The Effect of Economic Indicators on the Volatility of Indian Stock Market: Using Independent Component Regression

*Ranajit Chakrabarty **Asima Sarkar

ABSTRACT

This paper studies the impact of economic indicators on the volatility of the Indian stock market. Volatility of the most characterizing indicator of the Indian stock market i.e. Nifty has been calculated by using a GARCH (1,1) model. Twelve economic indicators have been taken to see the effect of them on the GARCH volatility of the Indian stock market indicator i.e. Nifty. Since for GDP, only quarterly data is available, for rest of the indicators quarterly average have been taken for the study. While using the linear regression model taking GARCH Volatility of Nifty as the dependent variable and the 12 economic indicators as the independent variables, multicollinearity among most of the economic indicators (7 out of 12) is experienced, so it is not possible to drop all of these variables. Analyzing the data it has been found that no economic indicators are following Normal distribution. To eradicate the multicollinearity, an Independent Component Analysis (ICA) has been adopted to get the independent components of those economic indicators which are showing high multicollinearity. After having the independent components of those 7 economic indicators, a linear regression model has been fitted to the data. It has also been seen that GDP is significant neither in the linear regression model before ICA nor after ICA. So, it is judicious to drop this independent variable (GDP) so as to increase the number of data points, since rest of the variables are having monthly data points. After taking the monthly data of the rest of the 11 indicators, the same set of analyses have been performed and has been seen that the result of the Independent Component Regression has been improved

1. Introduction

The co-movement of the stock market and the macroeconomic variables are being extensively studied in developed capital markets since 1970s. The educational motivation for studying the effect of the macroeconomic indicators on the stock market volatility is the plethora of literatures on the same.

Lee (1992) examines the causal relationship among asset returns, interest rates, real activity and inflation using a multivariate Vector Auto Regression (VAR) model on the postwar U.S. data. This study shows that prior stock returns causes real stock returns. It experiences a strong positive response of industrial production growth to real stock returns. But this paper does not

* Department of Business Management, University of Calcutta, 1, Reformatory Street, Kolkata-700019 Email: ranajit4@hotmail.com, Phone: 9103324499418.

** Department of Basic Science and Humanities, Institute of Engineering and Management, Salt Lake, Electronics Complex, Sector V, Salt Lake, Kolkata-700091, Email:, Mobile: 9832243083.

find any causal relationship between the stock returns and the inflation rate.

The definition of the efficiency of a financial market is stated as the response of the current values or prices to the arrival of each of the new information and also the reflection of that information on the returns. In lucid language, it can be said that, there is no investors who can predict the future prices on the basis of readily available information so as to make profit out of it, if the market is an efficient market. Fama (1970) asserts that the Efficient Market Hypothesis (EMH) has important role to the policy making and the stock broking industry. Economic theory suggests that the level of economic activities should be reflected by the movement of stock prices or the stock market indices. Hence the causal relationship between the macroeconomic variables and the stock market volatility is important for the macroeconomic policies of a country. Chong and Goh (2003) examine the effect of money supply and interest rate on the stock prices. This study concludes that according to EMH all the information currently known from the economic indicators will be reflected on the current stock prices resulting to which no investor will be able to earn exponential profit by predicting the future stock market movement.

Considering this matter, the relationship between macroeconomic variables and economic activity in developing countries still needs lengthy analysis and more research attention. The purpose of this paper is to investigate empirically the relationship between stock market volatility and other macro variables in India. This paper has been segregated into two sections: A) Quarterly data analysis and B) Monthly data analysis.

In the first section, twelve macroeconomic indicators which are Consumer Price Index (CPI), Gross Domestic Product (GDP), India Industrial Production (IIP), Inflation Rate (IR), Interbank Interest Rate (IIR), Money Supply M1 (M1), Money Supply M2 (M2), Money Supply M3 (M3), India Foreign Exchange Reserves (IFER), Export (E), Balance of Trade (BT) and Import (I) have been taken into consideration. While taking the GDP as one of the explanatory variable in this study, it was obvious that the data of all other variables are to be taken in quarterly mode. Since Nifty is the most efficient indicator of the National Stock Exchange (NSE), it has been taken as the dependent variable. Using a GARCH (1,1) model, the volatility of the Nifty has been calculated and then the new series of the Nifty volatility has been used as the response variable and the quarterly returns of all the twelve economic indicators have been taken as the set of explanatory variables. A linear model is fitted to these set of variables and after that a Variance Inflation Factor (VIF) is calculated to understand the presence of multicollinearity amongst the macroeconomic variables. Seven out of twelve variables have been found to have high multicollinearity (>4). There are a number of ways to eradicate the multicollinearity amongst the independent variables; the first and foremost is to drop those variables, second is to transform the variables by using some standard transformations, third is to use a Principal Component Regression (PCR). For this study, as it can be seen that the majority of the variables are showing multicollinearity, it is almost impossible to drop all these variables since it may lose the generality of the study. Moreover, this paper deals with economic and stock market variables which do not usually show a Gaussian characteristic in their nature and so all the variables have been tested for the Normality by using a Jarque Bera statistic and it was found that almost no variables are following a Gaussian distribution. As it is already known that, PCR is based on the assumption of Gaussian distribution, PCR could not be used for eradicating the multicollinearity of the independent variables. Having the underlying assumption of Non-Gaussian distribution, Independent Component Analysis (ICA) has been employed for this purpose. After removing multicollinearity among those variables showing high multicollinearity, again a linear model is fitted to the response variable (Nifty GARCH Volatility) and the explanatory variables (returns of the 5 indicators not showing multicollinearity and the Independent Components (IC) of the indicators showing multicollinearity). And it has been observed that the result of the linear model before employing ICA have been improved after the adoption of the ICA. VIF is also calculated for the later model and there is no multicollinearity found among the explanatory variables. It has also been identified that GDP does not have a statistically significant contribution to the movement of the stock market volatility and above all except GDP all other data series are available in monthly mode. So, it has been decided to drop the variable GDP from the study so as to maximize the number of data points and this leads to the second section of this paper.

