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Causal Relationship between Real Activity and Stock Price in India

Ajay Prasad Uniyal, Assistant Professor, Govt P.G. College, New Tehri, Tehri Garhwal, Uttarakhand, ndia.

Dr. H.M. Singh, Assistant Professor, Govt. P.G. College Karnprayag, Chamoli, Uttarakhand, India.

Abstract - Stock market accelerates industrial growth and development through the mobilization and allocation of savings, risk diversification, liquidity creating ability and corporate governance improvement. It is believed that movements of stock prices depend on macroeconomic factors. The most important factor among the macro economic variables which are believed to influencing stock prices, is the real activity measured in terms of growth in Industrial Production. It is believed that stock market is a proactive market as it reflects the true conditions of the economic health. However, doubts are expressed in many quarters whether the recent stock market exuberance has anything to do with economic reality of the country. The study is motivated with two broad objectives in mind: first, it will examine the real activity relevance of stock market fluctuations and second, it will test the 'efficient market hypothesis' that the changes in stock prices cannot be predicted on the basis of past real activity information.. By applying the techniques of ADF Unit-root, Johensen Cointegaration, Vector error correction, Granger Causality /Block Exogeniety Wald test and Variance decomposition the study test the long-run and short-run causality between the BSE Sensex and the Industrial production. The monthly time series data for the period January 1991 – December2016 used for analysis. The Dickey-Fuller unit root test results indicate that both the series are integrated of order one. The Johansen cointegration test results indicate that there is a long run equilibrium relationship between the stock price and industrial production. The results from the VECM suggest that stock price Granger-cause industrial production in long run but not vice versa. The results of Wald test suggest that there is no short-run causality between stock price and industrial production. The variance decomposition of LNSENSEX shows that one unit shock in LNIIP explain arround 0.74% of its total variance after ten days. Remaining 99.26% variability is because of other unknown factors. On the other hand The variance decomposition of LNIIP show that the percentage of the variance that is attributable to the shock in LNSENSEX is 6.25 % of its total variance after 10 days, remaing 93.75% of the variance can be attributed to other unknown factors.

Keywords: Industrial production, BSE Sensex, Cointegration, VECM, Granger causalit

I. INTRODUCTION

Stock market accelerates industrial growth and development through the mobilization and allocation of savings, risk diversification, liquidity creating ability and corporate governance improvement. It is believed that movements of stock prices depend on macroeconomic factors. The most important factor among the macro economic variables which are believed to influencing stock prices, is the real activity measured in terms of growth in Industrial Production. The discounted-cash-flow valuation model states that stock prices reflect investors' expectations about future real economic variables such as corporate earnings, or its aggregate proxy, industrial production. If these expectations are correct on average, lagged stock returns should be correlated with the contemporaneous growth rate of industrial production. That is, real stock returns should provide information about the future evolution of industrial production. Relationship between stock returns and Index of Industrial Production can be viewed in two ways. One view is to see the stock market as the leading indicator of real activity meaning that stock market rationally signals changes in real activity. Another view is that Index of industrial Production influence and predicts stock returns. Stock return predictability by economic variables such as Industrial production is a well recognized phenomenon. It defines the relation of the variability of stock returns with the behaviour of Industrial production. A rational justification of return predictability based on industrial production can be understood in terms of variation in risk aversion and changing investment opportunity. It is believed that there is a direct relation between the macroeconomic indicators and stock return

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predictability. In case of industrial production in the economy, its behaviour not only indicates the behaviour of the production of goods in the economy but also indicates the change in income of the population over a period of time and the changes in the supply and demands of goods in the economy. This will give rise to a time changing risk premium on stocks. The ratio of labour income as a result of industrial production to aggregate consumption assumed to be an economically and statistically significant predictor of stock market excess returns over the risk free rate. Knowledge of sensitivity of stock markets to Index of Industrial Production and vice versa is important in areas of investment, finance and business environment. The analysis of the behaviour of the stock markets with real activity is necessary since this is the most sensitive segment of the economy and by analysing it the perception of the market as a whole can be easily observed.

The study is organised as follows after the introduction, the next section consists of Literature review and research gap, in the third section objectives, data descriptions and methodology are explained. Finally, the last section consists of conclusion, suggestion and policy implication.

