What drives the stock markets ? evidence from India

Fadzil, Anas and Masih, Mansur

INCEIF, Malaysia, Business School, Universiti Kuala Lumpur, Kuala Lumpur, Malaysia

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Anas Fadzil[1] and Mansur Masih[2]

Abstract: This study wants to investigate what drives the stock markets. India was taken as a case study. The standard time series techniques were used. The macroeconomic variables used were industrial production index, wholesale price index and exchange rate. The results demonstrate that the stock markets and macroeconomic variables are cointegrated suggesting the existence of a long-run equilibrium relationship between stock markets and macroeconomic variables. The findings further tend to indicate that stock markets are driven mainly by the WPI, which represents Inflation followed by the exchange rate. Therefore, the policy makers should focus on the inflation rate and exchange rate to stabilize the stock markets.

Keywords*:* Stock Market Index, Macroeconomic Variables, VECM, VDC, India

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[1] INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia.

2 **Corresponding author**, Senior Professor, UniKL Business School, 50300, Kuala Lumpur, Malaysia.

Email: mansurmasih@unikl.edu.my

1.0 Introduction

Globalization and financial sector reforms in India have changed the financial landscape of the Indian economy. Since the commencement of the financial sector reforms in the beginning of 1990's, the implementation of various reforms measures includes a number of structural and institutional changes in the different segments of the financial markets which brought a dramatic change in the functioning of the financial sector of the economy (Agrawalla, 2006). The positive change to the financial market has ever since promoted economic growth by providing an investment channel which attract domestic as well as foreign investment capital. This phenomenon is vital to the development and prosperity of India as one of the emerging markets in the world.

The stock market of the emerging economies is much different from the developing economies. While the former has been considered as matured, the latter began to develop rapidly in the last two decades. The emerging market has been characterized as the most volatile stock market despite the various attempts to develop and stabilize the stock market. The emerging markets are likely to be more volatile to other factors like the changes level of economic activities, changes in the political, changes in international economic situation and other macroeconomic factors as well. These factors would need to be taken into consideration when evaluating the economic fundamentals of the emerging market.

An efficient capital market drives the economic growth by stabilizing the financial sector. According to Efficient Market Hypothesis (Fama, 1970), in an efficient capital market, stock prices adjusted rapidly to the new information available, hence there investors would not be earning abnormal profits. The stock prices that reflect all information about the stock should include expectations of the future performance of the Companies as well. If the conclusion of Efficient Market Hypothesis is to be believed, then the changes of any macroeconomic variables should not affect the stock returns much. Therefore, if the stock prices reflect these assumptions correctly, then it should be used as a major indicator for the economic activities (Ray, 2012).

The determinants of macroeconomics variables of a particular country might be different from other countries. For example, the macroeconomic variables of India would be different from the macroeconomic variables of Malaysia. Therefore, study needs to be carried out to understand what could be the macroeconomics variables of India that could influence the stock prices. The findings could be used by other countries that have similar characteristics like India. Since India has been recognized as one of the fastest growing economies, it is relatively important to study such relationship. Moreover, India has changed after the liberalization policy. Policymakers could learn the changes that have been brought by the Indian Government and understand further how these changes have been implemented.

The aim of this study is to analyze the relationship between the stock prices and macroeconomic variables in India. This paper makes use of the latest available econometric techniques and examines the efficiency of the Indian stock market. Macroeconomic variables like industrial production, inflation and exchange rate are the important factors which affect the Indian capital market. The monthly data for 14 years starting from January 2000 were used for the study. The findings indicate that the BSE and macroeconomic variables are cointegrated hence suggests the existence of long-run equilibrium relationship between BSE and macroeconomic variables. The results showed that the industrial product and exchange rate were positively related to BSE however inflation was negatively related to BSE.

The findings from this study are expected to serve as an extension to the existing literature by providing some meaningful insight to the policy makers as well as the practitioners for them to regulate and administer developing countries like India. The macroeconomic variables used are considered to be emphasized as the policy instruments by the Government to stabilize the stock prices by administrating the industrial production and managing the exchange rate and inflation. The paper is organized as follows. The summary of the literature reviews which investigated the determinants of the stock prices is discussed in Section 2. The data sources as well as the econometric methodology is explained in Section 3. The empirical results are reported and commented in section 4. Finally, the conclusion of the study is provided in Section 5.