In the second section, data of all the variables have been taken monthly and the same set of analyses have been performed on the data set and then it has been seen that the result of the linear model has been improved in this section may be due to the enhancement of the data points which leads to better fitting of the model.

2. Literature Review

Economic growth of a country is directly related to the growth of the stock market of the same country (Levine and Zervos 1996; Levine, 2002; Nieuwerburgh et al., 2006; Enisan and Olufisayo 2009). Ample no. of researchers has devoted their time to study the behavior of stock exchange as stock exchanges show a complicated pattern of behavior. It has been observed that stock markets of any country are highly sensitive to the national and international events and the reaction to these stimuli is immediate. Stock exchanges are generally said to be the measuring tape of the financial condition of a country and that reacts to political, economic, national and international environment. This is why; volatility is one of the major characteristic of a stock market for a researcher to understand the general health of a country's financial market (Hameed and Ashraf, 2006). Recent global meltdown which occurred during the last phase of the year 2008 has affected all over the world. This recession is more devastating than the Asian financial crisis in 1997 and this recession in 2008 is being considered to be the greatest financial crisis after the great recession of 1930s (Llanto and Badiola, 2010). This crisis originated in United States in second half of 2007 with the mortgage crisis and got worst momentum in the year 2008. Developing countries were awfully affected by this crisis and experienced a downward growth in their economies (276 E3. J. Bus. Manage. Econ.). From the beginning of this crisis net capital inflows of money and resources got reduced drastically. FDI investments and portfolio investments got shrunk at the onset of this recession especially in the developing countries (Iqbal, 2010). Sudden decline is experienced in cross boarder stock markets from the first month of 2008 (Usman, 2010).

Not surprisingly, a large body of literature is devoted to the study of the stock market and its effects on macroeconomic variables. The co-movement between the macroeconomic indicators' volatility and the stock market volatility is analyzed and for the U.S. for the period from

1857 t0 1987. Financial asset volatility was found to be a good predictor of macroeconomic volatility (Schwert 1989). The stock return highly correlates with future production growth rates for the period 1953- 1987 in the U.S. (Fama 1990). Lee (1992) investigated causal relationships and dynamic interactions among asset returns, real economic activity, and inflation in the postwar US using a VAR approach. It was found that the stock returns help to explain real economic activities and also explain the variation in inflation to some extent. The causal relationship between the underlying macroeconomic policies and the stock returns is not established by using monthly data from 1970 to 1990 for 11 industrialized countries (Dropsy and Nazarian-Ibrahimi 1994). Real economic activity, inflation, stock returns, and monetary policy have been found to be highly interdependent and this dependence is validated by a data analysis using VAR model (Park and Ratti 2000). Monthly U.S. data from 1955 to 1998 is taken and it is found that shocks due to monetary tightening generated statistically significant movements in inflation and expected real stock returns, and it is also found that these movements are not found in opposite directions. In recent years, emerging markets have attracted increasing attention in the global integrated stock market. Vigorous research on the relationship between stock market behavior and various multiple macroeconomic variables for emerging countries has been conducted in the past decade. The analysis of the relationship between the stock market and various multiple macroeconomic variables using monthly data for South Korea from 1980 to 1992 was done (Kwon, Shin, and Bacon 1997). The Korean stock market showed more sensitivity towards macroeconomic indicators than that of the U.S, stock market and Japanese stock market as well. Empirical approach was employed to examine the extent to which stock market prices predicted future economic growth using annual data for 23 countries, including 15 developing countries, between 1951 and 1993 (Aylward and Glen 2000). The study asserts prediction of the economic growth by stock prices with variation in the extent of prediction in different countries. So, a stronger correlation is found in case of the G-7 countries than the developing countries. Exploring the relationship between the stock returns for the ASEAN-5 countries and five macroeconomic variables, it is found that in the long term all five stock price indices are positively correlated whereas those are negatively correlated when it comes to aggregate price level (Wongbangpo and Sharma 2002). Prior to and after the liberalization of financial market, a strong influence of macroeconomic factors on the stock returns has been established (Mukhopadhyay and Sarkar 2003). The result suggests for the post-liberalization period (since 1995), real economic activity, inflation, money supply growth, foreign direct investment, and the NASDAQ index were significant in explaining variations in Indian stock returns. In summary, the relationships between stock markets and macroeconomic variables have been examined in several developed and developing countries.

