Chapter 4: Capital Flows and their Macroeconomic implications

4.1 Introduction

The previous chapters dealt with the theories related to capital flows, historical trends of India's macroeconomic indicators over the last two decades, causality among the macroeconomic variables, etc. This chapter is devoted to understanding foreign capital flows implications on the recipient economy's macroeconomic and monetary policies. It is perceived that spillover effects of capital flows add to macroeconomic and monetary policy responses. Therefore, understanding these responses or effects in macroeconomic settings across time and space is critical with a coherent analysis of constantly evolving monetary, financial, and other policies. The mere economic rationale could not decide the direction of capital flows across geography. Instead, movements of capital are accompanied by many non-economic factors too. The impact of capital flows on the recipient countries is also not consistent across the economies. Each country has its own set of experiences. Hence, most studies on this subject focus on the empirical evidence-based realities of different countries or regions to give a meaningful understanding of macroeconomic implications of capital flows (Jeane, 2013; Agarwal, 1997; Chakroborty, 2003; Sara and Carmen, 2005).

A surge in international capital has marked the recent wave of financial globalization. Post globalization, the volume of capital inflows into developing countries increased substantially. The quality of capital getting into the developing countries also improved. The developing countries have high growth rates and a high degree of economic integration with the outside world, which occupies a considerable share of total foreign capital inflows.

There are wide viabilities in the experiences of developing countries with the bout of capital inflows. Many developing countries also experienced fluctuations in the periodic growth rates and financial crisis during the high degree of capital inflows (Bayulgen, 2004; Taylor and Lico 1999; Prasad and Rajan 2007). Countries that do not have meticulous checks and balances to regulate inflows of capital plunged into crisis. There are many inducing solid supply-side factors, drive international investors into developing countries' financial markets. Therefore, it is necessary to place prudential norms and regulations that could strengthen markets and dynamically improve the framework for capital flows management.

Financial globalization coupled with liberalization by many countries has brought the management of capital flow to prominence. Macroeconomic policies and financial institutional infrastructure are essential factors that significantly influence the expected benefits from foreign capital to the host country. However, there are considerable diversities among the developing countries on several parameters such as systemic efficiency, development of infrastructure, human resources, and other supporting factors. The steady and stable magnitude of capital flows promotes economic growth and positively influences the countries' financial behavior.

4.2 Methodology of the study

Many traditional methodologies exist to examine the interdependence among time series variables, such as investigating correlation coefficients, estimating an OLS regression model, etc. For a non-stationary series running a simple OLS model can result in spurious regression results. Therefore, using a simple regression model is often fraught with caution and should be avoided. Correlation measures co-movements between two series is an intrinsically short-term measure, and it may be unstable in the long run. Both OLS and correlation analysis have many limitations for time-series data of the nature used in this analysis and may lead to incorrect estimation.

Considering these limitations, we have applied Johansen & Julius' (1992) cointegration test to examine the macroeconomic indicators' long-run interdependence for the Indian economy. To use cointegration in a series, it is necessary to ensure all series must be stationary and integrated in the same order. The difference of series may convert a non-stationary series to stationary series. Suppose a series is stationary without a difference. In that case, it is said to be integrated at order 0 and denoted by I(0), but if it becomes stationary with first differencing, it is represented by I (1) and likewise for the higher order of differencing. All data sets are non-stationary at the level form and stationary or integrated at the same order after differencing is a prerequisite to running cointegration analysis.

Unit root test analysis is performed on the time-series variables to check for stationarity in the data series. The Augmented Dickey-Fuller (ADF) test (1979, 1981) tests for unit root. Further, the KPSS (1992) test and Phillip Perron (PP) were performed to validate ADF test results. Unlike the ADF test, the KPSS methodology examines the series for a null hypothesis of stationarity against the alternate hypothesis of non-stationarity. All these methodologies were conducted for concerned time-series variables in both levels and the first difference forms.

For the Cointegration test, the unrestricted and well-specified VAR model is estimated. A well-specified VAR model should be free of serial correlation. The model's lag length is selected based on the statistical information criterion AIC, BIC, and SIC. Engle & Granger's cointegration methodology is generally suitable for a single equation system or in bivariate settings. However, there are certain limitations of working with this methodology with more than two variables. An alternative methodology proposed by Johansen is considered superior and can handle multivariate relationships that could be framed in analyzing economic phenomena under investigation. Johansen uses a Vector Auto Regression (VAR) framework. The Johansson cointegration methodology was applied after estimating a good fitted VAR model based on the selected lags. We have run two separate models for FII and FDI and have included all other variables in both models. There are eight variables in each of the two equations; hence only eight cointegrating vectors are possible for each model. Trace statistics and the Max Eigen Value test statistics are estimated for both the cointegrating equations.

