The role of foreign capital in economic growth is much discussed nowadays but remarkably little analysed. The basic objective of this chapter is to investigate the causal long run relationship between FCIs and economic growth of India. The FCIs-growth linkage assumes that the foreign capital inflows provide a significant amount of contribution to the economic growth. To examine the same, first the researcher developed a model on the basis of source of financing available to an economy i.e. domestic capital and foreign capital. After that the researcher employed co-integration test and Error Correction Model (ECM) technique.

The recent wave of financial globalization and its aftermath has been marked by a surge in international capital flows among the industrial and developing countries, where the notions of tense capital flows have been associated with high growth rates (Edwin, 1950) in some developing countries. Some countries have experienced periodic collapse in growth rates and financial crisis over the same period. There is an ongoing debate on the pros and cons of Capital inflows i.e. is there any strong positive connection between foreign capital inflows (FCIs) and growth? Evidence on this very important question is far from ambiguous, with China lending support and Brazil negating it. Since 1994, Brazil has attracted enormous FDI from the developed countries, but neither the growth rate nor the export prospects have showed commensurate results. The study by Carkovic and Levin (2002) failed to find strong evidence of positive correlation between FDI inflows and output growth. The comments made earlier about the feasibility of economic development without dependence on foreign borrowing are relevant too. Historically, all of the three countries- Japan, South Korea and Taiwan very carefully regulated foreign investment inflow during their period of growth (Griffin, 2009). Theoretical and empirical research on the role of foreign capital in the growth process has generally yielded conflicting results (Waheed, 2004). Conventionally, the two-gap approach justifies the role of foreign capital for relaxing the two major constraints to growth (Chenery and Burno, 1962; Mckinnon, 1964). In the neoclassical framework, however, capital neither explains differences in the levels and rates of growth across countries nor can large capital flows make any significant difference to the growth rate that a country could achieve (Krugman, 1993). Fitz Gerald (1998) theoretically argues that higher capital inflows lower interest rates, which help increase investment and economic growth. In their attempt to measure the link between growth and capital inflows into India, Marwah and Klein (1998) starts by discussing the two alternative frameworks for analysing the impact of inflows: (a) a macroeconomic growth model in which the
effect of FDI is examined through its effects on the saving ratio and the capital output ratio and (b) a multifactor production function is estimated to capture the changes induced by FDI in the relevant parameters. Adopting framework (b) they assume constant returns to scale and four main inputs- labour, domestic capital, foreign capital and imports. The econometric analysis is based on annual observations for the period 1951-89 or appropriate sub periods. Results suggest that for every one percentage growth point, 0.351 is generated by growth of domestic and foreign capital nested together, 0.569 by labour and 0.08 by imports. The contribution of the two types of capital to the growth in productivity can be allocated in proportion to their respective weights in the total nest.

In this chapter an attempt has been made to establish the relationship between foreign capital and economic growth of the Indian economy. The purpose of foreign capital to under developed countries is to accelerate their economic development upto a point where a satisfactory growth rate can be achieved on a self-sustaining basis. Capital flows in the form of private investment; foreign investment, foreign aid and private bank lending are the principal ways by which resources can come from rich to poor countries. The transmission of technology, ideas and knowledge are other special types of resource transfers. Capital flows have begun to play a significant role in India’s growth dynamics.

**METHODOLOGY**

In this chapter the researcher’s aim is to examine the impact of foreign capital flows (FCIs), which include FDI and FPI on economic growth of India. India has been receiving significant amount of foreign capital since the beginning of 1990s. Thus the reference period for this study is 1992-2010. Different type of studies were undertaken in order to understand the impacts of foreign capital inflows (FCIs) on the economic growth (Aghion et al, 2006; Rodrik, 2006; Lane et al, 2002; Henry, 2006; Borensztein et al, 1998; Tressel and Thierry, 2007; Bekaert et al, 2005). Most of the studies have focused on the impact of foreign direct investment on economic growth (Figlio and Blonigen, 2000; Alfaro et al, 2004; Ramachandran, and Shah, 1997; Djankov and Hoekman, 1998; Aitken and Harrison, 1999 and Borensztein et al 1998). Few studies were focused on foreign aid (Boone, 1996; Knack, 2001; Dalgaard et al 2001 and Easterly et al 2004). And, some of the studies focused on the impact of FCI on the domestic savings, investments and capital formation. While some other researchers paid much attention to study the impact of FCI on the debt burden, GDP growth rate etc (Razin et al, 1998; Mohan, 2008; Joshi, 2007; Marc and Gail, 2005). Some other studies focused upon the impact of FCI on the different sectors of the economy like the agricultural sector, energy and the industrial sectors, social sectors (like health and education etc.).

It is difficult to analyze the effect of foreign capital inflows on all the sectors and variables in a single study and as described earlier that the major objectives of this chapter is to analyze the impact of foreign capital inflows (FCIs) on growth rate of
India. Therefore, the researcher narrows down the analysis only to the impact of FCIs on GDP growth. But, GDP growth of an economy depends upon the various other factors like saving, investment and capital formation. The general objective of this study is to examine the relationship between FCIs and economic growth in India using recent advancement in the time-series techniques. The specific objectives are to identify factors affecting economic growth in Indian economy and to test co-integration relationship between a few variables affecting GDP growth in India. Total 18 observations over the period of the study 1992-2010 have been used for analysing the relationship. The data for the study have been taken from the handbook of statistics on Indian Economy published by RBI (Reserve Bank of India).

**MATHEMATICAL MODELLING**

The FCIs-growth linkage assumes that the foreign capital inflows provide a significant amount of contribution to economic growth. There are number of factors which contribute to GDP growth of any country including consumptions, investment, domestic and foreign capital etc. Among all these factors some factors plays a very vital role. Therefore, the researcher observes the relationship between the GDP and some factors, which contribute to the GDP. Assumes a Production function in the form of

\[(1) \quad Y = (L, K)\]

Where, \(Y\) represents real aggregate output, \(K\) is the capital and \(L\) is the land. In this production function the researcher assumes that the land is the fixed factor because the researcher apply the above production function on an economy *i.e.* India. And \(K\) (Capital) is divided into two parts that is Domestic capital and International capital. Output is measured in terms of GDP growth. As the domestic capital data was not available the researcher used the Gross domestic capital Formation (GDCF) as a proxy variable to the Domestic Capital. Therefore, the production function becomes

\[(2) \quad GDP_{FC} = f(FCIs, GDCF)\]

By total differentiation of the equation (2) with respect to time and division of both the sides of resulting time derivative by GDP, we can specify the linear growth model of the form:

\[(3) \quad \frac{dY}{dt} = \alpha_1 + \alpha_2 FCIs + \alpha_3 GDCF\]

Where a variable with a dot over it indicates its first derivative, i.e. \(dY/dt\); and \(\alpha_1\)’s are the respective elasticities. For the application of multivariate co-integration techniques, the equation (3) can be represented in the following linear logarithmic regression form,

\[(4) \quad LGDP_t = \alpha_1 + \alpha_2 LFCIs_t + \alpha_3 LGDCF_t + \varepsilon_t\]

Where, \(L\) represents the natural logarithms of the variables and \(\varepsilon\) the stochastic error term. As the first difference reflects the rate of change of each variable, equation (4) can be used to examine both the short and long run relationship between the economic indicators. The investigation of long run relationship between LGDP, LFCIs, LGDCF
in a co-integration framework begins with an examination of properties of the data. If the variables are integrated of order one, the determination of the co-integration rank using Johansen and Juselies (1990) maximum likelihood co-integration procedure follows. Once a long-run equilibrium relationship is established, Granger causality is then tested using the error correction set up of Engle and Granger (1987).

