we begin by characterizing the time trend of the data included in our analysis. The data consists of annual observations on the log of GDP (LGDP), log of GDP net of exports and imports (LGNT), log of exports of goods and services (LEX); log of investment to output ratio (LIO) where investment is proxied by Gross Domestic Fixed Capital Formation (GDFCF) and the log of terms of trade (LTOT). All the figures (apart from LTOT) are obtained from the International Financial Statistics (IFS) and are real in the sense that they have been deflated using the 1995 prices. The LTOT series are obtained from the Handbook of International Trade and Development Statistics (United Nations).

4.1 STOCHASTIC AND DETERMINISTIC TRENDS

A trend is said to be deterministic if it is perfectly predictable. On the other hand, a trend is stochastic when it is variable and it cannot be perfectly predicted. In order to know whether a trend is stochastic or deterministic, one may run a regression of the form:

$$Y_t = a + bt + U_t \text{ ——————} (4.1.1)$$

If the estimated residuals from this regression are stationary, then equation (4.1.1) represents a trend stationary process and if the residuals are not stationary, then the equation shows a difference stationary process.

4.2 STATIONARITY TESTS[11] AND ORDER OF INTEGRATION

There exist important differences between stationary and non-stationary time series in that shocks to a stationary time series are necessarily temporary and overtime the effects of the shocks will gradually disappear. In other words, the series will revert back to its long run mean level. Conversely, non-stationary series have permanent components whose means and variances are dependent on time.

The stationarity property of the data series is investigated by testing for the presence of a unit root.

4.2.1 Dickey-Fuller (1979) and Augmented Dickey-Fuller (1981) Tests

From the above discussion it can be inferred that pretesting the variables in a regression for stationarity is of utmost importance. The remainder of this section considers the formal testing procedures for the presence of unit roots.

Dickey and Fuller (1979) actually consider 3 different regression equations that can be used to test for the presence of unit roots:

11. A series is said to be stationary if its mean and all autocovariances are unaffected by a change in time origin. For textbook treatment, refer to Gujarati (1995) and Enders (1995)

$$\Delta y_t = \gamma y_{t-1} + \epsilon_t \quad \text{———} (4.2.1.1)^{12}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \epsilon_t \quad \text{———} (4.2.1.2)$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_1 t + \epsilon_t \quad \text{———} (4.2.1.3)$$

The main difference between the above three regressions (4.2.1.1) through (4.2.1.3) concerns the inclusion of the deterministic element a_0 and $a_1 t$. The first is a pure random walk model, the second adds an intercept also known as a drift term and the third one incorporates both a drift and a linear time trend. It is important to ensure that the ϵ_t series approximates white noise. If the error term ϵ_t is autocorrelated, then the equations can be modified by adding lagged values of Δy_{t-i}.

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_1 t + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \epsilon_t \quad \text{———} (4.2.1.4)$$

When the DF test is applied to equations like (4.2.1.4), it is called the ADF test **(Dickey and Fuller, 1981).**

According to **Enders (1996)**, the coefficients of the lagged values of Δy_{t-i} in equation (4.2.1.4) are not of general interest. The idea is to include enough terms for the error term to be serially independent. In all the regressions, the parameter of critical importance is γ; if $\gamma = 0$, then the y_t sequence is said to contain a unit root and hence y_t is said to be non-stationary.

12. where ΔY_t refers to the first difference of Y_t defined as $Y_t - Y_{t-1}$

4.2.2 Order of Integration

Prior to testing for the cointegrating properties of the variables, it is necessary to ascertain the order of integration. To this end, an Augmented-Dickey Fuller test (1981) is initially carried out on the time series of each variable in their level form. If we do not reject the null hypothesis that a particular variable has a unit root, the test procedures are then reapplied after transforming the variable into first differenced form. If the null of non-stationarity on the first differenced form can be rejected, that is, the first differenced series is stationary, we may then establish that the time series is integrated of order one which is written as I(1).

Briefly, defining d to be the number of times that a series needs to be differenced in order to be unit root-free, such a variable is said to be integrated of order d denoted by I(d). For example, the first differenced stationary variable is said to be an I(1) variable. Likewise, an I(0) variable is said to be a level stationary variable.

