CHAPTER – III

DATA AND METHODOLOGY

3.1 Introduction

This chapter presents the research framework of the study, methodology, models and their support on *a priori* and empirical grounds, testing methods, properties of the data to be employed and the related econometric issues.

3.2 Research Framework

It is a time-honored practice to follow some theoretical guidelines whenever practicable and, therefore, it seems appropriate to present the flow chart (Figure – 3.1) upon which our research is based. An attempt has been made to tag on the succeeding edifice regarding our research program implementation. Our study is purely dependent on secondary data and we have tried this framework to the extent applicable to its nature of work.

3.3 Sources, Nature and Periods of Data

Present study is related to the relationship between budget deficit and trade deficit in Nepal for the period 1964 - 2004. The source of the data sets of the present study is *International Financial Statistics (IFS)*, a publication of International Monetary Fund (IMF). We have mainly used the Year Books of 1992, 2004 and 2007 of the IFS as an authenticated secondary source of data. We have used the nominal as well real data of Budget Deficits and Trade Deficits under study. Base period is 1985

(1985=100) for the real data. . For cross checking, publications of Nepal government and Nepal Rastra Bank (Central Bank of Nepal) have been used since these are the sole and authentic sources to IMF too.

3.4 General Methodology and Hypothesis Testing

This research study takes into considerations of the propositions of the *'Lucas Critique'*, because macroeconomic variables of the national income identity are more inclined to policy shifts which affect their simultaneous relationships. For example, economic performances would exhibit completely different sketches corresponding to controlled or decontrolled economic policies. So, we have also attempted to utilize the testing modality in a way to "*let the data speak for themselves*".

A shower of research articles has described the testing apparatus of a time series sequence for the presence of unit roots. Many kinds of testing methods and models are available in this field. In general, *"Unit Root Test"*; *"Co-integration Test"*; *"Vector Auto-regression (VAR)"*; *"Error Correction Model (ECM)"* and *"Granger Causality"* are the more pronounced and experimented techniques in the applied econometric literature. This research will also attempt to follow the same path for causality testing. Again *'Hypotheses Set'* in the aforesaid headings will be tested on the perspective of the models specified earlier.

Along this course, time series data may be found to be 'non-stationary' containing a unit root (Gujarati, 1995, p.714). VAR estimates are more efficient if variables included in the VAR model are either stationary or co-integrated. So, data will be tested for stationary of concerned variables by applying ***Augmented Dickey-Fuller Test (ADFT)***. Afterwards, *co-integration* of the variables will be checked. Then, *Granger causality* test will be conducted to find the direction of causality among the variables in the specified models.

This study is basically guided by classical econometric structure[12] and Classical Linear Regression Model (CLRM). For the analysis of the study we have used various econometric tools. Several models, which are based on econometric analysis, have been used for the present work. These models will be specified in appropriate chapters as and when needed. Testing for stationarity is based on *Unit Root Test* and ACF / PACF (correlogram). *Cointegration Test, Vector Error Correction Modeling, Granger Causality Test, Vector Autoregression (VAR)* model, *Impulse Response Function* and *Variance Decomposition* analysis are some of the important econometric tools used in the present study.

3.5 Research Methodology: Basic Features of Some Test Procedure:

We seek to explain some basic features of the Test Procedures for the study of stationarity of the variables concerned, *'Co-integration'* of the variables showing their long-term relationship, *Vector Error Correction Mechanism* for the study of short-run relationship among them, *Granger Causality* study and *VAR modeling* with *Impulse Response Function* and *Variance Decomposition* etc. These are being presented in the following sub-sections (3.5.1 – 3.5.8 and 3.6 – 3.12).