INTEGRATION PROPERTIES OF THE DATA
The basic objective of this chapter is to investigate the long run relationship between FCIs and economic growth of India. To examine the same, the researcher employed co-integration test and Error Correction Model (ECM) technique. However the prime requirement of this technique is to test the order of integration and that has been done through unit root test only. Therefore the researcher first highlights the concept of unit root test and then the co-integration test and ECM technique.

UNIT ROOT TEST:
The researcher can test the stationarity of variable by using Augmented Dicky-Fuller (ADF) test and Phillips-Perron (PP) test. ADF is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejections of the hypothesis that there is a unit root at some level of confidence.

The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model

\[
\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t;
\]

Where \( \alpha \) is a constant, \( \beta \) the coefficient on a time trend and \( p \) the lag order of the autoregressive process. Imposing the constraints \( \alpha = 0 \) and \( \beta = 0 \) corresponds to modelling a random walk and using the constraint \( \beta = 0 \) corresponds to modelling a random walk with a drift.

By including lags of the order \( p \) (greek for 'rho') the ADF formulation allows for higher-order autoregressive processes. This means that the lag length \( p \) has to be determined when applying the test. One possible approach is to test down from high orders and examine the t-values on coefficients. An alternative approach is to examine information criteria such as the Akaike information criterion (AIC), Bayesian information criterion (BIC) or the Hannan-Quinn information criterion (HQIC). We use this alternative approach of determining the lag length based on AIC.

The unit root test is then carried out under the null hypothesis \( \gamma = 0 \) against the alternative hypothesis of \( \gamma < 0 \). Once a value for the test statistic is computed it can be compared to the relevant critical value for the Dickey–Fuller Test.

\[
DF_{T} = \frac{\gamma}{SE(\hat{\gamma})}
\]
If the test statistic is less (this test is non-symmetrical so we do not consider an absolute value) than (a larger negative) the critical value, then the null hypothesis of $\gamma = 0$ is rejected and no unit root is present.

One advantage of ADF is that it corrects for higher order serial correlation by adding lagged difference term on the right hand side. One of the important assumptions of DF test is that error terms are uncorrelated, homoscedastic as well as identically and independently distributed (iid). Phillips-Perron (1998) has modified the DF test, which can be applied to situations where the above assumptions may not be valid. Another advantage of PP test is that it can also be applied in frequency domain approach, to time series analysis. The derivations of the PP test statistic is quite involved and hence not given here. The PP test has been shown to follow the same critical values as that of DF test, but has greater power to reject the null hypothesis of unit root test.

**CO-INTEGRATION AND ERROR CORRECTION MODEL**

The central concept of co-integration test is the specification of models, which includes the long run movements of one variable relative to others. In other words, it clarifies the existence of long run equilibrium relationship between the two variables. If the time series variables are non-stationary in their levels, they can be integrated with integration of order one, when their first differences are stationary. These variables can be co-integrated as well, if there are one or more linear combinations among the variables that are stationary. If these variables are being co-integrated, then there is a constant long-run relationship among them.

The co-integration test was first introduced by Engel and Granger (1987) and then developed and modified by Stock and Watson (1998), Johansen (1988) and Johansen and Juselius (1990). The test is very useful in examining the long run equilibrium relationships between the variables.

Consider an unrestricted Vector Auto regression (VAR) model represented by,

\[
Y_t = \mu + \sum_{k=1}^{p} \Pi_k Y_{t-k} + \varepsilon_t
\]

Where, $\varepsilon_t$ is p dimensional Gaussian error with mean zero and variance matrix $\lambda$, $Y_t$ is an $(n \times 1)$ vector of I(1) variables, and $\mu$ is an $(n \times 1)$ vector of constants. As $Y_t$ is assumed to be non-stationary, and $\Delta Y_t = Y_t - Y_{t-1}$, equation (7) could be rewritten in the first difference notation reformulated in error correction form,

\[
\Delta Y_t = \mu + \sum_{k=1}^{p} \Pi_k \Delta Y_{t-k} + \Pi \Delta Y_{t-1} + \varepsilon_t
\]

Where $\prod_k = I - (\prod_1 - \cdots - \prod_k)$; and $\prod = I - (\prod_1 - \cdots - \prod_p)$. since $\varepsilon_t$ is stationary, the rank $r$ of the long-run matrix determines how many linear combinations of $Y_t$ are stationary. If the co-integrating rank $r$-0 so that $\prod=0$, the equation (8) is similar to a traditional first differenced VAR model. With $0 > r > n$, there is $r$ co-integrating vectors or $r$ stationary linear combinations of $Y_t$ where $\prod = a\beta'$, where both $a$ and $\beta$ are $(n \times r)$ matrices. The co-integrating vector $\beta$ has the property that $\beta' Y_t$ is stationary
although $Y_t$ is non-stationary. The co-integrating rank $r$ can be tested with statistics such as maximum eigenvalue ($\lambda_{\text{max}}$) test and trace test. The asymptotic critical values are in Johansen and Juselius (1990) and Osterwald-Lenum (1992). The results of VAR models are sensitive to lag length choice (Boswijk and Frances, 1992). They suggest the use of Johansen’s approach to determine the different lag lengths and to base the final and the significance of parameters of higher lags. A VAR model incorporating two lags of each variable is selected from the test applied.

**Granger Causality Tests from Error Correction Model**

In order to test whether long run growth relationship established in the model and the relationship will hold given the short-run disturbances, a dynamic error correction model was used based on the co-integration relationship. For this purpose the lagged residual error derived from the co-integration vector was incorporated into the general error model. This leads to specification of an error correction model. The presence of one co-integrating relationship permits the use of Engle and Granger (1987) error correction model in equation (8) for the two variables is written in equation (9),

$$
\Delta \text{LGDP}_t = \beta_1 + \sum_{k=1}^{m} \beta_{1k} \Delta \text{LGDP}_{t-k} + \gamma_{1k} \Delta \text{LFCCI}_{t-k} + \alpha_{1k} \Delta \text{LGDCF}_{t-k} + \lambda_{1k} \text{EC}_{t-1} + \varepsilon_1
$$

$$
\Delta \text{LFCCI}_t = \beta_2 + \sum_{k=1}^{m} \beta_{2k} \Delta \text{LGDP}_{t-k} + \gamma_{2k} \Delta \text{LFCCI}_{t-k} + \alpha_{2k} \Delta \text{LGDCF}_{t-k} + \lambda_{2k} \text{EC}_{t-1} + \varepsilon_2
$$

$$
\Delta \text{LGDCF}_t = \beta_3 + \sum_{k=1}^{m} \beta_{3k} \Delta \text{LGDP}_{t-k} + \gamma_{3k} \Delta \text{LFCCI}_{t-k} + \alpha_{3k} \Delta \text{LGDCF}_{t-k} + \lambda_{3k} \text{EC}_{t-1} + \varepsilon_3
$$

In the equation (9), $m$ is the lag length and $\text{EC}_{t-1}$ is the error correction term. The coefficient of the EC contains information about whether the past values of variables affect the current value of the variables under study. The size and the statistical significance of the coefficient of the error correction model measure the tendencies of each variable to return to equilibrium. For example if $\lambda_1$ in equation (9) is statistically significant it means that LGDP responds to disequilibria in its relations with exogenous variables. According to Choudry (1995), even if the coefficients of the lagged changes of the independent variables are not statistically significant, Granger causality can still exist as long as $\lambda$ is significantly different from zero. The short-run dynamics are captured through individual coefficients of the first difference terms.