2.0 Literature Review

In an efficient capital market, the stock prices will adjust quickly to the newly released and available information. This means the indicated stock prices has taken into consideration all latest information pertaining to the stocks. This also further means that the prices includes the expectations of the future performance and developments of the Company. Therefore, an investor should not be in the position to use readily available information to predict the stock prices movements and make profit from the stocks trading. Hence, if the stock prices truly reflect these assumptions, then it should be used as a major indicator for the economic activities. So the dynamic relationship between the stock prices and macroeconomics variables can be used to make nation's macroeconomics policies (Mysami, Howe, Hamzah, 2004).

There have been many studies carried out in order to examine the relationship between the stock prices and macroeconomics variables. The results shown significant short run and long run relationship between stock prices and the macroeconomics variables. Maysami and Koh (2000) examine the dynamic relationship between the Singapore stock markets and macroeconomics variables (exchange rate, long and short term interest rates, inflation, money supply, domestic exports and industrial production) using the vector error correction model (VECM) which covered the period from 1988 to 1995. They found that all the macroeconomics variables have cointegrating relations with the changes in Singapore's stock market levels.

Tsoukalas (2003) examined the relationship between the stock prices and macroeconomic factor (exchange rate, industrial production, money supply and CPI) from 1975 to 1998 by using vector autoregressive model (VAR) in the emerging Cypriot equity market. The results indicate a good relationship between the stock prices and macroeconomic variables. He found that the higher demand for services like tourism and off-shore banking, there were a strong relationship between the stock prices and exchange rate in Cypriot economy. He further adds that relationship between stock prices and other macroeconomics variables such as industrial production, money supply and consumer prices reflect macroeconomics policies implemented by Cypriot monetary and fiscal authorities.

Mysami, Howe and Hamzah (2004) found a positive relationship between the stock returns and inflation rate. Interestingly, their findings is contradictory to other studies that suggest a negative relationship. The reason given by the authors was the active role played by the Government in preventing the prices escalation after the economy continued to progress since the 1997 financial crisis. The relationship between the short and long run was found to be positive and negative respectively. This is because long run interest rate serves to be a better proxy for nominal risk-free component which is used in the discount rate for stock valuation models and may also serves as a proxy for expected inflation in the discount rate.

Mukherjee and Naka (1995) examined the effects of the stock prices and six macroeconomics variables (exchange rate, inflation, money supply, industrial production index, the long term government bond rate and call money rate) by using vector error correction model (VECM) which covered 240 monthly observations for each variable from 1971 to 1990. The empirical evidence shows that these macroeconomics variables are cointegrated that is there is an existence of a cointegrating relation among the variables. They found positive relationship between Tokyo stock prices and exchange rate, money supply and industrial production index whereas detected negative relationship between Tokyo stock prices and inflation.

Al-Khazali and Pyun (2004) found a positive relationship between stock prices and inflation in the Pacific-Basin: Australia, Hong Kong, Indonesia, Japan, South Korea, Malaysia, the Philippines, Singapore and Thailand. They found negative relationship between stock returns in real terms and inflation in the short run while the cointegration tests on the same markets display a positive relationship between the same variables over the long run. They suggested that the stock prices in Asia are like those in the U.S. and Europe countries which appeared to reflect a time-varying memory associated with inflation shocks that make stock portfolios a reasonably good hedge against inflation in the long run.

From the above discussions, we can see that there are many literature studies that has been carried out to examine the relationship between the stock prices and macroeconomics variables among others exchange rate, long and short term interest rates, inflation, money supply, domestic exports, industrial production index, long term government bond rate and call money rate. Therefore, I find it interesting to investigate the long run as well as short run relationship between the India stock market (Bombay Stock Exchange) and macroeconomics variables being the industrial production index, inflation and exchange rate.

3.0 Data and Methodology

Before we proceed to analyze the relationship between BSE, IIP, EXC and WPI, it is necessary to conduct a unit root test on the variables to test if the variables are stationary or non-stationary. This is due to stationary or non-stationary of a series can strongly influence its behaviour and properties. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to check if the variables are stationary or non-stationary in their log and differenced from respectively.

Augmented Dicky-Fuller (ADF) Test: an extension of Dickey-Fuller (DF) regression. ADF test allows for more dynamics in the DF regression and consequently is over parametrized in the first order case but correctly specified in the higher order case (Johansen, 1991 and Fuller, 1976).

Phillips-Perron (PP) Test: makes a correction to the t-statistics of the γ coefficient. Non-parametric statistical methods are used in considering the serial correlation in the error terms with no lagged difference terms added. Moreover, the PP lag length follows the default available in the quantitative software. The unit root test using both ADF and PP tests are run at the level and first difference of the series order to determine the number of unit roots in the series (Phillips et. all, 1988).