There has been a growing interest in recent years in relation to the impact of globalization on the integration of national economies through international trade, capital flows, foreign direct investment, and the spread of technology. In identifying the diversification of international investment portfolios, it has been seen that market inter-correlation is extremely important (Shamsuddin and Kim 2003). In addition to this, policy makers need to understand the influences on both economic growth and financial market performance, and the nature of the relationship between the two, in order to effectively manage their economies. According to some researchers economic growth is found to have huge influence on the profitability of firms by affecting the expected earnings, dividends of shares and stock price fluctuations (Fama 1990, Liua and Sinclairb 2008, Oskooe 2010). Furthermore, stock return volatility and the level of economic activity are linked through financial and operating leverages (Schwert 1989, 1990).

With regard to volatility, a unidirectional relationship between GDP and stock market volatility is captured (Diebold and Yilmaz 2008). Another study asserts the same finding i.e. positive influence on growth volatility from the stock market volatility (Caporale and Spagnolo 2003). In contrast to these studies, others have reported empirical evidence of a bidirectional relationship between stock market volatility and the volatility of GDP growth. GDP shocks offset stock market volatilities; however, stock market volatility may give a rise to GDP volatilities (Leon and Filis 2008).

In spite of plethora of literatures on the relationship between movement of the stock market and the economic indicators, there is still paucity of research papers on the relationship between the volatility of the stock market and the macroeconomic indicators. Moreover, there are a few which has addressed the problem of multicollinearity among the macroeconomic variables. This paper uses Independent Component Regression which has not been used for this purpose earlier.

3. Data and Methodology

3.1 Section A:

Daily data of Nifty for the period 1997 – 2012 has been taken from the NSE website. Monthly data of the eleven economic indicators (CPI, IIP, IR, IIR, M1, M2, M3, IFER, E, BT, I) are taken from the website: www.**tradingeconomics**.com. But since GDP data is not available in monthly mode rather it is available in quarterly mode so for GDP quarterly average data is taken for the study. Because of the nature of the GDP data, quarterly averages of rest of the variables have been calculated and then the returns have been calculated by differencing the last quarter value from the current quarter value.

$R_t = Q_t – Q_{t-1}$, where R_t is the quarterly return of an economic indicator at time t. Q_t and Q_{t-1} are the quarterly averages of an economic indicator at time t and t-1 respectively. For Nifty daily returns have been calculated from the data as following:

$R_{Nt} = N_t – N_{t-1}$, where R_{Nt} is the daily return of Nifty,

N_t and N_{t-1} are the closing values of Nifty on the t^{th} and $(t-1)^{th}$ day respectively.

Now, to calculate the volatility GARCH(1,1) model has been used. The GARCH(p,q) model is defined as follows:

$$Y_t = a_0 + a_1 X_t + \varepsilon_t, \ \varepsilon_t \sim N(0, \sigma_t^2) \qquad (1)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (2)$$

Using the GARCH(1,1) model, the series of volatility has been found out from the realized series of Nifty daily closing prices and then it has been taken as the response variable.

Table 1 : Result of the GARCH (1,1) model

Estimates of the coefficients	Standard Error	t value	p value
μ	0.11490	0.02039	0.0000***
ω	0.05598	0.01107	0.0000***
α_1	0.13314	0.01198	0.0000***
β_1	0.85478	0.01221	0.0000***

*** - H_0 is rejected at 0.1% level of significance.

Table 1.1: Descriptive Statistics of the Variables:

Variables	N	mean	Std. Dev.	Median	min	max	skew	kurtosis	Se
CPI	63	-0.04138	24.35011	0	-75.3633	150.38	2.804502	23.0105	3.067825
GDP	63	-0.00952	1.870632	0.1	-7.3	4.2	-1.40851	5.625903	0.235677
IIP	63	-0.00317	2.62283	0.166667	-10.0667	8.733333	-0.48584	3.379548	0.330446
IR	63	-0.05037	2.24698	-0.05	-7.1	5.853333	-0.11071	1.18604	0.283093
IIR	63	0.009365	0.730396	-0.03	-2.65667	1.346667	-0.79008	1.731404	0.092021
M1	63	-0.0455	387.3516	71.21667	-970.987	752.5433	-0.66126	0.455696	48.80172
M2	63	242.9673	5961.011	169.9267	-33113.7	33193.42	-0.10027	27.38286	751.0168
M3	63	20.18519	754.4395	43.42	-2109.81	2136.267	-0.35665	1.213533	95.05044
IFER	63	210.1344	763.9798	183.6567	-3431.9	3977.533	0.261812	14.8412	96.25241
E	63	18.38825	48.03034	12.81	-137.08	192.7	0.808805	3.724284	6.051253
BT	63	-16.2303	87.02638	0.98	-325.527	289.0533	-0.4957	3.562661	10.96429
I	63	34.88577	94.18501	14.03	-291.163	312.2833	-0.15329	4.123163	11.8662
Nifty GVQ	63	-0.02035	0.541983	-0.02605	-1.34167	1.432338	-0.36332	0.646763	0.068283

