CHAPTER I
INTRODUCTION

1.1 Introduction

The relationship between financial development and economic growth has long been established both at theoretical and empirical levels. The question bears upon whether financial factors are important in influencing economic development. Academicians have vastly different views on this issue. Some economists believe that financial aspects play a key role in the growth process. Goldsmith (1969) asserted that, the financial superstructure of an economy "accelerates economic growth and improves economic performance to the extent that it facilitates the migration of funds to the best user, i.e., to the place in the economic system where the funds will yield the highest social return". Greenwood and Jovanovic(1990), Pagano(1993) and King and Levine(1993) have all shown in their studies that financial development does have a positive impact on economic growth. Schumpeter (1912) and Patrick (1966) have argued that services provided by financial intermediaries are essential for promoting innovation in technology which has important growth effects. Gurley and Shaw (1955) in their theory made a direct link between financial markets and real activity. Their theory stressed that financial markets can extend borrowers' financial capacity and improve the efficiency of inter temporal trade and they can pool investors' funds and provide external finance to producers. According to them, financial markets are crucial to economic development because they enhance physical capital accumulation.

However, some economists believe that the role of finance in economic growth is either unimportant or of second-order importance. Lucas (1988) asserts that economists badly over-stress the role of financial factors in economic growth. Mayer (1988) finds that during the 1970’s and 1980’s, the stock market made a negative contribution to investment in the UK and US, and surprisingly, a small positive contribution in Germany and Japan where the role of the stock market is rather limited.
The fact that such prominent economists could hold views so diametrically opposed to each other is rather startling to the casual observer. But such disagreements regarding the importance of financial development in economic growth are not new.

The recent revival of interest in the link between financial development and growth stems from the insights and technique of endogenous growth models, which have mainly shown that there can be self-sustaining growth without exogenous technical progress and that the growth rates can be related to technology, income distribution and institutional arrangements. This provides the theoretical background that early empirical studies lacked: financial intermediation not only affects the level of the economy, but also the growth rate. The resulting models have provided new impetus to empirical research of the effects of financial development on growth and vice-versa. This body of literature, reviewed by Gertler (1988); Levine (1997); Bossone (2000); and Tsuru (2000), emphasizes how functions exercised by financial intermediation, such as mobilizing capital, helping to allocate resources, monitoring managers, and facilitating risk management, can affect economic growth. However, most of the empirical literature on growth that explicitly models finance as an explanatory variable in the growth process restricts itself to financial intermediation done by the banking sector and ignores the role of the non-banking sector, i.e. stock markets. More particularly, these studies have used highly aggregated indicators of financial intermediation, such as the ratio of M2 or private sector credit to GDP.

1.2 Rationale of the Study

Academics and practitioners have ignored the role of stock markets on economic development for a long time. The role of stock markets in our everyday life has become rather difficult to ignore. Recently, more attention has been given by the theoretical literature on the links between stock markets and economic growth, but the empirical evidence is still scarce. A primary reason for the lack of empirical literature on stock markets has been the absence of a standard set of indicators to measure the extent of stock market development.
The few empirical studies in this topic, however, perform cross-country growth regressions. The major focus of these studies is to identify the determinants of growth rather than causality issue between economic growth and stock market development (GoldSmith, 1969, McKinnon, 1973, Shaw, 1973). Stock market development may predict economic growth simply because it anticipates future growth; thus stock market development may be a leading indicator rather than a causal factor. In particular, this approach involves averaging out variables over long time periods, and using them in cross section regressions aimed at explaining cross-country variables of growth rates. Therefore, this technique cannot allow different countries to exhibit different patterns of causality, yet it is likely that in some countries the stock market is a leading sector whilst in others it lags behind the banking sector. This means that the causality result is only valid on average. Thus, these researches have not completely resolved the issue of causality but suggest strongly that stock market development is an important determinant of future economic growth. The questions about causality remain unsolved: does stock market development affect growth, does economic growth lead to more stock market development, or both?

Furthermore, cross-country growth regressions suffer from a variety of errors: measurement errors, statistical errors and conceptual errors. There is no defensible view for including different countries in the same regression. Also, since various factors change during the time period of study (governments, policies, preferences and business cycles), hoping to capture all these changes by certain explanatory variables averaged over time is rather optimistic. Consequently, interpreting the coefficient derived from such studies is rather difficult. As with other cross-sectional studies, the coefficients are only suggestive of partial correlations. This approach also by averaging of value over long period of time is not able to distinguish whether or not the development of stock markets affect the long-term growth rate of the economy, or it just influence the short-term level of development. A country experiencing short period of rapid growth and no growth after is treated the same empirically as the one experiencing moderate growth over long period. In summary, we believe that in these studies there is no consensus
judgment that stock markets cause growth and what evidence there is very much country-specific. Consistent with our view, the World Bank (1993) expressed that the economic policies are country-specific and their effectiveness depends on the effectiveness of the institutions which implement them.

Stock Market Development is a multi-dimensional concept. Macroeconomic factors are important when analyzing stock market development. The determinants of stock market development need to be examined in detail, since stock markets are said to have played a role in promoting economic growth.

Over the past few years, financial markets have become increasingly global. The integration of financial markets across boundaries had been initiated by the capital market integration in developed countries. Financial integration has become an important policy issue because it helps in efficient transmission of different monetary policy effects and provides an opportunity to diversify investment, thereby pooling risk and channelizing liquidity across markets. The positive impact of stock market development on economic growth is possible only when the stock market is efficient. In other words, stock market induces economic growth only when the former is efficient.

As with most developing countries, India has an organized stock market. The genesis of Indian stock market can be traced back to the eighteenth century. The regulatory framework for the capital market began to evolve with the framing of Capital Issues Control Act in 1947. In the decade of 1980’s, stock market began to occupy a prominent position in the financial markets and the economy. The economic policies that encourage private corporate sector, attractive rates of dividend and performance and growing inability of Direct Financial Institutions to provide funds for expansion of the private sector contributed to this change. The establishment of a regulator, Securities and Exchange Board of India in 1988 and the creation of an orderly framework for the markets gave a fillip to the amount of capital raised.
The decade of nineties ushered in a series of significant turnaround in the capital market. Severe macroeconomic and fiscal imbalances characterized the country’s economic situation. Burgeoning fiscal deficit, worsening balance of payment situation, escalating inflation and downward spiraling productivity took a heavy toll of India’s economy. The country in dire necessity of a way to wriggle out of the stalemate of economic affairs had to chart out an alternative path of economic policy. India embraced a new economic philosophy in July 1991 when the new economic policy of liberalization, privatization and globalization was introduced. Interwoven in this policy was the removal of existing administrative controls and impediments and opening up of the economy by encouraging private sector participation in many sectors. The stock market witnessed tremendous growth in terms of market capitalization, trading volume and liquidity during this time simultaneously with near double digit economic growth. Therefore the focus of study is primarily to unravel the linkage between the stock market development and real economic growth during this time period only.