Finally, we test structural hypotheses in a multivariate cointegration context using the methodology of 2OLS inference in cointegrated vector autoregressive models (VECMs). For this, the study proposed to test the following hypothesis:

- H1: There is a dynamic link between foreign capital inflow and economic growth.
- H2: There is an inbuilt dynamism between macroeconomic variables and indicators regarding foreign capital inflows.
- H3: Foreign exchange management, variation in the foreign exchange rates, and foreign capital flows are interlinked.
- H4: Macroeconomic management of capital inflows responded considerably to the variation in money supply and exchange rate.

- H5: Considerable changes in the capital flows can be explained by exchange rate reserve and volume of the growth rate of and export, import.

Given the hypothesis mentioned above, data was collected to understand the given research area and establish a cause and effect relationship among the variables. The study used inclusion/exclusion criteria for the collection of data for the shared variables. Moreover, the information was gathered and selected from the material such as official publications or archival data as per the inclusion criteria in the analysis from various sources like journals, government reports, research papers, and many other secondary sources. Before data analysis, the gathered data was checked for missing variables, outliers, etc. This is done with the help of the diagnostic testing of the data collected. To know whether there are any outliers or not, the outlier labeling rules were used. It helped to calculate outliers that were beyond the considered range of the study. The data were analyzed using statistical software “R” with the packages “urca” and ‘tsDyn.’

4.2.1 Unit root analysis

Unit root analysis is a process that helps to find results for the stochastic trend in the time series data. It is sometimes called a 'random walk with drift' test method. The presence of unit root in a time series data set shows a systematic pattern of the unpredictability of future movements. Unit root analysis is performed to make the data series stationary to eliminate these unexpected characteristics of the data set. The current study has used three-unit root tests - the Augmented Dickey-Fuller Test (ADF), Phillips–Perron (PP), and KPSS.

A data set Y_t (where t=1,2.....n) is supposed to be stationary if properties of the variable do not fluctuate with time. The white noise is a specific case of a stationarity time series data analysis. For instance, Y_t follows an ordinary appropriation N (μ, Σ^2) autonomous of t. Distinguishing a series of stationary or non-stationary properties helps to understand the emergence of non-stationarity. For instance, a non-stationary series could be made stationary in first difference (additionally called incorporated of order 1): Y_t is a non-stationary series. However, its first difference is $Y_t - Y_{(t-1),}$ maybe a stationary series. It is called a situation of an irregular walk.

An arrangement can likewise be fixed in the pattern. Stationarity tests permit checking if an arrangement is fixed. There are two distinct methodologies: stationarity tests, for example, the KPSS test that considers invalid specification of H_0 that the arrangement is fixed and thereafter tests for unit root. ADF and PP tests have the invalid theory opposite to the understanding that the structure has a unit root and thus isn't fixed. The Dickey-Fuller test is based on linear regression. An enhanced version test,i.e., the ADF test, was introduced to resolve serial correlation in the DF test. ADF is a complex model, but it also suffers from a high probability of type 1 error.

Another test called the Phillips–Perron (PP) test is a modification of the Dickey-Fuller test to determine unit root in the data series. The advantage of the PP test lies in the fact that it corrects autocorrelation and heteroscedasticity in the errors component of the data series.

4.2.1.1 ADF test

If the unit root is present in time series variables, the series is non-stationary; whereas differencing the series may reduce it to a static variable. Many statistical methods detect unit roots in AR (autoregressive) and ARMA (autoregressive moving average) time series variables. Unlike many other test statistics, ADF test specification requires well-defined AR and MA (moving average) coefficients. ADF (Augmented dickey-fuller) test is based on an approximation of an ARMA model for autoregression. The test regression gets rid of serial correlation in the error term of the data series. The ADF test chooses an upper bound maximum lag (Kmax) and subsequently drops the last lagged regressor depending on the significance test employing the Student's t distribution statistics. These steps are repeated until the last lagged regressor becomes significant. Otherwise, the last lagged regressor is dropped each time the equation is reestimated. If no endogenously lagged regressor becomes significant, Kmax will be zero as in the original DF test. This procedure asymptotically yields the correct lag order or true lag order with probability one. Alternatively, Akaike (AIC) or Schwarz (SC) can also be used to detect correct lagged order K_{max}. Before running the ADF test, all variables were defined. Time series test variables are expressed in their natural logarithmic forms. The general ADF test process is described by equation (1) below:

$$\textbf{AR (1)} \qquad \boldsymbol{\Delta Y_t = \alpha + \delta Y_{t-1} + \varepsilon_t} \ldots\ldots\ldots\ldots\ldots (\mathbf{4.1})$$