Assuming that the series follows an AR (p) process, the ADF test makes a parametric correction and controls for the higher order correlation by adding the lagged difference terms of the dependent variable to the right hand side of the regression equation. However, since the ADF test is often criticized for low power, the unit root test has been complemented with PP test, which adopts a non-parametric method for controlling higher order serial correlation in the series. In both ADF test and PP test the null hypothesis is that data set being tested has unit root. The unit root tests also provide the order of integration of the time series variables.

In a multivariate context, if the variables under consideration are found to be I (1) (i.e. they are non-stationary at level but stationary at first difference). With the non-stationary series, co-integration analysis has been used to examine whether there is any long run relationship exists. However, a necessary condition for the use of co-integration technique is that the variable under consideration must be integrated in the same order and the linear combinations of the integrated variables are free from unit root. According to Engel and Granger (1987), if the variables are found to be co-integrated, they would not drift apart over time and the long run combination amongst the non-stationary variables can be established.

To conduct the Co-integration test, the Engel and Granger (1987) or the Johansen (1991) approach can be used. The Engel-Granger two-step approaches can only deal with one linear combination of variables that is stationary. In a multivariate practice, however, more than one stable linear combination may exist. The Johansen's cointegration method is regarded as full information maximum likelihood method that allows for testing co-integration in a whole system of equations. The fourth step is Long Run Structural Modeling (LRSM). This test confirms whether a variable is statistically significant and tests the long run coefficients of the variables against theoretically expected values.

Vector Error Correction Model (VECM) is the fifth step, and it is used to test Granger causality. The VECM shows the leading and lagging variables but it is unable to show relative exogeneity and endogeneity. The sixth step is Variance Decompositions (VDCs) ranked the variables by determining the proportion of the variance explained by its own past shocks whereby the variable that is explained mostly by its own shocks (and not by others) is deemed to be the most exogenous of all. Step seven, the Impulse Response Function (IRF) and step eight, Persistence Profiles (PP) is in graph form. IRF exposes relative exogeneity and endogeneity (similar to VDC) while PP estimates the speed with which the variables get back to equilibrium when there is a system-wide shock (unlike the IRF which traces out the effects of a variable-specific shock on the long-run relationship).

4.0 Empirical Results

This section will perform the eight steps of the time series technique. The steps are as follows:

4.1 Testing the Stationary/ Non-Stationary of the Variables

ADF Test:

Before starting the process, the stationary of variable should be checked first. The variable is stationary if it always has a constant mean, a constant variance and a constant covariance throughout the time. In this step, the objective is to check whether the variables chosen were stationary or not. The checking can be done by using the Augmented Dickey-Fuller Unit Root Tests (ADF) and the Phillips-Perron Test (PP).

We begin our empirical testing by determining the stationarity of the variables used. In order to proceed with the testing of cointegration later, ideally, our Variables should be I (1), in that in their original level form, they are non-stationary and in their first differenced form, they are stationary. The differenced form for each variable used is created by taking the difference of their log forms. For example, DBSE = LBSE – LBSEt-1. We then conducted the Augmented Dickey-Fuller (ADF) test on each variable (in both level and differenced form). The table below summarizes the results.

Variable	Test Statistics	Critical Value	Implication
Variable in Level Form			
LIIP	-3.0407	-3.4389	Variable is non-stationary
LEXC	-3.0959	-3.4389	Variable is non-stationary
LWPI	-1.5963	-3.4389	Variable is non-stationary
LBSE	-2.4532	-3.4389	Variable is non-stationary
Variable in Differenced Form			
DIIP	-8.0326	-2.8799	Variable is stationary
DEXC	-3.6050	-2.8799	Variable is stationary
DWPI	-5.8256	-2.8799	Variable is stationary
DBSE	-5.3949	-2.8799	Variable is stationary

Relying primarily on the AIC and SBC criteria, the conclusion that can be made from the above results is that all the variables we are using for this analysis are I (1), and thus we may precede with testing of cointegration. The null hypothesis for the ADF test is that the variable is non-stationary. In all cases of the variable in level form, the test statistic is lower than the critical value and hence we cannot reject the null. Conversely, in all cases of the variable in differenced form, the test statistic is higher than the critical value and thus we can reject the null and conclude that the variable is stationary (in its differenced form). Note that in determining which test statistic to compare with the 95% critical value for the ADF statistic, we have selected the ADF regression order based on the highest computed value for AIC and SBC.