The study of this important issue is timely because there is no empirical evidence that provides policy makers with information concerning the particular causal patterns between the stock market development and the real sector in the Indian economy. In addition, there are points of view that doubt the existence of a positive impact of the stock market on economic growth in developing countries like India. The main reasons are to be found in market inefficiencies. This makes it likely that stock markets will be more like burgeoned casinos than institutions designate to ameliorating and mobilizing saving rates and enhancing investment decisions, technical innovation, and long run growth. Thus, by choosing an individual country-India, this study results will be more appropriate for policy decisions to developing economies in general and India in particular. In addition, providing empirical evidence of this important issue within specific-country experience will add to the literature on the role of stock market development on economic growth and opens an exciting topic for research.
1.3 Hypothesis

In this study the following hypothesis are tested:
i) There exists two-way causality between stock market development and economic growth.
ii) The stock market development is significantly influenced by the macroeconomic determinants of economic growth (represented by Index of Industrial Production), financial intermediation, macroeconomic stability and external factors.
iii) Indian Stock Market (e.g., Bombay Stock Exchange, BSE) is closely integrated with developed stock markets during the liberalized era.
iv) Indian stock market is weak form efficient

1.4 Objectives of the Study

The specific objectives of the study are as follows.
(1) Theoretically trace the critical role played by financial markets particularly stock market in the process of economic development
(2) Examine the role of stock market development on economic growth in a developing economy of India and the causal linkage between stock market development and economic growth in the post liberalization period.
(3) Examine the macroeconomic determinants of stock market development of India during the post reform period since 1991.
(4) Explore the pattern of integration of Indian Stock Market with the global developed stock markets after the liberalization and globalization of the Indian Economy.

1.5 Data and Methodology

The study evaluates the impact of the stock market development on economic growth, macroeconomic determinants, integration and efficiency of stock market
development by using India as a country-specific case with macro level data sets. An assortment of econometric methodologies is used to explore the above mentioned issues. The choice of different statistical and econometric techniques is based on their suitability to the objectives of the study.

The study has used a large number of data sources to collect data for further analysis. All empirical data are of time series. The data on Stock Market Development variables such as Market Capitalisation Ratio (MCR), Value Traded Ratio and Turnover ratio used in Chapter 4 and 5 are retrieved from the following data sources:

1) Website of Bombay Stock Exchange Ltd(http://www.bseindia.com/)
2) Website of National Stock Exchange Ltd(http://www.nseindia.com/)
3) Website of Securities and Exchange Board of India(http://www.sebi.gov.in/)
6) SEBI Bulletin, Various Issues.

The data on Economic Growth Variable, namely, Index of Industrial Production (IIP) and macroeconomic variables used in Chapter 4 and 5 are retrieved from the following data sources:

2) Economic Survey, Various Issues

The data on Stock Indices of BSE and NSE and indices of few global economies, namely, USA, UK, Germany, France, Japan and Australia used in Chapter 6 and 7 are retrieved from the source, Bloomberg.
The important statistical techniques and objectives for the analysis are as follows:

1.5.1 Causal Relation between Economic Growth and Stock Market Development

The causal connection between economic growth and stock market development is evaluated in chapter IV of the study. The data pertaining to Index of Industrial Production (IIP) with 2004-05 as the base year is used as a proxy variable for economic growth. Among the various stock market development indicators, the turnover ratio (TR) is used as an index for stock market development. The important statistical techniques used in this chapter are as follows.

1.5.1.1 Descriptive Statistics

In addition to the mean and medium of concerned variables such as IIP and TR, the Skewness, Kurtosis and Jarque-Bera statistics are estimated.

- Skewness is a measure of asymmetry of the distribution of the series around its mean. Skewness is computed as:

\[ S = \frac{1}{N} \sum_{t=1}^{N} \left( \frac{y_t - \bar{y}}{\hat{\sigma}} \right)^3 \]  

where \( \hat{\sigma} \) is an estimator for the standard deviation that is based on the biased estimator for the variance \( \hat{\sigma} = \sqrt{(N-1)/N} \). The skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail.

- Kurtosis measures the peakedness or flatness of the distribution of the series. Kurtosis is computed as

\[ K = \frac{1}{N} \sum_{t=1}^{N} \left( \frac{y_t - \bar{y}}{\hat{\sigma}} \right)^4 \]  

Where \( \hat{\sigma} \) is again based on the biased estimator of the variance. The Kurtosis of the normal distribution is 3. If the Kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal. If the Kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.
• Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the Skewness and Kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$Jarque - Bera = \frac{N}{6} (S^2 + \frac{(K-3)^2}{4}) \text{-------------------------(1.3)}$$

Where $S$ is the skewness and $K$ is the Kurtosis.

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as $\chi^2$ with 2 degrees of freedom. The reported probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis- a small probability value leads to the rejection of the null hypothesis of a normal distribution.

### 1.5.1.2 Granger Causality Test

To test for Granger causality and cointegration, we use the standard methodology proposed by Granger (1969, 1986) and Engle and Granger as described in Enders (1995). All tests are performed on natural logarithm of the indices’ of time series using OLS estimation procedure. In order to test for Granger causality between economic growth and stock market development indices of $IIP_t$ and $TR_t$ are used. The following equations are estimated.

$$\Delta IIP_t = a_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta IIP_{t-1} + \sum_{i=1}^{m} \alpha_{2i} \Delta TR_{t-1} + \varepsilon_{it} \text{-------------------------(1.4)}$$

$$TR_t = a_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta TR_{t-1} + \sum_{i=1}^{m} \alpha_{2i} \Delta IIP_{t-1} + \varepsilon_{it} \text{-------------------------(1.5)}$$

To evaluate the joint insignificance of the coefficients, a F test is estimated. The null hypothesis claims that IIP does not Granger cause TR or vice versa. Therefore, a rejection of the null hypothesis indicates a presence of Granger causality. For each pair of indices, we perform two Granger causality tests so that we can decide whether TR Granger causes IIP or IIP Granger causes TR or both, or none.
1.5.1.3 The Unit Root Tests

Once there exist any causal connection between variables, the next step is to evaluate if there exists any long run relationship between them. Even if, two variables depart in the short run, there may be a co-movement of these variables in the long run. The short-run deviation or disequilibrium may be corrected in the long-run. It implies that the variables are cointegrated in the long run. The testing of cointegration between variables starts from the unit root tests.