II. REVIEW OF LITERATURE

Existing financial research literature consists of voluminous empirical evidence regarding relationship between stock returns and real activity. A variety of papers have empirically investigated the linkage between stock returns and real activity mainly for the USA as well as for other developed countries' stock market. On other hand the empirical work for the emerging markets is very limited. The existing empirical evidence can be categorised according to the direction of the observed relation. As far as the relation running from stock returns to economic activity is concerned, in most cases, real activity is found to be positively related to stock returns. This finding covers long time periods and is stable for various definitions of data series and different research methodologies. Some studies observed that stock returns Granger cause real activity, have forecasting ability and can be used as a leading indicator for real economic activity. Evidence provided for USA on such a relationship, within one-directional context by Fama (1981) summarizes real economic activity with real variables such as real GDP, capital expenditure and the growth rate of money demand obtained monthly, quarterly and annually based on the availability of the data. Multiple regressions were formed to show the relationship between the stock returns and the real variables. The result documented strong positive relationship between the stock returns and the real variables [5].

Cutler, Poterba and Summers (1989), analyzed monthly stock returns for the 1926- 1985 period, as well as annual returns for the longer period 1871- 1986 period to determine whether unexpected macro-economic developments can explain a significant fraction of share price movements. They selected seven measures of monthly macroeconomic activity for the analysis of their impact on stock returns. Their analysis has two parts; first, they estimate regression models relating each macroeconomic variable to its own history and that of the other variables. They used vector auto regressions to examine the causal relationship among variables. they estimate unexpected component of each time series and to consider the explanatory power of these news measures in explaining stock returns, second they adopt a less structured approach to the examination of macroeconomic news. After controlling for the influence of lagged economic factors on prices and measure the incremental explanatory power of current and future values of macroeconomic time series. They observed positive relationship between stock returns and industrial production and concluded a 1% increase in production increases share prices by about four-tenths of 1% [3].

Fama (1990) examines this relation for the US and shows that monthly, quarterly and annual stock returns are highly correlated with future production growth rates for 1953-1987. The degree of correlation increases with the length of the holding period. He argues that the relation between current stock returns and future production growth rates reflects information about future cash flows that is impounded in stock prices. Future growth rates of industrial production, used to proxy for shocks to expected cash flows, explain 43% of the variance of annual returns. A model of the reaction of stock returns to information about real activity developed. The model says that, if information about the production of a given month evolves over many previous months, the production of a given month will affect the stock returns of many previous months. A given monthly returns than has information about many future production growth rates, but adjacent returns have additional information about the same production growth rates. The R2 from regression of monthly returns on future production growth rates will then understate the information about production in the sequence of returns. Consistent with the evidence, the model says that the proportion of the variation in returns due to information about production is captured better when longer-horizon returns are regressed on future production growth rates [6].

Schwert (1990) expands the data set to include the entire 1889-1988 period for the US and found the evidence in conformity with Fama. However, as both authors admit, their results are subject to the limitations inherent in the use of an in-sample procedure such as OLS, which selects the explanatory variables on the basis of goodness-of-fit. Disentangling correlation and predictability within that framework is an impossible task [15].

Jongmoo Jay Choi, Shmuel Hauser, Kenneth J. Kopecky (1999) examine the relationship between industrial production growth rates and lagged real stock returns for the G-7 countries using both in-sample cointegration and

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error-correction models and the out of sample forecast-evaluation procedure. The cointegration tests show a long run equilibrium relationship between the log levels of IP and real stock prices, while the error correction models indicate a correlation between IP growths and lagged real stock returns for all countries except Italy. The out of sample test show that in several sub-periods the US, UK, Japanese and Canadian stock markets enhance predictions of future IP [9].

Among the studies investigating the bi-directional interdependencies between stock returns and real activity, the majority of the empirical findings indicate a positive relationship running from stock returns to real activity. Lee (1992), concluded that stock returns appear to explain a significant part of the variability in real activity in the USA and real activity seems to react strongly and positively to shocks in stock returns [12]. Similar results are provided by Hassapis and Kalivitis (2002), for the G-7 countries [8].

In most cases, stock returns are positively related to real activity and are useful in forecasting real activity. Stock returns seem in majority of cases to Granger cause real activity and real activity reacts positively to shocks in stock returns. However, the empirical evidence provided by Canova and Nicolo (2000), inconsistent with the above results. More specifically, the latter results indicate that the response of real activity to shocks in stock returns is negligible [2].

