Causal Relationship between Stock Market and Macroeconomic Variables: Indian Evidence

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Abstract: Co-integration and causality are now recognised as the important modelling techniques for investigate the behaviour of macroeconomic variables. This study is conducted based on the above two techniques under VAR environment by considering annual data over a period from 1st April 1979 to 31st March 2020. The macroeconomic variables become stationary after first difference based on ADF and PP tests and integrated in the same order with optimum lag order of one. According to the Johansen co-integration test, three co-integrated equations are found which indicates presence of long-run equilibrium relationships and later confirmed by the VECM analysis when BSE is considered as the dependent variable. Even if, the evidence of short-run bilateral causality is observed between import and GDP and presence of uni-directional Granger causality is also seen from export to import.

Keywords: Co-integration; VECM; Causality; GDP; FDI; Export; Import

JEL Classification: C12; C15; C32

Introduction

The co-integration analysis and modelling for investigative the dynamics of the macro-economic variables has enormously changed the nature and direction of modelling of the macro-economic system. It provides an alternative way to assess the extent to which the variables under consideration are integrated. Generally, the co-integration relationship is used as a tool to examine the presence of long-run economic association among the variables and accordingly, various methods are developed. A lot of studies have extensively examined the relationship between the behaviour of stock market with the macroeconomic variables and this issue create a centre of attention to the researchers. Most of the studies have shown a clear link between the macroeconomic variables and the corresponding stock market. Some authors have opined that how economic variables affect the stock market but the effect of stock market and macroeconomic variables altogether have been less studied in the emerging economics like India.

It is well established that volatile stock market can change the economy in various ways. Generally, the growth of stock market is positively correlated with the growth of GDP and vice-versa. Similarly, if FDI comes into the economy then GDP will be augmented with the augmentation of the stock market which is a good sign for Indian Economy. Likewise, foreign trade (import and export) plays an important role in the economy. So, all these situations can be examined through co-integration analysis and within VAR environment.

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Literature Review

The relationship between stock market and macroeconomic variables has extensively studied in the literature. Some studies have depicted indecisive findings and the others have shown a significant relationship among them. Therefore, the researchers around the world are working on this issue seriously and they are trying to establish the relationship between the macroeconomic variables and thus the following studies are considered for developing the present study.

The concept of co-integration is first introduced by Granger (1981) and then extended further by Engle and Granger (1987); Eagle and Yoo (1987, 1991); Phillips and Ouliaris (1990); Stock and Watson (1988); Phillips (1991); Johansen and Juselious (1990); and Johansen (1988, 1991, 1994) and after that empirical studies have been conducted by the researchers around the globe. In 1986, Roll and Ross inspect the underlying association among the stock market and macroeconomic variables during the period from 1953 to 1983 and observe that stock market is significantly affected by the macroeconomic shocks (see Kim 2003). Bahmani et. al., (1992) inspects the association between the foreign exchange and stock market by considering the stock prices of S & P 500 index and observes unidirectional causality between them. Similarly, the causal association between Japanese stock market with the selected macroeconomic variables is examined by Mukherjee and Naka in 1995 and observe an equilibrium relationship between them in long run but they observe negative connection between the stock return and inflation. Abdalla & Murinde (1997) scrutinizes the causal relationship between the exchange rate and the stock prices in the emerging economies and observe presence of unidirectional causality between the selected variables in all the markets except Philippines where the stock prices Granger cause the exchange rate. Likewise, Gjerde and Saettem (1999) take the same initiative to scrutinise the fundamental association among the selected variables and stock market by applying MVAR technique and find that capital market positively reacts towards industrial production but negatively responds with the real interest rates. They also observe that stock price reacts in accordance with the oil prices' changes (see Nieh 2001). Phylaktis and Ravazzolo (2005) inspect the long run and short run association among the exchange rate and the stock price in Pacific Basin countries and observe absence of long run association apart from Hong Kong and at the same time long-run association exists when US stock market is considered. Similarly, Abdelaziz et. al., (2008) examines the association between the exchange rate and stock prices by considering four Middle East oil exporters' countries by applying co-integration technique and observe absence of co-integration but they also observe presence of long run association when oil price is considered. In 2000 Maysami et. al., inspects the causal association among some selected variables in Singapore, Japan and US stock markets and observe significant relation between the macroeconomic variables and the Singapore market in the long run (see also Hussainey & Ngoc 2009). They also identify that Singapore's market is positively co-integrated with the remaining markets (American & Japanese). Likewise, in 2002 Fang et. al., investigates the economic relationship between the Korean market and foreign exchange rate during the time of recession and observes that foreign exchange considerably affects stock market during recession (see also Bhattacharya & Mukherjee 2003, Muhammad & Rasheed 2003, Stavarek 2005). In 2009, Humpe and Macmillian again examine the causal association between the macroeconomic variables and the stock market in US and observe evidence in favour of long run correlation between them (see also Kim 2003). Again, Pal and Mittal in 2011 investigate the causal association between Indian stock market and macroeconomic variables and observe presence of co-integrated relationship among them and also seen that inflation affects stock market. In the same way, Naik and Pahdi (2012) examine the causal behaviour of Indian capital market over a period from 1994 to 2011 and observe a long-run relationship among them and this evidence is in line with the result of Mukherjee and Naka (1995). They also observe bidirectional causality between industrial production and stock prices while unidirectional causality exists between few variables. Masuduzzaman (2012) analyses causal link between US and UK stock markets by considering some selected macroeconomic variables during a period from 1999 to 2011 and observe significant link between them in the long run as well as in the short. Similarly, Dasgupta (2012) examines the causal relationships between the BSE and the selected macroeconomic variables under the VAR environment. He observes long-run relationships between the BSE and the index of industrial production, gold prices, money supply and foreign exchange reserve and along with this, in few cases he observes short run uni-directional as well as bi-directional causal relationships between them. Tripathi and Seth (2014) examine the causal relationship between the stock market performance and the selected macroeconomic variables in India. They find evidence of significant correlation among the stock market indicators with the macroeconomic variables and also identify unidirectional causality running from stock market to real economy. Similarly, Plihal (2016) scrutinizes the link between the macroeconomic variables and the German stock market. He finds unidirectional causality passes from stock market to macroeconomic variables. Additionally, bidirectional causality is transmitted from money supply to stock market and vice versa. Recently, Kotha et. al., (2016) examines the relationship between the Indian stock market and the selected macroeconomic indicators by applying VAR framework and observes presence of long-run relation with the exchange rate, interest rate, inflation and money supply. Similarly, in 2016 Latha et. al., examines the short and long run dynamic relationship between the Indian stock market and the macroeconomic indicators by applying ARDL technique. They depict that long run bi-directional relationship exist among them along with a presence of uni-directional causality running from Indian stock market to exchange rate. In 2017 Naushad examines the association between the Bombay Stock Exchange and the macroeconomic variables over a period from 2005 to 2013 and observes long-run heteroscedastic relationships between them. In 2018, Ali et. al., examines the impact of foreign trade performance on the economic development in Somalia over a period from 1970 to 1991 by applying Granger causality and Johansen co-integration techniques. They observe presence of long run relationships among the variables along with existence of bilateral relationship between import and export in the short-run and they conclude that Somalia require export-led growth strategy as well as export led import. In 2019, Demir Caner analyzes the impacts of macroeconomic determinants on the Turkish stock market over a period from 2003 to 2017 by using quarterly data under ARDL framework. The study points out that GDP, domestic currency, portfolio investment and FDI positively influence to enhance stock market while interest rate and crude oil prices react oppositely.