The study starts with the conventional unit root tests, to find out the order of integration. The important unit root tests used here are the Augmented Dickey-Fuller (Dickey and Fuller, 1979) test, Phillips-Perron (Phillips and Perron, 1988) test and the KPSS (Kwiatkowski et al. 1992) test. All of these unit root tests are used to test whether the data contains unit root (non-stationary) or is a stationary process. A series is said to be stationary if the mean and auto co variances of the series do not depend on the time factor. Any series that is not stationary then it is said to be non-stationary. A series is said to be integrated of order ‘d’ which can be denoted by I (d), means that it has to be differenced ‘d’ times before it becomes stationary. Otherwise, if a series by itself, let say stationary at levels, without having to be differenced, then that is said to be I(0). It is very essential to apply unit root tests for individual series to come up with some idea that whether the variables are integrated with same order or not. If the order of integration is same for the entire variables then it is quite possible that study can find out the long run and short run dynamic behavior of the variables by employing Engle-Granger cointegration test and error correction model.

In this study three different unit root tests are employed to test the null hypothesis of a unit root. These tests are the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.
i) Augmented Dickey-Fuller test (ADF)

Amongst the several tests that were developed in the literature to examine the presence of unit root, the Augmented Dickey-Fuller test (ADF), developed by Said and Dickey (1984), is a widely used one. The test is run as follows:

$$\Delta Y_t = \beta_1 + \beta_2 T + \delta Y_{t-1} + \sum_{i=1}^{k} \rho_i \Delta Y_{t-i} + \epsilon_t \tag{1.6}$$

Where $\Delta Y_t$ is the first difference of the concerned variable series, $\rho$ are coefficients to be estimated, $k$ is the number of lagged terms, $T$ is the deterministic trend term, $\beta_2$ is the estimated coefficient for the trend, $\beta_1$ is the constant, and $\epsilon_t$ is a pure white noise. The unit root tests the null hypothesis that $\delta = 0$ against the alternative hypothesis that $\delta < 0$. That is to say, if the null is accepted, this means that the series is a non-stationary one and follows a random walk.

ii) Phillips–Perron (PP) Tests

PP tests are proposed by Phillips and Perron (1988). These tests are similar to ADF tests. The difference between the PP and the ADF tests is in how they deal with serial correlation and heteroskedasticity in the errors. The PP is a non-parametric test that estimates the non Augmented Dickey-Fuller but modifies the test statistic so that its asymptotic distribution is not affected by serial correlation. Phillips-Perron test is a non-parametric test with the following specifications:

$$Y_t = \mu + \delta Y_{t-1} + \epsilon_t \tag{1.7}$$

$$Y_t = \mu + \beta \left( t - \frac{1}{2} T \right) + \delta Y_{t-1} + \epsilon_t \tag{1.8}$$

where $Y_t$ is the value of the variable selected at time $t$, $\mu$ is a constant, $\alpha$ and $\beta$ are parameters to be estimated within the model and $\epsilon_t$ is pure white noise error term. The first Equation includes only the constant term, whereas the second equation contains a constant term $\mu$ and a linear trend term $\beta(t-1/2T)$.

The hypotheses Phillips-Perron (PP) tests are represented as follows:
H0: there is a unit root in the series

H1: there is not any unit root in the series (stationary)

As the ADF is a parametric test, the PP test, developed by Phillips and Perron (1988), is conducted as well. The PP is a non-parametric test that estimates the non Augmented Dickey-Fuller but modifies the test statistic so that its asymptotic distribution is not affected by serial correlation.

iii) The Kwiatkowski, Phillips, Schmidt and Shin (KPSS) Test

Due to the limited success of the ADF test and the PP test in rejecting the null hypothesis of unit root, the KPSS test, developed by Kwiatkowski, Phillips, Schmidt and Shin (1992), is also applied. The KPSS, which is a parametric unit root test, uses a similar autocorrelation correction to the one applied by the PP; however, it assumes that the observed time series can be decomposed into the sum of a deterministic trend, a random walk with zero variance and a stationary error term. It thus tests the null hypothesis of trend stationarity.

Since the publication of the seminal paper by Kwiatkowski, Phillips, Schmidt and Shin(KPSS)(1992), there has been an increasing interest in testing for stationarity in economics time series. The KPSS test represents a useful alternative to hypothesis, and may conflict with tests that assume non-stationarity as a null hypothesis, thus, indicating that there may be real doubt as to the properties of the time series. The KPSS test accounts for the problem of autocorrelation in a similar (although parametric) way to PP test.

To perform the test, we first obtain the residual $\varepsilon$ from the regression of $y$ on a constant and a trend. It was found that standard unit root tests are not very powerful against relevant alternatives and fail to reject the null hypothesis for many economic series. KPSS (1992) consider the problem of testing for stationarity around a level or a
time trend against the alternative of a unit root. Under the null hypothesis, the model is represented as follows:

\[ Y_t = \delta t + \gamma_t + \varepsilon_t \]  

\( (1.9) \)

With auxiliary equation for \( \gamma_t \)

\[ \gamma_t = \gamma_{t-1} + \mu_t \]  

\( (1.10) \)

where \( Y_t \) denotes series of observation of variable of interest, ‘\( t \)’ is the deterministic trend, \( \gamma_t \) is random walk process, \( \varepsilon_t \) is the error term of the equation, by assumption it is assumed as stationary, \( \mu_t \) denotes the error term of the second equation and by assumption is series of identically distributed independent random variables of \( \text{E}(\mu_t) = 0 \), and constant variance, \( \sigma^2 \). A test for \( \sigma_{\mu_t}^2 \) is a test for stationarity (Maddala and Kim, 1998).

The KPSS statistic is based on the residuals \( \varepsilon_t \) from the OLS regression of \( Y_t \) on the exogenous variables. The test statistics is defined as:

\[ KPSS = T^{-2} \sum_{i=1}^{T} S_t^2 / \sigma_T l \]  

\( (1.11) \)

Where \( S_t = \sum_{i=1}^{t} \varepsilon_t \), the partial sum of residuals, \( T \) is the number of observation and the \( \sigma_T \) represent an estimate of the long run variance of residuals. Large value of KPSS lead to rejection of the stationarity null hypothesis, since that means the series deviate from its mean. In the (KPSS) unit root test hypotheses are stated as follows:

H0: there is not any unit root in the series (stationary).
H1: there is a unit root in the series.