**Estimation and Results**

Before applying the co-integration test and Error Correction Model, the researcher first establishes the maximum integration order ($d_{\text{max}}$) of the variables by carrying out an Augmented-Dickey Fuller (ADF) test and Dickey-Fuller (DF) test on the FCIs, GDP and GDCF series at their log levels and their log differentiated forms. The results of various unit root test are shown in Table 3.1.
Table 3.1: Result of Dickey-Fuller test and Augmented-Dickey Fuller test at log levels and log Differentiated forms of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>At Level</th>
<th>Without Trend</th>
<th>With Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>DF</td>
<td>ADF</td>
</tr>
<tr>
<td>LGDP</td>
<td></td>
<td>1.414359</td>
<td>2.539034</td>
</tr>
<tr>
<td>LFCI</td>
<td></td>
<td>-0.486895</td>
<td>-2.135845</td>
</tr>
<tr>
<td>LGDCF</td>
<td></td>
<td>-0.054677</td>
<td>1.200005</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>At First difference</th>
<th>Without Trend</th>
<th>With Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>DF</td>
<td>ADF</td>
</tr>
<tr>
<td>DLGDP</td>
<td></td>
<td>-1.300438</td>
<td>-0.781012</td>
</tr>
<tr>
<td>DLFCI</td>
<td></td>
<td>-2.594024**</td>
<td>-4.069724*</td>
</tr>
<tr>
<td>DLGDCF</td>
<td></td>
<td>-3.815589*</td>
<td>-3.708341**</td>
</tr>
</tbody>
</table>

*McKinnon Critical values at 1% level of significance
**McKinnon Critical values at 5% level of significance

Notations: LGDP = Natural log of GDP
LFCI = Natural log of FCI
LGDCF = Natural log of GDCF
DLGDP = First Difference of LGDP
DLFCI = First Difference of LFCI
DLGDCF = First Difference of LGDCF

The results presented in table 3.1 show that the values of DF and ADF unit root test at level and at their first difference of the different variables at their natural logarithms forms. It was found that all the variables i.e. GDP, FCI and GDCF are non-stationary at their level without trend values whereas FCI was found to be stationary when the trend is allowed in the series. But all the variables are found to be stationary at their first difference and GDP becomes stationary when the trend is allowed in the series. This represent that all the series are integrated of order one \([i.e. I (1)]\) and trend is allowed in the co-integrating series. Hence, it confirms the possibility of long run relationship between the variables.

To explore the long run (co-integrating) relationship among the variables the researcher applies the Johansen and Juselius approach of co-integration. Both the dependent and independent variables in the co-integrating regression model are in the natural logarithmic form which means that this kind of regression models are in the natural logarithmic form which means that this kind of regression is of double-log or log-linear form. The results of co-integration test are particularly eigenvalue; and trace statistics and presented in table 3.2:

\[\text{\ldots}\]
Table 3.2: Results of Co-integration Test (Using Johansen and Juselius Approach) Panel 3.2(a)

<table>
<thead>
<tr>
<th>Hypothesized No. of CE(s)</th>
<th>Eigen Value</th>
<th>Trace Statistics</th>
<th>5% critical value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>None*(r=0)</td>
<td>0.846781</td>
<td>53.10363</td>
<td>42.91525</td>
<td>0.0036</td>
</tr>
<tr>
<td>At most 1(r=1)</td>
<td>0.651445</td>
<td>21.21357</td>
<td>25.87211</td>
<td>0.1706</td>
</tr>
<tr>
<td>At most 2(r=2)</td>
<td>0.176259</td>
<td>3.296289</td>
<td>12.51789</td>
<td>0.8396</td>
</tr>
</tbody>
</table>

Note: *denotes rejection of the hypothesis at 5% level of significance. Trace Test denotes one co-integrating equation at 5% level of significance.

Panel 3.2(b)

<table>
<thead>
<tr>
<th>Hypothesized No. of CE(s)</th>
<th>Eigen Value</th>
<th>Max-Eigen Statistic</th>
<th>5% critical value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>None*(r=0)</td>
<td>0.846781</td>
<td>31.89006</td>
<td>25.82321</td>
<td>0.0070</td>
</tr>
<tr>
<td>At most 1(r=1)</td>
<td>0.651445</td>
<td>17.91729</td>
<td>19.38704</td>
<td>0.0807</td>
</tr>
<tr>
<td>At most 2(r=2)</td>
<td>0.176259</td>
<td>3.296282</td>
<td>12.51798</td>
<td>0.8396</td>
</tr>
</tbody>
</table>

Note: *denotes rejection of the hypothesis at 5% level of significance. Max-Eigen Test denotes one co-integrating equation at 5% level of significance. r denotes the number of co-integrating equations.

The above tables indicate the results of co-integration test in the two panel i.e. panel 3.2(a) shows the results of Trace statistics and panel 3.2(b) shows the results of Max-Eigen statistics. Both the testing strategies begins with r=0. Using both the Trace and Max-Eigen test statistics, one can reject r=0 against the alternative r=1 and r=2 but fails to reject the hypothesis of existence of more than one stationary linear combination. In other words, these tests indicate the presence of long-run equilibrium relationship among variables. As a result, an error correction model is constructed to determine the direction of causality. The results of Error Correction Model are shown in Table 3.3:

Table 3.3: Results of Error Correction Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.327452</td>
<td>0.14015</td>
<td>2.33650</td>
</tr>
<tr>
<td>CE₁</td>
<td>-0.973395</td>
<td>0.44247</td>
<td>-2.19993</td>
</tr>
<tr>
<td>ΔLGDP(-1)</td>
<td>-1.700330</td>
<td>1.06993</td>
<td>-1.58920</td>
</tr>
<tr>
<td>ΔLGDP(-2)</td>
<td>-1.692765</td>
<td>1.18634</td>
<td>-1.42687</td>
</tr>
<tr>
<td>ΔLFCI(-1)</td>
<td>-0.036000</td>
<td>0.01746</td>
<td>-2.06135</td>
</tr>
<tr>
<td>ΔLFCI(-2)</td>
<td>-0.009980</td>
<td>0.01999</td>
<td>-0.49926</td>
</tr>
<tr>
<td>ΔLGDCF(-1)</td>
<td>0.112025</td>
<td>0.22965</td>
<td>-0.48780</td>
</tr>
<tr>
<td>ΔLGDCF(-2)</td>
<td>0.022039</td>
<td>0.19422</td>
<td>0.11347</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.732260</td>
<td>S.E. of equation</td>
<td>0.041306</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.697988</td>
<td>F-Statistics</td>
<td>3.125682</td>
</tr>
</tbody>
</table>

The results present in table 3.3 indicate the statistics of error correction model. The results of error correction model conforms that a long-run causal flow runs from changes in FCIs, Capital formation and GDP. This is revealed by the estimated
coefficient (λ) of the error correction term (CEt) which is negative, as expected and statistically significant in terms of its associated t-value.