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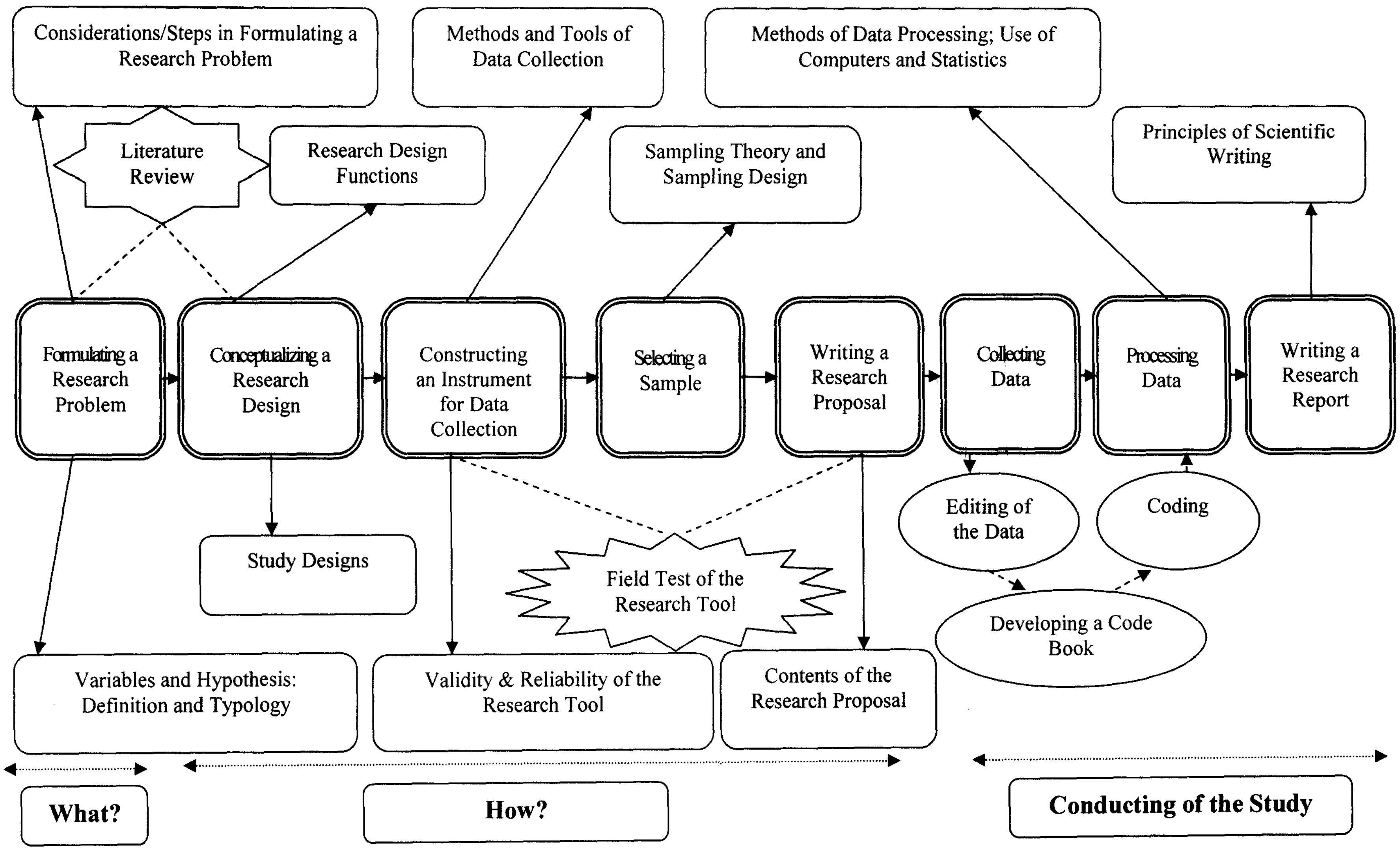
12 The other branch of econometrics is Bayesian Econometrics and enthusiastic readers are suggested to explore on it. Some of the interesting book are, Peter M lee, Bayesian Statistics: An Introduction, Oxford University Press, England, 1889 (Introductory); Dale J Porier, Intermediate Statistics and Econometrics: A Comparative Approach, MIT Press, Cambridge, Massachusetts, 1995 (Intermediate) and Arnold Zeller, An Introduction to Bayesian Inference in Econometrics, John Willey & Sons, New York, 1971 (Advanced).

Figure - 3.1

The Research Process[13]



13 Ranjit Kumar, Research Methodology, A Step-by-Step Guide for Beginners, SAGE Publication, 1999, pp 17.

3.5.1 Unit Root Tests (Stationarity Test)

When time series data are used in econometric analyses, the preliminary statistical step is to test the stationary of each individual series. Unit root tests provide information about stationarity of the data. Non-stationary data would contain unit roots. The main objective of unit root tests is to determine the degree of integration of each individual time series. Results derived from the regression models would produce 'Spurious Results' if we used the data without checking their Stationarity Properties.