We run a regression of the change in Yt as per equation 4.1 under the null hypothesis that we have a unit root in the data series. The corresponding null hypothesis is δ equals to zero, against the alternative hypothesis of δ is less than zero. It was the case for an AR-1 process which is represented by the following.

$$\mathbf{H_0 : \delta = 0}$$

$$\mathbf{H_1 : \delta < 0}$$

Unit root in the presence of higher-order processes, i.e., if Yt followed an AR-2 process, then we would regress δY_t on α and δY_{t-1} first and then we would include δY_{t-2}. Under the null hypothesis, we have a unit root in the AR-2 process. We can prove that δ should be equal to zero, and the alternative here that we have a stable AR-2 process is that δ is less than zero, and this generalizes quite well to any ordering process ε_t or any order of the AR process. In general, we included enough lags in our δ, so we have δY_{t-1} plus the sum equals 1.

There were two regression estimates, one with a constant and another with a trend. For lag selection, the AIC criterion selects the appropriate lag length. One needs to be parsimonious while choosing the lag order for inclusion in the model. Including a higher order of lag, the length makes it insignificant. Whereas a lower lag order does not serve the purpose to achieve serially uncorrelated model errors.

4.2.1.2KPSS test

KPSS is an LM test for testing trends and levels of stationarity. Unlike other tests in this class where the null hypothesis is a unit root process, the null hypothesis for the KPSS test is the presence of unit root in the ARMA process, and the alternative hypothesis is otherwise. KPSS adopts a conservative testing strategy. The hypothesis is framed so that one tries to reject the null hypothesis and accept the alternative hypothesis.

The following system of equations represents the test:

$$\mathbf{Y_t = \xi t + r_t + \varepsilon_t \ldots \ldots \ldots \ldots \ldots (4.2)}$$

$$\mathbf{r_t = r_{t-1} + \mu_t \ldots \ldots \ldots \ldots \ldots (4.3)}$$

Where r_t are a random walk, and the initial values of the r_0 is fixed and corresponds to the level.

4.2.1.3 Phillips and Perron(PP) test

Phillips and Perron is a non-parametric test for controlling serial correlation when testing for a unit root in the data series. Following two test regressions are considered for the analysis:

$$\mathbf{Y_t} = \boldsymbol{\mu} + \alpha\mathbf{Y_{t-1}} + \boldsymbol{\varepsilon_t} \ldots \ldots \ldots \ldots \ldots (\mathbf{4.4})$$

$$\mathbf{Y_t} = \boldsymbol{\mu} + \boldsymbol{\beta}/\mathbf{2T}) + \alpha\mathbf{Y_{t-1}} + \boldsymbol{\varepsilon_t} \ldots \ldots \ldots \ldots \ldots (\mathbf{4.5})$$

The critical values of Z statistics are identical to those of the DF-type tests. This test statistic has some advantage over the DF test as it eliminates the noise parameters in the DF statistic. But it also has another shortcoming as selecting optimal lag numbers for computing the long-run variances depends on the researcher's discretion. The test is applied to equation 4.5.

4.2.2 Johansen cointegration test

The cointegration method is widely used in applied economic work. Johansen procedure helps to understand whether the given time series has a cointegrating relationship with the shared variables or not. To understand the Johansen test, a clear understanding of the Vector Autoregressive Models needs to be considered. It is because the data analyzed under the Johansen test is multivariate time series data. The Johansen test can be easy to call with the R statistical environment's help and from the "urca" package. A separate model is run for FDI and FPI, considering the nature of these two inflows. Both trace and maximum eigenvalue test models are estimated separately for FDI and other macroeconomic indicators and FPI and other macroeconomic indicators. For the trace test, the null hypothesis of r cointegrating vectors against n cointegrating vectors are tested against an alternative hypothesis. The maximum eigenvalue tests the null hypothesis of r cointegrating vectors against r +1 cointegrating vectors.