It is evident from the above studies that the relationships between stock market performance and macroeconomic variables are well established in the developed countries. In developing countries, the research regarding these issues is scanty. Few of them establish the convergence of such relationship between a few macroeconomic variables. So far, they highlight wide fluctuations of results for other macroeconomic variables. So, the evidences of causal association among them are not homogeneous in nature. Basically, the selection of macroeconomic variables depends on some established studies and also assumptions. In this situation, this study tries to investigate the long and short run equilibrium relationships among the selected macroeconomic variables in Indian context under the VAR environment and along with the analysing of how a positive innovation or shock (impulse) can changes the behaviour of the macroeconomic variables under the VAR framework and here is the identity of this study being considered.

Data & Study Period

This study considers annual data of BSE, GDP, FDI, Export and Import for co-integration analysis. The justification for selecting these variables is that the economic development (GDP) and growth of stock market is closely related because when an economy is going to flourish in all aspects then its impact certainly falls on GDP. Similarly, the growth of stock market depends on the economic or financial activities perform by a country that also helps to enhance GDP. Similarly, if the stock market grows then it attracts inflow of FDI into the capital market that ultimately assists to economic development. Likewise, positive trade balance helps an economy to grow or vice-versa. The yearly data of GDP, FDI, export and import are collected from the various reports of RBI (Reserve Bank of India) and the Department of Commerce (Govt. of India). The annual data of BSE is obtained from the official website of the Bombay Stock Exchange. The study period ranges between the financial year 1979-80 and 2019-2020.

Methodology

A random variable is said to be normally distributed if the following assumption is satisfied.

$$e_i \sim N(0, \sigma^2) \tag{1}$$

It is the most commonly assumed and applied statistical distribution. So, if the assumption of normality doesn't hold then the OLS estimator (ˆ) remains the Best Linear Unbiased Estimator (BLUE), i.e. it has the minimum variance among all linear unbiased estimators. So, without normality standard t and F distribution cannot be used to perform statistical test. The normality test is first introduced by Fisher in 1948. But, in 1981, Jarque and Bera develop a normality test statistic which is being used widely. Thus, the following null hypothesis should be formulated before normality test as below:

H_0: Distributions follow normality

H_a: Distributions don't follow normality

The J-B test statistic is expressed in terms of the third and fourth moments of the disturbances, as under:

$$J-B=(n-k)\left(\frac{s^2}{6}+\frac{(k-3)^2}{24}\right) \tag{2}$$

Where, 'S' measures skewness ($S = \frac{«_3}{±^3} = \frac{«_3}{(«_2)^{3/2}}$); 'K' measures kurtosis ($K = \frac{«_4}{±^4} = \frac{«_4}{(«_2)^2}$) and 'n' represents number of observation. Here, the value of 'K' and 'S' will be 3 and 0 respectively when the distribution is normal. If the distributions are not normal in their original forms then they are converted into log forms to make them normal in this study. Here, the study considers five random variables (BSE, GDP, FDI, Import and Export) and the outcome is presented in table 1. It is observed from the table that the probability values of the J-B test statistics of the variables at their level forms are less than five percent (5%) level of significance that means rejection of the null hypotheses and may be concluded that the distributions of all the series are not normal but after log transformation it is also found that the probability values (in parenthesis) of the computed J-B test statistics are higher than five percent (5%) that indicates acceptance of the null hypotheses and may be concluded that the distributions are normal.

Table 1. Normality Test

Variable	**Observation**	**Skewness**	**Kurtosis**	**J-B**	***P*-value**
BSE (LnBSE)	41	1.28272 (-0.3982)	3.5990 (2.0130)	11.85635 (2.7478)	0.0026 (0.2531)
GDP (LnGDP)	41	0.9772 (0.3228)	2.6752 (1.6125)	6.7062 (4.0010)	0.0349 (0.1353)
FDI (LnFDI)	41	1.0333 (-0.3101)	2.4732 (1.9702)	7.7702 (2.4688)	0.0205 (0.2910)
Import (LnImport)	41	0.8787 (0.2994)	2.0718 (1.4782)	6.7488 (4.5689)	0.0342 (0.1018)
Export (LnExport)	41	0.8568 (0.1464)	2.0328 (1.5406)	6.6147 (3.7849)	0.0366 (0.1507)

From the above table it is proved that all the variables are normally distributed after log transformation. But, when we deal with macroeconomic time series data we face the problem of non-stationarity or unit-root and thus, the standard OLS regression procedures can easily lead to incorrect estimates of the parameters (spurious regression). So, before going to the co-integration analysis it must be confirmed that the macro-economic time series variables are stationary when their means and variances are constant over time and the covariance depends on the distance between the two time periods. So, to overcome this problem we may use difference operator to make the time series stationary. Now, consider the random walk model

$$Y_t = \alpha + \rho Y_{t-1} + e_t \qquad (3)$$

Where, Y_t is a series of observation at time "t". It is obvious that when $|\rho|=1$, Y_t faces the problem of unit root and is non-stationary and if this happens then the variances grow exponentially as "t" increases (Dickey & Fuller 1979). So, if we take first difference then the series looks like $\Delta Y_t = Y_t - Y_{t-1} = e_t$ that becomes stationary (white noise). So it is better to run regression ΔY_t on ΔX_t instead of Y_t on X_t. To test stationarity, ADF and PP tests are applied because of their widely application. Here, the error term is unlikely to be white noise, Dickey and Fuller extended their test procedure by inserting extra lagged terms of the dependent variable in order to eliminate autocorrelation problem in the test equation which is popularly known as Augmented Dickey Fuller test (ADF). Here, the selection of lag length on these extra terms is determined by Akaike Information Criterion (AIC) or Schwarz Bayesian Information criterion (SBIC) or Hannan Quinn Information Criterion (HQIC) or more usefully by the lag length necessary to whiten the residuals. The study uses AIC, SBIC and HQIC to choose the optimum order of lag.

The ADF test may be shown as under:

$$\Delta Y_t = \sim + \text{¢} Y_{t-1} + \sum_{i=1}^{k} {}_i \Delta Y_{t-i} + e_t \qquad (4)$$

Here it is assumed that the error terms are uncorrelated and they have constant variance. Similarly, Phillips and Perron (1988) develop a generalization of the ADF test technique that allows for fairly mild assumptions concerning the distribution of errors and they consider the following equation:

$$\Delta Y_t = \sim + \text{¢} Y_{t-1} + e_t \qquad (5)$$

Here, the PP test makes a correction to the "t" statistic of the coefficient "δ" from the AR(1) regression to account for the serial correlation in e_t. In a nutshell, PP test is just modification of the ADF "t" statistic that takes into consideration the less restrictive nature of the error process.