Dufour and Tessier (2006), investigated the causal relationship between monetary variables, real activity and stock returns for the USA and Canada found contradictory results. For the USA, they conclude that stock returns do not cause real activity while for Canada; they provide evidence on significant causal relations running from stock prices to real activity [4].

Kim (2003), examined causal relationship between stock returns and real activity for Germany the results show that stock returns play an indicative role regarding the development of future real activity [11].

Groenewold (2004), investigated the two-way relationship between the stock market and economic activity for Australia during the 1959-1999 period concluded that a positive stock market shock has a temporary negative effect on output [7].

Some prominent studies examined relationship between stock prices and macroeconomic variables in Indian context their findings are as follows:

Pethe and Karnik (2000), Investigated causal relationship between stock prices and industrial production for India during the period 1992 to 1997. They used monthly data on Sensex and Nifty for stock prices and index of industrial production for real activity by applying error correction model their study report uni-directional causality running from IIP to Stock Prices not vice-versa [14].

Ahmed (2008) , Investigated causal relationship among stock prices and macro economic variables in India during March 1995 to March 2007. He selected BSE Sensex and Nifty For stock prices and some key macro economic variables such as FDI inflows, industrial production index, money supply, exchange rates, interest rates and export. By applying Toda and Yamamoto Granger causality test and Johansen's co-integration test the study reported the presence of long run relationship between stock prices and FDI, stock prices and money supply, stock prices and IIP. Movement in BSE Sensex influences exchange rate and IIP. Results reveal that NSE Nifty cause exchange rate, exports, IIP and money supply, while interest rate and FDI cause NSE Nifty [1].

Singh (2010) , Examined relationship among stock prices and macro economic variables in Indian context for the period April 1995 to March 2009. He used monthly data on exchange rate, inflation , industrial production and BSE Sensex. By employing Granger causality test his study found bilateral causality between IIP and SENSEX [16].

Naik and Puja (2012), Examined relationship among stock prices and macroeconomic variables such as inflation, money supply, industrial production, exchange rate and interest rate. They used monthly data on BSE Sensex and IIP for the period April 1994 to June 2011 . By applying Johansen's co-integration and VECM they conclude that macro economic variables caused stock prices in long-run but not in short run. They found bi-directional causality between Sensex and IIP [13].

Joshi Pooja and Giri A.K. (2015), Investigated the long run and the short run relationship between stock price and a set of macroeconomic variables for Indian economy using monthly data from April 2004 to July 2014. By employing ARDL bounds testing approach to co-integration, VECM method and Variance Decomposition. Their results indicate a long run co-integrating relationship among the variables. Evidence suggests that the Index of Industrial Production, inflation and exchange rate influence stock prices positively, whereas, gold price influences the stock price negatively. The VECM result indicates that only long run causality running from all the variables used in the study to stock prices in India. The result of the variance decomposition shows that stock market development in India is mostly explained by its own shocks [10].

III. RESEARCH GAP

In contrary to the common belief that stock prices must reflect the economic fundaments, the empirical findings relating to the relationship between stock prices and macro-economic variables are rather mixed. Whereas, many studies suggest that stock prices reacts to changes in real activity and monetary variables, many other show that the relationship between them is rather feeble. This study made an effort to analyse the relationship between the industrial

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production and stock return behaviour. The effort is made to understand the nature of the time series data, the long term equilibrium relationship between the IIP and SENSEX, the contemporaneous and causal relationship between the IIP and SENSEX and then test the Efficient Market Hypothesis that it is impossible to beat the market because prices already incorporate and reflect all relevant information. One cannot outperform the overall market through expert stock selection or market timing, and the only way an investor can possibly obtain higher returns is by purchasing riskier investments. Stocks always trade at their fair value, making it impossible for investors to either purchase undervalued stocks or sell stocks for inflated prices. Asset prices fully reflect all available information. This study is supposed to contribute to the emerging line of research linking stock return predictability to economic real activities (IIP here) or vice-versa.

