CHAPTER 5

RESEARCH METHODOLOGY

5.1. Research Design

The study was undertaken to find out the impact of exchange rate fluctuations on the share prices in the Indian capital market. In line with this objective two important economic variables viz. share prices and exchange rates were identified as the subject of study. The exchange rate considered was the RBI reference rate of daily nominal spot rate i.e., rupee per US Dollar price as available for each foreign exchange market day under the study period. In as far as share prices are concerned the daily closing prices of each of the trading day during the period of study are taken at various levels starting with overall price indicators like SENSEX, the BSE 30 index, the larger group indices such as BSE 100, BSE 200, BSE 500, the Sectoral indices representing the stock price movements of various sectors of the economy and the individual company level daily closing share prices of selected companies, from the secondary markets of BSE and NSE.
5.1.1 The Data

The daily equity prices measured by their closing prices on each trading day at the BSE or NSE as applicable are taken at the following levels. Daily closing values of SENSEX to represent the overall market price of equity in the Indian capital market, the Sectoral indices representing the price of groups of shares and the stock price movement of individual company shares of selected companies which were/are part of NIFTY or SENSEX for the entire or significant part of the period 2000-2006.

5.1.2 Selection of Period, Stock Exchanges and Share Prices and Exchange Rates.

To study the exchange rate fluctuation the exchange rate of Rupee per US $ is taken as it remained the dominant foreign currency for India. It was also observed that the Indian rupee exhibits a peculiar trend in its value against the US dollar. It changes rapidly followed by long periods of placidity with minimal volatility before a further change. Such patterns were identified, categorized under special time zones and subjected to further investigation.

While the overall impact was measured in terms of the changes in the SENSEX further detailed analysis was carried out with respect to more broader indices like BSE 100 and BSE 200 and their exchange rate treated
correspondents such as DOLLEX 30, DOLLEX 100 and DOLLEX 200. The relative volatility of the rate of return for the corresponding pairs were studied in detail to check on the impact of exchange rate. Further Sectoral indices were considered to find whether the impact, if any, was varying according to the different industry sectors. To verify the specific impact on export oriented and import oriented companies, the study was extended to shares’ price movements of selected companies listed on BSE and /or NSE further categorizing them into export oriented and import oriented applying certain selection criteria.

The data collected were of wide coverage to make the study as comprehensive and extensive as possible. The data on SENSEX were taken for a span of 15 years from July 1991 to June 2006 while the grouped and sectoral indices were for the period 2001 to 2006 and individual company data were for the period 2000 to 2006. In all cases the daily closing prices/rates upto 30 June 2006 were included in the study.

5.1.3 Data sources

Data were collected from various sources, but mainly from the publications of BSE, NSE and RBI and the information available on the corresponding websites. CLINE - the database of Capital Market was also extensively used.
**Individual company share prices**: CLINE Data Base of Capital Market, www.bseindia.com (BSE) and www.nseindia.com (NSE)

**Index data**: Data on SENSEX, NIFTY, sectoral indices dollex series etc were collected from BSE and NSE publications and their websites- www.bseindia.com and http://www.nseindia.com and Economic times website(et intelligence) and Cline data base.

**Exchange rate**: the daily spot exchange rates and reference rate of Rupee to US Dollar were compiled from RBI monthly bulletins and the website www.rbi.org.in

The data obtained were compiled and collated as a daily series, however for the purpose of analysis it had to be subjected to sorting and matching at various stages.

Once the data was arranged on a daily basis it was further subjected to scrutiny to convert the same into a systematic daily time series based on five day week running from Monday to Friday. Any missing data for weekdays on account of intervening holidays or otherwise were substituted by value of the previous trading day from the corresponding series.
5.1.4 Limitations of the Study

Exchange rate and stock prices are believed to be influenced by a number of factors. While the inter relationship between the two is being studied, a bi-variate model is adopted and the influence of other variables is ignored.

It is assumed that the financial policies of the country will continue to evolve in the same direction and mood of increasing liberalization and globalization.

