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INTERDEPENDENCE OF STOCK MARKET AND DOMESTIC MACROECONOMIC FACTORS IN INDIA

Nehkholen Haokip
Ph.D. Scholar , Department of Economics ,
Delhi School of Economic, University of Delhi.

ABSTRACT

This paper examine the interdependence between stock market and domestic macroeconomic factors in India using monthly data provided by the Reserve Bank of India from April 1991 to April 2016. We employ VAR (1)-MGARCH (1, 1) BEKK model and conditional correlation plots to study these relationship. The first methodology help us to study three types of spillover namely mean, shock and volatility. We observed that there is spillover in mean between inflation and stock market implying that an increase in inflation reduces stock market return. The shock from real output affects every other sectors and inflation is affected by shocks from all the other sectors. We observed that there is bidirectional shock spillover between real output and money supply and between inflation and money supply. We also observed bidirectional volatility spillover between stock market and real output and between exchange rate and money supply.The Reserve Bank of India which control money supply has an important role to play as shocks from monetary sector affect industrial production and inflation.

KEYWORDS: *stock market, macroeconomic variables, spillover, volatility, interdependence.*

1. INTRODUCTION

The objective of this paper is to study the interdependence between stock market and domestic macroeconomic factors in India. There have been many studies about the relationship between stock market and real economic activities. This is because stock market has been recognized to have a prominent role in a country's macroeconomic development. The study of volatility in financial market is important for various reasons. First, greater volatility in financial markets can have wide repercussion for the whole economy. For example, the stock market crash in 1987 reduced consumer spending in the USA (Garner, 1990) and fluctuations in foreign exchange markets impact trade (Maskus, 1990). As a result, while establishing its monetary policy the US Federal Reserve explicitly takes into account the volatility of stocks, bonds, currencies and commodities (Nasar, 1992). Similarly, the Bank of England makes frequent references to market sentiments in its monetary policy meeting. Secondly, volatility plays a central role in the pricing of derivative securities. According to the Black-Scholes formula, we need to know the volatility of the underlying asset to price an option as Investors and portfolio managers could bear certain levels of risk threshold.

Knowledge on the nexus between stock market volatility[1] and macroeconomic variables volatility is crucial to the investors in the equity market as well as to the policy makers. For investors, discovering the macroeconomic variables volatility could help them to appropriately forecast stock prices movements. If the volatility of macroeconomics variables can be used as reliable indicators for the stock market volatility, it can

[1]In this paper, the term volatility refers to conditional volatility which is a measure of expected volatility of a series at some future period $t + h$ that is conditioned on known information such as the history of previous series up to time t.

also help them in managing their investment portfolios. Meanwhile, from the macroeconomic point of view, it is important for policymakers to be able to identify relationships between stock market volatility and macroeconomic volatility. If stock market volatility leads macroeconomic volatility, policymakers could use stock market volatility as a leading indicator to predict future macroeconomic volatility. On the other hand, if stock market volatility does not lead macroeconomic volatility, it is not wise for a policy maker to focus on stock market volatility in order to reduce macroeconomic volatility.

Therefore, it is worthwhile to determine interdependence between stock market and macroeconomic variables and whether macroeconomic volatility can explain stock market volatility, or vice versa. Most importantly, there has yet a study conducted on this matter based on Indian data, it has become a driving motivation to conduct this study. This paper examine the following research questions:

(1) To study three types of spillover effects namely mean, shock[2] and volatility between stock market and domestic macroeconomic factors in India

(2) To study the conditional correlation between stock market and domestic macroeconomic factors in India

2. EMPIRICAL LITERATURE REVIEW

The empirical works on the link between macroeconomic factors and stock returns can be divided into two broad categories. The first category of such studies investigated the impact of macroeconomic factors on stock prices. The second category of studies focused on the relationship between the stock market volatility and volatility in the macroeconomic indicators. This study focus on the relationship between the stock market and macroeconomic variables through the spillover effects of mean, shock and volatility.

Since the introduction of ARCH and GARCH models by Engle (1982) and Bollersher (1986), there has been an explosion of empirical studies examining the dynamics of conditional stock market volatility empirically. Most of the studies, however, have been carried out in the context of developed markets. The well-liked literature on this topic is by Schwert (1989) which looked at the relationship between stock volatility and the volatility of real and nominal macroeconomic variables. Based on US data for several macroeconomic variables (namely inflation, industrial production, and money), Schwert found weak evidence that macroeconomic volatility can helpful in predicting stock return volatility. His study, however, point to a positive link between macroeconomic volatility and stock market volatility, with the direction of causality being stronger from the stock market volatility to macroeconomic variables. David and Kutan (2003) extended Schwert's study by accounting for volatility persistence in an international setting. Similar as Schwert, they also find the volatility of inflation and output growth rate has weak predictive power for conditional stock market volatility.

On the other hand, several studies did provide evidence for the impact of the overall health of the economy on unconditional stock market volatility. Officer (1973), for example, shows that aggregate stock volatility increased during the Great Depression, as the volatility of money and industrial production grew. His study showed that stock volatility was at similar levels before and after the depression. Liljeblom and Stenius (1997), using Finnish data, found that changes in conditional stock market volatility were related to conditional macroeconomic volatility (namely inflation, industrial production, and money supply). Morelli (2002) examined the relationship between the conditional volatility in the UK stock market and a number of macroeconomic variables. He found a significant relationship between stock market and macroeconomic volatility with respect to the ability of macroeconomic volatility in predicting stock market volatility.

Several studies also have been conducted in the case of emerging markets. Engle and Rangel (2005) studied emerging markets, as well as developed market, by accounting for volatility clustering using Spline-GARCH model. They found that volatility in macroeconomic variables such as GDP growth, inflation and short-term interest rate are important explanatory variables that increased unconditional stock market volatility. Chowdhury and Rahman (2004) investigated the relationship between the volatility of

[2] Shock spillover is also known as News effect

macroeconomic variables and the stock returns in Bangladesh. By using VAR models, they found that macroeconomic volatility significantly cause stock market volatility.

In the Indian context, Pethe and Karnik (2000) employed co-integration and error correction model to examine the inter-relationship between stock price and macroeconomic variables using monthly data from April 1992 to December 1997. Their analysis revealed that the state of economy and the prices on the stock market do not exhibit a long run relationship. Bhattacharya and Mukherjee (2006) examined the relationship between the Indian stock market and seven macroeconomic variables by employing the VAR framework and Toda and Yamamoto non-Granger causality technique for the sample period of April 1992 to March 2001. Their findings also indicated that there was no causal linkage between stock returns and money supply, index of industrial production, GNP, real effective exchange rate, foreign exchange reserve and trade balance. However, they found a bi-directional causality between stock return and rate of inflation.

However, studies like Ray and Vani (2003) employed a VAR model and an artificial neural network (ANN) to examine the linkage between the stock market movements and real economic factors in the Indian stock market using the monthly data ranging from April 1994 to March 2003. The results revealed that, interest rate, industrial production, money supply, inflation rate and exchange rate have a significant influence on equity prices, while no significant results were discovered for fiscal deficit and foreign investment in explaining stock market movement.

Ahmed (2008) employed the Johansen's approach of co-integration and Toda –Yamamoto Granger causality test to investigate the relationship between stock prices and the macroeconomic variables using quarterly data for the period of March, 1995 to March 2007. The results indicated that there was an existence of a long-run relationship between stock price and FDI, money supply, index of industrial production. His study also revealed that movement in stock price caused movement in industrial production. Pal and Mittal (2011) investigated the relationship between the Indian stock markets and macroeconomic variables using quarterly data for the period January 1995 to December 2008 with the Johansen's co-integration framework. Their analysis revealed that there was a long-run relationship exists between the stock market index and set of macroeconomic variables. The results also showed that inflation and exchange rate have a significant impact on BSE Sensex but interest rate and gross domestic saving (GDS) were insignificant.

2.1 Contribution to the Literature

In spite of significant number of studies in Indian context about the nexus between macroeconomic variables and stock prices, however there is no study[3] investigating the interdependence between domestic macroeconomic variables and stock market in India by means of three spillover effects mentioned earlier. It is basically this issue which this chapter will investigate.