PP Test:

PP test also can be used to test whether the variables are stationary or not. The result is concluded based on the P-value. P-value shows the error we are making when we are rejecting the null. Moreover, the p-value will be determined based on which level of confidence that you are choosing 95% or 90%. Therefore, if the p- value is less than the confidence interval, you will reject the null. If p-value is higher than the confidence interval, the null cannot be rejected. As mentioned above, the null hypothesis for this test states that the variable is non- stationary. The table below summarizes the results.

Variable	Test Statistics (P-Value)	Results
DIIP	[0.186]	Variable is non-stationary
DEXC	[0.088]	Variable is non-stationary
DWPI	[0.150]	Variable is non-stationary
DBSE	[0.722]	Variable is non-stationary

PP results for ‘Differenced’ Form

Variable	Test Statistics (P-Value)	Results
D2IIP	[0.000]	Variable is stationary
D2EXC	[0.000]	Variable is stationary
D2WPI	[0.000]	Variable is stationary
D2BSE	[0.000]	Variable is stationary

4.2 Determination of order or lags of the Var Model

Before proceeding to the cointegration test, it is compulsory to determine the optimum order (or lags) of the vector autoregressive model. We put the variables in log-differenced form. Referring to Table below, it is found that there is a contradicting optimum order given by the highest value of AIC and SBC. As expected, SBC gives lower order (order 1) as compared to AIC (order 5). This difference is due to the AIC tries to solve for autocorrelation while SBC tries to avoid over-parameterization.

	Choice Criteria	
	AIC	**SBC**
Optimal Order	5	1

Given this apparent conflict between recommendation of AIC and SBC, we address this in the following manner. First, we checked for serial correlation for each variable and obtained the following results.

Variable	Chi-Square (P-Value)	Implication (at 5%)
DIIP	0.015	There is serial correlation
DEXC	0.246	There is no serial correlation
DWPI	0.828	There is no serial correlation
DBSE	0.325	There is no serial correlation

Although the test shows these results we will move further in with the study using 5 lags (According to the result we obtained from AIC) because using a lower order, we may encounter the effects of serial correlation. The disadvantage of taking a higher order is that we risk over-parameterization. However, with the amount of data point available taking into consideration we decided to go with VAR order of 5.

4.3 Testing Cointegration

The cointegration test is very important in the sense that it will check whether all variables are theoretically related. If they are cointegrated, it means that there is a co-movement among these variables in the long term reaching the equilibrium, although they move differently in the short term. This test is very useful because it will prove the untested hypothesis or theory.

Johansen's test:

Once we have established that the variables are I (1) and determined the optimal VAR order as 5, we are ready to test for Cointegration. We have performed two tests to identify cointegration between the variables; namely Johansen method and Engle-Granger method. The Johansen method uses maximum likelihood (i.e. eigenvalue and trace) and may identify more than one cointegrating vectors while the Engle-Granger method can only identify one cointegrating vector. According to the Johansen method (Table below), we have found that there is at least one cointegrating vectors between the variables which confirm cointegration. This test considers the available number of cointegrating vectors or r. In the case when the null hypothesis is $r = 0$, there is no cointegration when we fail to reject the null. On the other hand, there is cointegration if the null is rejected.

Criteria	Number of Cointegrating Vectors
Maximal Eigenvalue	1
Trace	1
AIC	4
SBC	1
HQC	1

From the above results, we select one cointegrating vector based on the Eigen value and trace test Statistics at 95% level. The underlying VAR model is of order 5. From the result shown above, we are inclined to believe that there is one cointegrating vector based on intuition as well as familiarity that, there is relationship between stock market and macroeconomics variables and that the movement in macroeconomics variables are affecting the changes in the stock market prices in some way or other, to varying degrees. Based on the above statistical result as well as our insight, for the purpose of this study, we shall assume that there is one cointegrating vector, or relationship.

Statistically, the above results indicate that the variables we have chosen in some combination result in a stationary error term. The economic interpretation, in our view, is that the four variables are theoretically related, in that they tend to move together in the long run. In other words, the four variables are cointegrated. That is their relations to one another is not merely spurious or by chances. This conclusion has an important implication for investors' .Given that these series are cointegrated. Above is based on the Johansen method.

Engle-Granger method:

Alternatively, we have used the Engle-Granger method.