We can examine the stationarity of the datasets through following three methods:

(i) Graphics

Graphical representation of the data gives an initial idea about the possibility of stationarity or non-stationarity in the data concerned. If the time series is non-stationary, its moving trend (path) is normally seen in continuous rise or decline in the variable concerned (See Fig. 1.1 also). We will present the individual graphical representations of the concerned variables to examine if these were stationarity or non-stationarity by nature.

(ii) Battery of Tests

Battery of Tests suggests a set of relevant tests for examining the nature of stationarity of the datasets concerned. Such methods are being discussed in sub-sections (3.5.2 – 3.5.8) in the text follows.

(iii) Correlogram

Correlogram is also one of the popular ways of having idea whether there is any stationarity or no-stationarity in the datasets concerned.

3.5.2 Dickey Fuller Unit Root Test

The test of unit root was proposed by David A. Dickey and Wayne A. Fuller in 1976.

For the Dickey-Fuller tests, the relevant model is,

$$y_t = \beta_0 + \beta_1 t + u_t \qquad (3.1)$$

where, $$u_t = \alpha u_{t-1} + \varepsilon_t \qquad (3.2)$$

Here ε_t is a covariance stationary process with zero mean. The reduced form for this model is

$$y_t = \gamma + \delta t + \alpha y_{t-1} + \varepsilon_t \qquad (3.3)$$

where $\gamma = \beta_0 (1-\alpha)$ and $\delta = \beta_1 (1-\alpha)$.

This equation is said to have a unit root if $\alpha=1$ (in which case $\delta=0$)

3.5.3 Augmented Dickey Fuller Unit Root Test

In order to test for the existence of unit roots, and to determine the degree of differencing necessary to induce stationarity, we have applied the *Augmented Dickey-Fuller test.* Dickey and Fuller (1976, 1979), Said and Dickey (1984), Phillips (1987), Phillips and Perron (1988), and others developed modified version of the Dickey-Fuller tests when ε_t is not white noise. These tests are called *Augmented Dickey-Fuller (ADF) tests.* The results of the *Augmented Dickey-Fuller test (ADF)* help determine the form in which the data should be applied in any econometric analysis. The alternative forms are as follows:

$$\Delta y_t = \gamma + \alpha y_{t-1} + \sum_{j=2}^{k} \theta_j \Delta y_{t-j+1} + e_t \qquad (3.4)$$

$$\Delta y_t = \gamma + \delta t + \alpha y_{t-1} + \sum_{j=2}^{k} \theta_j \Delta y_{t-j+1} + e_t \qquad (3.5)$$

$$\Delta y_t = \alpha y_{t-1} + \sum_{j=2}^{k} \theta_j \Delta y_{t-j+1} + e_t \qquad (3.6)$$

where, y_t = Model Variables (TD and BD) of Nepal;

Δy_t = First differenced series of y_t.

Δy_{t-j+1} = First differenced series of y_t at $(t- j+1)^{th}$ lags. (j = 2 -------- k)

The equation (3.4) contains a constant as exogenous, while equation (3.5) bears a constant along with a linear trend. However, equation (3.6) presents an auto-regressive process with no constant and linear trend.

3.5.4 The D-F GLS Unit Root Test

The DF-GLS test has been developed by Elliott, Rothenberg and Stock (1996), and the test possesses grater precision than ADF Test in identifying non-stationarity. This test has also been used in this study

The DF-GLS t-test is performed by testing the hypothesis $a_0=0$ in the regression equation:

$$\Delta y_t^d = a_0 y_t^d + a_1 \Delta y^d_{t-1} + \text{------} + a_p \Delta y^d_{t-p} + \text{error} \qquad (3.7)$$

where, y_t^d is the locally de-trended series y_t .The local de-trending depends on whether we consider a model with drift only or a linear trend.