3. DATA AND METHODOLOGY

We use monthly data provided by the Reserve Bank of India from April 1991 to April 2016. We chose Bombay Stock Exchange to represent Indian Stock market as it is the most prominent stock market in India. Among the various indexes in the Bombay Stock Exchange, we select the most popular index BSE30 commonly known as SENSEX. We choose the following macroeconomic variables based on their theoretical and empirical relevance in the literature. The Index of Industrial Production (IIP) is chosen to represent output as the data on GNP/GDP is not available on monthly basis. We chose Wholesale Price Index to represent Inflation; M3 to represent money supply and exchange rate of Indian rupee to US dollar to represent the external sector.

[3]We came across just one paper for Indian study by Kumariand Mahakud(2015) which use Univariate ARCH model. This paper use a better technique of Multivariate BEKK-GARCH model that can explain the dynamics between stock volatility and macroeconomic volatility in much richer ways.

3.1 Unit root testing

It is a well-known fact that financial time series display unit-root behaviour. However the return series or the first difference of the series are usually stationary. (See Tsay, 2005). To test for the stationarity of these series[4], this paper employs the formal Dickey Fuller Test.

The null hypothesis under the Dickey Fuller test is that there is unit root in the return series i.e($\gamma = 1$). The Alternative hypothesis is 'there is no unit root in the return series i.e $\gamma < 1$. This paper conduct unit root test for three different models of the return series. The formal derivation of this test is not pursued in this paper (See Enders, 2004).

3.2 Vector Autoregressive Model (VAR)

After we test for the presence of unit root in all the series, we formulate a VAR model[5] by selecting the appropriate lag length on the basis of lag length selection criteria and lag exclusion tests. A VAR model of order 1 for a time series y_t can be represented as follows:

$$y_t = \varphi_0 + A' y_{t-1} + \varepsilon_t$$

Where φ_0 is a K-dimensional vector and K is the number of variables. A is a KxK matrix of parameters and ε_t is a sequence of serially uncorrelated random vectors with mean zero and unconditional covariance matrix Σ_t which must be positive definite.

3.3 The ARCH model

Engel (1982) introduced the concept of ARCH[6] model to study the time varying heteroskedastic nature of financial data. Most of the financial data exhibit volatility clustering in periods of both high and low volatility. The ARCH model has been used to capture the time varying volatility of financial time series. Later on a more generalized model of the ARCH model were introduced. In this section we will focus on the emergence of multivariate version of the ARCH model from its univariate version.

The ARCH model has three distinct specifications namely the conditional mean equation, the conditional variance equation and the conditional error distribution. These specifications are described one by one:

The mean equation for the return process can be described as follows:

$$r_t = \mu + \varepsilon_t$$

Where μ is assumed to be a constant or follow an ARMA[7] process. The innovation term ε_t is time-varying and may be described by the following process:

$\varepsilon_t = z_t \sigma_t$ Where $z_t \sim N(0,1)$ and $cov(z_t, \sigma_t) = 0$

$\Longrightarrow \varepsilon_t \sim N(0, \sigma_t^2)$

The conditional variance equation may be specified as an ARCH (p) process which is as follows:

$h_t = \sigma_t^2 = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots \dots \dots + \alpha_q \varepsilon_{t-p}^2$

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[4] We take the logarithm of the first difference of these series because original series is non-stationary.

[5] A VAR(1) model is chosen for the data by lag length criteria and lag exclusion test

[6] ARCH stands for Autoregressive conditional heteroscedasticity model

[7] ARMA stands for Autoregressive Moving average model. ARMA(p,q) can be represented as $X_t = C + \sum_{i=1}^{p} \emptyset_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$

$$= \omega_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2$$

Where in general $\omega_0 > 0$, $\alpha_i \geq 0$ for all i to ensure that h_t(variance) is strictly positive. To ensure the stationarity of an ARCH (p) model we require, $\sum_{i=1}^{p} \alpha_i < 1$. Since, σ_t^2 is the one-period ahead forecast variance based on past information, it is called the conditional variance equation. The ARCH (p) process basically says that the expected volatility at time period t(today) depends on the intercept and the squared errors of the previous p days.

Engle (1982) in his pioneering work assumed that the error term, z_t follows a Gaussian (normal) distribution. However, Mandelbrot (1963) and many others have noted that the distribution of many financial time series appear to be leptokurtic and often have fatter tails than the normal distribution. So other researchers sometime use Student's-t distribution and the Generalised error distribution.

3.4 The GARCH Family

While the ARCH model is simple to estimate but it often requires many parameters to adequately describe the volatility process of financial time series. Bollersev (1986) proposes a more parsimonious representation of the ARCH model known as the Generalised Autoregressive Conditional Heteroscedascity (GARCH) model. The GARCH(p, q)model can be represented by:

$$h_t = \omega_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, h_{t-j}$$

Where again $\omega_0 > 0$, $\alpha_i \geq 0 \beta_j \geq 0$ and $\sum_{i=1}^{max\,(p,q)} (\alpha_i + \beta_j) < 1$. Here it is understood that $\alpha_i = 0$ for $i > p$ and $\beta_j = 0$ for $j > q$. The later constraint on $\alpha_i + \beta_j$ implies that the unconditional variance h_t evolves over time. The GARCH(p, q)model reduces to a pure ARCH (p, q) model if $q = 0$.
The simplest GARCH(p, q) specification is GARCH$(1,1)$model which is as follows:

$$h_t = \omega_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad where\ 0 \leq \alpha_1, \beta_1 \leq 1 \quad (\alpha_1 + \beta_1) < 1$$

The conditional variance equation specified above for GARCH$(1,1)$ is a function of three terms: a constant term(ω_0), the ARCH term (ε_{t-1}^2) and the GARCH term(h_{t-1}). The ARCH term is basically the news about volatility from the previous period while the GARCH term is the last period's forecast variance.

3.5 Multivariate GARCH models

We introduce the idea of multivariate GARCH model as the univariate GARCH model cannot capture the co-movements of various financial time series. A multivariate model can capture the dependence in the co-movements of different time series and hence generate a more reliable model than separate univariate models.

The specification of MGARCH models should take account into two things. First it should be flexible enough to state the dynamics of the conditional variances and covariances. Second, the number of parameters in an MGARCH model increases rapidly with the dimension of the model. So, the specification should be parsimonious for the purpose of model estimation and interpretation of the model parameters. Sometimes, parsimony may reduce the number of parameters and the relevant dynamics in the covariance matrix may not be captured. So we need to get a balance between the parsimony and the flexibility when designing the specification of the multivariate GARCH model. Lastly, the covariance matrix should be positive definite in multivariate GARCH models.
We briefly review several specification of multivariate GARCH models below:

3.5.1 VEC/DVEC-MGARCH models

The VEC-MGARCH model was introduced by Bollerslev, Engle and Wooldridge in 1988. It was the first MGARCH model in which every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross-products of returns. The model can be expressed below:

$$vech(H_t) = C + \sum_{j=1}^{q} A_j\, vech(\varepsilon_{t-j}\,\varepsilon_{t-j}^{'}) + \sum_{j=1}^{p} \beta_j\, vech(H_{t-j})$$

where $vech(.)$ is an operator that stacks the columns of the lower triangular part of its argument square matrix, H_t is the covariance matrix of the residuals, N presents the number of variables, *t* is the index of the *t* th observation, C is an *N* (*N*+1)/2 × 1 vector, A_j and B_j are *N*(*N*+1)/2 × N(N+1)/2 parameter matrices and ε is an *N* × 1 vector. The condition for H_t to be positive definite for all *t* is not restrictive. The number of parameters is equal to $(p + q)\ x\ (N(N+1)/2)^2 + N(N+1)/2$, which is large.

To ensure the positive definiteness of H_t and reduce the number of parameters, a restricted version of VEC known as DVEC was proposed by Bollerslev, *et al* (1988). It assumes the A_j and β_j are diagonal matrices. This ensure that H_t is positive definite for all *t*. But the DVEC model with with (*p*+*q*+1)×*N*×(*N*+1)/2 parameters is too restrictive and does not take into account the interaction between different conditional variances and covariances.