Variable	Test Statistics		Critical Value	Results
	AIC	SBC		
LIIP	-3.6196	-3.6733	-1.9588	Non-stationary
LEXC	-1.5133	-1.9588	-4.1693	Non-stationary
LWPI	-5.6655	-5.2601	-4.1693	Stationary
LBSE	-2.5083	-2.9193	-4.1693	Non-stationary

Here, it is found that of four variables at least one variable has the error term as stationary, which means that there is at least one cointegration between the variables. This result support earlier Johansen method test of cointegration.

4.4 Long Run Structured Modeling (LRSM)

This step will estimate theoretically meaningful cointegrating relations. We impose on those long-run relations and then test the over-identifying restrictions according to theories and information of the economies under review. In other words, this step will test the coefficients of our variables in the cointegration equations against our theoretical expectation. This LRSM step also can test the coefficients of our variables whether they are statistically significant.

Earlier, we have mentioned that we want to see the impact of macroeconomics variables on stock prices. In other words, our focus variable in this paper is stock market index (BSE) price. Thus, we first normalized LBSE (i.e. normalizing restriction of unity) at the 'exactly identifying' stage (Panel A). Next, we imposed restriction of zero on one of the macroeconomic variable at the 'over identifying' stage (Panel B).

When we normalized LBSE, we found that all the coefficients of the cointegrating vector are significant. However, when we imposed restriction of zero on WPI we found that the over identifying restriction is rejected (with a p-value of (.047) error while rejecting the null) and as a result we proceed with 'Panel A' and continue to include WPI as one of our variable in the following tests.

Table. Exact and over identifying restrictions on the Cointegrating vector

Variable	Panel A	Panel B
DIIP	7.0750*	6.5985
	(1.0949)	(1.0086)
DEXC	2.5600*	2.1076
	(.05594)	(.5341)
DWPI	-2.6228*	0.0000
	(0.4351)	(*None*)
DBSE	1.0000	1.0000
	(*None*)	(*None*)
TREND	0.0399	.0244
	(0.0114)	(0.0058)
Chi-Square	(None)	3.9403 (0.047)

***Indicates significance**

In general, the signs of all variables are in line with theoretical predictions. The co-integration results reveal that stock returns are positively and significantly related to the level of real economic activity as proxied by the index of industrial production. A positive relationship between stock price and real output is consistent with Ratanapakorn and Sharma, (2007), who found similar results on USA. The positive relationship indicates that increase in industrial production index increase the corporate earning which enhances the present value of the firm and hence the stock prices increase. It may also increase the national disposable income and therefore more retail investment in the stock market. The negative relationship between stock price and inflation support the proxy effect of Fama (1981) which explains that higher inflation raise the production cost, which adversely affects the profitability and the level of real economic activity; since the real activity is positively associated with stock return, an increase in inflation reduces the stock price. Pal and Mittal (2011), also found a negative relationship for India. However, this finding is contrary Ratanapakorn and Sharma, (2007) who finds a positive relationship between inflation and stock price suggesting that equities serve as a hedge against inflation.

4.5 Vector Error Correction Model (VECM)

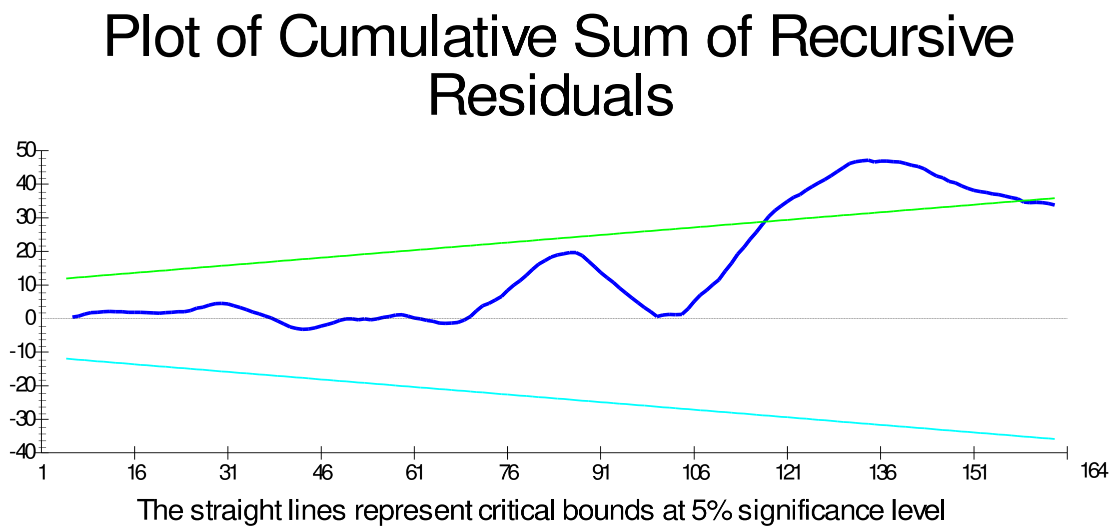
Error-correction term (ECT) is the stationary error term, in which this error term comes from a linear combination of our non-stationary variables that makes this error term to become stationary if they are cointegrated. It means that the ECT contains long-term information since it is the differences or deviations of those variables in their original level form. VECM uses the concept of Granger causality that the variable at present will be affected by another variable at past. Therefore, if the coefficient of the lagged ECT in any equation is insignificant, it means that the corresponding dependent variable of that equation is exogenous. This variable does not depend on the deviations of other variables. It also means that this variable is a leading variable and initially receives the exogenous shocks, which results in deviations from equilibrium and transmits the shocks to other variables. On the other hand, if the coefficient of the lagged ECT is significant, it implies that the corresponding dependent variable of that equation is endogenous. It depends on the deviations of other variables. This dependent variable also bears the brunt of short-run adjustment to bring about the long-term equilibrium among the cointegrating variables.