(i) DF-GLS unit root test without time trends (a model with drift only):

$$y_t^{\mu} = \alpha y^{\mu}_{t-1} + \sum_{i=1}^{k} \Psi i \, \Delta y^{\mu}_{t-i} + u_t \quad (3.8)$$

(ii) DF-GLS unit root test with time trends (a model with linear trend):

$$y_t^{\tau} = \alpha y^{\mu}_{t-1} + \sum_{i=1}^{k} \Psi i \, \Delta y^{\tau}_{t-i} + u_t \quad (3.9)$$

3.5.5 Phillips –Perron Unit Root Test

Phillips (1987), Phillips and Perron (1988) have generalized the Dickey-Fuller (DF) tests to situations where disturbance processes, ε_t are serially correlated. The PP is intended to add a 'correction factor' to the DF test statistic.

Let the AR (1) model be,

$$Yt = \mu + \varphi_1 Y_{t-1} + \varepsilon_t, \ [t = 1, \text{---------}, T] \quad (3.10)$$

with $Var(\varepsilon_t) \equiv \sigma_\varepsilon^2$.

If ε_t is serially correlated, the ADF approach is to add lagged ΔY_t to 'whiten' the residuals. To illustrate the alternative approach, the test statistic $T(\varphi_1\text{-}1)$ has been considered which is distributed as ρ_μ in the maintained regression with an intercept but no time trend. The PP modified version is,

$$Z\rho_\mu = T(\varphi_1\text{-}1) - CF \quad (3.11)$$

where the correction factor CF is,

$$CF = 0.5(s^2_{Tl} - s_\varepsilon^2) / \left(\sum_{t=2}^{T} (Y_{t-1} - \bar{Y}_{-1})^2 / T^2\right) \quad (3.12)$$

and, $$s_\varepsilon^2 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^2 \quad (3.13)$$

$$s^2_{Tl} = s_\varepsilon^2 + 2\sum_{s=1}^{l} W_{sl} \sum_{t=s+1}^{T} \varepsilon_t \varepsilon_{t-s} / T \qquad (3.14)$$

$W_{sl} = 1 - s/(l+1)$ and $\varepsilon_t = Y_t - \mu - \varphi_1 Y_{t-1}$

$$\bar{Y}_{-1} = \left(\sum_{t=2}^{T} Y_t \right)/(T-1) \qquad (3.15)$$

3.5.6 The KPSS unit root test

Another frequently used method for the test of stationarity is the KPSS Test developed bby Kwiatowski et al. The KPSS test is an analog of Phillips-Perron test. The model for KPSS test is:

$$\varphi(L)y_t = \alpha_t + \beta t + \varepsilon_t \qquad (3.16)$$

$$\alpha_t = \alpha_{t-1} + \eta_t \quad \alpha_0 = \alpha \quad (t = 1,2,\text{----------}T)$$

where $\varepsilon_t \sim IID(0, \sigma_\varepsilon^2)$, $\eta_t \sim IID(0, \sigma_\eta^2)$

ε_t and η_t are independent and $\varphi(L)$ is a p^{th} order lag polynomial. The relevant hypotheses for the test of stationarity in this model are,

H_0: $\sigma_\eta^2 = 0$

against,

$H_1 > 0$

Under H_1 the process defines an ARIMA model structure.

It has been argued that tests with stationarity as null can be used to confirm the results of the usual unit root tests. The two tests are:

Test 1 (usual test)	Test 2 (KPSS test)
H_0: y_t is non-stationary (unit root) H_1: y_t is stationary	H_0: y_t is stationary H_1: y_t is non-stationary (unit root)

If both tests reject their nulls, their will be no confirmation. But if test 1 rejects the null but test 2 does not (or vice versa) the confirmation can be drawn (G. S. Maddala 2001:553).

3.5.7 ERS Point Optimal Test

The *ERS Point Optimal test* is largely based on the following quasi-differencing regression equation:

$$d(y_t/\alpha) = d(x_t/\alpha)'\delta(\alpha) + \eta_t \qquad (3.17)$$

where, x_t stands for either a constant or a constant along with trend and $\delta(\alpha)$ be the ordinary least square (OLS) estimates from this regression. The residual from this equation is:

$$\eta_t(\alpha) = d(y_t/\alpha) - d(x_t/\alpha)'\delta(\alpha) \qquad (3.18)$$

Let, SSR (α) = $\sum \eta_t^{\,2}(\alpha)$ be the sum of squared residuals function. The ERS point optimal test statistic of the null that α =1 against the alternative that $\alpha = \bar{\alpha}$, is then defined as;

$$P_T = SSR(\bar{\alpha}) - \bar{\alpha}\, SSR(1) / f_0 \qquad (3.19)$$

where, f_0, is an estimator of the residual spectrum at frequency zero. In order to compute the ERS test, it is necessary to specify the underlying set of exogenous regressors x_t and a technique for estimating f_0.