The changes in lagged capital formation have positive and significant effects on real GDP growth. However, FCI exerts significant negative, but diminishing effect on the economic growth rates. This is revealed from the negative sum of the coefficients of subsequent lagged FCI values. The reason behind the negative relationship between FCI and economic growth rate is probably due to high amount of Foreign Institutional Investments (FII) in foreign capital inflows and FII is highly volatile in case of India. The numeric of adjusted $R^2$ at 0.6979 shows a high explanatory power of the model. The F statistics at 3.1256 suggest that a moderate interactive feedback effect exists within the system. The significance of F statistics further indicates Granger causality among variables. To find out the direction of causality the results of granger causality test is shown in table 3.4. The optimum number of lags is determined by the AIC criterion.

### Table 3.4: Results of Granger causality tests

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>F-statistics</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCI does not Granger Cause GDP</td>
<td>72.4491*</td>
<td>0.0000</td>
</tr>
<tr>
<td>GDP does not Granger Cause FCI</td>
<td>3.32409**</td>
<td>0.0705</td>
</tr>
<tr>
<td>GDCF does not Granger Cause GDP</td>
<td>23.4609*</td>
<td>0.0001</td>
</tr>
<tr>
<td>GDP does not Granger Cause GDCF</td>
<td>1.57726</td>
<td>0.2618</td>
</tr>
<tr>
<td>GDCF does not Granger Cause FCI</td>
<td>3.48973**</td>
<td>0.0632</td>
</tr>
<tr>
<td>FCI does not Granger Cause GDCF</td>
<td>3.85156**</td>
<td>0.0503</td>
</tr>
<tr>
<td>No. of length specified by AIC criterion</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Conclusion: FCI<=>GDP, GDCF=>GDP, GDCF<=>FCI

Note: <==> Bidirectional causality, => unidirectional causality
*significant at 1% level
**significant at 10% level.
Source: self computed

In table 3.4, F-statistics indicates that the null hypothesis, GDP does not granger cause GDCF, cannot be rejected and all other null hypothesis can be rejected at 1% and 10% level of significance. The result shows that there is bidirectional causality between FCI and GDP; it means that the any change in FCI causes GDP and vice-versa. Similarly, there is bidirectional causality between GDCF and FCI. But there is a unidirectional causality between GDCF and GDP, it means GDCF causes GDP but GDP does not causes GDCF. In other words, there is statistical evidence that any forecast about the GDP growth of India depends on the movement of FCIs and GDCF but any forecast about the GDCF does not depends on the GDP growth.

**CONCLUSION**

This chapter empirically examines the linkage between FCIs, Gross domestic capital formation and GDP growth in the context of India by using time series data for a period of 1992-2010. First of all, stationarity is checked and found that all the series
are non-stationary at their level but becomes stationary at their first difference. The Johansen co-integration results established the long run relationship between the variables. The results show that GDCF contributes positively to the GDP but FCI after liberalization contributes negatively to the GDP because of the increase in highly risky and volatile portfolio investment. The significance of CE4 and F-statistics indicates causal and long term relation among the variables and supports the result of Johansen co-integration results. The granger causality test found the causality between GDP growth, FCIs and GDCF. There is a bidirectional causality between FCI and GDP; GDCF and FCI but there is a unidirectional causality between the GDCF and GDP.

REFERENCES


CHAPTER 3 (B)

FIIs AND INDIAN STOCK MARKET: A CAUSALITY INVESTIGATION

While the volatility associated with portfolio capital flows is well known, there is also a concern that foreign institutional investors might introduce distortions in the host country markets due to the pressure on them to secure capital gains. In this context, present chapter attempts to find out the direction of causality between foreign institutional investors (FIIs) and performance of Indian stock market. To facilitate a better understanding of the causal linkage between FII flows and contemporaneous stock market returns (BSE National Index), a period of nineteen consecutive financial years ranging from January 1992 to December 2010 is selected. Granger Causality Test has been applied to test the direction of causality.

INTRODUCTION

FII flows were almost non-existent until 1980s. Global capital flows were primarily characterized by syndicated bank loans in 1970s followed by FDI flows in 1980s. But a strong trend towards globalization leading to widespread liberalization and implementation of financial market reforms in many countries of the world had actually set the pace for FIIs flows during 1990s. One of the important features of globalization in the financial service industry is the increased access provided to non local investors in several major stock markets of the world. Increasingly, stock markets from emerging markets permit institutional investors to trade in their domestic markets. The post 1990s period witnessed sharp argument in flows of private foreign capital and official development finance lost its predominance in net capital flows. Most of the developing countries opened their capital markets to foreign investors either because of their inflationary pressures, widening current account deficits, and exchange depreciation; increase in foreign debt or as a result of economic policy. Positive fundamentals combined with fast growing markets have made India an attractive destination for foreign institutional investors. Portfolio investments brought in by FIIs have been the most dynamic source of capital to emerging markets in 1990s (Bekaert and Harvey, 2000). India opened up its economy and allowed Foreign Institutional Investment in September 1992 in its domestic stock markets. This event represent landmark event since it resulted in effectively globalizing its financial services industry. Initially, pension funds, mutual funds, investment trusts, Asset Management companies, nominee companies and incorporated/institutional portfolio managers were permitted to invest directly in the Indian stock markets. Beginning 1996-97, the group was expanded to include registered university funds, endowment, foundations, charitable trusts and charitable. Till December 1998,
investments were related to equity only as the Indian gilts market was opened up for FII investment in April 1998. Investments in debt were made from January 1999. Foreign Institutional Investors continued to invest large funds in the Indian securities market. For two consecutive years in 2004-05 and 2005-06, net investment in equity showed year-on-year increase of 10%. Since then, FII flows, which are basically a part of foreign portfolio investment, have been steadily growing in importance in India.