1.5.1.4 Cointegration test

Cointegration exits for variables means despite variables are individually non-stationary, a linear combination of two or more time series can be stationary and there is a long-run equilibrium relationship between these variables. If the error term in (1) or (2) is stationary while the regressors are individually trending, there may be some transitory correlation between the individual regressors and error term. However, in the long run,
the correlation must be zero because of the fact that the variables must eventually diverge from stationary ones. Thus the regression on the level of the variables is meaningful and not spurious. In this chapter, the cointegration is tested by using single equation of Engle Granger method.

1.5.1.5 The Engle Granger Method and Error Correction Method (ECM)

The cointegration and long run relationship between stock market development and economic growth are evaluated based on the Engle Granger method. According to this method, suppose we expect that there exists a single long-run relationship between the two I(1) variables Y and X of the form: \( Y = \beta_0 + \beta_1 X \). Two steps involved in this procedure. As a first step, estimate by OLS the long run relationship using the cointegrating regression:

\[
Y = \hat{\beta}_0 + \hat{\beta}_1 X + u \tag{1.12}
\]

It is estimated as:

\[
\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X \tag{1.13}
\]

Defining and saving the disequilibrium errors as:

\[
u = Y - \hat{Y} = Y - (\beta_0 + \beta_1 X) \tag{1.14}\]

If Y and X are cointegrated, u should be stationary I(0). If ‘u’ is stationary, there exists a long run relationship between these variables and in the long run the market disequilibrium will be corrected to certain extent by the movement of these variables. The Engle Granger method is known as residual method for evaluating the cointegration. Once it is cointegrated, then the Residual based Error Correction model will be the next step, which is given as below.

From the basic model of \( Y = \beta_0 + \beta_1 X + u \), the Error Correction model (ECM) specification is as follows.
\[ \Delta Y = \gamma_0 + \gamma_1 \Delta X + \gamma_2 (Y_{t-1} - \beta_0 - \beta_1 X_{t-1}) + \nu \]

The interpretation is that Y is purported to change between t-1 and t as a result of change in X between t-1 and t and in part to correct for any disequilibrium that existed in previous period. The Cointegrating vector is \([ \beta_0 \beta_1 ]\). \( \beta_1 \) measures the long run relation between Y and X, \( \gamma_1 \) measures the short run relation between \( \Delta X \) and \( \Delta Y \) and \( \gamma_2 \) speed adjustment back to equilibrium.

### 1.5.1.6 Vector Autoregressive Model (VAR)

The simultaneity relation between variables is tested with the help of VAR model. Various literature survey results indicate that economic growth and stock market development are mutually interrelated and these relationships may be time lagged also. VAR model helps us to decipher the mutual interconnection between variables with time lag.

The Vector Auto Regression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system.

The mathematical representation of a VAR is:

\[ Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + B X_t + \varepsilon_t \]

where \( Y_t \) is a vector of ‘k’ endogenous variables, \( X_t \) is a vector of ‘d’ exogenous variables, and \( A_1 \ldots A_p \) and \( B \) are matrices of coefficients to be estimated, and \( \varepsilon_t \) is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

Since only lagged values of the endogenous variables appear on the right-hand side of the equations, simultaneity is not an issue and OLS yields consistent estimates.
Moreover, even though the innovations $\varepsilon_t$ may be contemporaneously correlated, OLS is efficient and equivalent to GLS since all equations have identical regressors. As an example, suppose that Index of Industrial Production (IIP) and stock market indicator. Turnover Ratio (TR) are jointly determined by a VAR and let a constant be the only exogenous variable. Assuming that the VAR contains two lagged values of the endogenous variables, it may be written as:

$$IIP_t = a_{11}IIP_{t-1} + a_{12}TR_{t-1} + b_{11}IIP_{t-2} + b_{12}TR_{t-2} + c_1 + e_{1t} \quad \text{----------------(1.17)}$$

$$TR_t = a_{21}IIP_{t-1} + a_{22}TR_{t-1} + b_{21}IIP_{t-2} + b_{22}TR_{t-2} + c_2 + e_{2t} \quad \text{----------------(1.18)}$$

where ,$a_{ij}$, $b_{ij}$ and $c_j$ are the parameters to be estimated.

Along with the VAR results, the statistical results such as $R^2$, Adjusted $R^2$, F-statistics, Durbin-Watson test and various lag information criteria such as Akaike info criterion (AIC), Schwarz criterion (SC) and Hannan-Quinn criterion (HQC) are estimated.

(i) **R-Squared**

The R-squared($R^2$) statistics measures the success of the regression in predicting the values of the dependent variable within the sample. In standard settings, $R^2$ may be interpreted as the fraction of the variance of the dependent variable explained by the independent variables. The statistics will equal one if the regression fits perfectly, and zero if it fits no better than the simple mean of the dependent variable.

$$R^2 = 1 - \frac{\hat{e}'\hat{e}}{(y-y)(y-y)}; \quad \bar{y} = \sum_{t=1}^{T} \frac{y_t}{T} \quad \text{---------(1.19)}$$

Where $\bar{y}$ is the mean of the dependent (left-hand) variable, $y$ is the dependent variable, ‘$e$’ is the error term and T is the number of observation.
(ii) Adjusted R-Squared

One problem with using $R^2$ as a measure of goodness of fit is that the $R^2$ will never decrease as we add more regressors. In the extreme case, we can always obtain an $R^2$ of one if we include as many independent regressors as there are sample observations. The adjusted $R^2$ is commonly denoted as $\overline{R^2}$, penalizes the $R^2$ for the addition of regressors which do not contribute to the explanatory power of the model. The adjusted $R^2$ is computed as:

$$\overline{R^2} = 1 - (1 - R^2) \frac{T-1}{T-k}$$  

The $\overline{R^2}$ is never larger than the $R^2$, can decrease as you add regressors, and for poorly fitting models, may be negative.

(iii) Standard Error of the Regression(S.E. of the Regression)

The standard error of the regression is a summary measure based on the estimated variance of the residuals. The standard error of the regression is computed as:

$$s = \sqrt{\frac{\sum_{t} \hat{\varepsilon}_t \hat{\varepsilon}_t}{T-k}}$$  

Where ‘k’ is equal to number of variables.