5.2 Tools, Techniques and Tests Used

5.2.1 Graphical and Visual exploration was used in the first stage to identify patterns, if any, of time series formation and for ear-marking sub periods for further analysis. This was carried out perusing through the systematically arranged daily data series for the period of study and observing the patterns through careful scrutiny of graphs drawn on the daily data series.

5.2.2 Descriptive statistics. Measures like mean, standard deviation, coefficient of variation etc were used to study the intensity of fluctuations and relative volatility of the two variables in different time zones and for various sub-segments of the market under various industry groups.

5.2.3 Episodic analysis. The major happenings during the period relating to foreign exchange rate and equity market were identified and the responses
of the variables tracked and the patterns of behaviour studied to understand the nature of relationship.

5.2.4 Correlation and Regression. Pearson’s Coefficient of Correlation and Ordinary Least Square Regression techniques were applied to a limited extent.

Early studies\(^1\) used correlation between the two variables—exchange rate and stock prices. While theoretical explanation was clear, the empirical evidence gave mixed and contradicting results. Moreover, Correlation and regression analysis on time series data are not free from depicting spurious relationships. Empirical work from the early stage was focused on the linkage between the returns in the stock and foreign exchange markets and did not use the levels of the data series. Such a limitation was due to econometric assumptions about insufficient stationarity of financial data series. Stationarity is strictly required in regression analysis to avoid spurious inferences. By differencing the variables some information regarding a possible linear combination between the levels of the variables may be lost. The use of co-integration technique overcomes the problem of non-stationarity and allows an investigation in both the levels and differences of exchange rates and stock prices\(^2\). The sophisticated methods of causality and co-integration are being used by researchers for time series analysis, more so, since 1992 and these are software supported.

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\(^1\) (Aggarwal, 1981 ; Soenen and Hennigar, 1988)  
\(^2\) (Phylaktis and Ravazzolo, 2000).
In the present study also correlation and regression were used in the preliminary stage. However, Time series analysis was adopted and used extensively on the various categories of data as well as for different sub-periods for the later half of the study period (2000-2006). More precisely there is heavy dependence on the modern econometrics tools of causality and co-integration while carrying out the analysis.

5.2.5 Time Series Analysis

5.2.5.1 Time Series Defined

A time series is a time ordered sequence of observations taken at regular intervals over a period of time. There are basically two types of time series models.

Additive model represented by \( Y_t = T_t + C_t + S_t + I_t \)

and Multiplicative model. \( Y_t = T_t \cdot C_t \cdot S_t \cdot I_t \)

where, \( Y_t \) is the observed value of the time series, and the components are \( T = \text{trend} \), \( C = \text{cyclical} \), \( S = \text{seasons} \) and \( I \) the random error.

For the study under consideration the multiplicative model is chosen as this model is found to be a more realistic representation for economic data like stock prices and exchange rates. A multiplicative model can
however be converted into additive by taking the logarithm of the values and using the Log series for further analysis.

\[ \log Y_t = \log (T_t) + \log(C_t) + \log (S_t) + \log(I_t) \]

### 5.2.5.2 Time Series - a Stochastic Process

A time series is a stochastic process\(^3\) which is a collection of random variables sequenced in the order of time. A type of stochastic process that has received a great deal of attention and scrutiny by time series analysts is the so called stationary\(^4\) stochastic process.

Statistically a stationary process is a stochastic process whose probability distribution at any fixed time or position is the same, \(i.e\) it has a constant unconditional mean and variance over time.

Stationarity is an essential property for standard econometric analysis, without which we cannot obtain consistent estimates. Most macroeconomic and financial time series are non-stationary, which means that such variables have no clear tendency to return to a constant value or a linear trend.

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\(^3\) Ever since Economics Laureate Trygve Haavelmo’s work, it has been standard to view economic time series as realizations of stochastic processes.

\(^4\) If a time series is stationary ,its mean, variance and auto co variance (at various lags) remain the same no matter at what point we measure them; ie they are time invariant
Using non-stationary macroeconomic variables in time series analysis causes spuriousness problems in regression. Stationarity is used as a characteristic tool in time series analysis where the raw data are often transformed to become stationary. It is therefore, considered important that the time series properties of the data series are identified before proceeding with further analysis.