Figure 3 (B).1: Net FII Inflows in India between 1992-2010 (Rs. In Crore)

Source: Handbook of Statistics on the Indian Securities Market, SEBI

Figure 3(B).1 shows the movement of Net FII flows in India. The above figure shows the FII flows are negative in 1998-99 because of East Asian crisis and after that FII flows started to increase and increased up to 2007-08 and again in 2008-09, there is sudden decline in FII flows due to global financial crisis. Foreign institutional investors pulled out close to Rs 50,000 crore (Rs 500 billion) at the domestic stock market in 2008-09, almost equalling the inflow in the 2007-08, FIIs’ net outflows have been Rs 47,706.2 crore (Rs 477.06 billion) till March 30 in the financial year 2008-09 as against huge inflows of Rs 53,000 crore (Rs 530 billion) in the previous fiscal, according to information on the SEBI. FII flows into India remained strong since April 2009. According to data released by the SEBI, net FII inflows (debt and equity combined) in 2009-10 stood at US$30.25 billion (over Rs. 1.43 trillion)-the highest at any point in time during the last three financial years, driven by both the equity and debt segment. During the quarter ended March 2010, the FII (debt and equity combined) flows into India stood at US$ 9.26 billion driven by strong debt flows as against US$ 6.63 billion for the quarter ended December 2009 and US$7.93 billion for the quarter ended September 2009. In the previous quarters, the FII inflows were predominantly in the equity segment while in the last three months there have been significant investments in the debt segment as well. Anecdotal evidence suggests that the debt investments made by FIIs have largely been in better rated short term debt papers driven by attractive yields.
FIIS AND STOCK MARKET BEHAVIOUR

FII investment as a proportion of a developing country's GDP increases substantially with liberalization as such integration of domestic financial markets with the global markets permits free flow of capital from 'capital-rich' to 'capital-scarce' countries in pursuit of higher rate of return and increased productivity and efficiency of capital at global level. Clark and Berko (1997) emphasize the beneficial effects of allowing foreigners to trade in stock markets and outline the “base-broadening” hypothesis. The perceived advantages of base-broadening arise from an increase in the investor base and the consequent reduction in risk premium due to risk sharing. Other researchers and policy makers are more concerned about the attendant risks associated with the trading activities of foreign investors. They are particularly concerned about the herding behaviour of foreign institutions and potential destabilization of emerging stock markets.

In 1990s, several research studies have explored the cause and effect relationship between FII flows and domestic stock market returns but the results have been mixed in nature, Tesar and Werner (1994, 1995), Bhon and Tesar (1996), and Brennan and Cao (1997) have examined the estimates of aggregate international portfolio flows on a quarterly basis and found evidence of positive, contemporaneous correlation between FII inflows and stock market returns. Jo (2002) has shown empirically tested instances where FII flows induce greater volatility in markets compared to domestic investors while Bae et al. (2002) has proved that stocks traded by foreign investors experience higher volatility than those in which such investors do not have much interest.

There have been attempt to explain the impact of FIIs on Indian stock market. Most of the studies generally point the positive relationship between FII investment and movement of the National Stock Exchange share private index, some also agree on bidirectional causality stating that foreign investors have the ability of playing like market makers given their volume of investment (Babu and Prabheesh in 2008; Agarwal, 1997; Chakrabarti, 2001; and Trivedi and Nair, 2003, 2006). Whereas, Takeshi (2008) reported unidirectional causality from stock returns to FII flows irrelevant of the sample period in India whereas the reverse causality works only post 2003. However, impulse function shows that the FII investments in India are more stock returns driven. Perhaps the high rates of growth in recent times coupled with an increasing trend in corporate profitability have imparted buoyancy to stock markets, triggering off return chasing behaviour by the FIIs. Kumar (2001) inferred that FII flows do not respond to short-term changes or technical position of the market and they are more driven by fundamentals. The study finds that there is causality from FII to Sensex. This is in contradiction to Rai and Bhanumurthy (2003) results using similar data but for a larger period. A study by Panda (2005) also shows FII investments do not affect BSE Sensex. No clear causality is found between FII and
NSE Nifty. Mazumdar (2004) studied the impact of FII flow in Indian stock market focusing on liquidity and volatility aspects. Her study reveals that FII has enhanced liquidity in the Indian stock market while there is no evidence of increased volatility of equity returns. Sundaram (2009) found FII data to be I (0) i.e. it does not have a unit root at conventional level. It also gives positive unidirectional granger causality results i.e. stock returns Granger cause FII. No reverse causality is seen even after inserting a structural break in 2003, as some of the researchers suggest.

**METHODOLOGY AND DATA SOURCE**

There have been quite a few episodes of volatility in the Indian stock market over past decade induced by several adverse exogenous developments like East Asian Crisis in mid-1997, imposition of economic sanctions subsequent to Pokhran Nuclear explosion in May 1998, Kargil War in June 1999, stock Market Scam of early 2001 and the Black Monday of May 17, 2004 when the market was halted for the first time in the wake of a sharp fall in the index. In the first quarter of 2008-09, market was again halted in the wake of sharp fall in the index. A sharp decline in FII flows coincided with the above events and this has prompted the Indian policy makers to announce a number of changes in FII regulations like enhancing the aggregate FII investment limit (in February 2001), permitting foreign investors to trade in exchange traded derivatives (in December 2003) etc. in order to regenerate the foreign investors’ interests in the Indian capital market. So, to facilitate a better understanding of the causal linkage between FII flows and stock market movements, a period of nineteen consecutive financial years ranging from January, 1992 to December, 2010 is selected for the empirical study.

The present chapter is based on secondary market data of monthly net FII flows (i.e., gross purchase-gross sales by foreign investors) into the Indian equity market and monthly averages of BSE National Index is a market capitalization weighted index of equity shares of 100 companies from the ‘Specified’ and ‘Non-specified’ list of the five stock exchanges – Mumbai, Calcutta, Delhi, Ahmadabad and Madras – and its monthly values are averages of daily closing indices. Since the market for equity shares is subject to much larger fluctuations than the bond market, the emphasis is on equity market in the present study. Both the secondary data for the relevant sample period are obtained from RBI website. The following variables are used in the model. 

\[ B_t = \ln (B) \]

Where, B is the monthly averages of BSE national index.

It is important to note that, as mentioned earlier, BSE National Index is representative market capitalization weighted index of five major stock exchanges of the country and
hence use of BSE National Index monthly returns as the measure of Indian stock market returns in the case analysis appears justified.)

**Analytical Tools**

Empirical work based on the time series data assumes that the underlying time series is stationary. According to Engle and Granger (1987) “a time series is said to be stationary if displacement over time does not alter the characteristics of a series in a sense that probability distribution remains constant over time”. In other words, the mean and variance of the series are constant over time and the value of covariance between two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed.

Before going to use the Granger causality test one should test the normality and stationary properties of the variable in case of time series data. As our data is time series in nature, first one has to test normality by using Jarque Bera test and then stationarity of variables using different unit root tests.