4.3 COINTEGRATION TESTS

According to **Engle and Granger (1987)**, two series are said to be cointegrated of order d, b denoted by CI(d,b) if the two variables are each individually integrated of order d and there exists a linear combination which is integrated of order (d-b) where $b > 0$ and $d > b$. Following the definition of **Engle and Granger (1987)**, exports and GDP are said to be cointegrated of order one CI(1, 1) if they are individually I(1) but some linear combination of the two series is I(0).

Before testing for causality between exports and GDP growth, it is important to check for the cointegrating properties of all our variables. Cointegration aims at explicitly dealing with the relationship between non-stationary time series. Any equilibrium relationship among non-stationary variables implies that the variables are cointegrated and that they cannot move independently of each other. Since, there is a link among the trends of the cointegrated variables, there must be some relation between the dynamic path of each variable and the current deviation from the equilibrium relationship.

In particular, cointegration allows individual time series to be integrated of order one or I(1) in the terminology of **Engle and Granger (1987)** but requires that a linear combination of these series be I(0). Therefore, the basic concept of cointegration is to search for linear combinations of individually non-stationary time series that are themselves stationary.

This prompts us to apply the Engle and Granger approach **(Engle and Granger, 1987)** and the Johansen estimation techniques **(Johansen and Juselius, 1990)** to confirm if any cointegrating relation holds between LEX and LGDP for model specification 1 and LEX and LGNT for model 2.

That cointegration already implies causality between exports and growth seems somewhat surprising since cointegration is concerned with long run equilibrium whereas causality refers to short run forecastability **(Marin, 1991)**. The intuition behind this is that for the exports and growth series to have an attainable long run equilibrium, there must be some causation between them to provide the necessary dynamics.

4.3.1 Engle-Granger Two-Step Procedure (Engle and Granger, 1987)

A vast body of statistical theory has been developed to test for cointegrated time series models **(see Engle and Granger, 1987; Stock and Watson, 1988; Phillips and Ouliaris, 1990; Johansen, 1991, among others)**. Among these tests, the residual based procedure has been one of the most frequently used procedures. These procedures were recommended by **Engle and Granger (1987)** and rigorously analysed by **Phillips and Ouliaris (1990)**. They are used in the same manner as the unit root tests discussed in section 4.2.1 but the data are the residuals from the cointegrating regression and the alternative hypothesis of cointegration is now the main hypothesis of interest.

When testing for cointegration by the Engle and Granger methodology, it is necessary to pretest the variables for their order of integration. By definition, cointegration requires the variables to be integrated of the same order, then as discussed in section 4.0, the classical regression model can be applied **(see Gujarati, 1995)**. If all the variables are I(0), it is not important to proceed for cointegration. If the variables are integrated of different orders, it is possible to conclude that the variables are not cointegrated[13] **(Enders, 1995)**.

The Engle–Granger two-step procedure, as its name implies, involves two stages. In the first step, if the order of integration results indicate that all the variables used in the analysis are I(1), then the long run equilibrium relationship, also known as the cointegrating equation, is estimated. In our present study, the long run equilibrium

13. With more than 2 variables, various subsets may be cointegrated. For example, a group of I(2) variables may be CI(2,1) and this group may be cointegrated with a set of I(1) variables.

relationships take the following forms:

Model 1: $LGDP_t = a_0 + a_1LEX_t + a_2LIO_t + a_3LTOT_t + e_t$ ————(4.3.1.1)

Model 2: $LGNT_t = b_0 + b_1LEX_t + b_2LIO_t + b_3LTOT_t + u_t$ ————(4.3.1.2)

Where the variables are as defined in Chapter Three and e_t and u_t are the error terms.

In order to determine if the variables are cointegrated, the OLS residuals from regressing equations (4.3.1.1) and (4.3.1.2) must be tested for stationarity. Considering the autoregressions of the residuals:

$\Delta e_t = c_1 e_{t-1} + \upsilon_t$[14] ————(4.3.1.3)

$\Delta u_t = d_1 u_{t-1} + \mu_t$ ————(4.3.1.4)

where e_t and u_t are the estimated residuals of the long run relationships and Δ is the difference operator.