3.5.2 BEKK-MGARCH models

BEKK-MGARCH model was devised by Baba, Engle, Kraft and Kroner in 1990 in which a new parameterization of the conditional variance matrix H_t was defined to ensure its positive definiteness.It achieves the positive definiteness of the conditional covariance by formulating the model in a way that this property is implied by the model structure.

The form of the BEKK model is as follows

$$H_t = CC^{'} + \sum_{j=1}^{q}\sum_{k=1}^{K} A_{kj}^{'}\ \varepsilon_{t-j}\,\varepsilon_{t-j}^{'}\,A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} \beta_{kj}^{'}\ H_{t-j}\,\beta_{kj}$$

where A_{kj} , β_{kj} and *C* are *N*×*N* parameter matrices, and *C* is a lower triangular matrix.

The purpose of decomposing the constant term into a product of two triangular matrices is to guarantee the positive semi-definiteness of H_t. The first-order BEKK model is

$$H_t = CC^{'} + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + B'H_{t-1}B$$

The BEKK model also has its diagonal form by assuming A_{kj} , β_{kj} matrices are diagonal. It is a restricted version of the DVEC model. The most restricted version of the diagonal BEKK model is the scalar BEKK one with *A* = *aI*and *B* = *bI*where *a* and*b* are scalars.

A BEKK model for a bivariate MGARCH (1,1) can be specified as below:

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}^{'} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}\begin{bmatrix} \varepsilon_{1,t-1}^{2} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}^{2} \end{bmatrix}\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{'} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}\begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix}\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}^{'}$$

The coefficients a_{11} and a_{22} can be interpreted as own market shock on the future uncertainty of the time series variables 1 and 2 respectively. The coefficient a_{21} represents the effect of a shock on the time series variable 2 on the future uncertainty of the time series variable 1. The same interpretation applies for the coefficienta_{21}. The Coefficient b_{12} represents the effect of last period's variance in variable 1 on the current period volatility of variable 2. The same interpretation applies for the coefficientb_{21}.

3.5.3 Constant Conditional Correlations (CCC) models[8]

The Constant Conditional Correlation model was introduced by Bollerslev in 1990 to primarily model the conditional covariance matrix indirectly by estimating the conditional correlation matrix. The conditional correlation is assumed to be constant while the conditional variances are varying. Obviously, this assumption is impractical for real financial time series.

Dynamic Conditional Correlations (DCC) models

The Dynamic Conditional Correlation model was proposed by Engle in 2002. It is a nonlinear combination of univariate GARCH models and it is also a generalized version of the CCC model. The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t$$

Where

$$D_t = diag\left(h_{11t}^{1/2}, \ldots \ldots, h_{NNt}^{1/2},\right)$$

and each h_{iit} is described by a univariate GARCH model. Further,

$$R_t = diag\left(q_{11t}^{1/2}, \ldots \ldots, q_{NNt}^{1/2},\right) Q_t diag\left(q_{11t}^{1/2}, \ldots \ldots, q_{NNt}^{1/2}\right)$$

Where $Q_t = \left(q_{ijt}\right)$ is the *N*×*N* symmetric positive definite matrix which has the form:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha U_{t-1}U_{t-1}^{'} + \beta Q_{t-1}$$

Here $U_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{iit}}}$, α and β are non-negative scalars that $\alpha + \beta < 1$, $\bar{Q}$ is the *N*×*N* unconditional variance matrix of U_t.

The shortcoming of the model is that all conditional correlations follow the same dynamic structure. The number of parameters to be estimated is (*N*+1)×(*N*+4)/2, which is relatively smaller than the complete BEKK form with the same dimension when *N* is small. When *N* is large, the estimation of the DCC model can be performed by a two-step procedure which decreases the complexity of the estimation process. In brief, in the first place, the conditional variance is estimated via univariate GARCH model for each variable. The next step is to estimate the parameters for the conditional correlation. The DCC model can make the covariance matrix positive definite at any point in time.

4. RESULTS AND DISCUSSIONS

4.1 Unit root

We employ three different regression of Augmented Dickey Fuller to test for the presence of unit root. The difference between the three regressions concerns the presence of the deterministic elements a_o and$a_2 t$. The first is a pure random walk, the second adds an intercept or drift term, and the third term includes both a drift and linear time trend. We see if the three models reject the null hypothesis of unit root.

[8]Due to problem of convergence we do not present the results for CC and DCC models.

If the random walk model does not reject the null hypothesis, we proceed to see the result of the model with intercept and trend term. If the model with intercept and trend term reject the null hypothesis, we conclude that the series is stationary.

In table 1, we look at the unit root properties of monthly variables of Sensex, IIP, M3, Exchange rate and WPI. For the variables Sensex, IIP, Exchange Rate and WPI all the three models reject the null hypothesis of unit root. For M3, the random walk model indicates unit root but since the model with intercept term and trend term rejects the null hypothesis, we conclude that M3 is stationary.

Table 1: Results of Unit root testing

Variables/Model	$r_t = \gamma r_{t-1} + \varepsilon_t$	$r_t = a_o + \gamma r_{t-1} + \varepsilon_t$	$r_t = a_o + \gamma r_{t-1} + a_2 t + \varepsilon_t$
Stock Market (Sensex)	-13.29696 (0.000)	-13.53285 (0.000)	-13.52271 (0.000)
Output (IIP)	-5.311234 (0.000)	-16.42816 (0.000)	-16.51300 (0.000)
Money Supply (M3)	-1.192892 (0.2130)	-4.473039 (0.000)	-21.05467 (0.000)
Exchange Rate	-14.03138 (0.000)	-14.41468 (0.000)	-14.46414 (0.000)
Inflation (WPI)	-4.721369 (0.000)	-10.98331 (0.000)	-11.32539 (0.000)

*Value inside the bracket are p-values

4.2 VAR (1)-BEKK (1, 1) Results

The VAR (1)-BEKK (1, 1) model estimates two equation namely the mean equation and the variance equation. The mean equation gives the mean spillover while the variance equation gives both the shock and volatility spillover.

Mean Spillover (See table 2)

The estimation results for VAR (1)-MGARCH (1, 1) BEKK are shown in table 2. We look at the mean equation to study the spillover in mean between different variables. We obtained the following results from the mean equation:

(a) Stock market (Sensex)

We find that there is spill over in mean from WPI to Sensex at 5% level of significance. The coefficient is negative. This means that when WPI increases, real profit falls and the stock return falls.

(b) Output (IIP)

We see that there is spill over in mean from Exchange rate and WPI to IIP at 1% and 5 % level of significance respectively. The coefficient for exchange rate is negative implying that when exchange rate increases (i.e. depreciates vis-à-vis US dollar) the cost of imports (such as oil and other inputs for manufacturing) increases. Since India is oil importing country this hurts our industry and hence the IIP falls. The coefficient for WPI is positive implying that a rise in price induce the industry to produce more output as higher price means more profit for the firms.

Table 2: Results from estimation of Mean Equation of VAR (1)-BEKK (1, 1) model

	Sensex(j=1)	IIP(j=2)	M3(j=3)	Exrate(j=4)	WPI(j=5)
Constant	1.659075365 (0.00227904)	0.742169364 (0.00004879)	1.370776143 (0.0000)	0.247092157 (0.13180104)	0.128655668 (0.03576702)
Sensex(-1)	0.186548489 (0.00361175)	0.013458999 (0.36984207)	0.007791102 (0.33549949)	-0.021498409 (0.14204828)	0.015831361 (0.0000113)
IIP(-1)	-0.104778431 (0.59242068)	-0.483118690 (0.0000)	0.047119296 (0.03339784)	0.097460619 (0.03915394)	0.022985862 (0.06252413)
M3(-1)	-0.170401276 (0.55101166)	-0.034013307 (0.73329355)	-0.158584571 (0.05528861)	-0.014259906 (0.85061529)	0.095123582 (0.00253106)
Exrate(-1)	-0.226547574 (0.26710290)	-0.160264341 (0.00106985)	0.016752426 (0.43246746)	0.176439817 (0.03365206)	0.024054920 (0.21296387)
WPI(-1)	-1.223344646 (0.01795304)	0.380339675 (0.05872572)	0.029544562 (0.75159428)	-0.338767372 (0.11905785)	0.391569096 (0.00000)
Diagnostic Test for Multivariate Q-statistic	Test Statistic	Degrees of freedom	Significance level		
Q(6)	170.63056	150	0.11928		

*values inside the bracket are p-values

(c) Money Supply (M3)

There is mean spill over from IIP to M3.The coefficient for M3 is positive. When IIP increases, output is more. So the demand for money rises. If RBI follows Taylors rule then money supply will rise.