A stochastic process is said to be stationary if its mean, variance and the co variance are constant over time and the value of the covariance depends only on the lag between the time periods.

If a time series is stationary, its mean, variance and auto co variance (at various lags) remain the same no matter at what point we measure them; i.e. they are time non-variant.

If \( Y_t \) represents a stochastic time series it is said to be stationary, if the following conditions are satisfied for all values of \( t \) and \( k \) such that,

1. Mean \( \text{E}(Y_t) = \text{E}(Y_{t+k}) = \mu \)
2. Variance \( \text{V}(Y_t) = \text{E}(Y_t - \mu)^2 = \text{E}(Y_{t+k} - \mu)^2 = \sigma_y^2 \)
3. The Co variance \( \gamma_k = \text{E}(Y_t - \mu)(Y_{t+k} - \mu) \)

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7 Auto co- variance refers to the variance between \( Y_t \) and its own lag.
8 In the time series literature such a stochastic process is called weakly stationary which are integrated I(0)
That is, the mean ($\mu$), variance ($\sigma_y^2$) and covariance ($\gamma_k$) are constant and time invariant\(^9\).

### 5.2.5.3 Non-Stationary Stochastic Processes

If a time series is not stationary it will have time varying mean or a time varying variance or both and the findings cannot be generalized over various time period and cannot be of much use for policy makers.

The classical example of non stationary time series is expressed in the random walk model \(^{10}\) (RWM), which can take either of the following two forms:

- A random walk without drift
- A random walk with drift

Asset prices, stock prices and exchange rates are believed to follow a random walk model, which is a non stationary stochastic process. However, the first difference of a random walk time series is stationary and is

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\(^9\) In econometric literature it is referred to as Covariance stationary or weakly stationary process. A strongly stationary process need not have a finite mean and/or variance.

\(^{10}\) The term random walk is often compared with a drunkards walk. Leaving the bar the drunkard moves a random distance $u_t$ at time $t$ and continues to walk indefinitely and will eventually drift farther and farther away from the bar. The same is said about stock prices. Today’s stock price is equal to yesterday’s stock price plus a random shock.
represented by an AR(1) model. Proponents of Efficient Market Hypothesis (EMH)\textsuperscript{11} believe that stock prices are essentially random.

\subsection*{5.2.5.4 Stationarity Test}

A quick way of telling if a process is stationary is to plot the series against time. If the graph crosses the mean of the sample many times, chances are that the variable is stationary; otherwise that is an indication of persistent trends away from the mean of the series.

Several methods are available which describe the stationary or non-stationary nature of the time series and the one which has gained popularity and has become synonymous with non-stationarity and random walk is the \textit{Unit Root Process}\textsuperscript{12}.

A unit root process will only cross the mean of the sample very infrequently, and the process will experience long positive and negative strays away from the sample mean.. Where as the Random Walk Model is a specific case of stochastic process a more general class of stochastic process is the \textit{integrated process}. A process that has a unit root is also called \textit{integrated of

\textsuperscript{11} The EMH relies on the efficient use of information by investors and is often referred to as “informational efficiency”. Fama (1970) defined three forms of market efficiency, namely, weak, semi-strong and strong. Each one is concerned with the adjustment of stock prices to one relevant information subset.

\textsuperscript{12} Tests of the unit root (non-stationarity) hypothesis were developed by Fuller (1976), Dickey and Fuller (1979, 1981), Phillips and Perron (1988), and others. Differencing a variable with a unit root removes the unit root of the series.
order one\textsuperscript{13}, denoted as $I(1)$. Similarly if a time series has to be differenced twice to make it stationary, such a series is integrated to the order two and is denoted as $I(2)$. A time series which is stationary is a process integrated to order zero and is denoted as $I(0)$. Most economic time series are generally $I(1)$ and become stationary only after taking the first difference.

5.2.5.4.1 Unit Root Test

For a time series analysis to be meaningful any spurious correlation in the data should be isolated. This is done by establishing the degree of integration of each variable by checking for stationarity of the series.