The parameters of interest in equations (4.3.1.3) and (4.3.1.4) are c_1 and d_1. If we cannot reject the null hypothesis that $c_1 = 0$ and $d_1 = 0$, we can conclude that each residual series contains a unit root. Hence, we conclude that the variables are not cointegrated. On the other hand, the rejection of the null implies that the residual series are stationary and that the variables are cointegrated.

In Engle and Granger two-step procedure tests using more than two variables (as in our

14. Since the e_t and u_t sequences are residuals from regression equations, there is no need to put an intercept term (**Enders, 1995**).

present study), there can be more than one cointegrating vector. One drawback of this procedure is that the Engle-Granger methodology cannot separately estimate multiple cointegrating vectors. Moreover, the Engle-Granger procedure relies extensively on a two-step estimator. The first step is to generate the series e_t and u_t and in the second step, these generated series are used to estimate regressions of the forms (4.3.1.3) and (4.3.1.4). Thus, any error introduced in step one is carried forward into step two. However, the **Johansen (1988)** maximum likelihood estimators avoid using the two-step estimators. Also, it can estimate and test for the presence of multiple cointegrating vectors.

Moreover, **Banerjee et al. (1986)** and **Phillips and Ouliaris (1990)** show that there may be significant small sample biases (which could be the case in this paper) in such OLS estimates of the cointegrating vectors and the limiting distributions of the DF and ADF tests are not well defined, implying that the power of these tests are low.

In contrast, **Johansen and Juselius (1990)** postulate the use of two likelihood ratio tests: λmax and λtrace which they believe have well defined limiting distributions.

Taking the limitations of the Engle-Granger two-step procedure into consideration, we cannot, therefore, base our analysis entirely on the results of the Engle-Granger two-step procedure. We thus proceed with the Johansen methodology.

4.3.2 The Johansen Methodology (Johansen, 1988; Johansen and Juselius, 1990)

Johansen (1988) defines a distributed lag model of a vector of variables, X, as

$$X_t = \pi_1 X_{t-1} + \pi_2 X_{t-2} + \ldots + \pi_k X_{t-k} + \epsilon_t \quad \text{———} (4.3.2.1)$$

Where X_t is a vector of N variables and ϵ_t is an independently and identically distributed N dimensional vector. If the variables in X are not stationary, then they suggest rewriting equation (4.3.2.1) in first differenced form (in a fashion similar to ADF test) as follows:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} - \pi X_{t-k} + \epsilon_t \text{ ——— } (4.3.2.2)$$

where $\Gamma_i = -1 + \pi_1 + \pi_2 + \ldots + \pi_i$; $i = 1, \ldots, k$ and $\pi = -(I - \pi_1 - \pi_2 - \ldots - \pi_k)$

The long run or cointegrating (NxN) matrix is given by π which includes the number of cointegrating vectors, r, between the variables in X. It is to be noted that the rank of π equals the number of cointegrating relationships existing in the "detrended" data **(see Enders, 1996)**. If there exists only one cointegrating vector, then the rank of π is one.

By checking the significance of the characteristic roots of π, it is possible to obtain the number of distinct cointegrating vectors. If we define two (Nxr) matrices, α and β such that $\pi = \alpha\beta'$, then the rows of β will form the r cointegrating vectors. **Johansen and Juselius (1990)** demonstrate that β, the cointegrating vector, can be estimated as the eigenvectors associated with the r largest and significant eigenvalues. They further prove that one can test the hypothesis that there are at most r cointegrating vectors by calculating the two likelihood test statistics known as λ trace and λmax tests respectively.

$$\lambda trace = -T \sum_{i=r+1}^{N} \ln(1 - \hat{\lambda}_i) \text{ ——— } (4.3.2.3)$$

$$\lambda max = -T \ln(1 - \hat{\lambda}_{r+1}) \text{ ——— } (4.3.2.4)$$

where $\hat{\lambda}_i$s are the estimated values of the characteristic roots obtained from the estimated π matrix and T is the number of observations used. **Johansen (1988)** and **Johansen and Juselius (1990)** suggest a maximum likelihood estimation procedure to obtain an estimate of λtrace and λmax as outlined by equations (4.3.2.3) and (4.3.2.4).