(d) Exchange Rate

We have mean spill over from IIP to Exchange rate. The coefficient of exchange rate is positive. When IIP increase, we had more output and hence income. When we had more income we want to import more. The demand for dollar rise when we import more and hence the value of dollar increases thereby depreciating rupee. (i.e. exchange rate)

(e) Inflation (WPI)

There is mean spill over from Sensex to WPI and from M3 to WPI. The coefficient of Sensex is positive. This is because when stock return rises, wealth increases fuelling price rise. The coefficient of M3 is positive. When money supply rises, people have more money with them. So, when more money are chasing after few goods, we see a rise in price.

Shock interdependence (See table 3)

We look at the variance equation to understand the shock interdependence between various variables. We study the shock spill over between various variables as follows:

(a)Stock market (Sensex)

For Sensex, we find that the coefficients of A(1,1) and A(2,1) are statistically significant at 1% and 5% level respectively. So there is shock spillover from IIP to Sensex and Sensex is affected by its own past shock. Since the coefficients have same signs, shocks with same (opposite) signs in the two series will lead to an increase (decrease) in future uncertainty of Sensex. Also Coefficient of A(2,1) > A(1,1), then cross shock spillover from IIP to Sensex is more important than Sensex own past Shock Spillover in determining future uncertainty of Sensex.

(b) Output (IIP)

For IIP, we find that the coefficients of A(2,2), A(3,2) and A(5,2) are significant at 1%, 5% and 1% level respectively. This means there is shock spillover from M3 and WPI to IIP. IIP own past shock also affect the current period uncertainty of IIP.

The coefficients A(2,2) and A(3,2) have different signs. So shocks with opposite (same) signs in the two series will lead to increase (decrease) future uncertainty of IIP .Again, the coefficients of A(2,2) and A(5,2) have same signs. so shocks with same (opposite) signs in the two series will lead to an increase (decrease) in future uncertainty of IIP. We also noted that A(5,2)>A(3,2)>A(2,2). So shock from WPI are more important shock from M3 and IIP own past shock in determining the future uncertainty of IIP.

(c) Money Supply (M3)

For M3, the coefficients of A(2,3) and A(5,3) are both significant at 5%level. This means there is shock spill over from IIP to M3 and from WPI to M3. We also noted that A(2,3)>A(5,3) So shocks in IIP has more impact than shock in WPI in the future uncertainty of M3.

(d) Exchange Rate

For exchange rate, the coefficients of A(1,4), A(2,4) and A(4,4) are statistically significant at 5%, 5% and 1% level respectively. This means that there is shock spillover from Sensex to Exchange rate, IIP to exchange rate. Exchange rate is also affected by its own past shock.

The coefficients of A(4,4) and A(1,4) have the same signs. So shocks with same (opposite) signs in the two series will lead to an increase (decrease) in future uncertainty of Exchange rate. The coefficients of A(2,4) and A(4,4) have different signs. So shocks with opposite (same) signs in the two series will

Table 3: Results from estimation of Variance Equation of VAR(1)-BEKK(1,1) model

	Sensex(j=1)	IIP(j=2)	M3(j=3)	Exrate(j=4)	WPI(j=5)
A(j,1)	0.196785266 (0.00782562)	0.420813029 (0.03290797)	0.475231299 (0.43986792)	0.198790092 (0.61541529)	0.652658522 (0.35397290)
A(j,2)	0.015306772 (0.62198233)	0.315115904 (0.00039355)	-0.222989264 (0.04417916)	-0.135381665 (0.17752319)	1.193766693 (0.00356021)
A(j,3)	0.008982617 (0.18386876)	-0.051295469 (0.02460454)	0.102985248 (0.37417230)	-0.029520750 (0.23428701)	-0.199852168 (0.01762806)
A(j,4)	0.062288751 (0.03445922)	-0.226676597 (0.02050923)	0.036605282 (0.83130911)	0.680768461 (0.00056913)	-0.003916942 (0.99188973)
A(j,5)	0.014109135 (0.09716058)	-0.063163030 (0.00329491)	-0.111576321 (0.05916359)	0.078807490 (0.00302465)	-0.097408620 (0.56395868)
B(j,1)	0.948057082 (0.00000)	-1.230210736 (0.00000)	0.720656893 (0.36877904)	-0.075036214 (0.90386671)	0.816215218 (0.38033520)
B(j,2)	0.107849147 (0.00000)	0.733521759 (0.0000)	0.140427222 (0.74238191)	0.034102364 (0.81877551)	0.748125888 (0.40376981)
B(j,3)	-0.003479635 (0.84580884)	0.031150750 (0.67981770)	0.911636121 (0.00000)	0.087347997 (000486777)	-0.292153909 (0.09018289)
B(j,4)	-0.002602146 (0.95657510)	0.221075226 (0.20544198)	-0.570879453 (0.01343106)	0.700067895 (0.00000)	-1.432957128 (0.00004162)
B(j,5)	-0.002322425 (0.84688227)	-0.014386031 (0.52964670)	0.029669479 (0.78233223)	0.037483668 (0.58419174)	0.668572826 (0.000000)

Diagnostic Test for Multivariate Q-statistic	Test Statistic	Degrees of freedom	Significance level		
Q^2(6)	86.34347	150	0.9999		

*values inside the bracket are p-values

lead to increase (decrease) future uncertainty of Exchange rate. We also noted that A(4,4)>A(2,4)>A(1,4). So past shock of exchange rate is most important in determining the future uncertainty of exchange rate than shocks from Sensex or IIP. This could be because exchange rate is influenced more by global factors than by domestic factors.

(e) Inflation (WPI)

For WPI the coefficien ts A(2,5) and A(4,5) are statistically significant at 5% level while the coefficients A(1,5) and A(3,5) are statistically significant at 10% level of significance. This means cross shock spill overs from all other sectors are affecting the future uncertainty of WPI. So, WPI is very sensitive to shocks from other sectors.

From the discussions above we noted the following:

IIP shocks affect every other sectors and WPI is affected by shocks in all the sectors. There is bidirectional shock spillover from IIP and M3; WPI and M3. Since A(3,2)>A(2,3) cross shock spillover from M3 to IIP is more larger than cross shock spillover from IIP to M3. Again, A(5,3)>A(3,5) So cross shock spillover from WPI to M3 is greater than the cross shock spillover from M3 to IIP.

Volatility Interdependence (see table 3)

(a) Stock market (Sensex)

The coefficients of B (1, 1) and B (2, 1) are both statistically significant at 1% level. This means that there is volatility spill over from IIP to Sensex and past volatility of Sensex also affect current period volatility of Sensex. Since the coefficients B (1,1) and B(2,1) have different signs, previous period volatility with opposite (same) signs in the two series will lead to increase (decrease) current period volatility in Sensex. We also observed that B(2,1)>B(1,1). So cross volatility spillover from IIP to Sensex is more important than Sensex own volatility spillover in determining volatility of Sensex.

(b) Output (IIP)

For IIP, the coefficients of B(1,2) and B(2,2) are both significant at 1% level. This means that there is volatility spillover from Sensex to IIP and current period volatility of IIP is also affected by its own past volatility. The coefficients of B(1,2) and B(2,2) are of same sign. So previous period volatility with same (opposite) signs in the two series will lead to increase (decrease) volatility in IIP. We also noted that B(2,2)>B(1,2). So IIP own volatility spillover is more important than cross volatility spillover from Sensex to IIP in determining the current period volatility of IIP

(c) Money Supply (M3)

For M3, the coefficients of B(3,3), B(4,3) and B(5,3) are significant at 1%, 1% and 10% level respectively. The coefficients of B(3,3) and B(4,3) have same signs. So previous period volatility with same (opposite) signs in the two series will lead to increase (decrease) volatility in M3. The coefficients of B(3,3) and B(5,3) have different signs. So previous period volatility with opposite (same) signs in the two series will lead to increase (decrease) current period volatility in M3. We also noted that B(3,3)>B(5,3)>B(4,3). So M3 own past volatility is most important in determining its current volatility than past volatility spillover from exchange rate and WPI.