**Normality Test**

The Jarque-Bera (JB) and Anderson Darling (AD) tests are used to tests whether the closing values of stock market and FII follow the normality distribution. The JB test of normality is an asymptotic or large sample test. It is also based on the OLS residuals. This test first computes the skewness and Kurtosis measures of the OLS residuals and uses the following test statistic:

\[ JB = n \left( \frac{S^2}{6} + \frac{(K - 3)^2}{24} \right) \]

Where \( n \) = sample size, \( S \) = skewness coefficient, and \( K \) = kurtosis coefficient. For a normally distributed variable, \( S=0 \) and \( K=3 \). Therefore, the JB test of normality is the test of Joint hypothesis that \( S \) and \( K \) are 0 and 3 respectively. Under null hypothesis that the residuals are normally distributed, Jarque and Bera showed that asymptotically (i.e., in large samples) the JB statistic follows the chi-square distribution with 2 df. If the \( p \) value of the computed chi-square statistic in an application is sufficiently low, one can reject the hypothesis that the residuals are normally distributed. But if \( p \) value is reasonably high, one does not reject the normality assumption. The Anderson-Darling normality test, known as the \( A^2 \) is used to further verify the findings of JB test.

**Unit Root Test (Stationarity Test)**

Unit root test is used to test whether the averages of BSE and FII flows are stationary or not. The researcher can test the stationarity of variable by using Augmented Dicky-Fuller (ADF) test and Phillips-Perron (PP) test. ADF is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The
more negative it is, the stronger the rejections of the hypothesis that there is a unit root at some level of confidence.

The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_p \Delta y_{t-p+1} + \varepsilon_t,$$

where $\alpha$ is a constant, $\beta$ the coefficient on a time trend and $p$ the lag order of the autoregressive process. Imposing the constraints $\alpha = 0$ and $\beta = 0$ corresponds to modelling a random walk and using the constraint $\beta = 0$ corresponds to modelling a random walk with a drift.

By including lags of the order $p$ (Greek for 'rho') the ADF formulation allows for higher-order autoregressive processes. This means that the lag length $p$ has to be determined when applying the test. One possible approach is to test down from high orders and examine the $t$-values on coefficients. An alternative approach is to examine information criteria such as the Akaike information criterion (AIC), Bayesian information criterion (BIC) or the Hannan-Quinn information criterion (HQIC). We use this alternative approach of determining the lag length based on AIC.

The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. Once a value for the test statistic is computed it can be compared to the relevant critical value for the Dickey–Fuller Test.

$$DF_{\gamma} = \frac{\gamma}{SE(\gamma)}$$

If the test statistic is less (this test is non-symmetrical so we do not consider an absolute value) than (a larger negative) the critical value, then the null hypothesis of $\gamma = 0$ is rejected and no unit root is present.

One advantages of ADF is that it corrects for higher order serial correlation by adding lagged difference term on the right hand side. One of the important assumptions of DF test is that error terms are uncorrelated, homoscedastic as well as identically and independently distributed (iid). Phillips-Perron (1998) has modified the DF test, which can be applied to situations where the above assumptions may not be valid. Another advantage of PP test is that it can also be applied in frequency domain approach, to time series analysis. The derivations of the PP test statistic is quite involved and hence not given here. The PP test has been shown to follow the same critical values as that of DF test, but has greater power to reject the null hypothesis of unit root test.

**Granger Causality Test**

Granger causality test was developed in 1969 and popularized by Sims 1972. According to this concept, a time series $X_t$ granger causes another time series $Y_t$ if series $Y_t$ can be predicted with better accuracy by using past values of $X_t$ rather than by not doing so, other information is being identical. If it can be shown, usually through a series of F-tests and considering AIC of lagged values of $X_t$ and with
lagged values of $Y_t$ also known), that those $X_t$ values provide statistically significant information about future values of $Y_t$ times series then $X_t$ is said to Granger cause $Y_t$ i.e. $X_t$ can be used to forecast $Y_t$. The pre condition for applying Granger Causality test is to ascertain the stationarity of the variables in the pair. Engle and Granger (1987) show that if two non-stationary variables are co-integrated, a vector auto-regression in the first difference is unspecified. If the variables are not co-integrated; therefore, Bivariate Granger causality test is applied at the first difference of the variables. The second requirement for the Granger Causality test is to find out the appropriate lag length for each pair of variables. For this purpose, the researcher used the vector auto regression (VAR) lag order selection method available in Eviews. This technique uses six criteria namely log likelihood value (Log L), sequential modified likelihood ratio (LR) test statistic, final prediction error(F&E), Akaike information criterion (AIC), Schwarz information criterion(SC) and Kannan-Quin information criterion (HQ) for choosing the optimal lag length. Among these six criteria, all except the LR statistics are monotonically minimizing functions of lag length and the choice of optimum lag length is at the minimum of the respective function and is denoted as a * associated with it.

Since the time series of FII is stationary or I(0) from the unit root tests, the Granger causality test is performed as follows:

$$\Delta B_t = \alpha_1 + \beta_{11} \Delta B_{t-1} + \beta_{12} \Delta B_{t-2} + \cdots + \beta_{1n} \Delta B_{t-n} + \gamma_{11} F_{t-1} + \gamma_{12} F_{t-2} + \cdots + \gamma_{1n} F_{t-n} \varepsilon_{1,t}$$

$$F_t = \alpha_2 + \beta_{21} F_{t-1} + \beta_{22} F_{t-2} + \cdots + \beta_{2n} F_{t-n} + \gamma_{21} \Delta B_{t-1} + \gamma_{22} \Delta B_{t-2} + \cdots + \gamma_{2n} \Delta B_{t-n} \varepsilon_{2,t}$$

Where $n$ is a suitably chosen positive integer; $\beta_j$ and $\gamma_j$, $j = 0, 1, \ldots, k$ are parameters and $\alpha$’s are constant; and $\varepsilon$’s are disturbance terms with zero means and finite variances.

($\Delta B_t$ is the first difference at time $t$ of BSE averages where the series in non-stationary. $F_t$ is the FII flows at time $t$ where the series is stationary)

**VARIANCE DECOMPOSITION**

The vector auto-regression (VAR) by Sims (1980) has been estimated to capture short run causality between BSE averages and FII investment. VAR is commonly used for forecasting systems of interrelated time series and for analysing the dynamic impact of random disturbances on the system of variables. In VAR modelling the value of a variable is expressed as a linear function of the past, or lagged, values of that variable and all other variables included in the model. Thus all variables are regarded as endogenous. Variance decomposition offers a method for examining VAR system dynamics. It gives 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 of course directly affect that variable, but it will also be transmitted to all of the other variables in the system through the dynamic structure of VAR (Chirs Brooks, 2002). Variance decomposition separates the variation in an endogenous
variable into the component shocks to the VAR and provides information about the relative importance of each random innovation in affecting the variables in the VAR. In the present study, BVAR model has been specified in the first differences as given in following equations:

\[
\Delta X_t = \alpha_1 + \sum_{j=1}^{k} (\alpha_{11}(i)\Delta X_{t-j}) + \sum_{j=1}^{k} (\alpha_{12}(j)\Delta Y_{t-j}) + \varepsilon_{x_t}
\]

\[
\Delta Y_t = \alpha_2 + \sum_{j=1}^{k} (\alpha_{21}(i)\Delta X_{t-j}) + \sum_{j=1}^{k} (\alpha_{22}(j)\Delta Y_{t-j}) + \varepsilon_{y_t}
\]

Where \(\varepsilon_{x,y}\) are the stochastic error terms, called impulse response or innovations or shock in the language of VAR.