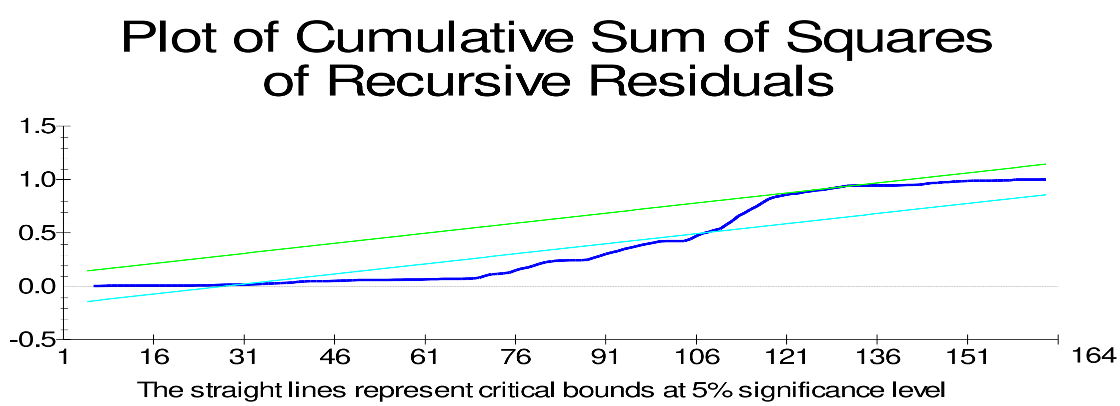
The previous four steps tested theories and confirm that there is cointegration between the variables but it did not show which the leader and the lagged variables. Step 5 onwards allows us to answer this shortcoming. The statistical results generated from these steps will be welcomed by policy makers. Policy makers want to know which variable is the leader to focus their policies on those variables to make the biggest impact. Thus, we have performed VECM and the results are summarized in Table below.

Variable	Chi-Square (P-Value)	Implication (at 5%)
LIIP	0.000	Variable is endogenous
LEXC	0.756	Variable is exogenous
LWPI	0.065	Variable is exogenous
LBSE	0.593	Variable is exogenous

The statistical results showed that exchange rate wholesale price, and stock market is exogenous while industrial production is endogenous. The diagnostics test allows us to check for specification problem in terms of autocorrelation, functional form, normality and heteroskedasticity. In addition, the coefficient of et-1 tells us how long it will take to get back to long-term equilibrium if that variable is shocked. The coefficient represents proportion of imbalance corrected in each period. For instance, in the case of the IIP Industrial production index, the coefficient is 0.12 this implies that, when there is a shock applied to this index, it would take, on average, 8.3 months for the index to get back into equilibrium with the other indices.

In addition, we have used the CUSUM and CUSUM SQUARE (Figure below) to check the stability of the coefficients. The CUSUM and CUSUMSQ tests employ the cumulative sum of recursive residuals based on the first set of observations and is updated recursively and plotted against the break points Here, it is found that the parameters are structurally unstable which indicates structural breaks. Structural breaks may be corrected by using dummy variables. The present scope of our project does not cover remedying the structural breaks and hence it has not been undertaken. Since VECM does not give information about relative exogeneity and endogeneity, we will have to perform the next step to identify the ranking of the variables.