(iv) Sum-of-Squared Residuals

The sum-of-squared residuals can be used in a variety of statistical calculations, and is presented as

$$\hat{\varepsilon}' \hat{\varepsilon} = \sum_{t=1}^{T} (y_t - X'b)^2$$  

(v) Log Likelihood

Likelihood ratio tests may be conducted by looking at the difference between the log likelihood values of the restricted and unrestricted versions of the equation.
The log likelihood is computed as:

\[ I = \frac{T}{2} (1 + \log (2\pi) + \log (\bar{\varepsilon}' \bar{\varepsilon} / T)) \]

\[ \text{--------------------------------------------}(1.23) \]

\[(vi) \quad \textbf{Durbin-Watson Statistic}\]

The Durbin-Watson Statistic measures the serial correlation in the residuals. The statistic is computed as

\[ DW = \frac{\sum_{t=2}^{T} (\bar{\varepsilon}_t - \bar{\varepsilon}_{t-1})^2}{\sum_{t=1}^{T} \varepsilon_t^2} \]

\[ \text{--------------------------------------------}(1.24) \]

As a rule of the thumb, if the DW is less than 2, there is evidence of positive serial correlation. If the DW statistic is very close to one, it indicates the presence of serial correlation in the residuals.

\[(vii) \quad \textbf{Mean and Standard Deviation (S.D.) of the Dependent Variable}\]

The mean and the standard deviation of \( y \) are computed using the standard formulae:

\[ \bar{y} = \frac{\sum_{t=1}^{T} y_t}{T} \]

\[ \text{--------------------------------------------}(1.25) \]

\[ s_y = \sqrt{\frac{\sum_{t=1}^{T} (y_t - \bar{y})^2}{T - 1}} \]

\[ \text{--------------------------------------------}(1.26) \]

\[(viii) \quad \textbf{Akaike Information Criterion}\]

The Akaike Information Criterion(AIC) is computed as:

\[ \text{AIC} = -2l/T + 2h/T \]

\[ \text{--------------------------------------------}(1.27) \]

Where l is the log likelihood

The AIC is often used in model selection for non-nested alternatives- smaller values of AIC are preferred. For example, we can choose the length of a lag distribution by choosing the specification with the lowest values of the AIC.
(ix) Schwarz Criterion

The Schwarz Criterion (SC) is an alternative to the AIC that imposes a larger penalty for additional coefficients:

\[
SC = -2l/T + (k \log T)/T
\]

\[\text{(1.28)}\]

(x) Hannan-Quinn Criterion

The Hannan-Quinn Criterion (HQ) employs yet another penalty function:

\[
HQ = -2(l/T) + 2k \log(\log(T))/T
\]

\[\text{(1.29)}\]

(xi) F-Statistics

The F-Statistics reported in the regression output is from a test of the hypothesis that all of the slope coefficients (excluding the constant, or intercept) in a regression are zero. For ordinary least squares model, the F-statistics is computed as:

\[
F = \frac{R^2/(k-1)}{(1-R^2)(T-k)}
\]

\[\text{(1.30)}\]

Under the null hypothesis with normally distributed errors, this statistics has $F$-distribution with $k-1$ numerator degrees of freedom and $T-k$ denominator degrees of freedom. The p-value given just below the F-statistic, denoted Prob(F-statistic), is the marginal significance level of the F-test. If the p-value is less than the significance level we are testing, say 0.05, we reject the null hypothesis that all slope coefficients are equal to zero.

1.5.1.7 Variance Decomposition and Impulse Response Analysis

*Impulse responses* trace out the responsiveness of the dependent variables in the VAR to shocks to each of the variables. So, for each variable from each equation separately, a unit shock is applied to the error, and the effects upon the VAR system over time are noted. Thus, if there are $g$ variables in a system, a total of $g^2$ impulse responses could be generated. The way that this is achieved in practice is by expressing the VAR model as a VMA -- that is, the vector autoregressive model is written as a
vector moving average. Provided that the system is stable, the shock should gradually die away.

To illustrate how impulse responses operate, consider the following bivariate VAR(1)

\[ y_t = A_1 y_{t-1} + u_t \]  

where \( A_1 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \)

The VAR can also be written out using the elements of the matrices and vectors as

\[
\begin{bmatrix}
y_{1t} \\
y_{2t}
\end{bmatrix} = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix}
y_{1t-1} \\
y_{2t-1}
\end{bmatrix} + \begin{bmatrix} u_{1t} \\
u_{2t}
\end{bmatrix}
\]  

Consider the effect at time \( t=0,1,\ldots \), of a unit shock to \( y_{1t} \) at time \( t=0 \)

\[
y_0 = \begin{bmatrix} u_{10} \\ u_{20} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}
\]  

\[
y_1 = A_1 y_0 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix}
\]  

\[
y_2 = A_1 y_1 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0.5 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.25 \\ 0 \end{bmatrix}
\]

and so on. It would thus be possible to plot the impulse response functions of \( y_{1t} \) and \( y_{2t} \) to a unit shock in \( y_{1t} \). Notice that the effect on \( y_{2t} \) is always zero, since the variable \( y_{1t-1} \) has a zero coefficient attached to it in the equation for \( y_{2t} \).

Now consider the effect of a unit shock to \( y_{2t} \) at time \( t=0 \)

\[
y_0 = \begin{bmatrix} u_{10} \\ u_{20} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}
\]  

\[
y_1 = A_1 y_0 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix}
\]  

\[
y_2 = A_1 y_1 = \begin{bmatrix} 0.5 & 0.3 \\ 0.0 & 0.2 \end{bmatrix} \begin{bmatrix} 0.3 \\ 0.2 \end{bmatrix} = \begin{bmatrix} 0.21 \\ 0.04 \end{bmatrix}
\]  

20
and so on. Although it is probably fairly easy to see what the effects of shocks to the variables will be in such a simple VAR, the same principles can be applied in the context of VARs containing more equations or more lags, where it is much more difficult to see by eye what the interactions between the equations are.

The Impulse function estimated from Eviews statistical software (version 6) provides the following options for transforming the impulses:

- **Residual- One Unit** sets the impulses to one unit of the residuals. This option ignores the units of measurement and the correlations in the VAR residuals so that no transformation is performed. The responses from this option are the MA (moving average) Coefficients of the infinite MA order Wold representation of the VAR.

- **Residual- One Std. Dev.** Sets the impulses to one standard deviation of the residuals. This option ignores the correlations in the VAR residuals.

- **Cholesky** uses the inverse of the Cholesky factor of the residual covariance matrix to orthogonalize the impulses. This option imposes an ordering of the variables in the VAR and attributes all of the effect of any common component to the variable that comes first in the VAR system.