(d) Exchange rate

The coefficients of B(3,4), B(4,4) and B(5,4) are significant at 5%, 1% and 1% level respectively. This means there is cross volatility spillover from M3 to Exchange rate and from WPI to exchange rate. Past volatility of exchange rate also effect current volatility of exchange rate.

The coefficients of B(3,4) and B(4,4) have different signs. So previous period volatility with opposite (same) signs in the two series will lead to increase (decrease) current period volatility in Exchange rate. Similarly the coefficients of B(4,4) and B(5,4) have different signs. So previous period volatility with opposite (same) signs in the two series will lead to increase (decrease) current period volatility in Exchange rate. B(5,4)>B(4,4)>B(3,4). So cross volatility spillover from WPI to Exchange rate is the more important than cross volatility spillover from M3 and exchange rate own volatility spillover in determining volatility of exchange rate.

(e) Inflation (WPI)

For WPI the coefficient B(5,5) is statistically significant at 1% level. This means that only past volatility of WPI affects current period volatility of WPI. This is quite different from Shock spillover results where shocks from every sector effect future uncertainty of WPI.

From the above discussion we noted the followings:

There is Bidirectional spillover for Sensex and IIP and also for Exchange rate and M3. We note that B(2,1)>B(1,2) i.e., Cross volatility spillover from IIP to Sensex is larger than Cross volatility spillover from Sensex to IIP. Again, B(3,4)>B(4,3) i.e., cross volatility spillover from M3 to Exchange rate is larger than the cross volatility from Exchange rate to M3

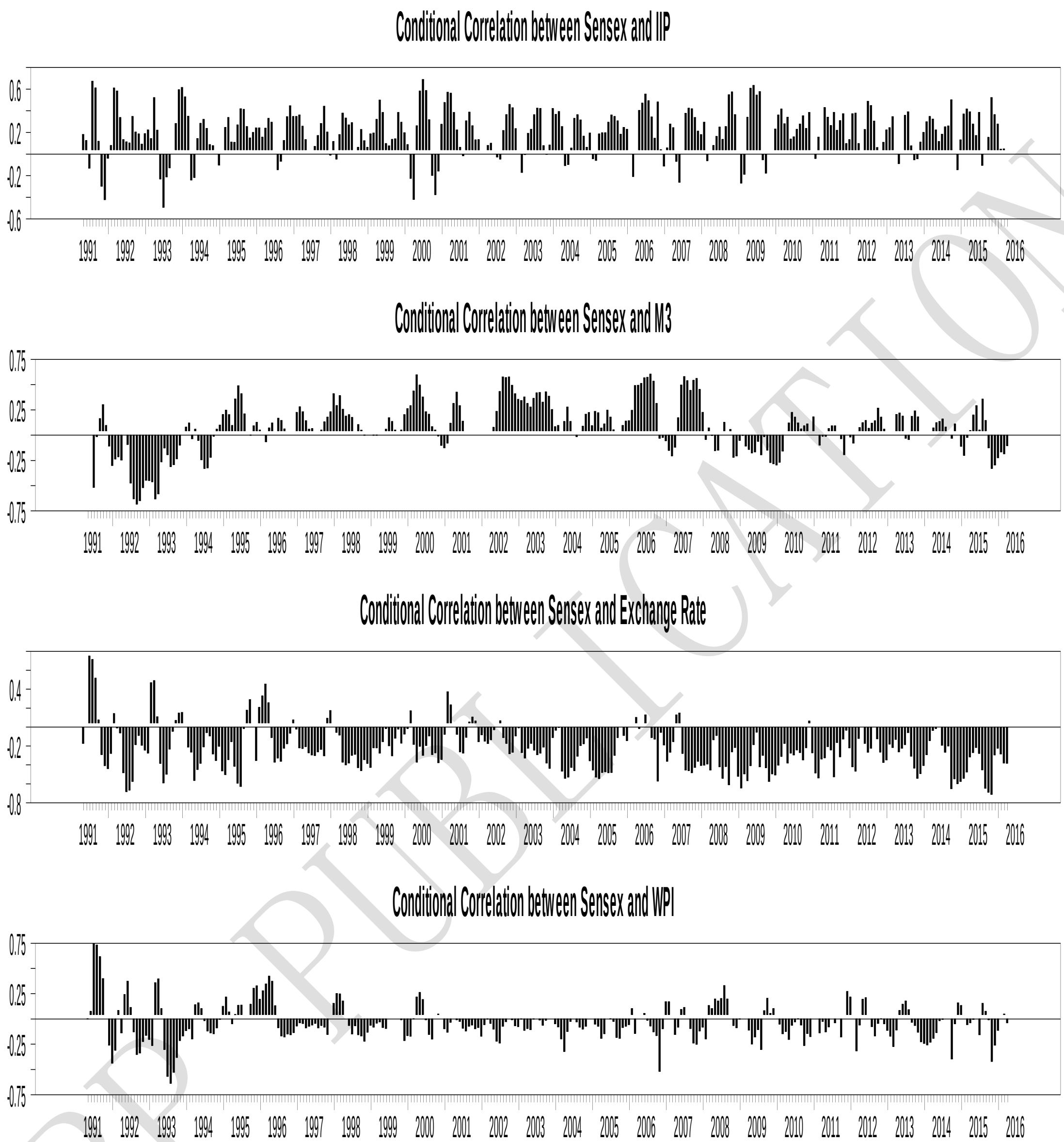
Diagnostic Testing

The adequacy of the mean and the variance equation are tested by the multivariate Q-statistic for standardized residuals and squared standardized residuals. The p-value for standardized residuals and squared standardized residuals are 0.11928 and 0.999 respectively. Thus we cannot reject the null hypothesis of no serial correlation in the mean and variance equation at 1% level of significance. Hence the model is adequate and both the mean and the variance equation are correctly specified.

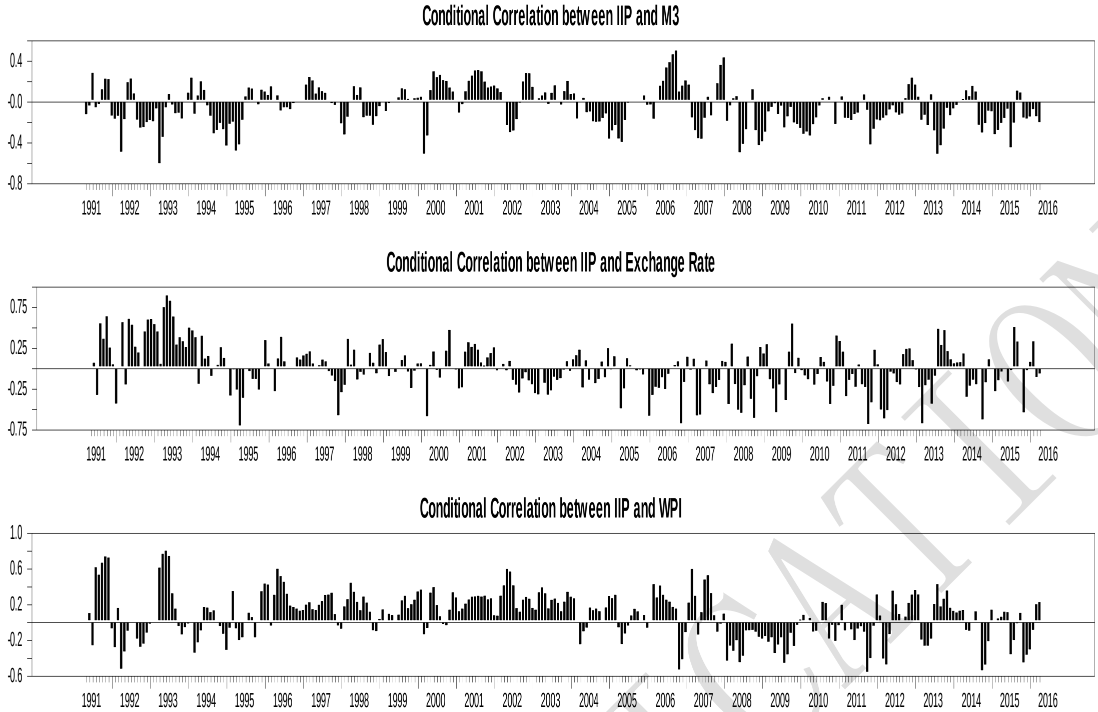
4.3 Conditional correlation plots

We also plot the time varying conditional correlations among various variables. The figures are given below in figure1. We find that the conditional correlation between Sensex and IIP is positive for most of the period indicating that when IIP moves up, the Sensex also goes up. The conditional correlation between Sensex and M3 is negative in some period and positive in other period. It is also found to be negligible in some periods. For Sensex and exchange rate, the conditional correlation is negative for most of the period signifying that when Rupee depreciates the Sensex falls. This could be because when domestic currency depreciates foreign investors reallocate their investment from Indian stock market to foreign stock market. The conditional correlation between Sensex and WPI is found to be small for most of the time periods. This means there is no significant relationship between inflation and stock market in India.