4.6 Variance Decomposition (VDC)

The forecast error variance decomposition presents a decomposition of the variance of the forecast error of a particular variable in the VAR at different horizons. It will break down the variance of the forecast error of each variable into proportions attributable to shocks in each variable in the system including its own. The variable, which is mostly explained by its own past shocks, is considered to be the most leading variable of all. While we have established that the IIP is the endogenous index, we have not been able to say anything about the relative exogeneity of the remaining indices. In other words, of the remaining indices, which is the most exogenous variable compared to others. As the VECM is not able to assist us in this regard, we turn our attention to variance decomposition (VDC). Variance Decompositions (VDCs) are made up of orthogonalized VDC and generalized VDC. We started out applying orthogonalized VDCs and obtained the following results

Forecast at Horizon = 24 (months)

	LIIP	LEXC	LWPI	LBSE
LIIP	0.5024	0.0127	0.1407	0.3440
LEXC	0.0042	0.9525	0.0350	0.0080
LWPI	0.0089	0.0267	0.9079	0.0562
LBSE	0.0437	0.3179	0.0745	0.5636

Forecast at Horizon = 48 (months)

	LIIP	LEXC	LWPI	LBSE
LIIP	0.3538	0.0094	0.1904	0.4462
LEXC	0.0043	0.9504	0.0381	0.0070
LWPI	0.0070	0.0297	0.9026	0.0606
LBSE	0.0453	0.3272	0.0819	0.5454

For the above two tables, rows read as the percentage of the variance of forecast error of each variable into proportions attributable to shocks from other variables (in columns), including its own. The columns read as the percentage in which that variable contributes to other variables in explaining observed changes. The diagonal line of the matrix (highlighted) represents the relative exogeneity. According to these results, the ranking of indices by degree of exogeneity (extent to which variation is explained by its own past variations) is as per the table below:

No.	Index
1	LEXC
2	LWPI
3	LBSE
4	LIIP

Initially, we found this result is similar to our VECM result. Because we have found in VECM that the endogenous variable is LIIP, and in VDC the same variable is in fourth ranking so this confirm with our previous result. However, we should not forget that sometimes this one could give us wrong result because of the two important limitations of orthogonalized VDCs. Firstly it assumes that when a particular variable is shocked, all other variables are "switched off". Secondly and more importantly, orthogonalized VDCs do not produce a unique solution. The generated numbers are dependent upon the ordering of variables in the VAR. Typically, the first variable would report the highest percentage and thus would likely to be specified as the most exogenous variable. This is the case in our data, where LEXC, which appears first in the VAR order, is reported to be the most exogenous. To experiment with the extent to which this is true (that orthogonalized VDCs are "biased" by the ordering of variables), we changed the order of the VAR and found out completely different result.

Following this discovery, we decided to rely instead on Generalized VDCs, which are invariant to the ordering of variables. In interpreting the numbers generated by the Generalized VDCs, we need to perform additional computations. This is because the numbers do not add up to 1.0 as in the case of orthogonalized VDCs. For a given variable, at a specified horizon, we total up the numbers of the given row and we then divide the number for that variable (representing magnitude of variance explained by its own past) by the computed total. In this way, the numbers in a row will now add up to 1.0 or 100%. The tables below show the result.

Forecast at Horizon = 24 (months)

	LIIP	LEXC	LWPI	LBSE
LIIP	0.5088	0.0129	0.1382	0.3399
LEXC	0.0036	0.8002	0.0469	0.1492
LWPI	0.0097	0.0290	0.9304	0.0307
LBSE	0.0343	0.2488	0.0611	0.6556

Forecast at Horizon = 48 (months)

	LIIP	LEXC	LWPI	LBSE
LIIP	0.3635	0.0098	0.1784	0.4480
LEXC	0.0036	0.7987	0.0505	0.1470
LWPI	0.0076	0.0323	0.9258	0.0341
LBSE	0.0353	0.2546	0.0667	0.6432

We can now more reliably rank the indices by relative exogeneity, as depicted in the table below.

No.	**Variable Relative Exogeneity**	
	At Horizon = 24	**At Horizon = 48**
1	LWPI	LWPI
2	LEXC	LEXC
3	LBSE	LBSE
4	LIIP	LIIP

From the above results, we can make the following key observations:

• From the above result we can see that our most exogenous variable is WPI in both horizon.

• The Generalized VDCs confirm the results of the VECM in that LIIP is the most endogenous variable.