The null hypothesis is as follows:

H_0: δ = 0 (non-stationary)

H_a: δ < 0 (stationary)

The outcome of the stationary test based on ADF and PP test statistics of the time series data are presented in table 2. It is observed that variables are non-stationary at their level forms based on both the test statistics because the probability values are higher than five percent (5%) in all cases meaning that they are non-stationary. But after using difference operator, all the series become stationary at their first differences and thus we reject the null hypotheses of non-stationary.

Table 2. Unit root test

Var.	ADF				PP				Order of Integration
	Level		1st Difference		Level		1st Difference		
	t-stat.	Prob.	t-stat.	Prob.	t-stat.	Prob.	t-stat.	Prob.	
LnBSE	-1.3693	0.5872	-8.6072	0.0000	-1.8611	0.4928	-8.6488	0.0000	I(1)
LnGDP	0.5170	0.9853	-6.5213	0.0000	0.5756	0.9873	-6.5213	0.0000	I(1)
LnFDI	0.0525	0.9577	-4.6797	0.0005	-0.2358	0.9254	-4.8052	0.0004	I(1)
lnIMP	-0.2219	0.9273	-4.2513	0.0018	-0.2961	0.9165	-4.2001	0.0021	I(1)
LnEXP	-0.8181	0.8030	-6.3112	0.0000	-0.5013	0.8804	-7.5631	0.0000	I(1)

*Significant at 5 percent level.

Source: author's own calculation

It is also very much imperative to find out the order of integration of the variables for co-integration analysis. Let's considers Y_t in equation three which is a non-stationary series. Now, if Y_t is differenced once and the differenced series becomes stationary then it may be said Y_t is integrated of order 1 [$Y_t \sim I(1)$]. Now, if Y_t is differenced twice and the differenced series becomes stationary then it may be said Y_t is integrated of order two [$Y_t \sim I(2)$]. In the same fashion, if Y_t is differenced "d" times to make it stationary then it is integrated of order [$Y_t \sim I(d)$]. According to the Ganger theorem if Y_t and X_t are I(d) then there exists a linear combination of them that is integrated of order "b", where b < d. It follows that both Y_t and X_t are I(1) then the linear combination of them must be I(0) and therefore, we don't face the problem of spurious regression while estimating regression equation. It is observed from the above table that the series are stationary at first differences and the order of integration is one [I(1)] in all cases here.

After testing stationarity and confirming order of integration then it is very much important in the context of co-integration analysis to select optimal lag length that is also significant to develop error correction model (ECM). According to Braun and Mittmik (1993), the estimate may be inconsistent if the lag length differs from the true lag length. So, the model is unspecified if the lag length is too small and over parameterized if it is too large (see Wooldridge, 2009, pp. 576). Here, the study uses AIC, SBIC and HQIC that has been explained above to choose optimal leg length. The lag length is said to be optimum that minimizes loss function and yields the residuals that are closet to white noise residuals. Thus, for a multivariate VAR with 'k' variables, 'T' observations, a constant term, and lag length p, the information criteria are given below:

$$AIC(p) = \ln\left|\overline{\Sigma}(p)\right| + \frac{2}{T}(k^2 p) \tag{6}$$

$$SBIC(p) = \ln\left|\overline{\Sigma}(p)\right| + \frac{\ln(T)}{T}(K^2 p) \tag{7}$$

$$HQIC(p) = \ln = \left|\overline{\Sigma}(p)\right| + \frac{2\ln\ln T}{T}(k^2 p) \tag{8}$$

Where, $\overline{\Sigma}$ is the quasi-maximum likelihood estimate of the innovation covariance matrix (see, Sin and White 1996).The lag order estimate $\hat{p}$ is chosen to minimise the value of the criterion function for $\{p : 1 \le p \le \overline{p}\}$ where $\overline{p} \ge p_0$ (see Quinn 1980; Paulsen & TjQstheim 1985). So, $\hat{p}^{SIC} \le \hat{p}^{AIC}$ *for* $\mathrm{N} \ge 8$, $\hat{\mathrm{p}}^{\mathrm{SIC}} \le \hat{P}^{HQC}$ for all T, and $\hat{\mathrm{p}}^{\mathrm{HQC}} \le \hat{p}^{AIC}$ for $\mathrm{T} \ge 16$.

Table 3 presents the outcome of optimum lag length order based on three criterions. It is found that the optimum lag length order based on the entire criterion is one indicated by the star sign in the table.

Table 3. Selection of Optimum Lags Order

Lags	AIC	SIC	HQIC
0	3.5277	3.7432	3.6044
1	-2.7964*	-1.5036*	-2.3365*
2	-2.5320	-0.1618	-1.6887
3	-2.6727	0.7748	-1.4461

*Indicates lag order selection, AIC: Akaike Information Criterion; SBIC: Schwarz Bayesian Information Criterion & HQIC: Hannan Quinn Information criterion

Source: author's own calculation

After checking stationarity, order of integration and optimum lag order selection of the macro-economic variables considered for this study then we may go to check co-integration relationship among the variables. According to Asteriou et. al., (2007), the thought of co-integration was first introduced by Granger (1981) and then extended by Engle and Granger (1987), Engle and Yoo (1987), Phillips and Ouliaris (1990), Stock and Watson (1988), Phillips (1986 & 1987), Johansen and Juselious (1990) and Johansen (1988, 1991 & 1995). Harris (1995) says that co-integration means presence of stable association in the long-run from which an economic system converges in due course. So, co-integration becomes an overriding requirement for any economic model using non-stationary time series data. If the variables don't co-integrate then we face the problem of spurious regression and as a result the parameters estimations will be meaningless. Suppose, two variables Y_t and X_t have long-run equilibrium relationship and to establish this it requires that a linear combination of Y_t and X_t must be stationary [I(0)] and this can be estimated from the following regression equation as under:

$$Y_t = \alpha_0 + \beta X_t + \varepsilon_t \quad (9)$$

From the above regression now considers the residuals and then run the following auxiliary regression:

$$\hat{\varepsilon}_t = Y_t - \hat{\alpha}_0 - \hat{\beta} X_t \quad (10)$$

If $\hat{\varepsilon} \sim I(0)$, then the variable Y_t and X_t are said to be co-integrated and they have a long-run or equilibrium relationship. Asteriou (2007) also says that if we consider more than two variables in regression model then there is a possibility of having more than one co-integrating vector that means the variables in the model might form many equilibrium relationships and thus the maximum-likelihood co-integration technique proposed by Johansen & Juselius (1990) is used that is expressed through VAR framework as follows:

$$Z_t = n + k_1 \Delta z_{t-1} + k_2 \Delta z_{t-2} + ... + k_p \Delta z_{t-p} + \Pi z_{t-p} + e_t \quad (11)$$