3.5.8 Ng and Perron (NP) Tests

Ng and Perron (2001) estimate four test statistics that are based upon the GLS de-trended data y_t^d. These test statistics are modified forms of Phillips and Perron Z_α

and Z_t statistics, the Bhargava (1986) R_1 statistics and the *ERS Point Optimal statistic*. The terms are defined as following:

$$k = \sum_{t=2}^{T} (y^{d}_{t-1})^2 \Big/ T^2 \qquad (3.20)$$

The modified statistics can be represented as:

$$MZ^{d}_{\alpha} = [T^{-1}(y_t^{d})^2 - f_0] / 2k$$

$$MZ^{d}_{t} = MZ_{\alpha} \times MSB$$

$$MSB^{d} = (k/f_0)^{1/2} \qquad (3.21)$$

$$MP^{d}_{t} = \{ \bar{c}^2 k - \bar{c} T^{-1} (y^{d}_{T})^2 \Big/ f_0 \qquad \text{if } x_t = \{1\}$$

$$= \{ \bar{c}^2 k - (1-\bar{c}) T^{-1} (y^{d}_{T})^2 \Big/ f_0 \qquad \text{if } x_t = \{1, t\}$$

Where, $\bar{c}$ = {-7 if x_t = {1}

= -13.5 if x_t = {1, t}

The NP tests require a specification for x_t and a choice of method for estimating f_0.

3.6 Correlogram

One of the simple, intuitive and interesting methods of testing 'stationarity' is running a correlogram. Correlogram is nothing but simply a graphical representation of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The nature of stationarity can also be found almost accurately in most of the cases with the help of Correlogram.

3.7 Co-integration Test

The co- integration test represents the gesticulation of long-run equilibrium relationships between two variables say y_t and x_t. Let, $y_t \sim I(1)$ and $x_t \sim I(1)$. Then y_t and x_t are said to be co-integrated if there exists a β such that $y_t - \beta x_t$ is I (0).This is denoted by saying y_t and x_t are CI (1, 1). Different types of co-integration techniques are available for the time series analyses. These tests include the Engle and Granger test (1987), Stock and Watson procedure (1988) and Johansen's method (1988).

3.7.1 Engle-Granger Co-integration Test

The Engle and Granger approach is also known as a residual test. If the variables included in an equation are integrated of the same order, say (1), the error term should be stationary, i.e., I (0). Let us consider M time horizon time series (Y_{t1}-----Y_{tM}), each of which is I(1), and the following two regression models, the first with drift and no trend and the second with drift and trend, which help running Engel-Granger cointegration test.

$$Y_{t1} = \beta_0 + \sum_{j=2}^{M} \sum \beta_j y_{t-j+1} + \varepsilon_t \tag{3.22}$$

$$Y_{t1} = \beta_0 + \beta_1 t + \sum_{j=2}^{M} \beta_j y_{t-j+1} + \varepsilon_t \tag{3.23}$$

A test for no cointegration is assigned by a test for a unit root in the estimated error terms e_t of ε_t. This can be achieved by applying ADF test to the residuals using the following equation:

$$\Delta e_t = \alpha e_{t-1} + \sum_{j=1}^{p} \Phi_j e_{t-j} + v_t \qquad (3.24)$$

The null hypothesis $\alpha = 0$ is tested using the τ statistic.