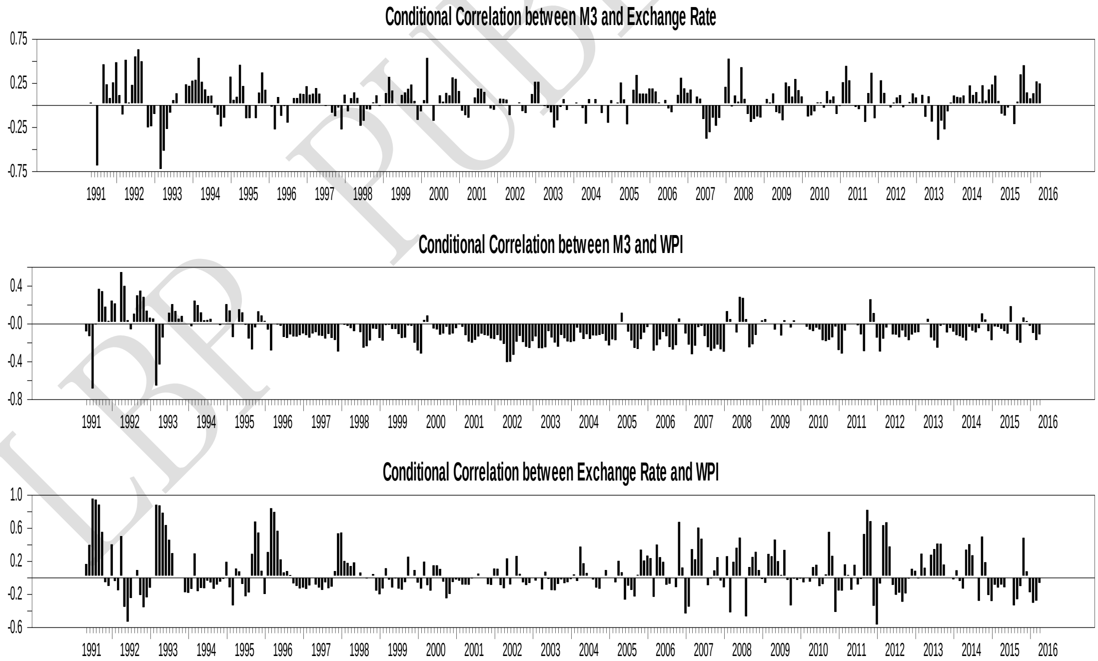
Figure 1: Conditional correlations plots from VAR(1)-BEKK Model



Estimates of time-varying correlations of a VAR(1)- BEKK(1,1) model



Estimates of time-varying correlations of a VAR(1)- BEKK(1,1) model



Estimates of time-varying correlations of a VAR(1)- BEKK(1,1) model

The conditional correlation plot between IIP and M3 shows that it is positive at some time period and negative at other period of time. We could observe similar result but weak conditional correlation between IIP and exchange rate. The conditional correlation for IIP and WPI is positive for the time period between 1996 and 2006. There is weak conditional correlation between M3 and exchange rate. This could be because exchange rate is affected by external factors and not by domestic factors. The conditional correlation between M3 and WPI is weak but negative for most of the time period but positive for few periods. The conditional correlation between exchange rate and WPI is weak but has both negative and positive correlations.

5. CONCLUSION

We tried to study the interdependence between stock market and macroeconomic variables in India using monthly data provided by the Reserve Bank of India from April 1991 to April 2016. For this we employ both VAR (1)-MGARCH (1, 1) BEKK model and conditional correlation plot. The former methodology will help us to analyse the relationship between stock market and macroeconomic variables in terms of three types of spill over namely mean, shock and volatility. From the multivariate GARCH model of BEKK, We observed that there is spill over in mean between WPI and Sensex implying that an Increase in WPI reduces Sensex return. There is also mean spill over from Exchange rate to IIP; WPI to IIP; IIP to M3; IIP to Exchange Rate; Sensex to WPI; IIP to WPI and from M3 to WPI.

The Shock spill over is observed from Sensex to Exchange Rate; IIP to Sensex; IIP to M3; IIP to Exchange Rate; IIP to WPI; M3 to IIP; M3 to WPI and WPI to Sensex. The shock from IIP affects every other sectors and WPI is affected by shocks in all other sectors. We thus observed that there is bidirectional shock spill over between IIP and M3 and between WPI and M3. However the cross shock spill over from M3 to IIP is larger than the cross shock spill over from IIP to M3. Again the cross shock spill over from WPI to M3 is greater than the cross shock spill over from M3 to IIP

The Volatility Spill over is observed from Sensex to IIP; IIP to Sensex; M3 to Exchange Rate; Exchange Rate to M3; WPI to M3 and WPI to Exchange Rate. So there is bidirectional volatility spill over between Sensex and IIP and between exchange rate and M3. The Cross volatility spill over from IIP to Sensex is larger than cross volatility spill over from Sensex to IIP. We also find that cross volatility spill over from M3 to Exchange rate is larger than the cross volatility from Exchange rate to M3

We found from the above analysis that IIP shocks affect every other sectors. We have bi-directional shock spill over between IIP and M3 and between M3 and WPI. We also have bi directional volatility spill over between Sensex and IIP and IIP and between exchange rate and M3.The volatility in IIP has more than impact on Sensex than the opposite. The cross volatility spill over from M3 to Exchange rate is larger than from exchange rate to M3.

The Reserve Bank of India which control money supply has an important role to play as shocks from monetary sector affect industrial production and WPI. The shocks from IIP and WPI in turns affects Sensex. The volatility in M3 affects exchange rate. IIP Volatility affect Sensex Volatility more than the opposite. So investor can gauge Sensex Volatility from IIP Volatility. WPI volatility also affect exchange rate and M3 volatility. So if we want to reduce the volatility of exchange rate and M3 we need to maintain stable price policy. Therefore we find that these results have important implications for macroeconomic policies and portfolio choice.

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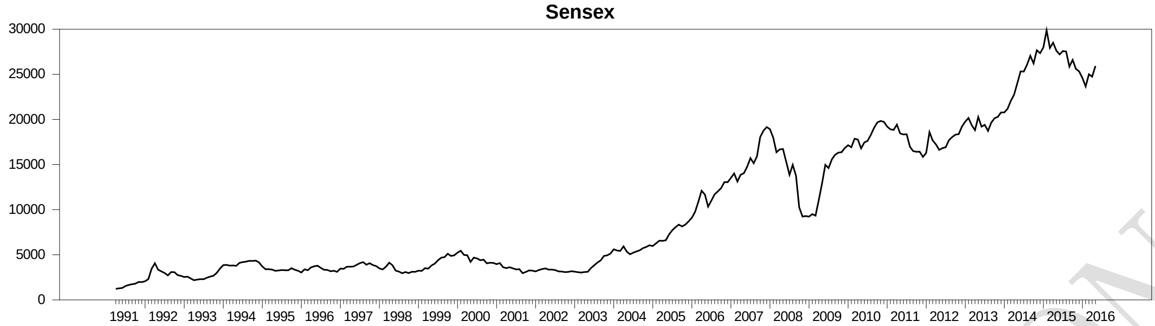
Appendix