λtrace tests the null hypothesis that the number of distinct cointegrating vectors is less or equal to r. From equation (4.3.2.3), it can be inferred that λtrace = 0 when $\hat{\lambda}_i = 0$. The larger the deviation of the estimated characteristic root from zero, the larger the λtrace statistic. On the other hand, λmax tests the null that the number of cointegrating vectors is r against the alternative of r+1 cointegrating vectors. Similar to λtrace, if the estimated value of the characteristic root is close to zero, λmax will be very small.

In short, in order to conclude this section , this paper adopts two important ways to test for the presence of cointegrated variables. The Engle-Granger methodology seeks to determine whether the residuals of the equilibrium relationship are stationary. The **Johansen (1988)** methodology determines how many of the characteristic roots of π are less than unity[15].

4.4 ERROR-CORRECTION MODELING AND CAUSALITY TESTS

4.4.1 Causality Tests (Granger, 1969)

Generally, correlation between two variables does not give any indication about what is

15. For further detail, refer to **Enders (1995)**

the cause and what is the effect. The usual hypothesis about exports and growth is that an expansion in exports leads to output growth but the direction of causation could be the other way, from economic growth to exports. This may happen when a country's output is rising because of accumulation of human and physical capital, learning by doing or new technology inflows which thereupon produce more than what can be absorbed domestically and the rest is exported. Thus, it can be said that economic growth caused the exports.

Before dealing with the error-correction models, Granger tests are used to provide inferences on causality. Thus causality models will be presented in this section.

In the case of causality from export growth to GDP growth, the following models are used:

$$\Delta LGDP_t = \sum_{i=1}^{k} b_{1i}\,\Delta LGDP_{t-i} + \sum_{j=1}^{k} b_{2i}\,\Delta LEX_{t-j} + E_{1t} \text{ ------- } (4.4.1.1)^{16}$$

$$\Delta LEX_t = \sum_{j=1}^{k} d_{1i}\,\Delta LEX_{t-i} + \sum_{i=1}^{k} d_{2i}\,\Delta LGDP_{t-j} + E_{2t} \text{ ------- } (4.4.1.2)^{16}$$

where it is assumed that E_{1t} and E_{2t} are uncorrelated

In the Granger sense (1969), a variable like LEX, in this case, causes another variable (LGDP) if the current value of LGDP can better be predicted by using past values of LEX

16. Some studies like **Kwan et al.** (1999) include an intercept in testing for causality. In this paper, it is not included since e-views do not use the intercept in running the regressions

than by not doing so. Thus, LEX granger causes LGDP if past values of LEX augment the predictive power of LGDP. The Granger causality test procedure involves testing for the significance of the parameters b_{1i}s, b_{2i}s, d_{1i}s and d_{2i}s. Since, the Granger causality tests are very sensitive to the number of lags used, it can be argued that it is preferable to include more rather than fewer lags in the analysis, since the theory is based mainly on the relevance of past information **(see Gujarati, 1995).** In this study, the Schwartz Criterion, which was employed by **Shan and Sun (1999)**, is used to aid the selection of the optimal lag length. Basically, the value of the Schwartz Criterion must be as small as possible. By choosing the number of lags that minimizes the Schwartz Criterion, one is also minimizing the residual sum of squares (RSS).

Equation (4.4.1.1) postulates that the current value of a change in LGDP is related to past changes in LGDP itself as well as changes in the values of LEX. Equation (4.4.1.2) can be interpreted in a fashion similar to equation (4.4.1.1). By using equations (4.4.1.1) and (4.4.1.2), four types of causality can be distinguished depending on the significance of the estimated coefficients of the parameters.

One-way (uni-directional) causality from ΔLEX to ΔLGDP is found if the estimated coefficients of the lagged ΔLEX in equation (4.4.1.1) are statistically significant (that is $\Sigma b_{2i} \neq 0$) and the coefficients of the lagged ΔLGDP in equation (4.4.1.2) are not statistically different from zero ($\Sigma d_{2i} = 0$).

On the other hand, one-way causality from ΔLGDP to ΔLEX exists if the set of lagged ΔLEX coefficients in (4.4.1.1) is not statistically different from zero (that is, $\Sigma\, b_{2i} = 0$)

and the set of lagged ΔLGDP coefficients in (4.4.1.2) is statistically different from zero.