Objectives:

The study is motivated with two broad objectives in mind: first, it will examine the real activity relevance of stock market fluctuations and second, it will test the 'efficient market hypothesis' that the changes in stock prices cannot be predicted on the basis of past real activity information. The present study aims at the following:

1. To study the impact of Industrial production on stock returns.

2. To study the direction of long and short-run causality between Industrial Production and stock- returns.

3. To evaluate the information efficiency of stock market with respect to Industrial Production.

Hypothesis:

The basic null-hypothesis of this study is the non-causality between the Industrial production and aggregate stock prices. On the basis of statistical test employed in the study, the following hypothesis will be tested:

Augmented Dickey-Fuller (ADF) Unit Root Test

H0: The series is not stationary.

Ha: The series is stationary.

Johensen Co-integration Test

H0: There is no co- integration (long run relationship) between stock prices and industrial production.

Ha: There is co- integration (long run relationship) between stock prices and industrial production.

Granger Causality/Block Exogeniety Wald Test under VECM

If stock price is dependent variable:

H0: Industrial production does not cause stock price.

Ha: Industrial production cause Stock price.

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H0: Stock price does not cause Industrial production.

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If we reject the Ho, then we accept the Ha, setting the significance level to 5% and 1% at Degree of Freedom = n-2.

IV. METHODOLOGY

Period of the Study- The study covers a period of 26 years from January 1991 to December 2016.

Data- In this study monthly Index of Industrial production proxy for real activity and BSE Sensex data as a proxy of stock-prices in India have been used.

Sources of Data- Secondary data have been used in this study collected from different sources. The data on Index of Industrial production are obtained from the Hand Book of Indian Statistics published by the Reserve Bank of India while BSE SENSEX data are obtained from the website of BSE.

Analysis of Data- Since all the variables used in this study are time series, appropriate econometrics techniques used for time series analysis have been applied and EViews software has been used for data analysis. A general overview of these techniques has been presented in the following section.

Johansen Cointegration- Cointegration is an economy property of time series variables. If two or more series are themselves non-stationary, but a linear combination of them is stationary, then the series are said to be cointegrated. Generally a linear combination of two I (1) variables should also follow I (1) process, but if the series are cointegrated, the stochastic trend of one series is exactly cancelled out by the stochastic trend of other series and their linear combination follows I (0) process Johansen Cointegration test (Johansen 1988, 1991). Johansen's test is considered most powerful among the various tests presently available.

Johansen's test is based on reduced rank VAR method. Let us take an example of following ECM

$$\Delta \mathbf{Z}_t = \mathbf{A}_1 \Delta \mathbf{Z}_{t-1} \ldots\ldots\ldots\ldots \mathbf{A}_{p-1} \Delta \mathbf{Z}_{t-p} + \mathbf{BH'Z}_t + \boldsymbol{\varepsilon}_t$$

where, Z is the vector of 'k' cointegrating variables, Δ is the first difference operator. A1........p-1 are 'k×k' matrices of parameters reflecting model's short term structure, while BH' shows long-run equilibrium structure of the model. B is 'k×k' matrix of error correction term coefficients, reflecting the speed of adjustment from disequilibrium and H is 'k×k' matrix of cointegrating long-run relationships.

Johansen's procedure is designed to identify the number of long-term equilibrium relationships (r) or the order of the matrix H where, r≤ (k-1). H has k columns representing k possible cointegrating relations and k rows representing k variables. Therefore, H matrix shows the loading vectors of

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k variables to k possible cointegrating relation. Johansen's test seeks to determine whether any column of H is statistically indistinguishable from zero vectors; which can be done based on the eigen values of these column vectors. If suppose there are r real cointegrating relationship among the variables then there will be r non-zero eigen-values and rest of the k-n eigen-values will be statistically not different from zero. For example if we have four variables sharing a single equilibrium relationship than matrix H will have only one non-zero eigen-value and three zero eigen-values. But if there are two different equilibrium relationships exist between these four variables, we will have two non-zero and two zero eigen-values.

If all the k eigen-values are zero, the cointegration rank is zero implying that there is no cointegration relationship among the variables and VAR may be safely reformulated in-first differences without error correction term.

It is important to note that the test of cointegration does not differentiate between a single stationary variable and a stationary linear combination of two or more than two variables constituting a cointegrating relationship. Sometimes it is also possible that a cointegrating relationship indicated by cointegration test is contributed by only one stationary variable included in the VAR. In this case only one variable will load in that cointegration vector. Before executing a cointegration test, therefore, it must be ensured that all the variables included in the test are integrated of a common order d where d>0.