**IMPULSE RESPONSE FUNCTION**

Since the individual coefficients in the estimated VAR models are often difficult to interpret, the practitioners of this technique often estimate the so-called impulse response function (IRF). The IRF traces out the response of the dependent variable in the VAR system to shocks in the error terms. So, for each variable form 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 \(m\) variables in a system, total of \(m^2\) impulse responses could be generated. In our study there are four impulse responses possible for each phase, however we have considered only two which are of our interest. In econometric literature, but impulse response functions and variance decomposition together are known as innovation accounting (Enders, 1995).

**EMPIRICAL ANALYSIS**

As outlined in the methodology the empirical analysis of impact of FII flows on Indian stock market is conducted in the six parts:

First: The normality test is has been conducted for \(F_t\) and \(B_t\). The Jerque Bera statistics and Anderson darling test are used for this purpose. The results are shown in Table (3 (B).1) along with descriptive statistics. The skewness coefficient, in excess of unity is taken to be fairly extreme (Chou 1969). High or low Kurtosis value indicates extreme leptokurtic or extreme platykurtic (Parkinson1987). Skewness value 0 and Kurtosis value 3 indicates that the variables are normally distributed. As per the statistics of Table 3(B).1 frequency distributions of variables are not normal.

<table>
<thead>
<tr>
<th>Table 3 (B).1: Descriptive Statistics of FIIs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
</tr>
<tr>
<td>Mean</td>
</tr>
<tr>
<td>Median</td>
</tr>
<tr>
<td>Maximum</td>
</tr>
</tbody>
</table>
Minimum -13461.39
Standard deviation 5254.431
Skewness 1.926040
Kurtosis 10.18559
Jarque-Bera 631.4772
Probability 0.000000
Anderson Darling (Adj. Value) 21.36305
Probability 0.000000
Result Not Normal

These results are further supported by Jarque-Bera (probability = 0) and Anderson Darling (probability = 0). Zero value of probability distribution indicates that the null hypothesis is rejected. Or FII flows are not normally distributed.

Table 3 (B).2: Descriptive Statistics of BSE National Index

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Time period (January 1992 to December 2010)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3440.320</td>
</tr>
<tr>
<td>Median</td>
<td>1938.505</td>
</tr>
<tr>
<td>Maximum</td>
<td>10795.30</td>
</tr>
<tr>
<td>Minimum</td>
<td>960.1400</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>2763.419</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.262780</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.206250</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>60.99942</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
</tr>
<tr>
<td>Anderson Darling</td>
<td></td>
</tr>
<tr>
<td>(Adj. Value)</td>
<td>23.06024</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
</tr>
<tr>
<td>Result</td>
<td>Not Normal</td>
</tr>
</tbody>
</table>

The results present in table 3 (B).2 shows that these results supported by Jarque-Bera (probability = 0) and Anderson Darling (probability = 0). Zero value of probability distribution indicates that the null hypothesis is rejected. Or BSE national index averages are not normally distributed. However, BSE national index averages shows less variable than FII flows as indicated by their Standard Deviation.

Second: Stationary test has been conducted by BSE national index averages and Net FII flows. Simplest way to check the stationarity of variables is to Plot time series graph and observed the trend in mean, variance and co-variances. A time series is said to be stationary if their mean and variance of the series are constant. BSE national
Index averages seems to be trend in its mean since it has a clear cut upward movement which is the sign of non constant mean. Further, Vertical fluctuation is not the same at different portions of the series, indicating that variance is not constant. Thus, it is said that the series BSE national index averages are not stationery (Figure 3(B).2).

**Figure 3(B).2: BSE National Index Averages Time Series**

![BSE National Index Averages Time Series](image)

**Figure 3 (B).3: Net FII Flows Time Series (in Rs. Crore)**

![Net FII Flows Time Series](image)

In case of Net FII flows time series (Figure 3(B).3), means and variance seems to be constant, which indicates presence of stationery in the time series. In addition to visual inspection, econometric tests are needed to decide the actual nature of time series. Or In simply, the researchers conforms the above decisions by applying Unit root tests. The results of various unit root tests namely DF, ADF and PP test are shown in table 3(B).3 and 3(B).4.

**Table 3(B).3: Unit Root Test of BSE National Index Averages**

<table>
<thead>
<tr>
<th>Variable: BSE</th>
<th>At Level</th>
<th>At First Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t- statistics</td>
<td>p-value</td>
</tr>
<tr>
<td>Without Trend Values</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The results present in table 3(B).3 shows that the values of the different unit root test \textit{i.e.} DF and ADF and PP values and their p-values support the results of the time series graph. It was found that BSE is non-stationary in both the cases with trend values and without trend values. BSE is stationary when the trend is allowed only according to the Dickey Fuller test at 10% significance level but ADF and PP test does not support the view of DF test. So it is concluded that the BSE is non-stationary series at level. Therefore, we can also check the stationarity at first difference. At First difference, all the unit root tests show that the BSE is stationary in all the cases at 1% significance level. So, it was found that the BSE is stationary at their first difference.

<table>
<thead>
<tr>
<th>Variable: FII</th>
<th>At Level</th>
<th>At First Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Without Trend Values</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF</td>
<td>-4.14925</td>
<td>0.0000</td>
</tr>
<tr>
<td>ADF</td>
<td>-4.60525</td>
<td>0.0020</td>
</tr>
<tr>
<td>PP</td>
<td>-10.4613</td>
<td>0.0000</td>
</tr>
<tr>
<td><strong>With Trend Values</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DF</td>
<td>-10.61406</td>
<td>0.0000</td>
</tr>
<tr>
<td>ADF</td>
<td>-10.7099</td>
<td>0.0000</td>
</tr>
<tr>
<td>PP</td>
<td>-11.2578</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The results presents in table 3(B).5 shows that the values of different unit root test results of Net FII flows. It was found that the FII is stationary in all the cases at 1% significance level.

Third: Correlation test has been conducted between FII and BSE. Correlation test can be seen as first indication for the existence of interdependency among time series. Table 3(B).5 shows the correlation coefficients between BSE averages and FII's investment.
Table 3(B).5: Correlation Matrix between FII and BSE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>BSE</th>
<th>FII</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSE</td>
<td>1.00000</td>
<td>0.43482</td>
</tr>
<tr>
<td>FII</td>
<td>0.43482</td>
<td>1.00000</td>
</tr>
</tbody>
</table>

It was found that there is a moderate degree of correlation between FII flows and BSE averages (table 3(B).5). Further, it was found that the movement in the BSE averages or FII flows does not strongly influence market movement as the coefficient of determination of the bse and FII is not high \( r^2 = 0.1890 \). The correlation needed to be further verified for the direction of influence by the Granger causality test for long term movement among the returns of stock markets, by the co-integration. To perform co-integration test, time series must be non-stationary and in our findings FII comes out be stationary at level which rejects the applicability of co-integration test. So, we can’t predict anything about long term relationship between BSE and FII on the basis of co-integration test. As the researcher applied Granger Causality test to find out the relationship between FII flows and BSE National Index.