ML estimators of cointegration vectors for an autoregressive process developed by Johansen and Juselius [1990] as in equations 4.6 is used for analysis. The use of canonical correlation analysis reduces the information content of observations in the multi-dimensional space to lower-dimensional cointegrating vectors. It allows for a determined extent of multicollinearity.

$$\mathbf{Y_t = \Pi_1 Y_{t-1} + \cdots + \Pi_k Y_{t-p} + \mu + \phi D_t + \varepsilon_t \ldots\ldots for\ t = 1, \ldots\ldots T \ldots (4.6)}$$

Johansen process determines the cointegration rank r followed by estimating cointegrating vectors. The process tabulated trace statistics up to five cointegration relations to compare critical values test statistics for various quantiles with a likelihood-ratio test statistic for the null hypothesis. Besides the trace statistic, maximal eigenvalue statistics for testing the existence of r versus r + 1 cointegration relationships are also suggested to be used. For estimating cointegrating vectors, eigenvectors to the corresponding eigenvalues are used. The adjustment matrix is dependent on the choice of the optimizing cointegrating vectors. The estimated cointegrating vectors are displayed in Table 20.

4.2.3 Vector Error Correction Model (VECM)

VECM is used to describe the general framework of the dynamic relationship between the study variables. For this purpose, the first step is to determine whether the given data is stationary. If the data are not stationary, then they need to be converted into a stationary position with pseudo-first-order differences. In the current study, the selected data for the variables were non-stationary. With the help of first-order derivatives, the data were brought under the stationary state, and then the VECM was applied. The VECM is just a particular VAR case wherein the cointegrating relationships among the variables are considered. Then the analysis of the same is done. The data for FDI and FPI are used to estimate a VEC model. The decision to use the VECM was made because the time series data selected for analysis was not stationary at different levels of the selection, and the variables used were cointegrated with each other in their levels. We have used four statistical estimates Akaike Information Criterion (AIC), Schwarz Criterion (SC) and Hannan Quinn Criterion (HQ), Akaike's Final Prediction Error Criterion (FPE). To run VECM, "tsDyn" package of r-software was used. We have used the Engle-Granger two-step approach (2OLS) to estimate VECM. For the VECM, we have set a lag three based on the lag selection criteria. The directory used is the data loaded with FDI and FPI in India for the study variables. First, the unit root analysis is performed that requires some judgment about the specification and shows whether the current data includes a constant or linear trend or drift and lag lengths that augment the regular tests. After this, the Johansen test was done to find out the cointegrating equations for the study. It was found that there are two cointegrating vectors estimated with 2OLS cointegration variables. The parameter slope was 261, and the sample size considered for the current study was 62. The analysis indicates that the FDI and FPI variables respond to the disequilibrium of the policies considered for the capital flows.

To understand the short-term dynamics and causal relationship between foreign capital inflows with the selected set of important macroeconomic variables, Vector Autoregressive

(VAR) using the VECM framework is employed. We can determine the cointegrating relationship once we determine the frequency at which the two-time series are integrated. To test for cointegration, we used the rank test based on the Maximum-likelihood method of the cointegrating rank. The test allows for five distinguished specifications of deterministic terms (Doornik et al.1998), such as unrestricted constant and trend, unrestricted constant and restricted trend, unrestricted constant and no trend, restricted constant and no trend, and no constant nor trend.

Finally, the vector error-correction model is used. When the VAR variables are cointegrated, VECM is used to examine the deviation in equilibrium and the correction factor. A representative VECM for two variables are defined as follow:

$$\mathbf{y_t = \beta_{y0} + \beta_{y1}\Delta y_{t-1} + \cdots + \beta_{yp}\Delta y_{t-p} + \gamma_{y1}\Delta x_{t-1} + \cdots}$$
$$\mathbf{+\gamma_{yp}\Delta x_{t-p} - \lambda_y(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}) + \vartheta_t^y} \qquad (\mathbf{4.7})$$

$$\mathbf{\Delta x_t = \beta_{x0} + \beta_{x1}\Delta y_{t-1} + \cdots + \beta_{xp}\Delta y_{t-p} + \gamma_{x1}\Delta x_{t-1} + \cdots}$$
$$\mathbf{+\gamma_{xp}\Delta x_{t-p} - \lambda_x(y_{t-1} - \alpha_0 - \alpha_1 x_{t-1}) + \vartheta_t^x} \qquad \mathbf{(4.8)}$$

Where, $y_t = \alpha_0 + \alpha_1 x_t$ is the long-run cointegrating relationship between the two variables;

λ_y and λ_x are the error-correction parameters that measure how y and x react to deviations from long-run equilibrium.

VECM model of more than two variables must consider the possibility of more than one cointegrating relationship or the latest cointegrating vector prevalent among the variables. The testing procedure for cointegrating relationships to allow for more than one cointegrating equation is a general practice in more than two variables. The model allows for multiple error-correction terms in each equation.