Augmented Dickey Fuller Test:

As it has been seen that before the first order difference of the data, all the variables were non-stationary, so the data of all the variables have been differenced once. Now, to test the stationarity of all the variables considered in this study, an Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1981) test has been employed. The following equations are estimated for each of the time series:

$$\Delta X_{t-1} = \alpha_0 + \alpha_1 t + \alpha_0 X_{t-1} + \sum_{i=2}^{k} \beta_i \, \Delta X_{t-i} + \square_{t-1},$$

Where Δ is the first forward difference operator defined as Ä$X_{t-1} = X_t - X_{t-1}$; t is the time trend; k denotes the number of lags used and õ$_{t-1}$ is the error term; ás and âs are parameters. The null hypothesis that series Xt is non-stationary can be rejected if â$_0$ is statistically significant with negative sign. The optimal lag k is chosen by using the Akaike Information Criterion (AIC).

Table 1.2 : Result of ADF

Variables	ADF Statistics	p value	Decision
CPI	-8.4023	0.01**	**Stationary**
GDP	-3.7838	0.02491*	**Stationary**
IIP	-4.197	0.009**	**Stationary**
IR	-8.0299	0.01**	**Stationary**
IIR	-3.6286	0.03809*	**Stationary**
M1	-6.3771	0.01**	**Stationary**
M2	-6.3044	0.01**	**Stationary**
M3	-8.871	0.01**	**Stationary**
IFER	-3.782	0.0251*	**Stationary**
E	-4.2092	0.01**	**Stationary**
BT	-6.5427	0.01**	**Stationary**
I	-6.1531	0.01**	**Stationary**
NiftyGVQ	-4.3268	0.01**	**Stationary**

** - H_0 is rejected at 1% level of significance.

* - H_0 is rejected at 5% level of significance.

After taking the first order difference of all the variables, it is observed that all the variables are stationary.

Now a linear model is fitted to the set of variables, taking NiftyGVQ as the dependent variable and all the 12 economic indicators as the independent variables as following:

$$NiftyGVQ_t = \mu + \sum_{i=1}^{12} \beta_i X_{it} + \square_t$$

Where $NiftyGVQ_t$ is the realized series of Nifty at time t, μ is the intercept of the linear model, β_i s are the coefficients of the i^{th} economic indicator, X_{it} are the i^{th} economic indicator at time t, i= 1,2,…, 12 and $\square_t$ is the error of the model. The model can also be re-written as:

$$NiftyGVQ = \mu + CPI_t + GDP_t ++ IIP_t + IR_t + IIR_t + M1_t + M2 + M3_t + IFER_t + E_t + BT_t + I_t + \square_t$$

Table 1.3 : Result of the Linear Model

Variables	Estimate	Standard Error	t statistic	p value
Intercept	4.462	1.261	3.538	0.00087 ***
CPI	-0.05069	0.01679	-3.018	0.00396 **
GDP	0.05358	0.05007	1.070	0.28964
IIP	-0.04003	0.01845	-2.170	0.03469 *
IR	0.0000895	0.01867	0.005	0.99619
IIR	0.1404	0.04512	3.112	0.00304 **
M1	0.00001192	0.0002087	0.057	0.95467
M2	-0.00000008853	0.00001670	-0.005	0.99579
M3	0.00007471	0.00007.257	1.030	0.30809
IFER	0.0001760	0.00005.393	3.264	0.00197 **
E	0.002262	0.004615	0.490	0.62620
BT	-0.003515	0.004677	-0.752	0.45571
I	-0.003691	0.004507	-0.819	0.41662
F-statistic : 4.172 with 12 and 51 d.f. $R^2 = 0.4953$				p-value: 0.0001517***

*** - H_0 is rejected at 0.1% level of significance. ** - H_0 is rejected at 1% level of significance.

* - H_0 is rejected at 5% level of significance. . - H_0 is rejected at 10% level of significance.

Variance Inflation Factor (VIF) of the above linear model has been calculated to capture the multicollinearity among the explanatory variables and tabulate in Table 4 as following:

$\mathbf{VIF_k = \frac{1}{1-R_k^2}}$, where VIF_k is the VIF for the k^th^ variable and R_k^2 is the R^2-value obtained by regressing the k^{th} predictor on the remaining predictors.

Table 1.4 : VIF

Variables	VIF	Variables	VIF
CPI	156.034685#	M2	4.71549
GDP	1.40031578	M3	904.282#
IIP	2.32581317	IFER	24.08553#
IR	1.43497276	E	1084.011#
IIR	2.27801306	BT	537.5638#
M1	396.476063#	I	2963.88#

VIF e" 5

From the results of the Table 1.4, it can be seen that the variables CPI, M1, M3, IEFR, E, BT, I are showing multicollinearity as the VIF of these indicators are greater than 5. Hence there is a need to eradicate this multicollinearity for which an Independent Component Analysis has been applied to find the independent components of those 7 indicators showing VIF greater than 5.