- **The (d.f.adjustment)** option makes a small sample degrees of freedom correction when estimating the residual covariance matrix used to derive the Cholesky factor. The \((i,j)\)-th element of the residual covariance matrix with degrees of freedom correction is computed as \( \sum e_{i,t}e_{j,t} / (T - p) \) where \( p \) is the number of parameters per equation in the VAR. The \( \text{(no. of d.f. adjustment)} \) option estimates the \((i,j)\)-th element of the residual covariance matrix as \( \sum e_{i,t}e_{j,t} / T \).

- **Generalized Impulses** as described by Pesaran and Shin(1998) constructs an orthogonal set of innovations that does not depend on the VAR ordering. The generalized impulse responses from an innovation to the \( j \)-th variable are derived by applying a variable specific Cholesky factor computed with the \( j \)-th variable at the top of the Cholesky ordering.
Variance decompositions offer a slightly different method for examining VAR system dynamics. They give the proportion of the movements in the dependent variables that are due to their ‘own’ shocks, versus shocks to the other variables. A shock to the \( i \)th variable will directly affect that variable of course, but it will also be transmitted to all of the other variables in the system through the dynamic structure of the VAR. Variance decompositions determine how much of the \( s \)-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable for \( s = 1, 2, \ldots \). In practice, it is usually observed that own series shocks explain most of the (forecast) error variance of the series in a VAR. To some extent, impulse responses and variance decompositions offer very similar information.

1.5.2 Macroeconomic Determinants of Stock Market Development

The fifth chapter examines the macroeconomic determinants of stock market development. Based on the various domestic and global literature reviews, the identified factors are classified into economic growth, financial intermediary development, macroeconomic stability and external factors. The value of GDP and its growth rate is generally accepted factor of economic growth. However, the monthly data on GDP is not available and hence the index of industrial production (IIP) is taken as a proxy variable for GDP. The values of IIP used are calculated with 2004 as base year. Among the various indicators of financial intermediary two important indicators are the ratio of M3 to GDP and the role of banking sector represented by credit-deposit ratio. Since the monthly data is not available for GDP, the Credit-deposit ratio is used as an index for financial intermediary development. There are two variables used for macroeconomic stability. They are the interest rate and inflation rate. The SBI prime lending rate is used for representing interest rate and month-to-month inflation based on WPI is used for representing the inflation rate for the analysis. The external factors are represented by the exchange rate of domestic currency and the flow of net FDI towards the country.

The important statistical tools used in this chapter are: the unit root test statistics of the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test. All selected variables in the analysis is integrated at first difference. The Engle Granger residual test shows that the
stock market development and macroeconomic variables are cointegrated in the long run.

The cointegrating equation in the present analysis is written as

\[ \Delta TR = \gamma_0 + \gamma_1 IIP + \gamma_2 \Delta \text{inflation} + \gamma_3 \Delta \text{interest} + \gamma_4 \Delta \text{netFDI} + \gamma_5 \Delta \text{Exchange} + \gamma_6 \Delta \text{CDR} + \gamma_7 [Y_{t-1} \cdot (\beta_0 - \beta_1 IIP_{t-1} + \beta_2 \text{inflation}_{t-1} + \beta_3 \text{interest}_{t-1} + \beta_4 \text{netFDI}_{t-1} + \beta_5 \text{Exchange}_{t-1} + \beta_6 \text{CDR})] + \epsilon_{t-1} \]

\[ \text{------------------------ (1.39)} \]

The Cointegrating vector is \([ \beta_0 \beta_1 ]\). \(\beta_i\)'s measures the Long run relation between stock market development and macroeconomic determinants, \(\gamma_1\) to \(\gamma_6\) measures the short-run relation between \(\Delta X\)'s (macroeconomic variables) and \(\Delta TR\) (stock market development) and \(\gamma_7\) speed adjustment back to equilibrium.

In this chapter also, the variance decomposition and impulse response analysis are done.

1.5.3 Integration of Indian Stock Market with Global Stock Markets

In chapter six the integration of Indian stock market with global stock markets is evaluated. Granger causality and cointegration analysis are done in this context. Since stock markets are integrated, the vector autoregressive method and Vector Error Correction model are used for evaluation of cointegration of stock markets in the long run. In VAR framework, a better choice of cointegration test is Johansen and Juselius (JJ) test.

To test for Granger causality and cointegration, we use the standard methodology proposed by Granger (1969, 1986) and Engle and Granger as described in Enders (1995). All tests are performed on natural logarithm of the indices’ time series using OLS estimation procedure. In order to test for Granger causality among stock market indices \(Y_t^1, Y_t^f\) we estimate the equation

\[ \Delta y_t^f = \alpha_0 + \sum_{i=1}^{m} \alpha_{1i} \Delta y_{t-i}^f + \sum_{i=1}^{m} \alpha_{2i} \Delta y_{t-i}^f + \epsilon_{1t} \]

\[ \text{------------------------ (1.40)} \]
and perform an F test for joint insignificance of the coefficients. The null hypothesis claims that \( Y_t^f \) does not Granger cause \( Y_t^I \) or vice versa. Therefore, a rejection of the null hypothesis indicates a presence of Granger causality. For each pair of stock market indices, we perform two Granger causality tests so that we can decide whether \( Y_t^f \) Granger causes \( Y_t^I \) or \( Y_t^I \) Granger causes \( Y_t^f \) or both, or none.

In order to examine the co-movement between the Indian stock market and the developed markets, we strictly follow the standard methodology available in the literature. We first study the relationship between the Indian stock markets and foreign markets by the simple regression:

\[
y_t^I = \alpha + \beta y_t^f + \epsilon_t \tag{1.42}
\]

where the endogenous variable \( Y_t^I \) represents the India’s stock index; the exogenous variable \( Y_t^f \) is the stock index of the foreign markets; \( \epsilon_t \) is the error term.

The validity and reliability of the regression relationship require the examination of the trend characteristics of the variables and cointegration test as the presence of unit root processes in the stock indices results in the spurious regression problem. Before testing for cointegration, we need to go for stationary test. In order to do so, we apply the augmented Dickey-Fuller (ADF), Phillips and Perron (PP) and KPSS unit root tests.