4.3. Results

Multiple approaches are followed to test for a unit root in the data series. Unfortunately, there is no unanimity on test type for a specific data series under given circumstances. Each test has its share of advantages and disadvantages. Therefore, a combination of tests with opposing null hypotheses seems to be a more pragmatic and practical approach in practice. For example, the ADF test adopts a sequential testing strategy more suitable when the data-generating process is unknown. Phillips-Perron test uses a non-parametric correction that captures weak dependence and heterogeneity of the error process. The KPSS test correctly addresses the hypothesis specification from the viewpoint of conservative testing.

As discussed in the preceding section, we run the ADF test with a null unit root hypothesis to check for the unit root in the data series. This test is conducted at both the levels and the first difference of the data. Other supplementary tests such as KPSS and Phillip Perron tests are also conducted to corroborate the ADF test results. We found that data in its level form has unit root present. To eliminate unit root first difference of the data series is performed.

First, ascertain if the utilized series are integrated in the same order to apply cointegration analysis. Then use the first difference form for all the variable series. Two multivariate cointegration, one for FDI and significant macroeconomic variables, and another for FPI and important macroeconomic variables, are used. Both the Trace and the Maximum Eigenvalue statistics were estimated in addition to the test for cointegration. Long-run or transitory forms of VECM are estimated.

4.3.1 Augmented Dickey-Fuller (ADF) test

The summary output of the ADF test regression is provided in Table 21. The test statistic values are compared with critical values to conclude the presence of stationarity. We first check whether the data is non-stationary without differencing and stationary after the first difference. This step is essential to determine if the two series are integrated in the same order to run a cointegration analysis. The ADF test is run with a null hypothesis of unit root, and rejection of hypothesis means the series does not have a unit root. Based on the ADF test, all variables are non-stationary at levels. In the first difference, all series are stationary at a 1% significance level.

Table 1: The summary output of ADF test regression

Variables	Variables form	ADF t-statistic	F-statistic	p-value	Ho
LNGDP	**Level**	**2.2042**	**2.432**	**0.096**	**Accept**
	First Diff	**-14.138**	**102.7**	**0.000***	**Reject**
LNWPI	**Level**	**3.0067**	**18.76**	**0.04**	**Accept**
	First Diff	**-3.9821**	**8.89**	**0**	**Reject**
LNFEX	**Level**	**2.1281**	**23.88**	**0.258**	**Accept**
	First Diff	**-3.1194**	**7.211**	**0.001**	**Reject**
LNEXR	**Level**	**1.1518**	**0.7418**	**0.4806**	**Accept**
	First Diff	**-4.2825**	**28.9**	**0**	**Reject**
CMR	**Level**	**-0.2176**	**0.3136**	**0.732**	**Accept**
	First Diff	**-7.4043**	**39.93**	**0**	**Reject**
LNM3	**Level**	**8.9768**	**119.1**	**0.002**	**Accept**
	First Diff	**-1.3874**	**34.96**	**0.001**	**Accept**
	Sec. diff	**-9.1103**	**197.1**	**0**	**Reject**
LNIMP	**Level**	**2.0229**	**4.354**	**0.01723**	**Accept**
	First Diff	**-5.1909**	**17.56**	**0**	**Reject**
LNIMP	**Level**	**2.1591**	**2.358**	**0.1034**	**Accept**

	First Diff	**-4.544**	**28.54**	**0**	**Reject**
LNFDI	**Level**	**1.5846**	**5.93**	**0.0045**	**Accept**
	First Diff	**-6.4895**	**60.78**	**0**	**Reject**
LNFPI	**Level**	**1.0311**	**1.055**	**0.3545**	**Accept**
	First Diff	**-6.5276**	**39.95**	**0**	**Reject**

Source: Author calculation

The above table shows that the p-values for GDP, FEX, EXR, CMR, MP, and FPI are significant at 5 % levels. Hence, it can be interpreted that the null hypothesis could be accepted at the level form for the variables mentioned above (the original version of the data). But in their first difference, the null hypothesis was rejected, and an alternative was accepted for ADF test regression without intercept and trend as per the estimates produced for ADF t-values. Therefore, based on the ADF test, we conclude that all series are non-stationary at levels and stationary in the first difference.

4.3.2 KPSS test

Table 22 has a summary of KPSS tests. Test on levels and first difference to check for unit root. In the KPSS test case, the null hypothesis of no unit root is assumed; hence this test examines the data for non-stationarity rather than stationarity in both levels and the first difference forms of the series.