Here, five macro-economic endogenous variables are considered for co-integration analysis and that can be written under matrix notation as under:

$$Z_t = (\ln BSE_t, \ln GDP_t, \ln FDI_t, \ln IMP_t, \ln EXP_t) \quad (12)$$

Here, Z_t is a 5*1 vector of non-stationary variables considered in log form and integrated of order one [I(1)] presented in table 2; 'n' is a 5*1 vector of parameters to be estimated and 'e_t' is a 5*1 vector of normally and independently distributed error term with their usual assumptions. The above VAR (p) model (Equation 11) may be reformulated in a Vector Error Correction Model (VECM) as below:

$$\Delta Z_t = n + \sum_{i=1}^{p} \Gamma_i \Delta Z_{t-i} + \Pi Z_{t-1} + e_i \quad (13)$$

Where, $\Pi = \sum_{i=1}^{p} k_{i-1}$ and $\Gamma i = -\sum_{j=i+1}^{p} k_j$

Matrix Π represents information regarding the long-run relationships (5*5 matrixes of parameters) and matrix Γ_i provides information regarding coefficients to be estimated (5*5 matrixes of coefficients). So, equation 13 is a purely Johansen's co-integration procedure. Now, matrix Π may be decomposed as follows:

$\Pi = \sim$; Where 'α' denotes the speed of adjustment to equilibrium coefficients and 'β' represents the long-run matrix of coefficients and thus, the term 'β' is equivalent to the error correction term ($Y_{t-1} - \alpha - \beta X_{t-1}$) in case of bivariate regression equation and this can be extended to multivariate equation.

Now, after specifying equation 13 with optimum lag order one (1) we can proceed to determine the number of co-integrating vectors and thus, here two different likelihood (LR) test ratios are applied (i) trace test and (ii) maximum Eigen value test.

Firstly, the trace test is defined as under:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \bar{\lambda}_i) \tag{14}$$

Here, 'T' denotes number of observations and $\hat{\lambda}$ is the ordered of Eigen value and 'n' is the number of separate series to be analysed. Here, the testable hypothesis as under:

H_0: number of co-integrating vector is $\leq$ r (r = 0, 1, or 2)

H_a: number of co-integrating vector is r

Similarly, the max Eigen value test can be written as under:

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{15}$$

Here, the following hypothesis is as under:

H_0: number of co-integrating vector is r

H_a: number of co-integrating vector is r + 1

Where, the null hypothesis r = 0 is tested against the alternative that r = 1 and r = 0 is also tested against the alternative r = 2.

Here, the critical values for both statistics are provided by Johansen and Juselious (1990). But, $\lambda_{\max}$ test is recognised as superior to find out the number of con-integrating vectors because it has sharper alternative hypothesis (Enders 2010) but the study tests both the statistics.

According to Asteriou et. el., (2007), in economics it is quite common that some variables are not only explanatory characteristics for a given dependent variable but they are also explained by the variables that they are used to determine. In this situation simultaneous equations (where endogenous and exogenous variables are clearly determined) are used. But Sims (1980) criticises this discrimination among the variables. He says that if there is simultaneity among a number of variables then all these variables should be treated in the same way that means there should be no distinction between dependent and independent variables and so, all the variable are treated as endogenous and therefore, each equation has the same set of regressors that leads to the development of the VAR models. In VAR model it is assumed that all the variables are stationary and even if the variables are not stationary at their level forms but make them stationary by applying differencing technique but they are not co-integrated. But, it is observed from the beginning that the variables are stationary at their first differences and order of integration is I(1) with optimum lag length one (1) and it is also observed from table 4 that according to the Johansen co-integration test there are at least three co-integrating equations based on test statistics (Trace statistics & Max-Eigen value) which indicates presence of equilibrium relationship in the long run.

Table 4. Johansen Co-Integration Test

Hypothhesized no. of CEs	Eigen value	Rank test (Trace)			Rank test (Max-Eigen value)		
		Trace Stat.	Critical Value (0.05)	P-value**	Max-Eigen Stat.	Critical Value (0.05)	P-value**
None*	0.656727	111.7823	69.81889	0.0000	39.56143	33.87687	0.0094
At most 1*	0.606123	72.22083	47.85613	0.0001	34.47355	27.58434	0.0056
At most 2*	0.422575	37.74728	29.79707	0.0049	20.31952	22.13162	0.0346
At most 3*	0.358446	17.49471	15.49471	0.0253	16.42288	14.26460	0.0224
At most 4	0.026793	1.004877	3.84146	0.3161	1.004877	3.841466	0.3161

*Trace & Max-Eigen value tests indicate three co-integrating equations at 5% significance level; *denotes rejection of the hypothesis at 5 percent level; **denotes MacKinnon-Haug-Michelis p-values

Note: author's own calculation

With this notion, vector error correction model (VECM) is developed here by inserting an error correction term (ECM) in the VAR model to examine the presence of long-run structural relationship of the endogenous variables along with the information regarding speed of adjustment from short run to long run (short-run adjustments dynamics). He, the co-integrating term is known as error correction term since the deviation from lone-run equilibrium is corrected gradually through a series of partial short-run dynamic adjustments. So, the VECM is a restricted VAR model.

According to Granger, the pth order VECM between $\Delta \ln X_t$ and $\Delta \ln Y_t$ may be written as:

$$\Delta \ln X_t = \sim_{10} + \sum_{i=1}^{p_{11}} {}_{11i} \Delta \ln X_{t-1} + \sum_{i=1}^{p_{12}} \text{¥}_{12j} \Delta \ln Y_{t-j} + \text{¢}_{13} ECT_{t-1} + e_{it} \tag{16}$$

$$\Delta \ln Y_t = \sim_{20} + \sum_{i=1}^{p_{21}} {}_{21i} \Delta \ln Y_{t-1} + \sum_{i=1}^{p_{22}} \text{¥}_{22j} \Delta \ln X_{t-j} + \text{¢}_{23} ECT_{t-1} + e_{it} \tag{17}$$

Where, α's are constant terms; 'β' and 'γ' are the regression coefficients to be estimated; 'e' is the random error term with its usual assumption; 'p' is the optimum lag order; the error correction term is denoted by ECT which is derived from the long-run co-integration relationship; and 'Δ' is difference operator.

Now, the two variables VECM can be extended and applied in multivariate VECM as below:

$$\Delta \ln BSE_t = \sim_0 + \sum_{i=1}^{p} {}_1 \Delta \ln BSE_{t-i} + \sum_{i=1}^{p} {}_2 \Delta \ln GDP_{t-i} + \sum_{i=1}^{p} {}_3 \Delta \ln FDI_{t-i} + \sum_{i=1}^{p} {}_4 \Delta \ln EXP_{t-i} + \sum_{i=1}^{p} {}_5 \Delta \ln IMP_{t-i} + \text{¢} ECT_{t-1} + e_{it} \tag{18}$$

$$\Delta \ln GDP_t = \sim_0 + \sum_{i=1}^{p} {}_1 \Delta \ln BSE_{t-i} + \sum_{i=1}^{p} {}_2 \Delta \ln GDP_{t-i} + \sum_{i=1}^{p} {}_3 \Delta \ln FDI_{t-i} + \sum_{i=1}^{p} {}_4 \Delta \ln EXP_{t-i} + \sum_{i=1}^{p} {}_5 \Delta \ln IMP_{t-i} + \text{¢} ECT_{t-1} + e_{it} \tag{19}$$