In Johansen's procedure, the eigen values are arranged in descending order and then the rank of cointegration r of matrix H is evaluated using the following two alternative maximum-likelihood ratio based statistics;

The Lamda Max ($\lambda \max$) Test:

This test examines the null hypothesis that the cointegration rank is equal to r against the alternative hypothesis that the cointegration rank is equal to $r+1$. The test statistic is calculated as follow:

$$\lambda_{\max}(r, r+1) = -Tin(1-\lambda_{r+1})$$

Where λ is the eigenvalue. The test is repeated for $r = 1....k$ until one fail to reject the null hypothesis.

The Trace Test:

This test examines the null hypothesis that the cointegration rank is equal to r against the alternative hypothesis that cointegration rank is k. The test is conducted in inverse sequence, that is $r = k, k-1, k-2....0$. The test statistic is computed as follow;

$$Trace = -T \sum_{i=r+1}^{k} \ln(1-\lambda_i)$$

Although both of these statistics are based on likelihood ratio approach, these do not follow the standard χ^2-distribution. Rather they have non-standard distribution. Johansen and Juselius (1990) have tabulated the simulation based critical values of these statistics. Osterwald and Lenum (1992) have conducted more comprehensive simulation experiments and produced revised critical values, which are now used by most of the econometric packages. These critical values are sensitive to deterministic trends included in VECM.

V. Vector Error Correction (VEC) Model

The vector error correction model (VECM) is a restricted Vector auto-regression (VAR) that has cointegration restrictions built into the specification, so that it is calculated for use with non-stationary series that are known to be cointegrated. The VEC specification restricts the long-run behavior of the endogenous variables to coverage to their cointegration relationship while allowing a wide range of short-run dynamic. The VECM is defined as follow:

$$\Delta X_t = \alpha_{10} + \theta_1 u_{t-1} + \sum_{i=1}^{p} \gamma_{1t} \Delta X_{t-1} + \sum_{j=1}^{p} \delta_{1j} \Delta Y_{t-1} + \varepsilon_{1t}$$

$$\Delta Y_t = \alpha_{20} + \theta_2 u_{t-1} + \sum_{i=1}^{p} \gamma_{2t} \Delta Y_{t-1} + \sum_{j=1}^{p} \delta_{2j} \Delta X_{t-1} + \varepsilon_{2t}$$

Where p is the order of the VAR, u_{t-1} is the lagged value of the error term obtained from the following regression:

$$X_t = \alpha + \beta Y_t + \gamma_t + u_t$$

In this equations, coefficients of $u_{t-1}(\theta_1$ and θ_2 respectively) are the error correction coefficients.

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Granger Causality (Block Exogenity) Test

In VAR model, the causality can be evaluated by examining the joint significance of lagged coefficients of one variable in the equation of another variable. This kind of significance testing is called the block significance test and it can be performed with the usual F-test or Wald-test used for evaluation of parameter restrictions. In context of the bivariate case presented above the causality can be examined by testing the following hypothesis using Wald test.

Hypothesis: 1

$$H0: \lambda_{12}{}^{1} + \lambda_{12}{}^{2} + \lambda_{12}{}^{3} = 0$$: y does not cause x

$$H1: \lambda_{12}{}^{1} + \lambda_{12}{}^{2} + \lambda_{12}{}^{3} \neq 0$$: y causes x

Hypothesis: 2

$$H0: \lambda_{21}{}^{1} + \lambda_{21}{}^{2} + \lambda_{21}{}^{3} = 0$$: x does not cause y

$$H1: \lambda_{21}{}^{1} + \lambda_{21}{}^{2} + \lambda_{21}{}^{3} \neq 0$$: x causes y