Independent Component Analysis (ICA):

ICA is a process of extracting a set of statistically independent data vectors from a given set of highly correlated vectors. Let $x_i(t)$ be an observed series for the i^{th} indicator at time step t with a mixing matrix A.

$$\text{Where } x_i(t) = \sum_{j=1}^{7} a_{ij} s_j(t)$$

$$\text{Let } X(t) = (x_1(t), x_2(t), x_3(t), \dots, x_7(t))^T$$

Now the problem is to extract independent data vectors by assuming that there is a de-mixing matrix W associated to the data as following:

$$Y(t) = WX(t) = WAS(t) \text{, where } A = [a_{ij}] \ i,j = 1, 2, \dots, 7, \ S(t) = (s_j(t)), \ j = 1, 2, \dots, 7.$$

If $W = A^{-1}$, then $Y(t) = S(t)$ and so perfect separation is occurred. W can be found out by assuming WA = PD, where P is a permutation matrix and D is a diagonal scaling matrix (Tong, Liu, Soon and Huang 1991).

It is now important to find out the matrix W under the following assumptions:

i) Vectors of S(t) are statistically independent.

ii) Utmost one variable follows Gaussian distribution and rest of the variables is non-Gaussian.

iii) S(t) are stationary in nature.

From the assumption ii) it can be seen that almost all the variables which the ICA is going to be applied on, should be Non-Gaussian. So, a Jarque Bera Statistic has been used to test the normality of the data vectors of all those seven variables.

Jarque Bera Test statistic is based on the null hypothesis

H_0 : the variable follows Gaussian distribution.

Against the alternative

H_1: it does not follow Gaussian distribution.

Table 1.5 : Result of Jarque Bera Statistic with d.f. 2

Name of Variable	Jarque Bera Statsitics	p value
CPI	1580.596	0.0000***
M1	5.9942	0.04889*
M3	6.1893	0.04529*
IFER	625.0285	0.0000***
E	48.0169	0.0000***
BT	40.136	0.0000***
I	50.04	0.0000***

*** H_0 is rejected at 0.1% level of significance

* H_0 is rejected at 5% level of significance

From Table 1.5, it can be seen that all the variables are Non-Gaussian at 0.1% level of significance except M1 and M3 which are Non-Gaussian at 5% level of significance. As a whole all the seven variables for ICA are non-Gaussian.

There are a number of ICA algorithms available to find out the independent components of a set of data vectors. A standard approach for batch ICA algorithms is the following two-stage procedure (Bogner 1992, Cardoso and Souloumiac 1993).

1. De-correlation or whitening : In other words, diagonalization of the covariance matrix of the input signals.

2. Rotation : The second stage minimizes a measure of the higher order statistics which ensures that the non-Gaussian output variables are as statistically independent as possible. It can be shown that this can be carried out by a unitary rotation matrix (Cardoso and Souloumiac 1993).

In this study, a fastICA algorithm has been used to perform the ICA on the data. The Algorithm is described below:

The data matrix X(t) is considered to be a linear combination of non-Gaussian (independent) components i.e. X = AS where columns of S contain the independent components and A is a linear mixing matrix. In short ICA attempts to 'un-mix' the data by estimating an un-mixing matrix W where XW = S. Under this model, the observed data series X(t) will tend to be 'more Gaussian' than the source components (in S(t)) due to the Central Limit Theorem. Thus, in order to extract the independent components this paper search for an un-mixing matrix W that maximizes the non-Gaussianity of the components.

In FastICA, non-Gaussianity is measured using approximations to neg-entropy (J) which is more robust than kurtosis-based measures and fast to compute.

Where $J(y) = = [E\{G(y)\} - E\{G(v)\}]^2$, v is the N(0,1) random variable.

The following choices of G are included as options

$$G(u) = \frac{1}{\alpha} \log\cosh \alpha u \text{ and } G(u) = -\exp(\frac{u^2}{2}).$$

The variables which showed high multicollinearity were super Gaussian (Kurtosis > 3) in nature. The first choice of G(u) performs better in case of super Gaussian variables, hence while running the fastICA algorithm, log-cosh distribution was chosen for the analysis of the data.

As soon as the independent components of the seven variables showing high multicollinearity is computed, another linear model is fitted to the data, taking NiftyGVQ as the dependent variable and 5 economic indicators not showing multicollinearity in its original form and the seven independent components of those variables showing high multicollinearity have been taken as the explanatory variables for the study as following:

$NiftyGVQ = \mu + CPI_{t@} + GDP_t ++ IIP_t + IR_t + IIR_t + M1_{t@} + M2 + M3_{t@} + IFER_{t@} + E_{t@} + BT_{t@} + I_{t@} + \square_t$

@ indicates the variables which have not been taken in their raw form rather the independent components of these variables have been taken for this study.