$$\Delta \ln FDI_t = \sim_0 + \sum_{i=1}^{p} {}_1 \Delta \ln BSE_{t-i} + \sum_{i=1}^{p} {}_2 \Delta \ln GDP_{t-i} + \sum_{i=1}^{p} {}_3 \Delta \ln FDI_{t-i} + \sum_{i=1}^{p} {}_4 \Delta \ln EXP_{t-i} + \sum_{i=1}^{p} {}_5 \Delta \ln IMP_{t-i} + \text{¢} ECT_{t-1} + e_{it} \tag{20}$$

$$\Delta \ln EXP_t = \sim_0 + \sum_{i=1}^{p} {}_1 \Delta \ln BSE_{t-i} + \sum_{i=1}^{p} {}_2 \Delta \ln GDP_{t-i} + \sum_{i=1}^{p} {}_3 \Delta \ln FDI_{t-i} + \sum_{i=1}^{p} {}_4 \Delta \ln EXP_{t-i} + \sum_{i=1}^{p} {}_5 \Delta \ln IMP_{t-i} + \text{¢} ECT_{t-1} + e_{it} \tag{21}$$

$$\Delta \ln IMP_t = \sim_0 + \sum_{i=1}^{p} {}_1 \Delta \ln BSE_{t-i} + \sum_{i=1}^{p} {}_2 \Delta \ln GDP_{t-i} + \sum_{i=1}^{p} {}_3 \Delta \ln FDI_{t-i} + \sum_{i=1}^{p} {}_4 \Delta \ln EXP_{t-i} + \sum_{i=1}^{p} {}_5 \Delta \ln IMP_{t-i} + \text{¢} ECT_{t-1} + e_{it} \tag{22}$$

Where, 'δ' represents coefficient of the error correction term (or speed of adjustment to it's of long-run equilibrium); β's are the coefficients of the lagged short-run associations (causality). The coefficients are to be estimated by using maximum likelihood estimation method.

The study also examines the direction of causality between the variables in VAR framework and thus, Granger causality (1969) test is used. To understand Granger causality, the study considers the following VAR models with one period lag has already been explained above:

$$\Delta lnBSE_t = \alpha_1 + \alpha_2\Delta lnBSE_{t-1} + \alpha_3\Delta lnGDP_{t-1} + \alpha_4\Delta lnFDI_{t-1} + \alpha_5\Delta lnIMP_{t-1} + \alpha_6\Delta lnEXP_{t-1} + \varepsilon_{1t} \quad (23)$$

$$\Delta lnGDP_t = \beta_1 + \beta_2\Delta lnGDP_{t-1} + \beta_3\Delta lnBSE_{t-1} + \beta_4\Delta lnFDI_{t-1} + \beta_5\Delta lnIMP_{t-1} + \beta_6\Delta lnEXP_{t-1} + \varepsilon_{2t} \quad (24)$$

$$\Delta lnFDI_t = \lambda_1 + \lambda_2\Delta lnFDI_{t-1} + \lambda_3\Delta lnGDP_{t-1} + \lambda_4\Delta lnBSE_{t-1} + \lambda_5\Delta lnIMP_{t-1} + \lambda_6\Delta lnEXP_{t-1} + \varepsilon_{3t} \quad (25)$$

$$\Delta lnIMP_t = \theta_1 + \theta_2\Delta lnIMP_{t-1} + \theta_3\Delta lnGDP_{t-1} + \theta_4\Delta lnBSE_{t-1} + \theta_5\Delta lnFDI_{t-1} + \theta_6\Delta lnEXP_{t-1} + \varepsilon_{4t} \quad (26)$$

$$\Delta lnEXP_t = \varphi_1 + \varphi_2\Delta lnEXP_{t-1} + \varphi_3\Delta lnGDP_{t-1} + \varphi_4\Delta lnBSE_{t-1} + \varphi_5\Delta lnFDI_{t-1} + \varphi_6\Delta lnIMP_{t-1} + \varepsilon_{5t} \quad (27)$$

Where, the values of the above variables at 't-1' represents one period lag value and the optimum lag order is determined in terms of AIC, SBIC and HQIC values explained above. The Granger causality tests are based on testing the joint significance of the lags of each variable in the system apart from its own lags. Thus, a test GDP Granger causes BSE is presented by testing the following hypothesis:

H_0: $\alpha_3 = 0$ (no Granger causality)

H_a: at least one of the restrictions fails

Where, the parameter α_3 is defined in the first equation (Equation 23) of the VAR framework and this hypothesis is commonly written as under:

H_0: GDP $\nrightarrow$ BSE

Ha: GDP $\rightarrow$ BSE

If $\hat{\alpha}_3$ in equation 23 is statistically different from zero (statistically significant) and $\hat{\beta}_3$ in equation 24 is not statistically significantly different from zero (insignificant) then, there is a unidirectional causality running from GDP to BSE that means GDP (Granger) causes BSE.

In the same way the reverse test that BSE Granger causes GDP is given by testing of the hypothesis as under:

H_0: $\beta_3 = 0$ (no Granger causality)

H_a: at least one of the restrictions fails

Where, the parameter β_3 are defined in equation 24 of the VAR framework and this hypothesis can be written as under:

H_0: BSE $\nrightarrow$ GDP

Ha: BSE $\rightarrow$ GDP

Here, also if $\hat{\beta}_3$ in equation 24 is statistically different from zero (statistically significant) and $\hat{\alpha}_3$ in equation 23 is not statistically significantly different from zero (insignificant) then, there is a unidirectional causality running from BSE to GDP that means BSE (Granger) causes GDP. If such situation arises where, $\hat{\ }_3, \tilde{\hat{\ }}_3, \tilde{\hat{\ }}_2$ and $\hat{\ }_2$ are statistically significantly different from zero (significant) then bilateral causality takes place and if opposite happens then the variables are independent each other.

The study also conducts variance decomposition analysis (VDC). It helps to determine how much of the variability in dependent variable is lagged by its own variance or it reflects the proportion of the forecast error variance of a variable which is explained by an unexpected change (due to innovation or shock) in itself as opposed to that proportion attributable to change in other interrelated variables. It also shows which of the independent variable is stronger in explaining the variability in the dependent variable over time or it focuses transparency of series due to any shock or innovation that flows from other series along with its own shock. Here, 10 years' VDC analysis is forecasted because the study considers annual data.

The study also applies some statistical properties such as serial correlation, heteroskedasticity and normality to check the goodness of fit of the above VECM models by considering the residuals which are derived from those models.

Finally, the parameter stabilization is an important assumption of any econometric model and thus, CUSUM test is applied. According to Brown et. al., (1975), CUSUM test is based on cumulative sums of scaled recursive residuals and plots the cumulative sum together with 5% critical lines against time. If the cumulative sum goes outside of the 5% critical lines, then it says about parameter instability (structural break) and vice-versa. It identifies parameter instability. The CUSUM test is based on the following recursive residual test statistic as below:

$$W_t = \sum_{j=k+1}^{T} \frac{w_t}{£_t}, \qquad \mathrm{j = k+1, ..., T} \tag{28}$$

with, $£^2 = \dfrac{\sum_{j=k+1}^{T}(w_t - \overline{w})^2}{T-K-1}$ and $\overline{W} = \dfrac{\sum_{j=k+1}^{T} w_t}{T-k}$

Where, 'w' denotes the recursive residuals; 'σ' is the standard error of the regression fitted to all "T" sample point; 'k' is the number of coefficients to be estimated.