Table 4: Descriptive statistics of monthly data

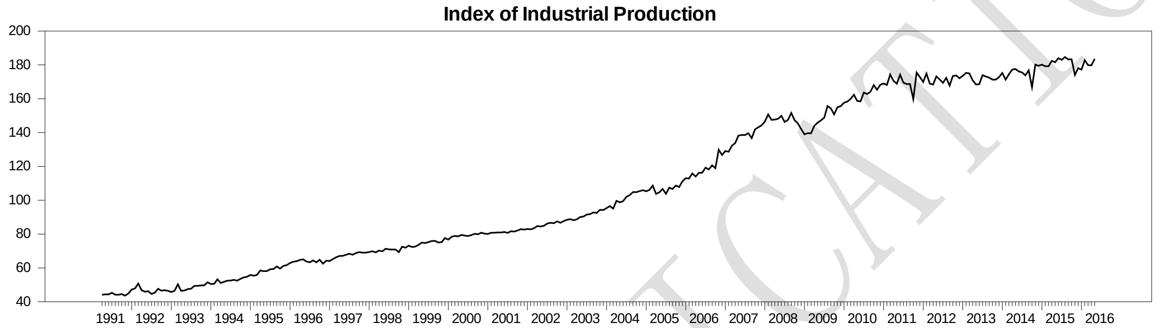
	Mean	Variance	Skewness	Kurtosis	JarqueBera	Probability
Sensex	1.012917	41.535482	0.271109	5.728650	415.272537	0.000000
IIP	0.473784	4.481102	0.144069	3.619721	165.366912	0.000000
M3	1.254377	0.545354	0.782885	2.903541	136.480719	0.000000
Exchange Rate	0.410802	4.603866	4.496569	36.487973	17711.952782	0.000000
WPI	0.483015	0.315067	0.281579	1.891800	48.863039	0.000000

Figure 2: Time plot for Sensex



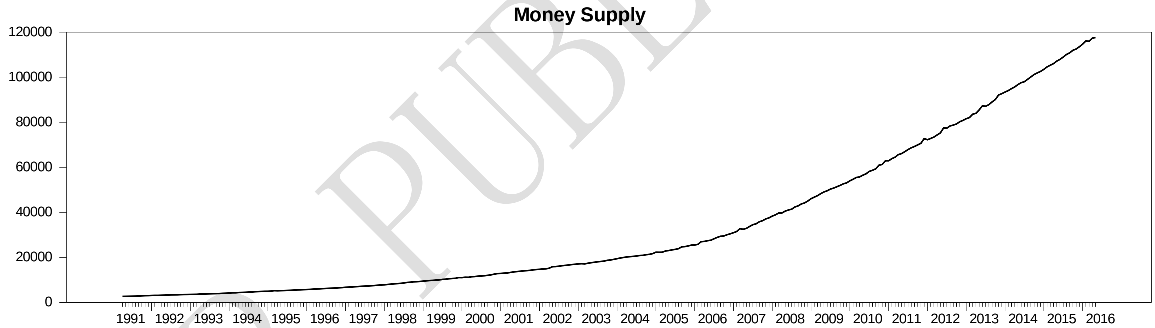
Time plot for Monthly Sensex

Figure 3: Time plot for Index of Industrial Production



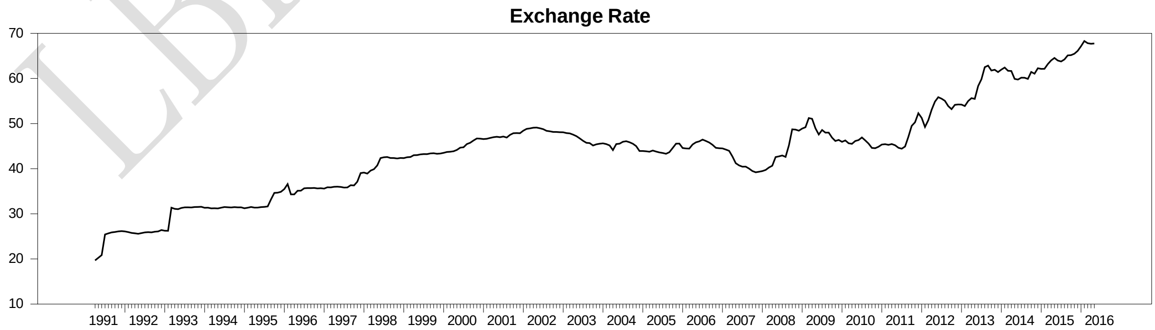
Time plot for Monthly IIP

Figure 4: Time plot for Money Supply



Time plot for Monthly M3

Figure 5: Time plot for Exchange Rate



Time plot for Monthly Exchange Rate

Figure 6: Time plot for Inflation

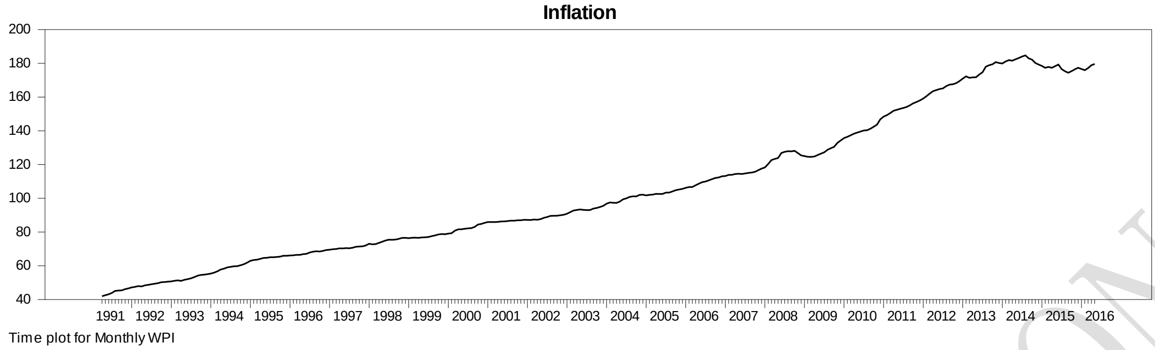


Figure 7: Time plot for log of first difference of Sensex

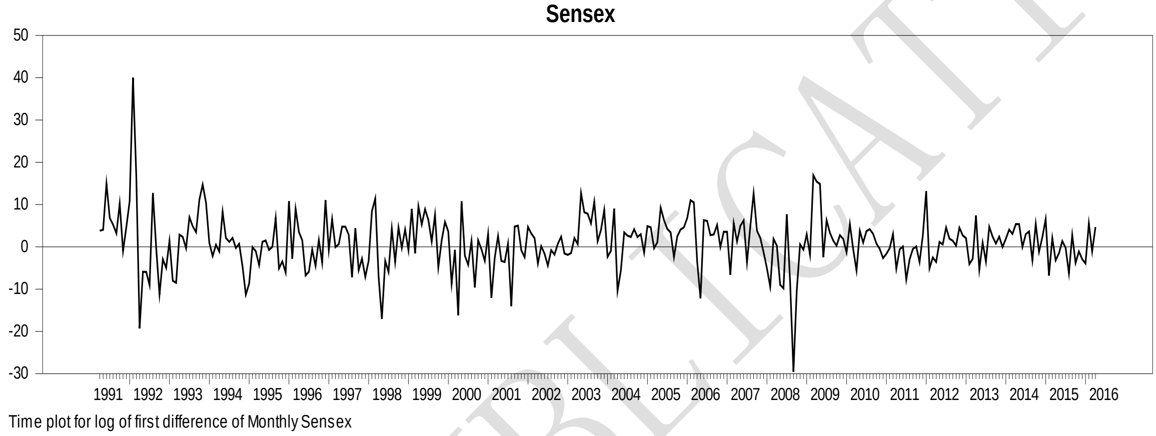


Figure 8: Time plot for log of first difference of Index of Industrial Production