Bilateral also known as two-way or feedback causality is confirmed if the sets of ΔLEX and ΔLGDP coefficients are statistically different from zero in both regressions (4.4.1.1) and (4.4.1.2).

Finally, the variables are independent if the sets of ΔLEX and ΔLGDP coefficients are not statistically significant in both of the above equations.

Before the error-correction models came into practice, the standard Granger tests were used to provide inferences on causality. However, **Granger (1988)** argues that the standard Granger tests are not likely to give valid causal inferences in the presence of cointegrated variables.

Therefore, the alternative test for causality is based on the error-correction models that incorporate information from the cointegrated properties of exports and output growth. The causality between exports and GDP can be tested using the two-equations error-correction models:

$$\Delta LGDP_t = \sum_{i=1}^{k} b_{1i}\,\Delta LGDP_{t-i} + \sum_{j=1}^{k} b_{2i}\,\Delta LEX_{t-j} + VECT_{t-1} + E_{3t} \text{ ——— } (4.4.1.3)$$

$$\Delta LEX_t = \sum_{j=1}^{k} d_{1i}\,\Delta LEX_{t-i} + \sum_{i=1}^{k} d_{2i}\,\Delta LGDP_{t-j} + VECT_{t-1} + E_{4t} \text{ ——— } (4.4.1.4)$$

where ECT_{t-1} is the lagged value of the residuals from the cointegrating equation of model 1. Uni-directional causality from exports to GDP exists if either the coefficients b_{2i}s are jointly significant or the coefficient of the error term, V, is significant or both. Thus, the inclusion of the error-correction term in equations (4.4.1.3) and (4.4.1.4) introduces an additional channel through which granger causality between exports and growth can be detected. The coefficient of the error-correction contains the information about whether the past deviations affect the current value of the variable. A significant coefficient implies that past equilibrium errors play an important role in determining the current outcomes.

These steps are then applied for each variable in both models.

4.4.2 Error-Correction Models (Engle and Granger, 1987)

Engle and Granger (1987)[17] prove that if the variables used in an analysis are cointegrated, that is if an equilibrium relationship exists among the variables, then the short run disequilibrium relationship can always be represented by an error-correction model. This result is referred to as Granger Representation Theorem. Thus, an error-correction model implies an underlying equilibrium relationship.

However, since the variables are not always in equilibrium, the long run relationship cannot be observed directly. All that can be observed is a disequilibrium relationship

17.They used only two variables in their analysis but **Engle and Yoo (1987)** used up to 5 variables.

involving lagged values of the variables which reduces to equation (4.3.1.1) whenever equilibrium happens to occur. We denote this equilibrium relationship by:

$$LGDP_t = b_0 + b_1LEX_t + b_{12}LEX_{t-1} + b_2LIO_t + b_{22}LIO_{t-1} + b_3LTOT_t + b_{32}LTOT_{t-1}$$
$$+ \alpha LGDP_{t-1} + e_t \text{ ——————(4.4.2.1)} \quad \text{where } 0 < \alpha < 1$$

The problem with equation (4.4.2.1) is that it is an equation in the levels of variables which are unlikely to be stationary. As a result, equation (4.4.2.1) is rearranged and reparameterised as follows:

Substracting $LGDP_{t-1}$ from both sides of equation (4.4.2.1) yields:

$$\Delta LGDP_t = b_0 + b_1LEX_t + b_{12}LEX_{t-1} + b_2LIO_t + b_{22}LIO_{t-1} + b_3LTOT_t + b_{32}LTOT_{t-1}$$
$$-(1-\alpha)LGDP_{t-1} + e_t$$

or

$$\Delta LGDP_t = b_0 + b_1\,\Delta LEX_t + (b_1 + b_{12})LEX_{t-1} + b_2\Delta LIO_t + (b_2 + b_{22})LIO_{t-1} + b_3\Delta LTOT_t +$$
$$(b_3 + b_{32})\,LTOT_{t-1} - (1-\alpha)LGDP_{t-1} + e_t \text{ —————(4.4.2.2)}$$