Result & Analysis

The outcomes of long-run equilibrium relationships among the macro-economic variables are estimated under VECM framework (from equation18 to equation 22) is presented in table 5. Here, the long-run relationships are identified through the coefficient of the error correction term presented in each equation i.e., equation 18, 19, 20, 21 and 22 under VECM structure. It is observed from the table that the coefficient of the error correction term of the macro-economic variable BSE (dependent) under vector error correction model 18 is negative and statistically significant that means presence of long-run equilibrium relationship running from GDP, FDI, export and import to Bombay stock exchange (BSE) that also indicates that Bombay stock market converge towards its long-run equilibrium state at a speed of 55.04 percent in a year after any shock or innovation. But, in case of other variables considered under VECM framework, the long-run equilibrium relationships provided by the coefficients of the error correction terms are absent.

Table 5. Long-Run Equilibrium Relationship (VECM)

Dependent variable	δECT	t-statistic	probability
LnBSE	-0.550499	-2.160677**	0.0401
LnGDP	0.014850	0.205864	0.8385
LnFDI	-0.034698	-0.388803	0.7006
LnEXP	0.807659	1.770371	0.0884
LnIMP	0.112862	1.445795	0.1602

**significant at 5 percent level
Source: author's own calculation

It is assumed that if error correction model shows presence of long-run relationship among the variables then there must be subsistence of short-run causal association between the variables. Thus, table 6 emphasizes the result of short-run causality of the macro-economic variables and their direction. Table 6 shows the result of short run Granger causality. It is observed that when BSE, FDI and export respectively are used as an endogenous variable in the VAR framework then there is no evidence of uni-directional or bilateral short-run causality between the macro-economic variables. But, when import is considered as a dependent variable in the VAR model then evidence of short run uni-directional Granger causality is observed or in other words, export Granger causes import because the estimated test statistic is significant and therefore null hypothesis is rejected here. Similarly, it is also found that when GDP and import are considered as the endogenous variables respectively in the VAR models then bilateral short-run granger causality is observed because the test statics are seen to be statistically significant and thus it me be opined that Indian economy is an import led economy. It is also evident that BSE, GDP, FDI and export are jointly Granger causes import (dependent variable) in the short-run because these macro-economic variables have significantly influence Indian import in the short run.

Table 6. Granger Causality (Short-run)

Dependent variable: ΔLBSE			
Excluded	**Chi-sq**	**df**	**Prob.**
ΔLGDP	0.439737	1	0.5072
ΔLFDI	0.210525	1	0.6464
ΔLIMP	0.829770	1	0.3623
ΔLEXP	0.209178	1	0.6474
All	1.452314	4	0.8351
Dependent variable: ΔLGDP			
ΔLBSE	0.014701	1	0.9035
ΔLFDI	0.318997	1	0.5722
ΔLIMP	5.387694	1	0.0203**
ΔLEXP	0.978375	1	0.3226
All	7.544689	4	0.1098
Dependent variable: ΔLFDI			
ΔLBSE	0.413123	1	0.5204
ΔLGDP	0.004539	1	0.9463
ΔLIMP	0.007600	1	0.9305
ΔLEXP	0.651250	1	0.4197

All	1.482850	4	0.8297
Dependent variable: ΔLIMP			
ΔLBSE	1.095300	1	0.2953
ΔLGDP	3.646817	1	0.0562**
ΔLFDI	0.389921	1	0.5323
ΔLEXP	6.259753	1	0.0124**
All	13.07614	4	0.0109**
Dependent variable: ΔLEXP			
ΔLBSE	0.633306	1	0.4261
ΔLGDP	1.616018	1	0.2036
ΔLFDI	0.091388	1	0.7624
ΔLIMP	0.753944	1	0.3852
All	2.923617	4	0.5707

**significant at 5 percent level

Source: author's own calculation

The outcomes of variance decomposition of the variables are given in the following tables. Here, table 7 presents the outcome of VDC of the variable BSE which spreads over from short period to long period. In the short period i.e. in the second year, the impulse or shock to BSE is 96.80 percent variation of the fluctuation in BSE (own shock), shock to GDP can cause 0.05 percent fluctuation in BSE, shock to import can cause 1.92 percent fluctuation in BSE, shock to FDI can cause 0.07 percent fluctuation in BSE and impulse to export can cause 1.13 percent fluctuation in BSE also. But in the long run i.e. in the tenth year, the variation of fluctuation due to own shock is reduced to 72.46 percent, shock to GDP in the long run almost remains same but variation of fluctuation of import, FDI and export has contributed variation to BSE 4.21 percent, 7.31 percent and 14.35 percent respectively.

Table 7. Variance Decomposition of ΔLBSE

Period	S.E.	ΔLBSE	ΔLGDP	ΔLIMP	ΔLFDI	ΔLEXP
1	0.339063	100	0	0	0	0
2	0.390801	96.80718	0.055341	1.92648	0.076839	1.134164
3	0.469631	87.7597	1.125366	1.683034	0.981711	8.450188
4	0.504266	82.90107	1.007371	1.661496	3.34703	11.08304
5	0.530884	79.36071	1.633753	1.57017	5.792662	11.64271
6	0.55262	77.5801	1.509994	3.15263	6.195413	11.56186
7	0.582002	76.10113	1.368321	3.735809	6.175062	12.61968
8	0.608716	75.10634	1.544827	3.619193	6.169327	13.56031
9	0.631104	73.6641	1.7163	3.819048	6.792917	14.00763
10	0.653681	72.46646	1.64339	4.213484	7.319584	14.35708

Note: author's Own Calculation

Similarly, table 8 shows the outcome of VDC of GDP. It is found in the short run that shock to GDP can cause its own fluctuation of variation is 77.03 percent but in the long run it is reduced to 67.39 percent. In case of BSE and export in the short as well as in the long run, the fluctuation of variation to GDP remain almost same due to innovation. It is seen that FDI can fluctuates the variation of GDP at a higher rate (29.39 percent) as compared to the short run (17.45 percent) and the changes of fluctuation of variation is remarkable. But, the fluctuation of variation of GDP has slightly reduced in the long run due to shock to import.