The unit root test of stationarity is based on the following set up.

\[ Y_t = \alpha + \rho Y_{t-1} + u_t, \text{ where } u_t \sim I(0) \text{ and } -1 \leq \rho \leq 1 \]

If $\rho = 1$, the model becomes a random walk model and $Y_t$ is non stationary.

\[ Y_t - Y_{t-1} = \alpha + \rho Y_{t-1} - Y_{t-1} + u_t \]

\[ = \alpha + (\rho-1) Y_{t-1} + u_t \]

rewritten as \( \Delta Y_t = \alpha + \delta Y_{t-1} + u_t \)

where $\Delta$ is the first difference and $\delta = (\rho-1)$

\textsuperscript{13} Granger(1981) developed the concept of the degree of integration
If we test the null hypothesis that \( \delta = 0 \) then \( \rho = 1 \); there is unit root and the time series under consideration is non-stationary.

Several methods are already developed for carrying out unit root test, of which the most widely used ones in literature are the Dickey Fuller (DF) and the Augmented Dickey Fuller (ADF) tests\(^{14}\) Phillips – Perron (PP) test and the Kwiatkosky, Phillips, Schmidt, and Shintest (KPSS) tests.

5.2.5.4.2 The Dickey Fuller and the Augmented Dickey -Fuller Tests

The Dickey Fuller **Unit Root Test** has three alternative specifications as follows depending on whether the random walk process may have no drift or it may have drift or it may have drift and deterministic and stochastic trends.

1. Without Constant or Trend \( \Delta Y_t = \delta Y_{t-1} + u_t \)

2. With Constant \( \Delta Y_t = \alpha + \delta Y_{t-1} + u_t \)

3. With Constant and Trend \( \Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + u_t \)

where \( t \) is the time or trend variable

The first is a pure random walk model, the second adds an intercept or drift term, and the third includes both a drift and linear time trend.

The parameter of interest is $\delta$; $\delta = (\rho-1)$ The Hypothesis tested is,

$$H_0 : \delta = 0 \text{ or } \rho = 1 \quad (\text{ie. } Y_t \text{ has a unit root therefore non - stationary})$$

$$H_1 : \rho < 1 \quad (\text{ie } Y_t \text{ has no unit root and hence stationary})$$

5.2.5.4.3 The Augmented Dickey-Fuller (ADF) test makes a parametric correction in Dickey-Fuller (DF) test for higher-order correlation by assuming that the series follows an AR($p$) process. The ADF approach controls for higher-order correlation by adding lagged difference terms of the dependent variable to the right-hand side of the regression.

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \theta \sum_{i=1}^{p} \Delta Y_{t-i} + u_t$$

‘$p$’ is the number of lags determined empirically and the hypothesis $\delta = 0$ is tested.

The t value of the estimated coefficient of $Y_{t-1}$ follows a "$\tau$" tau statistic. If $|t| \leq \text{ADF critical value}$, $\Rightarrow$ indicates the presence of unit root for the time series.
If $t > ADF$ critical value, $\Rightarrow$ reject null hypothesis, i.e., unit root does not exist.

5.2.5.4.4. The Phillips – Perron (PP) test

Phillips – Perron (P-P test) of unit root test also assumes that a zero drift unit root process underlies the observed time series $Y_t$ with a null hypothesis:

$$Y_t = Y_{t-1} + u_t$$

and the estimated OLS regression model can take different forms viz. with zero drift, $Y_t = \rho Y_{t-1} + u_t$ for AR(1) coefficient of $\rho < 1$, and in the second case the estimated OLS $Y_t = \alpha + \rho Y_{t-1} + u_t$, where $\alpha$ is the constant and the AR(1) coefficient of $\rho < 1$ and in the third case assumes the unit root process with arbitrary drift underlying the time series $Y_t$ and the estimated OLS regression model includes a constant and time trend $\beta_t$ and follows an AR(1) process with arbitrary drift and coefficient of $\rho < 1$ The test is based on the hypothesis

$$H_0: \rho = 1 \quad \quad H_1: \quad |\rho| < 1$$

in the equation $\Delta Y_t = \alpha + \rho Y_{t-1} + u_t$
The equation is estimated by OLS (with optional inclusion of constant and time trend) and then the $t$ statistic of the coefficient is corrected for serial correlation in the error term $u_t$ without adding lagged difference terms.