There are two most widely used cointegration tests namely Engle-Granger (1987) two model approaches and the Johansen (1998) and Johansen and Juselius (JJ) (1990) maximum likelihood estimator. Gonzalo (1994) provide empirical evidence to support the Johansen’s method is superior over other methods (ordinary least squares, nonlinear least squares, principal components and canonical correlations) for testing the number of so integrating relationship. Therefore, we employ the maximum likelihood method of Johansen (1988 and Johansen (1988) and Johansen and Juselius (1990) to test the cointegration. The JJ test is based on vector autoregressive model:

\[
Y_t = \alpha + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \ldots + \pi_{k-1} Y_{t-(k-1)} + \epsilon_t \tag{1.43}
\]
Where $Y_t$ is an $n \times 1$ vector of non-stationary variables integrated of the same order, $\alpha$ is an $n \times 1$ vector of intercept terms, $i\pi$ is an $n \times n$ matrix of coefficients and $\epsilon_t$ is an $n \times 1$ of error terms. The equation (2) can be expressed by its first different ECM as:

$$\Delta Y_t = \alpha + \tau_1 \Delta Y_{t-1} + \tau_2 \Delta Y_{t-2} + \ldots + \tau_{k-1} \Delta Y_{t-(k-1)} + \pi Y_{t-1} + \epsilon_t \quad \text{---(1.44)}$$

The existence of a long-run relationship among Indian stock market and its trading partners is examined based on the rank of an $n \times n$ matrix of coefficients of lagged level variables ($\Pi$), in equation (2). If the rank ($\pi$) = 0, the variables are not cointegrated. On the other hand, if rank ($\pi$) = $r$, therefore the variables share cointegrating vectors. Johansen and Juselius (1990) develop two test statistics to determine the number of cointegrating vectors namely the trace statistic and the maximal eigenvalue statistic. Since, the cointegration tests are very sensitive to the choice of lag length, Hall (1989) and Johansen (1992), recommend VAR specification that renders the error term serially uncorrelated by including sufficient lags. Therefore, we use the VAR specification to select the number of lags required in the cointegration test.

1.5.3.1 Granger Causality Tests Based on VECM

Granger (1988) concludes that if there is a cointegration vector among time series, there must be causality among these time series at least one direction. In order to examine the short-run dynamic and long-run relation between Indian stock market and its trading partner’s stock markets, the vector error correction model (VECM) is employed. According to Granger representation theorem, for cointegrated series CI (1,1), error correction term must be included in the model. Engle and Granger (1987) and Toda and Phillips (1993) specify that failure to incorporate this error correction term in the model leads to model misspecification. Therefore, this model referred to the literature as a VECM:

$$\Delta Y_{it} = \alpha + \xi Z_{t-1} + \sum_{l=1}^{m} a_l \Delta Y_{l,t-1} + \sum_{l=1}^{m} b_l \Delta Y_{2,l,t-1} + \sum_{l=1}^{m} c_l \Delta Y_{3,l,t-1} + \sum_{l=1}^{m} d_l \Delta Y_{5,l,t-1} + \sum_{l=1}^{m} \epsilon_l \Delta Y_{6,l,t-1} + \epsilon_t \quad \text{---(1.45)}$$
where, $Y_t$ denotes stock price index series for India, and its trading partners, USA, UK, Germany, Japan, France, Australia and Japan and the $\xi Z_{t-1}$ contains r cointegrating terms, reflecting the long run equilibrium relationship among these five stock markets. The Granger-causality tests are examined by testing whether the coefficients of $\Delta Y_{1,t-1}$, $\Delta Y_{2,t-1}$, $\Delta Y_{3,t-1}$, $\Delta Y_{4,t-1}$, $\Delta Y_{5,t-1}$ etc are statistically different from zero based on a standard F-test. The significance of error correction term is tested based on a standard T-test. If the variables are cointegrated, an OLS regression yields “super-consistent” estimators of the cointegrating parameters (Enders, 1995). Stock (1987) also proves that the OLS estimates of parameters converge faster than in OLS models using stationary variables.

Variance decomposition and impulse response analysis are done in this context also.

1.5.4 Efficiency of Indian Stock Market

The efficiency of Indian stock market is evaluated in the seventh chapter. Mainly the weak form of efficiency is tested in the study. The weak form efficiency is tested for BSE in India. One of the conditions for weak form efficiency is that the stock returns must follow a random walk model. For the evaluation of the existence of random walk mode, the following tests are used.

1.5.4.1 The Autocorrelation Test

Testing for serial correlation is a straightforward test of random walk. Autocorrelation, the serial correlation coefficient, measures the relationship between the value of a variable at the current period and its value in the previous period.

Rather than testing the statistical significance of individual autocorrelation coefficients, the joint hypothesis that all of the autocorrelation coefficients up to certain lags are simultaneously equal to zero can be tested by using the Ljung-Box Q statistic. This test is designed to test for autocorrelation in small samples and it does not require normality of returns. It is distributed as a chi-square with degrees of freedom equal to
the number of autocorrelations \( k \) (Gujarati, 2003). The null hypothesis of the test of lag \( k \) is that all autocorrelation coefficients up to order \( k \) are equal to zero whereas the alternative hypothesis is that they deviate from zero. The Ljung-Box Q statistic test is calculated as:

\[
Q_{LB} = N(N + 2) \sum_{j=1}^{k} \frac{\rho_j^2}{N-j}
\]

Where \( \rho_j \) is the \( j \)th autocorrelation and \( N \) is the number of observations.

1.5.4.2 The Runs Test

The runs test was the most commonly used non-parametric test of the Random Walk Hypothesis (RWH). It does not require that return distributions are normally or identically distributed and, the condition that most stock return statistics cannot satisfy. At the same time, it eliminates the effect of extreme values often found in the return data. This provides a solid alternative to parametric serial correlation tests in which distributions are assumed to be normally distributed.

Runs test is designed to examine whether successive return changes are independent. A run can be defined as a sequence of consecutive return changes with the same sign. The non-parametric run test is applicable as a test of randomness for the sequence of returns. Accordingly, it tests whether returns in Indian stock market return is predictable.

To perform this test, let, \( n_a \) and \( n_b \) respectively represent observations above and below the sample mean (or median), and \( r \) represents the observed number of runs, with \( n=n_a+n_b \).

\[
Z_r = \frac{r - E(r)}{\sigma(r)}
\]

The expected number of runs can therefore be calculated by employing the following formula:

\[
E(r) = \frac{n+2n_an_b}{n}
\]
The standard error represented by:

$$\sigma E(r) = \left[\frac{2n_an_b(2n_an_b-n)}{n^2(n-1)}\right]^{1/2}$$  

1.5.4.3 The Unit Root Tests

Unit root tests are widely used in the literature to examine whether the variable of interest follows a random walk. If the time series of the variable has a unit root that means that the series is non stationary; and hence, it follows a random walk. In this study three different unit root tests are employed to test the null hypothesis of a unit root. These tests are the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.