Reparameterising equation (4.4.2.2) further yields:

$$\Delta LGDP_t = b_1\,\Delta LEX_t + b_2\Delta LIO_t + b_3\Delta LTOT_t - (1-\alpha)[\,LGDP_{t-1} - a_0 - a_1LEX_{t-1} -$$
$$a_2LIO_{t-1} - a_3\,LTOT_{t-1}] + U_t \text{ —————(4.4.2.3)}$$

where $a_0 = b_0/(1-\alpha)$; $a_1 = (b_1 + b_{12})/(1-\alpha)$; $a_2 = (b_2 + b_{22})/(1-\alpha)$; $a_3 = (b_3 + b_{32})/(1-\alpha)$

Equation (4.4.2.3) can be given a very appealing interpretation. It can be regarded as stating that changes in LGDP depend on changes in LEX, LIO, LTOT and the disequilibrium error from the previous period which is the term in the square bracket. It, therefore, implies that the lower (higher) is LGDP compared to its equilibrium value, the greater (smaller) will be the immediate rise in $LGDP_t$. The value of LGDP is being corrected for the previous disequilibrium error (hence the term error-correction model). The parameters a_0, a_1, a_2 and a_3 can be regarded as parameters in the long run relationship. α and hence $(1-\alpha)$ determine the extent to which the disequilibrium in period t-1 is made up for in period t. Since $0< \alpha < 1$, only part of this disequilibrium is made up for in period t.

The coefficients of ΔLEX_t, ΔLIO_t and $\Delta LTOT_t$ – b_1, b_2 and b_3 respectively are short run parameters measuring the immediate impact on $LGDP_t$ of a change in a variable when the others are kept constant.

Because of the **Stock (1987)**'s superconsistency result, **Engle and Granger (1987)** suggest that the long run parameters a_0, a_1, a_2 and a_3 can be obtained by the application of OLS to the cointegrating regression. The residuals from this regression are then substituted in equation (4.4.2.3) in place of the disequilibrium errors. The second stage of the procedure is to apply OLS to:

$$\Delta LGDP_t = a_1\,\Delta LEX_t + a_2\Delta LIO_t + a_3\Delta LTOT_t - (1-\alpha)\,ECT1_{t-1} + U_t \text{———} (4.4.2.4)$$

where ECT1 is the error-correction term for the first model. The coefficient of $ECT1_{t-1}$, as discussed above, represents the deviation of the dependent variable from the long run equilibrium.

An error-correction model can be derived in a similar way for our second model where the only difference lies in the dependent variable which is $\Delta LGNT_t$ instead of $\Delta LGDP_t$

Since the variables are cointegrated, all the variables in equation (4.4.2.4) are stationary so that the standard OLS procedures are valid. **Engle and Granger (1987)** show that the estimators of the short run parameters obtained in this way are both consistent and as asymptotically efficient as they would have been had the true rather than the estimated values for the disequilibrium errors been used in the second stage.

Many studies used a general version of equation (4.4.2.4) where they introduce more dynamics by including higher order lagged differences. Thus, a general version of the error-correction model becomes:

$$\Delta LGDP_t = a_0 + \sum[a_{1i}\Delta LEX_{t-i} + a_{2i}\Delta LIO_{t-i} + a_{3i}\Delta LTOT_{t-i}] + \sum a_{4i}\Delta LGDP_{t-i} + \delta\, ECT1_{t-1} + U_t \text{ ——(4.4.2.5) } \textbf{for model 1}$$

An error correction model for **model 2** can be derived in a similar way which is given as follows:

$$\Delta LGNT_t = h_0 + \sum[h_{1i}\Delta LEX_{t-i} + h_{2i}\Delta LIO_{t-i} + h_{3i}\Delta LTOT_{t-i}] + \sum h_{4i}\Delta LGNT_{t-i} + \delta_1\, ECT2_{t-1} + \psi_t \text{ ——(4.4.2.6)}$$

It is worth noting that equations (4.4.2.5) and (4.4.2.6) are not the results. They are just a formal derivation of the error-correction models. The empirical results will be discussed in greater detail in Chapter Five.

4.5 CONCLUSION

This chapter gives a brief outline of the methodology that was applied and the results are discussed in the next chapter in order to examine the export-led growth hypothesis.