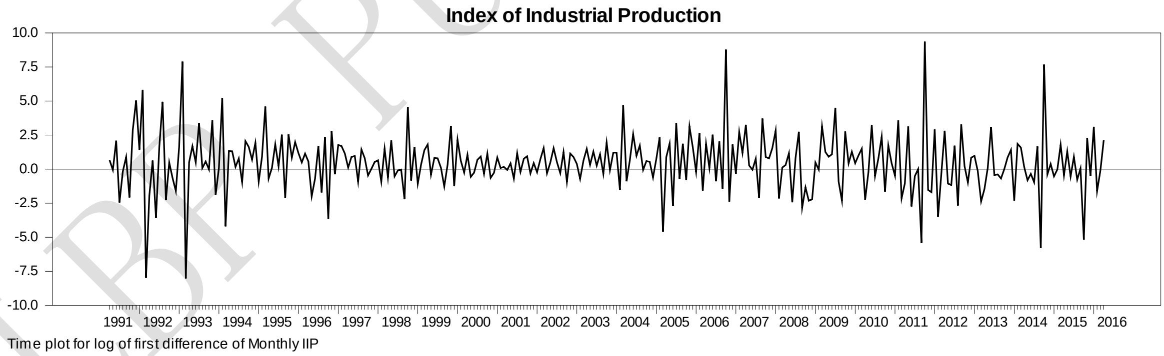


Figure 9: Time plot for log of first difference of Money Supply

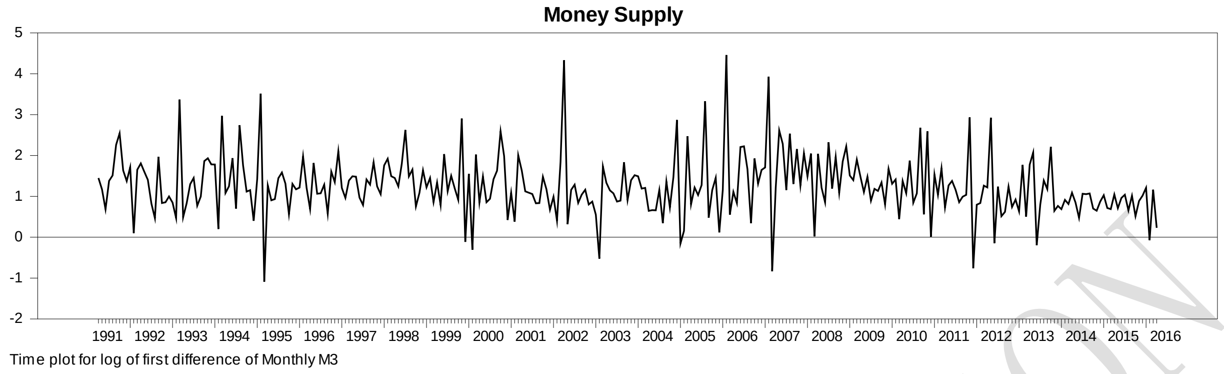


Figure 10: Time plot for log of first difference of Exchange Rate

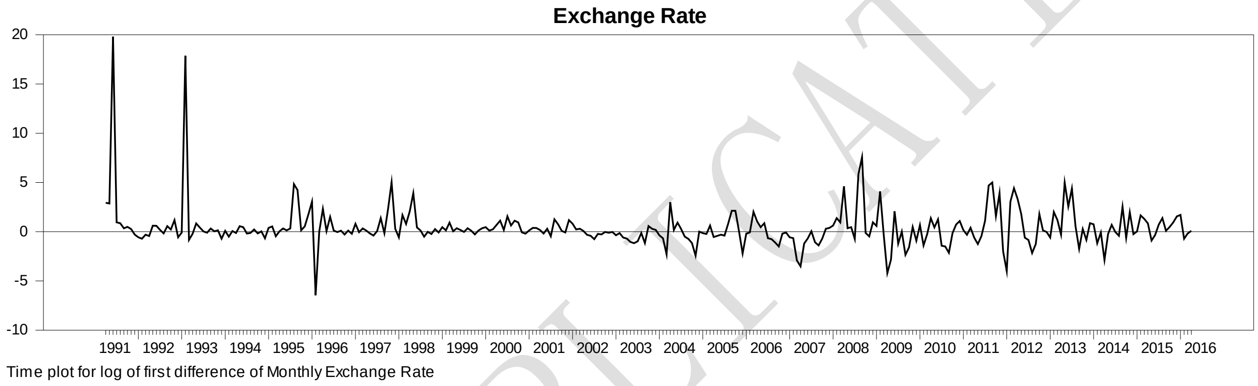


Figure 11: Time plot for log of first difference of Inflation

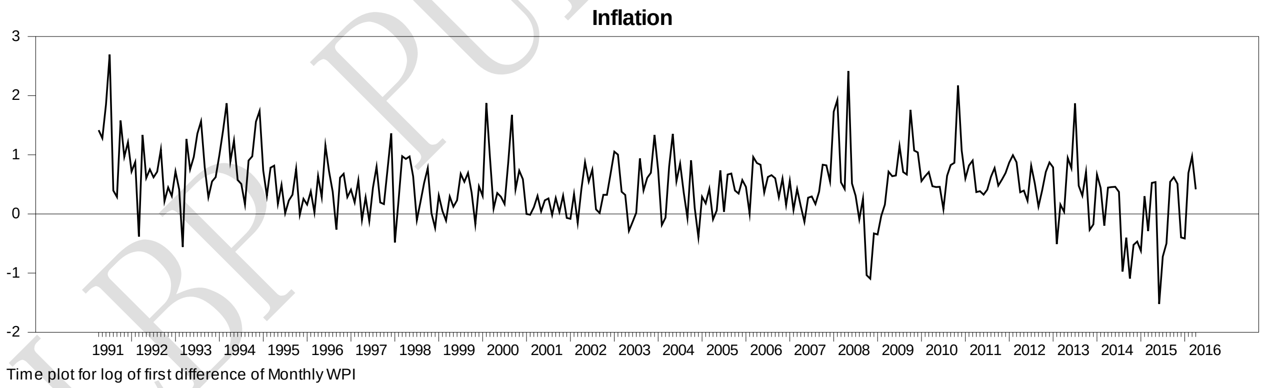
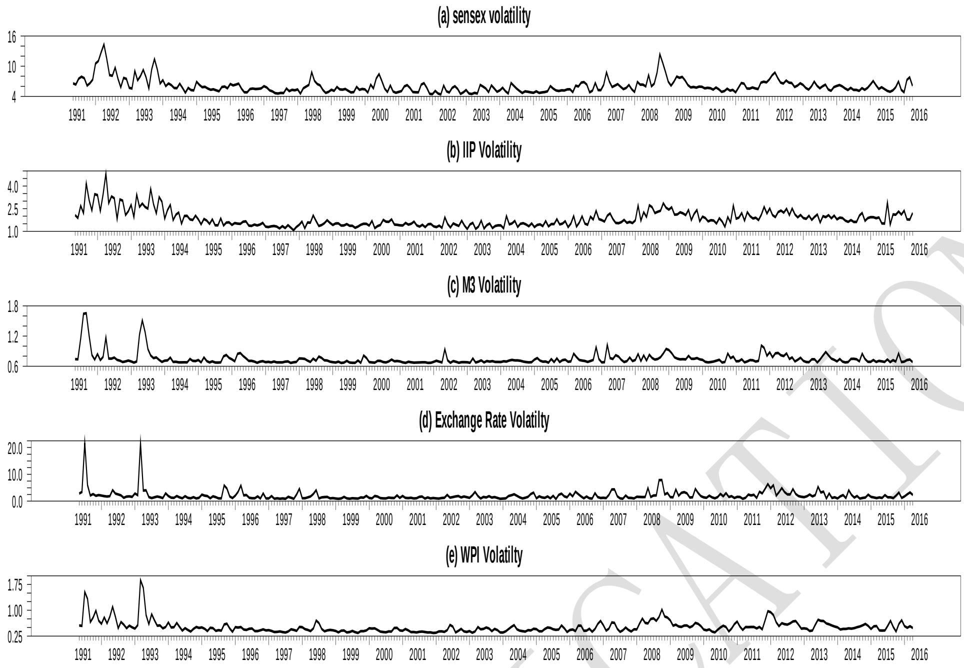


Figure 12: Time plot for volatility of Sensex, IIP, Money Supply, Exchange Rate and Inflation



Estimate volatilities of a VAR(1)-BEKK(1,1) model