3.7.2 Johansen Maximum Likelihood Co-integration Test

The Johansen maximum likelihood procedure analyses the relationship among stationary or non-stationary variables using the following equation:

$$X_t = \sum_{i=1}^{p} \prod_i X_{t-1} + \varepsilon_t \qquad (3.25)$$

This function can be presented according to the following VAR system:

$$\Delta X_t = \prod Xt-1 + \sum_{i=1}^{p-1} \phi i \Delta X_{t-1} + \mu + \varepsilon_t \qquad (3.26)$$

in which X_t is an n × 1 random vector, ε_t is NIID (0, Σ_ε), and μ is deterministic terms. The long-run relationships are derived through the coefficient matrix of $\prod$, denoted by r, which is between 0 and n. Then there are r linear combinations of the variables in the system that are I (0) or cointegrated. Under Johansen (1991), and Johansen and Juselius (1990) procedures, two tests are available for the determination of cointegrating vectors and for the estimation of their values. These tests are the Trace Test and the Eigen Value Test. In this method, a two-stage testing procedure has been followed. In the first stage, the null hypothesis of no cointegration hypothesis is tested against the alternative hypothesis that the data are cointegrated with an unknown cointegrating vector. If the null hypothesis is rejected, a second stage test is implemented with cointegration maintained under both the null and alternative.

Gonzalo (1994) has suggested that Johansen's procedure has certain properties which are superior to alternative co-integration testing methods.

3.8 Vector Error Correction Modeling

Vector Error Correction Modeling provides important information on the short-run relationship (short-run dynamics) between any two cointegrated variables. *Vector Error Correction test* has provided empirical evidence on the short run causality between real and nominal trade deficits and budget deficits in Nepal.

In the present study the vector error correction estimates have been specified using the following models. The models have been used in both cases i.e. involving TD and BD.

$$\Delta TD_t = \gamma_1+\rho_1 z_{t-1}+\alpha_1\Delta TD_{t-1}+\alpha_2\Delta TD_{t-2}+\alpha_3\Delta BD_{t-1}+\alpha_4\Delta BD_{t-2}+\varepsilon_{1t} \tag{3.27}$$

$$\Delta BD_t=\gamma_2+\rho_2 z_{t-1}+ \beta_1\Delta TD_{t-1}+ \beta_2\Delta TD_{t-2}+ \beta_3\Delta BD_{t-1}+ \beta_4\Delta BD_{t-2}+ \varepsilon_{2t} \tag{3.28}$$

$$\Delta NTD_t=\gamma_3+\rho_3 z_{t-1}+\alpha_1\Delta NTD_{t-1}+\alpha_2\Delta NTD_{t-2}+\alpha_3\Delta NBD_{t-1}+\alpha_4\Delta NBD_{t-2}+\varepsilon_{3t} \tag{3.29}$$

$$\Delta NBD_t=\gamma_4+\rho_4 z_{t-1}+\beta_1\Delta NTD_{t-1}+\beta_2\Delta NTD_{t-2}+\beta_3\Delta NBD_{t-1}+\beta_4\Delta NBD_{t-2}+\varepsilon_{4t} \tag{3.30}$$

Where, ΔTD_t = first difference of trade deficit (real); ΔBD_t = first difference of budget deficit (real); ΔNTD_t is first difference of the nominal trade deficit; ΔNBD_t is the nominal budget deficit; z_{t-1} = first lag of error term of co-integrating equation; ε_{1t} and ε_{2t} are white noise errors; α_1, α_2, α_3 and α_4 and β_1, β_2, β_3 and β_4 are the coefficients of lagged variables in the above models.

The focus of the vector error correction analysis is on the lagged z_t terms. These lagged terms are the residuals from the previously estimated cointegration equations. In the present case the residuals from two lag specifications of the cointegrating equations have been used in the vector error correction estimates. Lagged z_t terms provide an explanation of short-run deviations from the long-run equilibrium for the test equations above. Lagging these terms means that disturbance of the last period impacts upon the current time period. Statistical significance tests are conducted on each of the lagged z_t terms in equations (3.27) through (3.30). In general, finding a statistically insignificant coefficient of the z_t term implies that the system under investigation is in the short-run equilibrium as there are no disturbances present. If the coefficient of the z_t term is found to be statistically significant, then the system is in the state of the short-run disequilibrium. In such a case the sign of z_t term gives an indication of the causal direction between the two test variables.