Table 8. Variance Decomposition of ΔLGDP

Period	S.E.	ΔLBSE	ΔLGDP	ΔLFDI	ΔLEXP	ΔLIMP
1	0.095995	0.077976	99.92202	0	0	0
2	0.150661	1.743807	77.03615	17.45798	1.602853	2.159208
3	0.187336	1.672937	65.00597	30.78806	1.119848	1.413184
4	0.214582	1.286301	67.2811	29.02678	1.19423	1.211594
5	0.246166	1.541165	69.73528	26.55936	1.097291	1.066902
6	0.272894	1.758243	67.90183	28.48144	0.941566	0.916925
7	0.292588	1.68042	66.75761	29.77206	0.985978	0.803932
8	0.312861	1.593966	67.68455	28.99976	1.015511	0.706212
9	0.333213	1.619674	67.91062	28.8178	1.004657	0.647249
10	0.351145	1.654471	67.39412	29.39669	0.959951	0.594775

Source: author's own calculation

Likewise, the variance decomposition of FDI is given in Table 9. It is observed that the fluctuation of variation due to its own shock remains almost same in both the periods and changes are not remarkable. But, a significant upward change is seen when shock to BSE causes a wide fluctuation of variation to FDI in the long run approximately 38.83 percent as compared to the short run i.e. only accounts for 12.88 percent. Whereas, opposite situation is also observed in case of import. In the long run imports' shock causes fluctuation in variation to FDI is 56.67 percent as compared to the short run that is 83.53 percent. So in the long run the command of fluctuation of variation to FDI is reduced sharply but the amount of reduction is not small also.

Table 9. Variance Decomposition of ΔLFDI

Period	S.E.	ΔLBSE	ΔLGDP	ΔLFDI	ΔLEXP	ΔLIMP
1	0.607123	2.191882	0.000514	0.168889	97.63871	0
2	0.851592	12.88802	3.034043	0.531415	83.5381	0.008423
3	1.007188	20.85256	7.93112	0.609512	70.09081	0.515998
4	1.151254	26.09983	6.453049	1.049035	65.45486	0.943223
5	1.28554	30.32545	5.447808	1.121343	62.30952	0.79588
6	1.439154	33.55116	4.487864	0.904554	60.41813	0.638287
7	1.546159	35.31831	4.162676	0.783703	59.17578	0.559525
8	1.637184	36.97624	3.962882	0.699792	57.8552	0.50588
9	1.727698	37.94631	3.668416	0.644118	57.26052	0.480629
10	1.820169	38.83775	3.447414	0.601575	56.67802	0.435241

Source: author's own calculation

Again, table 10 presents the variance decomposition of export. It is found that the fluctuation of variation due to own shock is reduced to 3 percent in the long run as compared to the short run (9.30 percent) and the rate of reduction almost three times. But, a significant upward fluctuation of variation of 21.71 percent is seen to export in the long run due to shock to GDP as compared to the short run. Oppositely, a sharp reduction of fluctuation of variation to export of 5.09 percent is also found in the long run as compared to the short run (24.85 percent) due to shock to import. But, shock to FDI can cause 67.87 percent fluctuation of variation to export in the long run as compared to the short run (62.57 percent). Notably, the fluctuation of variation caused by FDI to export is remarkable both in the two periods. Although, the fluctuation of variation to export caused by shock to BSE is not remarkable both in the short run as well as in the long run.

Table 10. Variance Decomposition of ΔLEXP

Period	S.E.	ΔLBSE	ΔLGDP	ΔLFDI	ΔLEXP	ΔLIMP
1	0.103886	0.618152	2.457202	62.57827	9.493157	24.85322
2	0.167326	3.501864	8.010789	63.67415	9.302414	15.51078
3	0.235706	2.636031	21.04049	59.97953	7.29555	9.048404
4	0.299086	2.344662	20.47155	66.21781	4.805381	6.160601
5	0.350125	2.397327	19.08915	68.7783	3.836476	5.898752
6	0.389919	2.554044	20.60462	67.10499	3.542418	6.193927
7	0.426628	2.290418	21.9572	66.61164	3.454717	5.686025
8	0.462543	2.103182	21.71573	67.50835	3.375165	5.297568
9	0.493688	2.132024	21.45332	68.09355	3.161933	5.159177
10	0.522736	2.144434	21.87894	67.87407	3.007128	5.095424

Source: author's own calculation

Finally, the output of VDC analysis of import is presented in table 11. The own shock of import can cause fluctuation of variation of itself only 2.32 percent in the short run but in the long run it reduced to 0.98 percent. Although the own fluctuation is not notable. Similarly, the shock to BSE and export causes fluctuation of variation to import both in the short run and in the long run are not remarkable. But in case of GDP causes fluctuation of variation to import is significant in the long run (22.95 percent) as compared to in the short run (10.35 percent) and thus GDP has the adequate influence to changes variation of import here. While, the shock to FDI can cause changes of variation to import is 86.05 percent in the short run but in the long run it is reduced to 75.85 percent. Even though, FDI has the highest ability to influence the changes of variation to import due to shock as compared to the other variables.

Table 11. Variance Decomposition of ΔLIMP

Period	S.E.	ΔLBSE	ΔLGDP	ΔLFDI	ΔLEXP	ΔLIMP
1	0.118764	2.116694	1.603042	96.28026	0	0
2	0.213823	1.20777	10.35285	86.0502	0.067629	2.321556
3	0.298889	0.729915	18.88409	78.69152	0.158523	1.535953
4	0.381578	0.450797	21.52395	76.76394	0.098598	1.162711
5	0.447922	0.328533	21.08048	77.38247	0.078823	1.1297
6	0.50122	0.263688	21.74574	76.80237	0.072736	1.115462
7	0.550403	0.219168	22.68492	75.96793	0.068111	1.059864
8	0.596492	0.189242	22.70637	76.04352	0.064059	0.996811
9	0.638118	0.165426	22.69843	76.08215	0.059478	0.994516
10	0.676491	0.147483	22.9539	75.85665	0.060939	0.981027

Source: author's own calculation

Table 12 shows the outcomes of various residuals tests for checking the validity of the above VECMs and thus various tests are conducted here. It is found that the observed R^2 values of the residuals of all the variables are not statistically significant and thus null hypothesis is accepted that means residuals are free from serial correlation which is expected. Similarly, the null hypotheses of no heteroskedasticity are also accepted because observed R^2 are not statistically significant in all cases which is a good sign for model validity. Finally, the residuals are normally distributed of the VECMs because the J-B statistics are insignificant and thus null hypotheses (normal) are accepted in all cases which are desirable. Accordingly, it is confirmed from the above residual tests that the VECM is an appropriate model to examine equilibrium relationship among the variables and thus, the results are acceptable.

Table 12. Test for Checking VECM Validity

Dependent Variable	B-G LM test		B-P-G Het. Test		Normality Test	
	Obs* R^2	Prob.	Obs* R^2	Prob.	J-B Stat.	Prob.
Residuals of ΔLBSE	5.773471	0.0558	7.371930	0.9465	1.395793	0.497631
Residuals of ΔLGDP	0.401568	0.8181	12.34448	0.6528	5.578539	0.075241
Residuals of ΔLFDI	0.433783	0.8050	7.624837	0.9379	0.247562	0.733243
Residuals of ΔLEXP	2.118016	0.3468	25.08088	0.0489	0.288316	0.865751
Residuals of ΔLIMP	4.601216	0.1002	21.81441	0.1128	0.158473	0.923822

Note: Author's Own Calculation

Finally, the parameter stabilization of the VECMs is examined through CUSUM test and the outcomes are presented in various figures. It is observed that the cumulative sums of scaled recursive residuals are inside the 5% critical lines in all cases meaning that the parameters of the VECMs are stable there are no evidences of structural break in all the models.