5.2.5.4.5 The Kwiatkosky, Phillips, Schmidt, and Shintest (KPSS)test (1992).

The KPSS test, has stationarity as null hypothesis and seems to behave in a similar manner to the DF and PP tests with respect to identifying stationarity. However, since the null and alternative hypotheses are reversed when compared to the DF and PP tests, what we are looking at is the proportion of cases in which stationarity is accepted, for larger series the PP and ADF tests are considered better than KPSS test.

5.2.5.4.6. Transforming Non- stationary Time Series.

A non stationary time series can be transformed and stationarised The sharp rise in India’s stock markets since 2003 reflects its improving macroeconomic fundamentals through a Difference Stationary Process (DSP) or a Trend Stationary Process(TSP). If the series has a stable long-run trend and tends to revert to the trend line following a disturbance, it may be possible to stationarise it by de-trending. Such a series is said to be trend stationary.
However, sometimes even de-trending is not sufficient to make the series stationary, in which case it may be necessary to transform it into a series of period-to-period differences which suggests difference stationary process.

Consider two time series $X_t$ and $Y_t$. These two time series can be said to be co-integrated if:

(a) both these two time series are I(1) that have become stationary after first differencing, and

(b) there is some linear combination of $X_t$ and $Y_t$ that is I(0) or that is stationary.

When conditions (a) and (b) above hold, it is said that the time series $X_t$ and $Y_t$ are co-integrated. Co-integration is the statistical equivalent of the existence of a long-run equilibrium relationship between I(1) variables, which in turn means that any correlation over time between $X_t$ and $Y_t$ is not spurious.

Economists attempt to build models that will approximate it, that will have similar major properties so that one can conduct simple experiments on them, such as determining the impacts of alternative policies or the long-

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15 The first difference of a time series is the series of changes from one period to the next. If $Y(t)$ denotes the value of the time series $Y$ at period $t$, then the first difference of $Y$ at period $t$ is equal to $Y(t)-Y(t-1)$. Differencing a variable with a unit root removes the unit root.

16 In general for two I(1) variables, any linear combination among them, would be of the form: $Y_t = b_0 + b_1 X_t + u_t$ or $u_t = Y_t - (b_0 + b_1 X_t)$ or $u_t = Y_t - \alpha X_t$. 

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run implications of some new institution. Error Correction Models have been a popular form of macro model in recent years with co-integration as a common element.

5.2.5.5 Co-integration

A substantial part of economic theory generally deals with long-run equilibrium relationship generated by market forces and behavioral rules. Correspondingly most empirical econometric studies entailing time series can be interpreted as attempts to evaluate such relationship in a dynamic framework. The co-integration test is increasingly used in economics to examine the linear relationship between various variables. If a linear combination of exchange rates and share prices gives a stationary error term, $u_t$; then the variables are said to be co-integrated and it means there is a common stochastic trend among these variables that makes it unlikely for them to deviate from each other without limit.

The co-integration test can be thought of as a pre test to avoid spurious correlation\(^\text{17}\) for two time series which are individually non stationary.

\(^{17}\) Clive Granger and his associate Paul Newbold ( (1974)) pointed out that tests of variables in macroeconomic models by straightforward linear regression may often suggest a statistically significant relationship between variables where none in fact exists.
or exhibit random walk but seems to possess a stable long-run relationship.\textsuperscript{18}

For co-integration, a pair of integrated, or smooth series, must have the property that a linear combination of them is stationary.

If the series under consideration turn out to be integrated of the same order, it is possible to proceed testing for co-integration relationship between the integrated variables.

Two time series $X_t$ and $Y_t$ are said to be co-integrated, if there exists a parameter $\alpha$ such that, $u_t = Y_t - \alpha X_t$, where $X_t$ and $Y_t$ are non stationary and display unit root at levels that may be integrated to the order one.

If $u_t$ is subject to unit root analysis and find that it is stationary ie. $I(0)$ where $u_t$ is the residual of the regression of the two variables.