• The relative rank in exogeneity is somewhat stable as time passes. Between 24 months and 48 months.

• The difference in exogeneity between the indices is not significant.

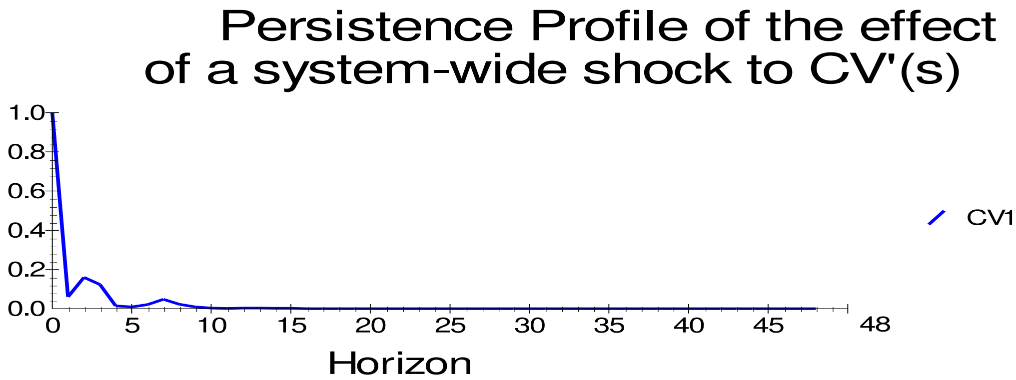
From the above result, we can conclude that, the WPI, which represent Inflation, will have a strong impact on BSE (stock market). Therefore, the policy makers should focus more and target the WPI.

4.7 Impulse Response Function (IRF)

The information, which is presented in the VDCs, also can be equivalently represented by Impulse Response Functions (IRFs). IRFs will present the graphical explanations of the shocks of a variable on all other variables. In other words, IRFs map the dynamic response path of all variables owing to a shock to a particular variable. The IRFs trace out the effects of a variable-specific shock on the long-run relations. For illustration purpose, we see in Appendix 7E that one standard deviation shock to LIIP (the most endogenous variable) is having least impact on the endogenous variables of LEXC, LWPI and LBSE.

4.8 Persistence Profile

The persistence profile illustrates the situation when the entire co-integrating equation is shocked, and indicates the time it would take for the relationship to get back to equilibrium. Here the effect of a system-wide shock on the long-run relations is the focus instead of variable-specific shocks as in the case of IRFs. The chart below shows the persistence profile for the co-integrating equation of this study, the chart indicates that it would take approximately 9 months for the co-integrating relationship to return to equilibrium following a system-wide shock.


Persistence Profile of the effect
of a system-wide shock to CV'(s)
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
35
40
45
48
Horizon
CV1

5.0 Conclusions

This study analyzed the relationship between the BSE stock market index and macroeconomic variables namely the industrial production index, the wholesale price index to represent inflation and the exchange rate. The methodology used in this study was time series econometric techniques including unit roots test, Johansen's cointegration test, vector error correction model (VECM) framework. The analysis used the monthly data for the period of January 2000 to August 2013 obtained from DataStream. It is believed that, the selected macroeconomic variable represent the state of the economy.

As a conclusion, the analysis showed that the Indian stock market index has a significant long-run relationship with the macroeconomic variables tested. The Johansen's co-integration test suggests that the stock market index has cointegrated with the macroeconomic variables. It is observed that in the long run, the stock prices are positively related to economic activity represented by industrial production index. A positive relationship between stock price and real output is consistent with Ratanapakorn and Sharma, (2007).

The wholesale price index that was proxied for inflation has found to be negatively related to stock price index. This support the proxy effect of Fama (1981) which explains that higher inflation raise the production cost, which adversely affects the profitability and the level of real economic activity since the real activity is positively associated with stock return, an increase in inflation reduces the stock price. Pal and Mittal (2011), also found a negative relationship for India. However, this finding is contrary to Ratanapakorn and Sharma, (2007) who finds a positive relationship between inflation and stock price suggesting that equities serve as a hedge against inflation.

This study confirms the beliefs that macroeconomic factors namely industrial production, inflation and exchange rates do affect the Indian stock market. However, the limitations of the study should not be over looked. This study is only testing the three selected macroeconomic variables whereas there are more relevant variables that could be included such money supply, level of GDP and level of government bonds. Inclusion of more variables with a longer time period may improve the results. The study can be extended by including more variables and analyzing sector wise stock index.

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