Table 1.6 : Result of the linear model after ICA

Variables	Estimate	Standard Error	t statistic	p value
Intercept	0.8053	0.3363	2.395	0.020329 *
CPI	-0.1570	0.05986	-2.622	0.011494 *
GDP	0.05358	0.05007	1.070	0.289637
IIP	-0.04003	0.01845	-2.170	0.034694 *
IR	0.00008951	0.01867	0.005	0.996192
IIR	0.1404	0.04512	3.112	0.003043 **
M1	-0.1345	0.06114	-2.200	0.032365 *
M2	0.03072	0.05225	0.588	0.559126
M3	-0.07047	0.05384	-1.309	0.196413
IFER	0.2385	0.05946	4.010	0.000199 ***
E	-0.05418	0.05659	-0.957	0.342929
BT	-0.1577	0.05210	-3.028	0.003860 **
I	-0.1829	0.07008	-2.610	0.011849 *
F-statistic: 4.172 with 12 and 51 d.f. $R^2 = 0.4953$				p-value: 0.0001517***

*** - H_0 is rejected at 0.1% level of significance.

** - H_0 is rejected at 1% level of significance.

* - H_0 is rejected at 5% level of significance.

. – H_0 is rejected at 10% level of significance.

Table 1.7: VIF (II)

Variables	VIF	Variables	VIF
CPI	1.369910	M2	1.043655
GDP	1.400316	M3	1.108093
IIP	2.325813	IFER	1.351750
IR	1.434973	E	1.224326
IIR	2.278013	BT	1.037766
M1	1.428853	I	1.877221

From Table 1.7, it is obvious that there exist no multicollinearity among any set of independent variables. Comparing the results of Table 1.3 and Table 1.6, it can be seen that after the application of ICA, number of significant variables has been increased as compared to the model before ICA. The linear model with multicollinearity i.e. before application of ICA gives only 4 significant variables (CPI, IIP, IIR and IFER) along with the intercept of the model whereas the linear model after ICA gives 7 significant variables (CPI, IIP, IIR, M1, IEFR, BT, I) along with the intercept of the model. Hence, ICA can be considered as an efficient tool for removing multicollinearity among the variables. From Table 6, it can be observed that there is a significant contribution of the variables CPI, IIP, IIR, M1, IEFR, BT and I on the movement of the Nifty GARCH volatility.

From Table 1.3 and Table 1.6, it could be found that GDP is not significant in any of the two models, hence it is judicious to drop the variable GDP since only because of this variable, all other variable had to be taken in quarterly average. Hence GDP is dropped from the study and the same set of analyses are carried out for monthly data of the eleven explanatory variables except GDP and monthly average of GARCH volatility of Nifty daily closing prices. And this leads to the second section of this paper.

Since the variable GDP is dropped from the study, all the indicators are taken in monthly mode and then return has been calculated for each of the eleven indicators as following:

$r_{mt} = I_{mt} - I_{m(t-1)}$, where r_{mt} is the return of indicators for monthly data at time t, I_{mt} and $I_{m(t-1)}$ are the monthly values of the indicators at time t and t-1 respectively.

Nifty GARCH volatility was already calculated for daily data in Section A, the same data has been used for Section B also. A monthly average of the Nifty GARCH volatility has been used as the response variable for this section.

Table 2.1: Descriptive statistics of the variables in monthly mode

Variable	n	mean	Std. Dev.	median	min	Max	skew	kurtosis	Se
CPI	191	0.750838	1.194979	0.65	-2.99	7.05	0.894381	4.126118	0.086466
IIP	191	-0.02042	3.021859	0.2	-9.7	11	-0.05556	1.545963	0.218654
InfR	191	-0.0166	1.111162	-0.02	-5.94	3.42	-0.64677	4.942745	0.080401
BIntR	191	0.003141	0.460513	0	-2.43	1.96	-0.45806	5.248061	0.033322
M1	191	82.49853	218.1991	47.08	-692.7	973.5	0.812548	3.876907	15.78833
M2	191	82.02728	10261.4	49.3	-100018	99971.6	-0.03062	91.42461	742.4888
M3	191	383.9865	435.3191	203.76	-398.7	1832	1.495856	1.694022	31.49858
ForEx	191	70.51047	1169.661	44.63	-11093.5	11296.19	0.068958	84.88364	84.63372
Export	191	6.578586	69.35901	2.41	-327.05	312.48	0.073766	5.060323	5.018642
Bal_Tr.	191	-4.89052	84.42604	-3.52	-397.02	314.37	-0.0984	5.4771	6.108854
Import	191	11.74325	82.23411	3.21	-245.5	409.7	0.495479	3.902386	5.950251
NiftyGVM	191	-0.00435	0.518566	0.01	-2.05	1.84	-0.12874	2.322772	0.037522

Stationarity of the monthly data of all the variables are checked by using ADF as in Section A.