3.9 Conventional Granger Causality Test

The model for *Conventional Granger Causality test* is based on the following equations:

$$BD_t = \sum_{j=1}^{m} a_j TDt_{-j} + \sum_{j=1}^{m} b_j BD_{t-j} + \varepsilon_t \qquad (3.31)$$

$$TD_t = \sum_{j=1}^{m} a_j BD_{t-j} + \sum_{j=1}^{m} b_j TD_{t-j} + \eta_t \qquad (3.32)$$

where,

BD_t and TD_t represent first difference of Budget Deficit (real) and Trade Deficit (real) respectively.

3.10 Vector Autoregression (VAR) Modeling

While testing the long-run dynamic relationship between modelriables concerned, we may not make any *a-priori* assumption of endogenity and exogeneity of variables concerned. In such situation, Vector Auto-regressive Model (VAR) can be applied. This model treats all variables systematically without making reference to the issue of dependence or independence. A VAR additionally offers a scope for *Intervention Analysis* through the study of *Impulse Response Functions* for the endogenous variables in the model. Moreover, a VAR model allows us to study the 'Variance Decompositions' for these variables and this help us understand the interrelationships among the variables concerned. We, therefore, seek to develop following models for the Twin Deficit Relationship for the economy of Nepal.

3.10.1 The VAR Model

The Vector Autoregression (VAR) Model for trade deficit (TD_t) and budget deficit (BD_t) for the economy of Nepal consists of the equations (3.33) and (3.34) as:

$$\Delta TD_t = \alpha_1 + \sum_{i=1}^{k} \beta_{1i} \Delta TD_{t-i} + \sum_{i=1}^{k} \gamma_{1i} \Delta BD_{t-i} + u_{1t} \quad (3.33)$$

$$\Delta BD_t = \alpha_2 + \sum_{i=1}^{k} \beta_{2i} \Delta BD_{t-i} + \sum_{i=1}^{k} \gamma_{2i} \Delta TD_{t-i} + u_{2t} \quad (3.34)$$

Where,

α_s = intercepts

u_{1t} and u_{2t} = Stochastic error terms (alternatively called as impulses or innovations or shocks in VAR Modeling)

$\sum_{i=1}^{k} \beta_{1i} \Delta TD_{t-i}$ and $\sum_{i=1}^{k} \gamma_{2i} \Delta TD_{t-i}$ = All Summation Values of Lagged Variables of Trade Deficit (TD_t) in the model

$\sum_{i=1}^{k}\gamma_{1i}\Delta BD_{t-i}$ and $\sum_{i=1}^{k}\beta_{2i}\Delta BD_{t-i}$ = All Summation Values of Lagged Variables of Budget Deficit (TD_t)

Furthermore, the VAR model consists of equations (3.33) and (3.34) which requires that

(i) ΔTD_t and ΔBD_t be stationary, and

(ii) u_{1t} and u_{2t} be white noise terms such that: $u_{1t} \sim iid\ N(0,\ \sigma^2 u_1)$, and $u_{1t} \sim iid\ N(0,\ \sigma^2 u_2)$

3.10.2 Impulse Response Function

Any shocks to any variable (presumably i-th variable) not only directly affect the respective variable (i-th variable) only, but also it would be transmitted to all of the endogenous variables in the model through dynamic (lag) structure of VAR. An impulse response function tries to find out the effect of one time shock to one of the innovations on current and future values of the endogenous variables. Due to this feature, *Impulse Response Function (IRS)* in VAR System is widely used in describing the dynamic behaviors variables in the system concerned to shocks in the residual of the time series under study.

Innovations are normally correlated and may be viewed it as having common properties those cannot be associated only to a specific variable. In order to explain the impulses, it is widely applied a transformation P to the innovations so that they become uncorrelated.

$$\upsilon_t = P\,{}^{\text{TM}}{}_t \sim (O, D) \qquad (3.35)$$

Where,

D = Diagonal co-variance matrix

3.10.3 Variance Decomposition

Specifically, Impulse Response Function discovers the effects of a shock to one and thereby transmitted to other endogenous variables in the VAR System. However, it cannot tell us the magnitude of shocks in the system. To overcome this problem, Variance Decomposition mechanism is applied to separate out the variation in an endogenous variable into the constituent shocks to the VAR System. So, Variance Decomposition is applied in the models to find out the information about relative importance of every random innovation in the question of its effects to the variables concerned in the VAR system.