Table 2: The summary output of the KPSS test

Variables	Form	test-statistic
LNGDP	**Level**	**0.12**
	First Diff	**0.087**
LNWPI	**Level**	**0.1426**
	First Diff	**0.1422**
LNFEX	**Level**	**0.1797**
	First Diff	**0.0939**
LNEXR	**Level**	**0.1747**
	First Diff	**0.1105**
CMR	**Level**	**0.1615**
	First Diff	**0.1155**

LNM3	**Level**	**0.1112**
	First Diff	**0.1459**
LNIMP	**Level**	**0.1666**
	First Diff	**0.1288**
LNEXP	**Level**	**0.1623**
	First Diff	**0.1451**
LNFDI	**Level**	**0.1221**
	First Diff	**0.0884**
LNFPI	**Level**	**0.1579**
	First Diff	**0.1076**

	10pct	**5pct**	**2.5pct**	**1pct**
Critical values	**0.119**	**0.146**	**0.176**	**0.216**

Source: Author calculation

All the series (in table 22) are significant in levels either at 1%, 5%, or 10% significant levels. In the first difference, all series are significant at 1% level, and hence the series is stationary.

4.3.3 Phillip Perron test

PP and ADF tests differ in how they treat serial correlation and heteroskedasticity in the error terms of the data series. The first-order difference was calculated and checked for each variable to get stationarity in the data for analysis. PP test result is presented in Table 23

Table 3: The summary output of PP test regression

Variables	**Form**	**test-statistic (Z-tau)**	**Ho**
LNGDP	**Level**	**-0.459**	**Accept**
	First Diff	**-13.794**	**Reject**
LNWPI	**Level**	**-0.0733**	**Accept**
	First Diff	**-5.4901**	**Reject**
LNFEX	**Level**	**-3.4065**	**Accept**
	First Diff	**-5.0374**	**Reject**
LNEXR	**Level**	**0.1828**	**Accept**
	First Diff	**-7.5346**	**Reject**
CMR	**Level**	**-3.9684**	**Reject**

LNM3	**Level**	**-1.1065**	**Accept**
	First Diff	**-10.392**	**Reject**
LNIMP	**Level**	**-1.4603**	**Accept**
	First Diff	**-6.36**	**Reject**
LNEXP	**Level**	**-1.5868**	**Accept**
	First Diff	**-8.1221**	**Reject**
LNFDI	**Level**	**-0.9996**	**Accept**
	First Diff	**-11.78**	**Reject**
LNFPI	**Level**	**-1.2224**	**Accept**
	First Diff	**-9.3289**	**Reject**

Source: Author calculation

We found that the test in level form behaves like a pure random walk, whereas differencing the series makes them stationary. This means we can perform the analysis with difference series instead of in the level form.

4.3.4 Cointegration test result

Cointegration is a methodology for simultaneous modeling of a set of time series and inference relationships among themselves. It finds a linear combination between two variables that yields a variable with lower integration order. Hence, it detects stable long-run relationships among non-stationary variables. Although individual series are non-stationary, the cointegrating vector ties them to each other. More precisely, an economics series may deviate from long-run equilibrium, but a mean reversion characterizes deviations to the stable long-run equilibrium.

Table 4: Cointegration rank without linear trend and constant for FDI

Hypothesis	**Maximal eigenvalue test**		**Trace test**	
	Lambda max	**1pct**	**Trace statistic**	**1pct**
r<=8	**6.29**	**12.97**	**6.29**	**12.97**
r<=7	**11.47**	**20.2**	**17.77**	**24.6**
r<=6	**22.18**	**26.81**	**39.95**	**41.07**

r<=5	**24.3**	**33.24**	**64.25**	**60.16**
r<=4	**26.83**	**39.79**	**91.08**	**84.45**
r<=3	**41.69**	**46.82**	**132.78**	**111.01**
r<=2	**47.79**	**51.91**	**180.57**	**143.09**
r<=1	**63.78**	**57.95**	**244.35**	**177.2**
r=0	**82.32**	**63.71**	**326.67**	**215.74**

Source: Author calculation

Table 24 presents the multivariate results on the FDI with other significant macroeconomic variables using both the Trace test and the Maximum Eigenvalue statistics. The minimum lag parameters for the equation are kept at 8. There are nine eigenvalues generated by the test, with the largest approximately equal to 0.746. The test statistics for the 9 hypothesis ranging from r =0,r<=8,….r <= 8. For each of these tests, test statistics and critical values at the confidence levels are 10 %, 5%, and 1%, respectively, are also generated. These critical values help to accept or reject the hypothesis at a specific level of significance. The best estimates of the rank of the matrix tell us about the required linear combinations of the number of time series to form a stationary series. The result suggests a minimum of one cointegrating vector between FDI and other macroeconomic variables per the maximum eigenvalue test and a minimum of five cointerating vectors per the trace test statistics.