5.2.5.5.1 Test For Co-integration.

Testing for co-integration involves three steps

- Testing the relevant time series for stationarity (unit roots),
- Testing for co-integration,
- Finally Error-Correction Modelling

\textsuperscript{18} C W J Granger(1981) if a linear combination of a set of $I(1)$ variables is $I(0)$, then the variables are co-integrated.
A non-stationary time series \( Y_t \) is said to be integrated of order \( d \), \([Y_t \sim I(d)]\), if it achieves stationarity after being differenced \( d \) times. To determine the order of integration, unit root tests have been developed. The most common test is known as Dickey-Fuller (DF) or Augmented Dickey-Fuller (ADF) tests. Engle and Granger (1987)\(^{19}\) has argued that ADF test allows for dynamics in the DF regression and consequently is over-parameterised in the first order case but correctly specified in the higher order cases.

An alternate approach to test for co-integration is developed by Johansen\(^{20}\) (1988, 1991). Johansen method uses the trace statistic and the maximum likelihood procedure to determine the presence of co-integrating vectors is widely used as a test for co-integration.

Time lagged correlations are common in econometric series where the independent variable affect the dependent variable with some lag of time. In regression analysis involving time series data if the dependent variable \( Y \) responds to another variable(s) \( X \)- the explanatory variable, with a lapse of time(lag) the relationship follows a distributed lag model as below.

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\(^{19}\) Engle and Granger (1987) were the first to formalize the idea of integrated variables sharing an equilibrium relation which turned out to be either stationary or have a lower degree of integration than the original series. They denoted this property by *cointegration*, signifying co-movements among trending variables which could be exploited to test for the existence of equilibrium relationships within a fully dynamic specification framework.

\(^{20}\) Johansen (1988) provided a maximum likelihood approach for deciding the number of cointegrating relationship.
\[ Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + u_t \]

If the model includes one or more lagged values of the dependent variable among its explanatory variable it is called auto regressive model as indicated below.

\[ Y_t = \alpha + \beta X_t + \gamma Y_{t-1} + u_t \quad \text{(Auto regressive model)} \]

5.2.5.5.2 The Error Correction Mechanism (ECM)

If the variables are co-integrated that is there is long term equilibrium relationship between the two, the error term in the model can be used to tie the short run disequilibrium behaviour to its long run value. The Error Correction Mechanism (ECM) corrects the disequilibrium. The Error Correction Mechanism (ECM) invented by Dennis Sargan and developed by Engle and Granger\(^{21}\) is a means of reconciling the short run behaviour of the economic variable with its long run behaviour. If the variables are non-stationary and are co-integrated, the issue of causation can be identified using the Vector Error Correction Model (VECM), which is a Vector Autoregressive (VAR) Model and is in first differences with the addition of a vector of co-integrating residuals. The error–correction model can be used to estimate the speed of adjustment towards equilibrium.

\(^{21}\) ECM first used by J D Sargan and A S Bhargava (1983) was developed later and popularized by Engle and Granger in the Granger representation theorem
A vector error correction (VEC) model is a restricted VAR designed for use with non-stationary series that are known to be co-integrated. The VEC has co-integration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their co-integrating relationships while allowing for short-run adjustment dynamics. The co-integration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. In its simplest form, when we consider a two variable system with one co-integrating equation and no lagged difference terms, the co-integrating equation is: $Y_t = \alpha + \beta X_t$ and the corresponding VEC model is:

$$\Delta Y_t = \alpha_1 (Y_{t-1} - \beta X_{t-1}) + u_{t1} \quad \text{and}$$

$$\Delta X_t = \alpha_2 (Y_{t-1} - \beta X_{t-1}) + u_{t2}$$

The term $(Y_{t-1} - \beta X_{t-1})$ is the Error Correction term. In long run equilibrium, this term is zero. However, if $X$ and $Y$ deviate from the long run equilibrium, the error correction term will be nonzero and each variable adjusts to partially restore the equilibrium relation. The coefficient $\alpha_i$ measures the speed of adjustment of the $i^{th}$ endogenous variable towards the equilibrium.
5.2.5.6 Granger Causality