VI. PROCESS OF DATA ANALYSIS

First, we transformed both the series Sensex and Index of Industrial production into their natural log to get lnsensex and lniip series. Second we employed ADF Unit Root Test to check the stationarity of both the series under consideration. Third we generated return series by taking log difference of both the series. . Since both the series are integrated of same order I (1) therefore, VECM is appropriate to examine the causality between the variables under consideration. VECM model allows for the estimation of long-run relationship in non-stationary data based on cointegaration between the variables in a VAR. Next on the basis of SIC we selected appropriate lag length for Cointegaration and VECM Model. After confirming the cointegarating relationship between Sensex and Index of Industrial Production. We employed Vector Error Correction Model (VECM), Granger Causality/ Block Exogeniety Wald Test and Variance Decomposition Test to investigate the direction of causality between stock returns and Index of Industrial Production.. The results of ADF Unit Root Test, Cointegaration, VECM, Granger Causality/ Block Exogeniety Wald Test and Variance Decomposition Test are shown in the following table:

Results:

Table – 1 Unit-root test

	ADF Tests			
	At Level		At First Difference	
	t-test	Probability	t-test	Probability
LNIIP	-1.8254	0.3678	-3.4009	0.0117
LNSensex	-1.7106	0.4249	-16.0984	0.0000

Table 1 presents the results of ADF unit root test. The results show that both the series LNIIP and LNSENSEX are non-stationary at level since probability values are 0.3678 and 0.4249 respectively which are greater than significance level 0.05. So, we cannot reject the null hypothesis of unit root, therefore, it is concluded that variables are non-stationary at level. But stationary at their first difference as the probability values are 0.0117 and 0.0000 respectively which are less than significance level 0.05. So we can reject the null hypothesis of unit root therefore, it is concluded that variables are stationary at first difference. The result of ADF unit root test suggests that both the series LNIIP and LNSENSEX are non-stationary at level but stationary at their first difference. It implies that both the series are integrated of same order I (1).

Table – 2 Cointegration Model Selection Criterion

Data Trend	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	2	0	0	0	2
Max-Eig	2	0	0	0	0

Since both the series are integrated of same order I (1) therefore we investigate that whether the series are cointegarated or not for this purpose we examine all the five model of Johansen cointegaration test .Table -2 presents summary of all model selection criterion. The summary indicate that only model first has two cointegrating relationships between the variables under consideration therefore we employed mode

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Table – 3 Johansen Cointegration Tests Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.039902	16.80424	12.32090	0.0083
At most 1*	0.013570	4.221718	4.129906	0.0474

Table – 3 presents the results of cointegration rank test. The results show that Observed value of Trace Statistic is greater than critical value of Trace statistic and the probability value is less than significance level .05 therefore, the null hypothesis of no cointegration is rejected and the Trace statistic suggest two cointegrating relationship between the variables.

Table - 4 Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.039902	12.58252	11.22480	0.0287
At most 1*	0.013570	4.221718	4.129906	0.0474

Table – 4 presents the results of cointegration rank test. The results show that Observed value of Max-eigen Statistic is greater than critical value of Max-eigen statistic and the probability value is less than significance level .05 therefore, the null hypothesis of no cointegration is rejected and the Max-eigen statistic suggest two cointegrating relationship between the variables.

Vector Error Correction Model:

According to Granger representation theorem if two variables are cointegrated with each other, their relationship can be expressed in the form of an Error Correction Model. After confirming the cointegarating relationship between Sensex and Index of Industrial Production. We employed Vector Error Correction Model (VECM) to investigate the direction of causality between stock returns and Index of Industrial Production. Since both the series are integrated of same order I (1) therefore, VECM is appropriate to examine the causality between the variables under consideration.VECM model allows for the estimation of long-run relationship in non-stationary data based on cointegaration between the variables in a VAR. The following Vector Error Correction Model is estimated to examine long-run causality between LNIIP and LNSENSEX. Apart from long run causality we can analyse the short run causality between the variables in VECM framework. The short run causality is implied in the VAR terms of the model. The individual coefficients of the VAR cannot be interpreted; but after putting suitable linear restrictions the causality can be inferred. We use the Wald test to examine the short run causality between the LNIIP and LNSENSEX.