1.5.4.4 The Variance Ratio Test

Campbell et al. (1997) report that unit root tests are not designed to test the predictability in stock price series. The Lo and Mackinlay variance ratio test is believed to be more powerful than the Dickey-Fuller unit root or the autocorrelation Q tests for testing the predictability in stock price series (Lo and Mackinlay, 1989). According to this test, the variance ratio statistics is based on the assumption that the variance of increments in the random walk series is linear in the sample interval. That is to say, if a
series follows a random walk, the variance of a $q^{th}$ differenced variable is $q$ times the variance of its first differenced variable.

\[ \text{Var}(R_t - R_{t-q}) = q \text{Var}(R_t - R_{t-q}) \]  

\[ \text{(1.50)} \]

The variance ratio is then calculated as:

\[ VR(q) = \frac{\var{R_t}{R_{t-q}}}{\var{R_t}{R_{t-q}}} = \frac{\text{Var}[R_t(q)]}{q \text{Var}[R_t]} = 1 \]  

\[ \text{(1.51)} \]

The null hypothesis of the test is that the variance ratio at lag $q$ is defined as the ratio of the variance of the $q$-period return to the variance of the one-period return divided by $q$, which should equal to one under the random walk hypothesis. If any of the estimated variance ratios differs significantly from one, then the random walk hypothesis is rejected. Lo and MacKinlay (1988) developed two test statistics to test the null hypothesis, one is with the assumption of homoscedasticity increments $Z(q)$ and the other is with the assumption of heteroscedasticity increments $Z^*(q)$.

For performing this test, we first calculate the compounded daily returns on the BSE series, find its variance and repeat the procedure for 2, 4, 8, 10, 16 and 32-day returns. We then calculate the variance ratios for all five times intervals, and test the following null hypothesis:

$H_0$: The VR at lag $q$ is defined as the ratio of the variance of the $q$-period return to the variance of the one-period return divided by $q$, which is unity under the random walk hypothesis.

An estimated variance ratio of less than one implies negative serial correlation, while a variance ratio of greater than one, or high $Z$ value implies positive serial correlation. The rejection of single or more therefore rejects the null hypothesis of the random walk.

1.5.4.5 The GARCH (1,1) Model

Conditional Heteroscedasticity (GARCH) one. Although various extensions to the GARCH model have been introduced to account for asymmetry effects, Brooks and Burke (2003) suggest that the basic GARCH (1,1) model is sufficient to capture all of the volatility clustering that is present from the data.

The basic of the GARCH (1,1) model is that forecasts of time varying variance depend on the lagged variance of the asset. And thus, an unexpected increase or decrease in the returns in the current period will lead to an increase in the expected variability in the next period. The basic model GARCH(1,1) can be expressed as:

\[ r_t = \mu + \phi \varepsilon_t^2 + \varepsilon_t \]  
\[ \varepsilon_t / \phi_{t-1} \sim N(0, h_t) \]  
\[ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \]

Where \( h_t \) is the variance, \( \omega \) is equal to \( \gamma V_L \) where \( V_L \) is the long run average variance rate, \( \varepsilon_{t-1}^2 \) is a shock from the prior period measured as the lag of the squared residual from the mean equation (the ARCH term), \( h_{t-1} \) is the conditional variance from last period; \( \omega, \alpha \) and \( \beta \) are parameters to be estimated where \( \omega > 0, \alpha \geq 0 \) and \( \beta \geq 0 \).

The GARCH (1,1) is considered as weakly stationary if the summation of \( \alpha \) and \( \beta \), which measures the persistence of volatility, is less than 1. If the summation of \( \alpha \) and \( \beta \) is very close to one, then this indicates that the market is inefficient as it shows high persistence in volatility clustering (Bahadur, 2010).

### 1.6 Design of the Study

In order to study the issues mentioned above, the remaining chapters of this study are organised as follows.

Chapter II examines the role assumed by financial market particularly the stock market in promoting economic growth process from the theoretical angles. It examines the role played by financial markets by various macroeconomic schools of thought on
theses such as financial repression and financial liberalization, endogenous growth models, stock market instability and the role of stock market integration.

Chapter III provides the growth and evolution of stock exchanges in the global context, the structure and characteristics of Indian Stock Markets and the trends in the development and operational procedures over the period of years.

Chapter IV examines the growth trajectory of India during the liberalized era, reviews the theoretical literature with regard to stock market and economic growth, the stock market development indicators are identified and an empirical attempt has been made to examine the link between stock market development and economic growth of India.

Chapter V identifies the macroeconomic determinants of stock market development in India and empirically analyses the causal linkages between stock market development variables and the macroeconomic variables.

Chapter VI investigates whether Indian Stock Markets are integrated with global developed stock markets during the post liberalization period from 1990-2012.

Chapter VII investigates whether Indian Stock markets are efficient during the period from 1990-2012.

Finally, Chapter VIII summarizes the results of the study and discusses some policy implications.

1.7 Scope and Limitations

The study offers an insight into the various aspects of Stock Market development which would be of interest to policy makers, administrators and regulators, who in turn, would adopt policies and regulations for promoting the development of an efficient
stock market. Stock market development is crucial for a developing economy and plays positive role in the growth of an economy.

In spite of the above mentioned scopes, this study is not without its limitations which might have affected the empirical results. The stock market indicators used in the empirical analysis may not be the appropriate measures for the stock market development. Due to non-availability of data on Gross Domestic Product on a monthly basis, the study was unable to use GDP as a measure of Economic growth. Instead, the study has used Index of Industrial Production (IIP) as a proxy for Economic Growth. Also, due to the same issue, Market Capitalisation Ratio and Value Traded Ratio could not be used as indicators of Stock Market Development. As we have shown before, stock markets can influence economic growth by performing different functions. They aggregate and mobilize capital, enhance liquidity, provide risk pooling and sharing, assess and select projects and management through producing information, and monitoring managers. It is quite difficult, however, to construct direct measures of these functions and also perfect measures certainly do not exist. Therefore, creating proxies may not accurately reflect how stock market functions are carried out. Also, due to non-availability of data of the macroeconomic indicators, during the period from 1991 to 1993, the empirical analysis for Chapter IV and Chapter V were conducted for the period from 1994 to 2012.

The limitations of the study points out for the need of future research in this area. A lot more research is needed on the effects of development of financial sector in developing countries. This study examines the empirical relationship between stock market development and economic growth at the macro level. At micro level, future research could assess the effect of stock market development on firms’ investment rates, technical changes and economic efficiency. This study should promote the implication of developing stock markets in developing countries. The conclusions derived from country’s experience may not be bound to apply to other countries but it opens up a new area of research.
REFERENCES