**Fourth:** To capture the degree and direction of the long term correlation between BSE and FII flows, granger causality tests are conducted. For the granger causality test, the researcher needed to find out the optimum lag length by applying VAR are shown in the table 3(B).6:

<table>
<thead>
<tr>
<th>Lag</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>38.53852</td>
<td>38.52013</td>
</tr>
<tr>
<td>1</td>
<td>33.97035*</td>
<td>33.91518</td>
</tr>
<tr>
<td>2</td>
<td>34.00448</td>
<td>33.91252</td>
</tr>
<tr>
<td>3</td>
<td>33.99523</td>
<td>33.86648</td>
</tr>
<tr>
<td>4</td>
<td>34.03152</td>
<td>33.86598*</td>
</tr>
<tr>
<td>5</td>
<td>34.09417</td>
<td>33.89185</td>
</tr>
<tr>
<td>6</td>
<td>34.17025</td>
<td>33.93114</td>
</tr>
<tr>
<td>7</td>
<td>34.23005</td>
<td>33.95416</td>
</tr>
<tr>
<td>8</td>
<td>34.26151</td>
<td>33.94884</td>
</tr>
</tbody>
</table>

Note: *indicates lag order selected by the criterion;  
SC: Schwarz information criterion  
HQ: Hannan-Quinn information criterion

It was found that the Vector lags order selection criteria of Schwarz information criterion (SC) i.e. (SC=1) and Hannan-Quinn information criterion (HQ) i.e. (HQ=4). It was found that the HQ is more than the SC. Therefore, the researcher used HQ for selecting the optimum lag length and for applying Granger causality test. Granger causality test statistics are shown in the table 3(B).7.
The results of granger causality test (present in table 3(B).7) shows that the F-statistics of FII and BSE was significant. Therefore, the null hypotheses were rejected and alternative (i.e. FII granger cause BSE and BSE granger cause FII were accepted. In other words, there is statistical evidence that any forecast about the movement of market depends on the movement of FII flows and vice-versa. It can also be shown from the following graph:

**Figure 3 (B). 4: Movement of BSE Averages and FII Flows**

The above graph shows that if there is movement in the BSE averages then FII flows are also affected. FII flows are more volatile than BSE averages because the graph show that if the BSE is increased or decreased by one points the FII flows are moved by more than one point. BSE Averages shows frequent downward trend which causes FIIIs to disinvest and this influence of BSE and FII flows are supported with the outcome that BSE granger cause FIIIs and FIIIs granger cause BSE.

**Fifth:** In the context of varying causal links of BSE with FIIIs net investment, Sim’s VAR were applied and short run causal links were explored by using Variance decomposition and Impulse response functions. Variance Decomposition determines how much of the n step ahead forecast error variance of a given variable is explained by innovations to each explanatory variable. Generally it is observed that own shocks explain most of the forecast error variance of the series in a VAR. Table 4.8 shows the results of Variance decomposition of FII and BSE at 2, 5 and 10 periods. In the case of Bivariate modelling of BSE and FII, BSE explains 91% of its own forecast error variance while FII explains only 9% of BSE variance; but FII explains 81% of its own forecast while BSE explains only 19% of FII variance. This indicated that BSE
defines FII more than FII defines BSE which conclude to the result that BSE causes FII in short run. It indicates that FII do not hesitate to pull out their money from Indian market whenever market faces downward trend.

Table 3(B).8: Results of Variance Decomposition

<table>
<thead>
<tr>
<th>Variance Decomposition of Variance Periods</th>
<th>BSE</th>
<th>FII</th>
</tr>
</thead>
<tbody>
<tr>
<td>BSE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 5 10</td>
<td>94.27</td>
<td>5.73</td>
</tr>
<tr>
<td>5 91.41</td>
<td>8.59</td>
<td></td>
</tr>
<tr>
<td>10 91.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FII</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2          20.00</td>
<td>80.00</td>
<td></td>
</tr>
<tr>
<td>5          19.18</td>
<td>80.82</td>
<td></td>
</tr>
<tr>
<td>10         19.14</td>
<td>80.86</td>
<td></td>
</tr>
</tbody>
</table>

Sixth: To investigate dynamic responses further between the variables, Impulse Response of the VAR system has also been estimated. The impulse response functions can be used to produce the time path of the dependent variables in the BVAR, to shocks from all the explanatory variables. The shock should gradually die away if the system is stable. The Impulse Response functions (IFRs) as generated by the VAR model are shown in figure 3(B).5.

Figure 3 (B).5: Response to Cholesky One S.D. Innovations ± 2S.E.

The response BSE to one standard deviation shock to FII is sharp and significant and dies after ten lags. Whereas response of FII to one standard deviation shock to BSE is also sharp and significant and dies after ten lags. It implies that FII s and BSE are correlated with each other. As indicated by variance decomposition, similar pattern of causality is also observed graphically using impulse response functions. Impulse response function indicated that BVAR (Bayesian VAR) is stable.
CONCLUSION

This chapter empirically investigates the causal relationship between BSE averages and FII flows in Indian economy. The researcher also investigates the degree of interdependency between BSE averages and FII flows. First of all, normality of time series is checked. And found that the BSE averages and FII flows both are not normally distributed. After that stationarity is checked and found that FII Flows are stationary at level but BSE averages are non-stationery at level. BSE averages are stationary at their first difference. In this chapter correlation test is also applied and shows that the BSE averages and FII flows are positively correlated with each other. The correlation is further verified by the direction of influence by Granger Causality test. Granger Causality test shows that Both FII and BSE Granger cause each other. In order to find out the short term causality between two time series, variance decomposition and Impulse Response function is used. Variance decomposition and Impulse response function provide the same result as the Granger Causality test provides.

END NOTES

1 The policy framework for permitting FII investment was provided under the Government of India guidelines vide Press Note dated September 14, 1992, which enjoined upon FIIs to obtain an initial registration with SEBI and also RBI’s general permission under FERA. Both SEBI’s registration and RBI’s general permissions under FERA were to hold good for five years and were to be renewed after that period. RBI’s general permission under FERA could enable the registered FII to buy, sell and realise capital gains on investments made through initial corpus remitted to India, to invest on all recognised stock exchanges through a designated bank branch, and to appoint domestic custodians for custody of investments held.

2 The Government guidelines of 1992 also provided for eligibility conditions for registration, such as track record, professional competence, financial soundness and other relevant criteria, including registration with a regulatory organisation in the home country. The guidelines were suitably incorporated under the SEBI (FIIs) Regulations, 1995. These regulations continue to maintain the link with the government guidelines by inserting a clause to indicate that the investment by FIIs should also be subject to Government guidelines. This linkage has allowed the Government to indicate various investment limits including in specific sectors.

3 Trivedi and Nair (2006) investigate the determinants of FII flows to India and the causal relationship between FII movement and indiaindian stock market. Their study finds return and volatility in the Indian stock market emerge as principal determinants of FIIs inflows.
REFERENCES
Bae, Kee-Hong, Kalok Chan and Angela Ng. (2002). "Investability and Return Volatility in Emerging Equity Markets", Paper presented at International Conference on Finance, National Taiwan University, Taiwan.