Table – 5 - Vector Error Correction Model (VECM)

Dependent Variable: D (LNSENSEX)
Method: Least Squares
Sample(adjusted):1991M04 2016M12
Included observations: 309
D(LNSENSEX)= C(1)*(LNSENSEX(-1) -1.8591LNIIP(-1)) +C(2)*D(LNSENSEX(1))+C(3)*D(LNSENSEX (-2))+C(4)*D(LNIIP(-1))+C(5)*D(LNIIP(-2))

	Coefficient	Std. Error	t-Statistic	Prob.	R-squared	0.012877
C(1)	0.000571	0.009661	0.059102	0.9529	Adjusted R-squared	-0.000111
C(2)	0.103847	0.057996	1.790595	0.0744	F-Test	.99144
C(3)	0.031738	0.057370	0.553207	0.5805	Sum squared resid	1.899683
C(4)	0.105087	0.083977	1.251385	0.2118	Log likelihood	348.2086
C(5)	0.164663	0.083886	1.962924	0.0506	Durbin-Watson stat	1.996915

Table – 5 presents the results of VECM. The results show that the coefficient of C (1) is neither negative nor statistically significant as probability value is 0 .9529 which is greater than significance level .05. This implies that the stock prices do not

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respond to the deviation from the equilibrium relationship. In other words, real activity does not cause stock prices in long run or there is no long-run causality running from real activity to stock prices

Table – 6 Wald Test:

Dependent Variable: D (LNSENSEX)

Null Hypothesis: C (4) =C (5) =0

Test Statistic	Value	Df	Probability
F-statistic	1.998590	(2, 304)	0.1373
Chi-square	3.997181	2	0.1355

Table - 6 presents the results of Wald Test. The results show that the probability value is 0.1373 and 0 .1355 respectively which are greater than significance level .05 therefore, it is concluded that there is no short –run causality running from real activity or Index of Industrial Production to stock prices.

Table – 7

Dependent Variable: D (LNIIP)

Method: Least Squares

Sample(adjusted):1991M04 2016M12

Included observations: 309

D(LNIIP) = C(1)*(LNIIP (-1) -0.5379*LNSENSEX(-1)) + C(2) *D(LNIIP(-1)) + C(3)*D(LNIIP(-2)) + C(4)*D(LNSENSEX(-1)) + C(5) *D(LNSENSEX(-2))

	Coefficient	Std. Error	t-Statistic	Prob.	R-squared	0.264376
C(1)	-0.041193	0.011693	-3.522909	0.0005	Adjusted R-squared	0.254697
C(2)	-0.514764	0.054672	-9.415574	0.0000	F-Test	27.31364
C(3)	-0.141439	0.054613	-2.589844	0.0101	Sum squared resid	0.805168
C(4)	0.002419	0.037757	0.064054	0.9490	Log likelihood	480.8301
C(5)	-0.063242	0.037350	-1.693237	0.0914	Durbin-Watson stat	1.810132

Table - 7 presents the results of VECM. The results show that the coefficient of C (1) is negative and its probability value is statistically significant as probability value is .0005 which is less than significance level .05. This implies that the real activity responds to any deviation from changes in stock prices in long-run. In other words, stock prices cause real activity in long run or there is a long-run causality running from stock prices to real activity or Index of Industrial Production .

Table – 8 Wald Test:
Dependent Variable: D (LNIIP)
Null Hypothesis: C (4) =C (5) = 0

Test Statistic	Value	Df	Probability
F-statistic	1.435371	(2, 304)	0.2396
Chi-square	2.870742	2	0.2380

Table - 8 presents the results of Wald Test. The results show that the probability value is 0 .2396 and 0 .2380 respectively which are greater than significance level .05 therefore, it is concluded that there is no short –run causality running from stock prices to real activity or Index of Industrial Production.

Table – 9 VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: LNSENSEX		
Excluded	Chi-sq	Prob.
LNIIP	3.997181	0.1355
Dependent variable: LNIIP		
Excluded	Chi-sq	Prob.

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LNSENSEX	2.870742	0.2380

Table – 9 presents the result of VAR Granger Causality/ Block Exogeniety Wald Test. The results show that probability value is greater than .05 in both the cases these are 0.1355 and 0 .2380 respectively, we cannot reject the Null Hypothesis of non causality. Therefore it can be concluded that there is no causality between Sensex and Index of Industrial Production meaning that both the variables are independent from each other or neither Sensex cause Industrial production nor Industrial production cause Sensex in short-run or there is no short-run causality between them.

Variance Decomposition Method employed to examine the sensitivity of stock returns to Industrial Production.