Table 2.2: Result of ADF Test

Variables	ADF Statistics	p value	Decision
CPI	-5.2356	0.01**	**Stationary**
IIP	-5.6251	0.01**	**Stationary**
IR	-5.0145	0.01**	**Stationary**
IIR	-5.2783	0.01**	**Stationary**
M1	-6.3098	0.01**	**Stationary**
M2	-9.3231	0.01**	**Stationary**
M3	-5.0206	0.01**	**Stationary**
IFER	-7.4527	0.01**	**Stationary**
E	-6.7653	0.01**	**Stationary**
BT	-8.0053	0.01**	**Stationary**
I	-7.7166	0.01**	**Stationary**
NiftyGVM	-9.4848	0.01**	**Stationary**

** - H_0 is rejected at 1% level of significance.

NiftyGVM is the monthly average of Nifty GARCH volatility of daily closing prices.

From the result of the Table 2.2 it can be concluded that after taking the first order difference, all the variables are stationary.

Now, a linear model has been fitted on the monthly data described as below:

$$NiftyGVM_t = \delta + \alpha_0 CPI_{mt} + \alpha_1 IIP_{mt} + \alpha_2 IR_{mt} + \alpha_3 IIR_{mt} + \alpha_4 M1_{mt} + \alpha_5 M2_{mt} + \alpha_6\, M3_{mt} + \alpha_7\, IFER_{mt} + \alpha_8 E_{mt} + \alpha_9 BT_{mt} + \alpha_{10} I_{mt} + \square_{mt}$$

Where, suffix "mt" stands for the monthly returns at time t and $õ_{mt}$ is error term of the model for monthly data at time step t. ä is the intercept of the model.

Table 2.3 : Result of the linear model

Variables	Estimate	Standard Error	t statistic	p value
Intercept	4.362	0.8772	4.973	0.0000 ***
CPI	-0.04770	0.01153	-4.138	0.0000 ***
IIP	-0.02477	0.01031	-2.402	0.017337 *
IR	0.0009073	0.01337	0.068	0.945979
IIR	0.1148	0.03068	3.742	0.000245 ***
M1	0.0001033	0.0001181	0.875	0.382852
M2	0.0000001671	0.000005491	0.030	0.975763
M3	0.00005097	0.00004205	1.212	0.227074
IFER	0.0001240	0.00003007	4.123	0.0000***
E	0.0007883	0.001780	0.443	0.658324
BT	-0.001900	0.001766	-1.076	0.283345
I	-0.001889	0.001717	-1.100	0.272766
F-statistic: : 7.216 with 11 and 180 d.f., R^2 = 0.306				p-value: 0.00000***

*** - H_0 is rejected at 0.1% level of significance.

** - H_0 is rejected at 1% level of significance.

* - H_0 is rejected at 5% level of significance.

. - H_0 is rejected at 10% level of significance.

Comparing the result of Table 1.3 and Table 2.3, it can be inferred that there is no change in the name and number of significant variables in both the models except the change in the level of significance of the test.

Table 2.4: VIF is calculated for this model as following

Variables	VIF	Variables	VIF
CPI	137.763934#	M3	568.983073#
IIP	1.635694	IFER	238.024972#
IR	1.401391	E	306.362347#
IIR	2.038285	BT	148.568081#
M1	238.024972#	I	810.390395#
M2	1.704803		

- VIF $\geq$ 5

From Table 1.4 and Table 2.4, it is observed that the variables which were showing multicollinearity in quarterly data are also showing the same in case of monthly data.

Before applying the ICA on these seven variables showing high multicollinearity, test for normality is performed on each of these variables by using a Jarque Bera statistic.

Table 2.5: Result of Jarque Bera test with 2 d.f.

Name of Variable	Jarque Bera Statsitics	p value
CPI	166.342	0.0000***
M1	145.4886	0.0000***
M3	96.5538	0.0000***
IFER	58601.79	0.0000***
E	210.8733	0.0000***
BT	246.9154	0.0000***
I	133.7005	0.0000***

*** - H_0 is rejected at 0.1% level of significance.

Again Independent components of these seven variables have been computed by using the same algorithm and then a linear model is fitted to the monthly data:

Model: $NiftyGVM_t = \delta + \alpha_0 CPI_{mt@} + \alpha_1 IIP_{mt} + \alpha_2 IR_{mt} + \alpha_3 IIR_{mt} + \alpha_4 M_{1\,mt@} + \alpha_5 M_{2\,mt} + \alpha_6 M_{3\,mt@} + \alpha_7 IFER_{mt@} + \alpha_8 E_{mt@} + \alpha_9 BT_{mt@} + \alpha_{10} I_{mt@} + \square_{mt}$

@ indicates the variables for which the independent components have been taken as the explanatory variables.

Table 2.6: Result of Linear model after ICA

Variables	Estimate	Standard Error	t statistic	p value
Intercept	0.9640	0.2168	4.446	0.0000 ***
CPI	-0.09828	0.04148	-2.369	0.018879 *
IIP	-0.02479	0.01.032	-2.403	0.017288 *
IR	0.0006685	0.01302	0.051	0.959114
IIR	0.1149	0.03050	3.767	0.000224 ***
M1	-0.1613	0.03816	-4.226	0.0000 ***
M2	0.0000001797	0.00000549	0.033	0.973938
M3	-0.08478	0.04837	-1.753	0.081350 .
IFER	0.1354	0.03857	3.511	0.000564 ***
E	-0.1893	0.04582	-4.131	0.0000 ***
BT	-0.1563	4.909e-02	-3.184	0.001712 **
I	-0.09084	0.03882	-2.340	0.020371 *

F-statistic: 7.216 with 11 and 180 d.f., p-value: 0.00000***R^2 = 0.306

*** - H_0 is rejected at 0.1% level of significance.

** - H_0 is rejected at 1% level of significance.

* - H_0 is rejected at 5% level of significance.