CUSUM Plots for Stability Diagnostic

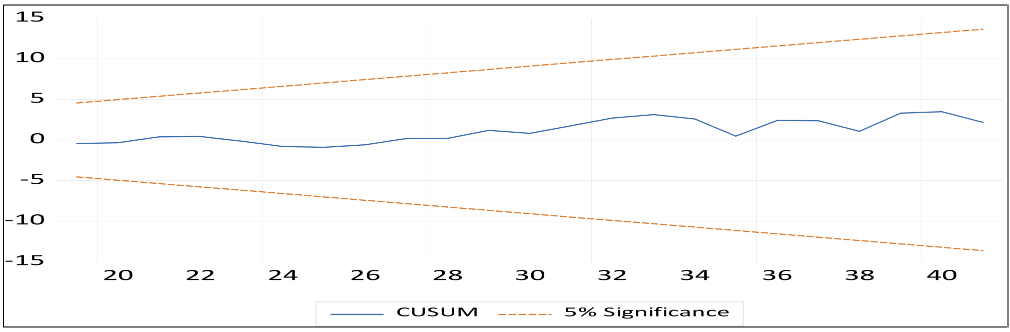

Figure 1. Residuals of BSE

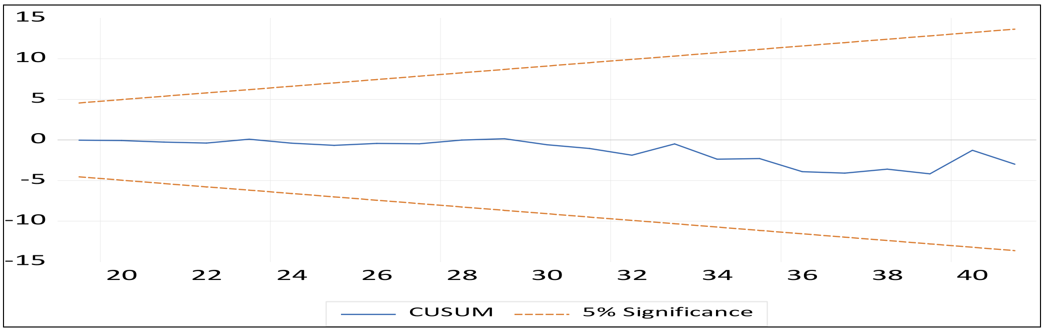

Figure 2. Residuals of GDP

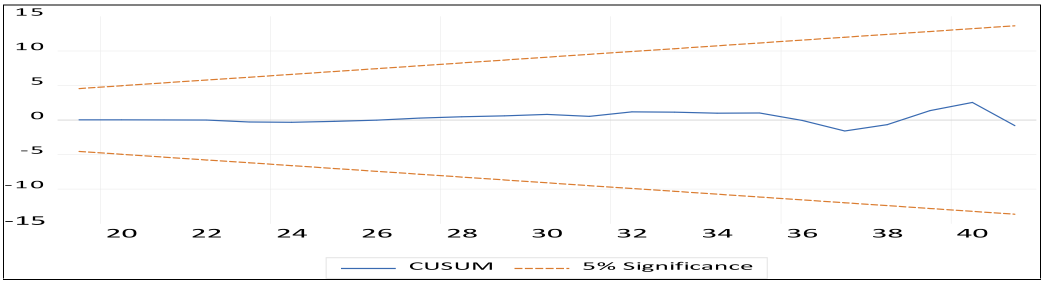

Figure 3. Residuals of FDI

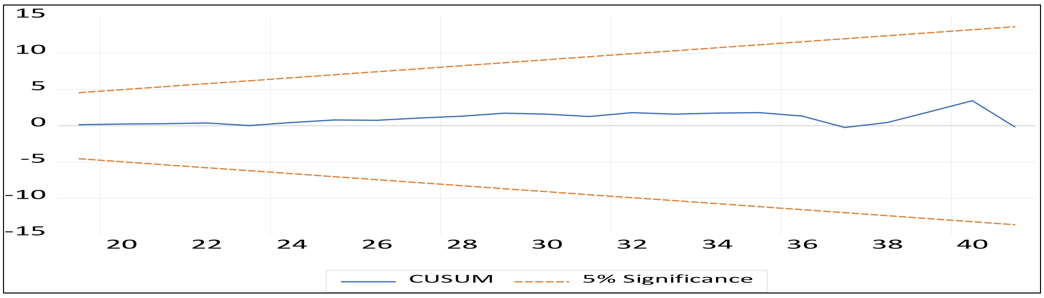

Figure 4. Residuals of Export

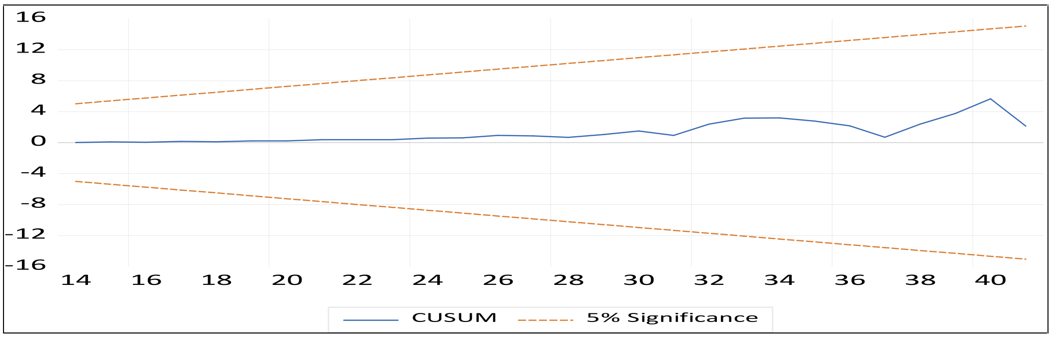

Figure 5. Residuals of Import

Conclusion

From the above discussion it is seen that the macro-economic variables are normally distributed after their log conversion and also stationary after their first differences. The variables are also integrated of order one with optimum lag length one. It is also observed from the co-integration analysis that the maximum co-integrated equation is three. The long-run equilibrium relationship is observed when BSE is considered as the dependent variable in the VECM framework. The presence of long run association is observed when GDP is the dependent variable and the speed of adjustment is 55.04 percent in a year after any shock. The bilateral causality is observed between import and GDP and it may be concluded that Indian economic development largely depends on import. Whereas, uni-directional causality is seen from export to import. But it is seen that all the macro-economic variables jointly Granger cause import in the short period. Variance decomposition technique analyses the changes of fluctuation of variation of the variables due to any shock to the endogenous variables. Finally, it is found from the residual tests that VECM is the appropriate model to check equilibrium association among the variables and CUSUM test authenticates about the stability of VECM model. It may be recommended that VECM approach may also be applied in other emerging economics for the improvement of understanding of the macroeconomic dynamics. The outcomes of this paper may be helpful to the policy makers to frame proper policy for the Government whether import is the only way to improvement Indian economy and the researchers may take this point for their further research for better understanding on the topic of co-integration and causality analysis.

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