Most recent studies in exchange rate – stock price relationship employ Granger causality\(^{22}\) testing technique. In a regression of \(Y\) on other variable \(X\) (including its own past values) if we include past or lagged values of \(X\) and it significantly improves the prediction of \(Y\) it can be said that \(X\) Granger causes \(Y\). A similar definition applies, if \(Y\) (Granger) causes \(X\). Causality can be expressed as:

\[
Y_t = \sum_{j=1}^{n} \alpha_j X_{t-j} + \sum_{j=1}^{n} \beta_j Y_{t-j} + u_{1t}
\]

and similarly for \(X\):

\[
X_t = \sum_{j=1}^{n} \lambda_j Y_{t-j} + \sum_{j=1}^{n} \delta_j X_{t-j} + u_{2t}
\]

where it is assumed that the disturbance terms \(u_{1t}\) and \(u_{2t}\) are uncorrelated.

The statement about causality\(^{23}\) has just two components:

1. The cause occurs before the effect; and

2. The cause contains information about the effect that that is unique, and is now in the other variable.

\(^{22}\) However, statistical relationship can never establish causal connection even when the association is strong, unless it is based on some strong theoretical foundation (Kendall and Stuart, 1961). It is for this reason that the Granger approach (1969) enjoys such popularity when dealing with casual relationship between exchange rates and stock indices as well as in other applied econometric research (Gujarati, 1995).

\(^{23}\) Robert Weiner (1960)
A consequence of these statements is that the causal variable can help forecast the effect of the variable after other data has first been used.

**Causality** can be *unidirectional* from X to Y (X |---> Y) when the estimated coefficients of lagged X are statistically different from zero in the model or can be vice versa i.e. *unidirectional* from Y to X (Y |---> X) or Feedback /bi directional causality X <!---> Y when the causation is both ways. It may be mentioned that the above test is applicable to stationary series. In reality, however, underlying series may be non-stationary. In such cases, one has to transform the original series into stationary series and causality tests would be performed based on transformed-stationary series. A special class of non-stationary process is the I(1) process (i.e. possessing a unit root). An I(1) process may be transformed to a stationary one by taking first order differencing. Thus, while dealing with two I(1) process for causality, equations must modified to be expressed in terms of differenced-series and must be modified by inserting the lagged-value of the co-integration regression i.e. Error Correction Term(ECT) as an additional explanatory variable.

\[
\Delta Y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j \Delta X_{t-j} + \sum_{j=1}^{n} \beta_j \Delta Y_{t-j} + \gamma \Delta ECT_{t-1} + u_t
\]

\[
\Delta X_t = \lambda_0 + \sum_{j=1}^{n} \alpha_j \Delta Y_{t-j} + \sum_{i=1}^{n} \delta_i \Delta X_{t-i} + \phi \Delta ECT_{t-1} + u_{2t}
\]
where $\Delta$ is the difference operator and $ECT_{t-1}$ represents an error correction term derived from the long-run co-integrating relationship between the I(1) processes $X_t$ and $Y_t$. This term can be estimated by using the residual from a co-integrating regression.

The choice of the number of lagged terms to be introduced in the distributed lagged model is very important as the direction of causality depend critically on it. The Akaike Information Criteria (AIC)$^{24}$, Final Prediction Error (FPE)$^{25}$ or Schwarz Information Criteria (SIC)$^{26}$ can be used. The choice is based on the lowest value of the criterion chosen, which is expected to minimize the prediction error. When the value of AIC, FPE or SIC is at its minimum the lag is at its optimum.

The theoretical framework of the various tools and relevant techniques have been explained in the foregoing sections. These tools were used for data analysis in the forthcoming section.

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24 Log form of the models is $\ln AIC_L = \ln\left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right)$, where RSS - residual sum of square, $n$ is the number of observations, $k$ is the number of regressors including the intercept, $l$ is the lag length.

25 $FPE(L) = \frac{(1 + \frac{k^2}{n})}{(1 - \frac{k^2}{n})} V$ is the variance ratio

26 Log form of the model is $\ln SIC_L = \frac{k}{n} \ln n + \ln\left(\frac{RSS}{n}\right)$