Table -10 Variance Decomposition of LNSENSEX

Period	S.E	LNSENSEX	LNIIP
1	0.079050	100.0000	0.000000
2	0.118488	99.80041	0.199587
3	0.150811	99.32248	0.677522
4	0.177212	99.30452	0.695480
5	0.200212	99.25923	0.740771
6	0.221082	99.24433	0.755672
7	0.240243	99.24371	0.756287
8	0.258132	99.24642	0.753583
9	0.274982	99.25424	0.745764
10	0.290971	99.26422	0.735777

Another summary statistic to present the results of a VAR analysis is variance decomposition analysis. The results of the variance decomposition are shown in Table - 10 . The variance decomposition of LNSENSEX series shows that one unit shock in LNIIP explain arround

0.74% of its total variance after ten days. Remaining 99.26% variability is because of other unknown factors.

Table – 11 Variance Decomposition of LNIIP

Period	S.E.	LNSENSEX	LNIIP
1	0.051464	2.234202	97.76580
2	0.056461	2.756996	97.24300
3	0.063586	2.296335	97.70366
4	0.069907	2.534134	97.46587
5	0.075001	2.805861	97.19414
6	0.080006	3.238175	96.76182
7	0.084532	3.831350	96.16865
8	0.088786	4.525035	95.47497
9	0.092821	5.336059	94.66394
10	0.096657	6.246472	93.75353

Another summary statistic to present the results of a VAR analysis is variance decomposition analysis. The results of the variance decomposition are shown in Table - 11 . The variance decomposition of LNIIP show that the percentage of the variance that is attributable to the shock in LNSENSEX is 6.25 % of its total variance after 10 days, remaing 93.75% of the variance can be attributed to other unknown factors.

VII. CONCLUSIONS

The objectives of the study were to investigate real activity relevance for stock market in our economy and to examine the efficiency of Indian stock market in terms of real

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activity information flow. For this purpose we have investigated dynamic interdependence between stock prices and industrial production in Indian economy. More specifically, we examined the long and short-run relationship, the kind and the strength of potential one and/or bi-directional linkages, running from stock prices to industrial production and/or from industrial production rates to stock prices. In this study, monthly BSE SENSEX data and Index of Industrial Production data have been used. All the data are log-transformed and Augmented Dickey Fuller (ADF) unit root test have been used to check the stationarity of data. In order to study the long and short-run relationship between Stock prices and Industrial Production, the Johensen Cointegration, Vector Error Correction Model, Granger causality/ Block Exogeniety Wald Test and Variance Decomposition are applied on the data. The VECM results indicate that there is uni-directional long-run causality between stock prices and industrial production, running from stock prices to industrial production not other way round meaning that the real activity responds to any deviation from changes in stock prices in long-run. In other words, stock prices cause real activity in long run where as the stock prices do not respond to the deviation from the equilibrium relationship. In other words, real activity does not cause stock prices in long run or there is no long-run causality running from real activity to stock prices. The results of Granger Causality/ Block Exogeniety Wald Test suggest that there is no short run causality between stock prices and industrial production. Variance decomposition or forecast error variance decomposition is used to aid in the interpretation of VAR model. The results indicate that one unit shock in LNIIP explain arround 0.74% of its total variance after ten days. Remaining 99.26% variability is because of other unknown factors. On the other hand . The variance decomposition of LNIIP show that the percentage of the variance that is attributable to the shock in LNSENSEX is 6.25 % of its total variance after 10 days, remaing 93.75% of the variance can be attributed to other unknown factors it implies that stock prices influence the indutrial production not vice-versa.

Suggestion: The results of the study are not consistently stable with the results of the previous studies due to difference between the variables used, the period covered and the research methodology employed. further research may be enhanced by incprporating more financial variables such as inflation, money supply, interest rates, balance of trade that may potentially affect the indian stock market.

Policy Implications: The results suggest that the stock market is informationally efficient with respect to industrial production or real activity fluctuation. If stock market is informationally efficient with respect to real activity, abnormal profit may not be earned consistently by using information on the changes in industrial production, accepting the efficient market hypothesis in Indian context. The findings of this study are important since informational efficiency in stock market implies on the one hand, that market participants are not able to develop profitable trading rules and thereby cannot consistently earn more than average market returns, and on the other hand, that the stock market is likely to play and effective role in channeling financial resources to the most productive sectors of the economy.

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