Table 5: Cointegration rank without linear trend and constant for FPI

Hypothesis	**Maximal eigenvalue test**		**Trace test**	
	Lambda max	**1pct**	**Trace statistic**	**1pct**
r<=8	**6.71**	**12.97**	**6.71**	**12.97**
r<=7	**9.89**	**20.2**	**16.6**	**24.6**
r<=6	**19.54**	**26.81**	**36.14**	**41.07**
r<=5	**24.26**	**33.24**	**60.4**	**60.16**
r<=4	**26.55**	**39.79**	**86.95**	**84.45**
r<=3	**42.4**	**46.82**	**129.35**	**111.01**

r<=2	**51.12**	**51.91**	**180.47**	**143.09**
r<=1	**62.41**	**57.95**	**242.88**	**177.2**
r=0	**80.61**	**63.71**	**323.49**	**215.74**

Source: Author calculation

Table 25 presents the multivariate results on the FPI with other significant macroeconomic variables. All the tests show that eigenvector components of the eigenvector are associated with the largest eigenvalue.

Table 6: Eigenvectors, normalized to the first column for FDI model using MLE

Var.	**fdi.l2**	**gdp.l2**	**wpi.l2**	**fex.l2**	**exr.l2**	**cmr.l2**	**m3.l2**	**imp.l2**	**exp.l2**	**Const.**
fdi.l2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
gdp.l2	**-38.4**	**-1.02**	**10.3**	**2.01**	**-19.04**	**-790.21**	**-154.24**	**45.73**	**27.19**	**-50.34**
wpi.l2	**-3.35**	**1.62**	**52.49**	**-12.12**	**-27.85**	**834.7**	**334.9**	**8.35**	**57.74**	**-49.62**
fex.l2	**-3.37**	**-0.28**	**6.68**	**-1.7**	**-1.75**	**5.59**	**90.6**	**46.09**	**-18.68**	**-26.54**
exr.l2	**-10.29**	**1.61**	**-22.24**	**0.24**	**8.98**	**-529.03**	**151.47**	**2.23**	**-14.54**	**-16.29**
cmr.l2	**-0.5**	**-2.87**	**3.91**	**5.33**	**-52.29**	**-379.4**	**49.83**	**13.9**	**19.14**	**-27.53**
m3.l2	**8.15**	**-6.26**	**-17.5**	**-3.31**	**33.75**	**-754.54**	**-77.24**	**290.64**	**53.89**	**-114.77**
imp.l2	**3.53**	**3.11**	**-11.28**	**-4.38**	**-15.26**	**-294.76**	**-18.3**	**10.53**	**1.42**	**-4.72**
exp.l2	**-6.45**	**-2.35**	**-7.09**	**6.9**	**10.62**	**427**	**-8.37**	**-23.01**	**-4.11**	**18.17**
Const.	**0.63**	**0.15**	**0.35**	**0.17**	**-0.41**	**32.43**	**-1.21**	**-12.61**	**-2.25**	**12.8**

Source: Author calculation

An eigenvector corresponds to a real nonzero eigenvalue, pointing in a direction where the transformation stretches it. The eigenvalue is the variable by which it is stretched, where the positive eigenvalue indicates that the variables are moving in a positive direction. Negative demonstrates that the direction is reversed. Hence, from table 26, it can be witnessed that the eigenvalues above one mean the first column's positive impact on the normalized FDI model. For the current study, the variables having a positive effect are M3 and IMP, i.e., money supply and imports.

Table 7: Eigenvectors, normalized to the first column for FPI model using MLE

Var.	**fdi.l2**	**gdp.l2**	**wpi.l2**	**fex.l2**	**exr.l2**	**cmr.l2**	**m3.l2**	**imp.l2**	**exp.l2**	**Constant**
fdi.l2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

gdp.l2	**32.98**	**2.2**	**4.53**	**7.84**	**22.43**	**110.62**	**18.8**	**26.72**	**135.47**	**30.72**
wpi.l2	**3.93**	**4.27**	**14.12**	**26**	**226.62**	**115.66**	**21.17**	**9.25**	**286.3**	**22.1**
fex.l2	**2.54**	**0.14**	**1.56**	**4.52**	**34.6**	**7.85**	**6**	**33.82**	**74**	**12.34**
exr.l2	**5.46**	**1.78**	**1.67**	**11.97**	**22.69**	**133.34**	**14.98**	**3.57**	**68.74**	**4.55**
cmr.l2	**3.16**	**5.29**	**2.53**	**2.33**	**184.43**	**94.14**	**5.92**	**4.86**	**81.24**	**13.68**
m3.l2	**12.74**	**0.32**	**3.81**	**3.65**	**154.33**	**137.66**	**3.57**	**164.53**	**299.13**	**59.33**
imp.l2	**2.54**	**2.21**	**5.69**	**7.03**	**18.57**	**71.72**	**4.36**	**2.91**	**0.44**	**2.11**
exp.l2	**5.74**	**4.31**	**6.55**	**3.32**	**23.7**	**84.41**	**2.37**	**9.95**	**18.62**	**7.99**
constant	**0.32**	**0**	**0.08**	**0.02**	**1.72**	**6.51**	**0.03**	**7.34**	**12.64**	**5.95**