. - H_0 is rejected at 10% level of significance.

Table 2.7: VIF (II)

Variables	VIF	Variable	VIF
CPI	1.23132	M2	1.704698
IIP	1.63546	M3	1.674321
InfR	1.374346	ForEx	1.064748
BIntR	2.013593	Export	1.724516
M1	1.042296	Bal_Tr.	1.078176
Import	1.502769		

From Table 2.6, it is seen that CPI, IIP, IIR, M1, M3, IEFR, E, BT, I i.e. 9 out of 11 economic indicators have significant contribution to the movement of the volatility of Indian stock market whereas looking back to Table 1.6, it can be seen that CPI, IIP, IIR, M1, IEFR, BT and I i.e. seven out of 12 indicators have significant contribution to the movement of volatility of Indian stock market. Considering the F statistics in both the tables, it is also seen that due to increment of the data points, the fitting of model is improved. From table 2.7, it is observed that there is no multicollinearity left after the application of ICA.

4. Conclusion

Leading economic indicators have significant role to play for the overall movement of the stock market volatility. CPI, IIP, IIR, M1, M3, IEFR, E,BT,I have significant effect on the monthly average of Nifty GARCH volatility, which means that keeping a close watch on these economic indicators, a recession or a boom in the market can be predicted. Although these indicators will not be helpful for the forecasting in short run but this study will be advantageous for the prediction in long run.

It can also be concluded that ICA can be used as a tool for eradicating multicollinearity in a regression model. This paper shows that after using the ICA, the multicollinearity encountered in the regression models has been removed.

The estimate of coefficients of CPI, IIP, M1, M3, E, BT and I are negative whereas that of IIR and IEFR are positive.

Consumer price index reflects changes in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as monthly or quarterly. The Laspeyres formula is generally used to compute CPI. It is one of the principal measures of inflation rate. In this study, as it is seen that CPI is negatively related to the stock market volatility which supports the result reported by Schwert (1981). Schwert (1981) found a negative correlation between stock market and consumer price index. The result of this study also confirms the result of the study reported by Carlton (1983). He suggested that the inflation has a statistically significant negative effect on volume traded. Chen, Roll and Ross (1986) found that inflation related variables were highly significant in the 1968 -77 period and insignificant both earlier and later.

IIP is an index which details out the growth of various sectors in an economy. Indian IIP focuses on sectors like mining, electricity and manufacturing. In case of India the base year was first fixed at 1993-94 but now the base year is changed to 2004-2005. IIP represents the status of production in the industrial sectors for a given period of time as compared to a reference period of time. It has already been seen that IIP is negatively correlated to the stock market volatility which contradicts the findings reported by Fama (1981). Mayasami and Koh (2000) conclude that productive activities symbolized by IIP should influence stock market.

This paper finds a positive significant role of IIR i.e. interest rate on the movement of stock market volatility. This result is similar to the result of the study conducted by Bulmash and Trivoli (1991). They found a posive correlation between the interest rate and the US stock market. Maysami and Koh (2000) also observed the same in case of Singapore stock market. All these results including the results of this study is valid for long-term, which may be due to the role of interest rate as a proxy to the variable discount rate which is used in the stock valuation model.

This study considers M1, M2 and M3 as representatives of money supply where M1, M2 and M3 are defined as following:

M1: Currency with the public + Deposit money of the public (Demand deposits with the banking system + 'Other' deposits with the RBI).

M2: M1 + Savings deposits with Post office savings banks.

M3: M1+ Time deposits with the banking system = Net bank credit to the Government + Bank credit to the commercial sector + Net foreign exchange assets of the banking sector + Government's currency liabilities to the public – Net non-monetary liabilities of the banking sector (Other than Time Deposits). (www.wikipedia.com)

This paper finds a negative contribution of M1 and M3 to the movement of NiftyGV (for monthly data) which is consistent with the findings of Mukherjee and Naka (1995). In contrast, Fama (1981) suggests a positive relation between money supply and stock price returns by using a simple quantity theory model.

Foreign-exchange reserves should only include foreign currency deposits and bonds. This paper finds a significant positive relationship between stock market and IFER which is similar to the result found by Yip (1996). He explains that a strong Singapore dollar limits imported inflation and hence is perceived as favorable news by the Singapore stock market, thereby generating positive returns.

There is a negative role of Export and Import to the volatility of Indian stock market which is not consistent with the findings of Maysami and Koh (2000). They find a positive impact of Export and Import in the Singapore's economy.

Balance of trade is the largest component of a country's balance of payments. It is basically the difference between export and import. This paper finds a significant negative contribution of balance of trade to the volatility of Indian stock market which supports the result of the study carried by Kumar (2011).

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