Source: Author calculation

Similar to the FDI model discussed above. In the FPI model, it was found that FPI has a positive impact on GDP, WPI, FEX, EXR, CMR, M3, IMP, and EXP.

4.3.5 VECM model result

To realize an upward growth process with minimal implications for changes in the financial systems, it is crucial to have a substantial magnitude of steady and stable capital inflows. This section is intended to examine the impact of capital flows on economic growth. This section will explore trends and composition of capital inflows, review the role of capital inflows in India, and examine if such inflows have contributed to economic growth. To achieve this, we employed two separate VECM for FDI and FPI to study their economic impacts.

Table 8: Cointegrating vector (estimated by 2OLS) for FDI model

Variables	**2OLS estimates**	**ECT**
d_fdi		**-1.0746**
d_gdp	**-0.0224**	**0.0093**
d_wpi	**-4.6739**	**-0.0089**
d_fex	**-0.4162**	**0.0232**
d_exr	**1.6653**	**-0.073**
d_cmr	**-0.25**	**-0.0278**
d_m3	**0.6068**	**0.0082**
d_imp	**-0.01529**	**0.1173**

d_exp	**0.5121**	**0.0329**

Source: Author calculation

Notes: All variables are in first differences; The ECT's were derived by normalising the two cointegrating vectors on FDI thereby resulting in one set of residuals for each model.

In table 28, it can be witnessed that GDP, WPI, FEX, CMR, and IMP are negatively related to the independent variables FDI and EXR, M3 and EXP are positively related..

Table 9: Cointegrating vector (estimated by 2OLS) for FPI model

Variables	**2OLS estimates**	**ECT**
d_fpi		**-1.2851**
d_gdp	**-0.73712**	**-0.0032**
d_wpi	**-2.70301**	**-0.012**
d_fex	**-1.15038**	**-0.0079**
d_exr	**2.872375**	**0.0103**
d_cmr	**-2.82703**	**-0.0011**
d_m3	**0.734912**	**0.0131**
d_imp	**-0.28696**	**-0.0309**
d_exp	**-0.01401**	**0.0039**

Source: Author calculation

In table 29 it can be witnessed that GDP, WPI, FEX, CMR, and IMP are negatively related to the independent variables of the FPI and M3 is positively related.

4.4 Conclusion

A country open to foreign capital can better take advantage of investment opportunities available across the globe and channel the investment to achieve higher domestic growth. However, along with significant economic development benefits, it also amplifies shocks, especially in developing economies. Academicians and policymakers are in constant search of sound shock absorbers in the face of the volatility of capital inflows. This empirical study attempts to lay out a framework of cointegration, a method to understand the determinants of capital inflows and their implication for India. The distinguishing features of impacts of both FDI and FPI on the macroeconomic indicators are very different from one another from the framework of estimated results. The general observations that emerge from the analysis are as follows.

FDI has a positive impact on economic growth, exports, and imports and, at the same time, produces reductive effects on inflation and money supply. FPI is not found to have any significant implication for economic growth. Capital is often accompanied by many other things as it brings cutting-edge technologies, expertise, and ancillary benefits to the economy. FDI has been found to bring in many positive externalities to the host economy through transfer of technical knowledge, industrial upgrading, experience for better management of labor force and capital, etc. Hence, foreign capital's role can’t be judged merely based on its role as a supplementary source of external capital, which may fill the much-needed developmental capital shortfall in the host country. More generally and without getting into much empirical underpinning, one can state that financial openness promotes financial development and prepares the government to absorb the real shock better as the risk of foreign capital is diversified.

In conclusion, economic integration benefits both capital importing and capital-exporting countries, much like the widely understood trade-in goods and services. Hence, this is a win-win proposition for both, provided that an economy follows robust financial stability and appropriate policy mechanism. At the same time, we need to learn how to maximize benefits and minimize the cost associated with the foreign capital flow (inflow or outflow).