DU Journal of Undergraduate Research and Innovation
Volume 2, Issue 2 pp 117-127, 2016

Macroeconomic Effects of Monetary Policy and Stock Price Shocks in India

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ABSTRACT

This paper explores the extent of interdependence between stock prices and monetary policies forthe Indian economy. A wide variety of theoretical and empirical models have been employed to analyse this relationship for other economies; these studies have provided some evidence to justify that monetary policy changes can impact asset prices and vice versa. We analyse the interaction between monetary policy and asset prices for India using Structural Vector Auto-regression. A study by Bjornland & Leitemo indicated that a great interdependence exists between stock prices and interest rate in the United States. Going by the finding that the propagation of a monetary policy change or shocks follows a similar order in terms of the variables it affects across time, we follow a similar methodology. For this study, four macroeconomic indicators or variable shave been taken and monthly frequency of data is used. The first variable is the stock index, which is taken to be the NIFTY index. The second variable is the interest rate, which is taken to beMumbai Interbank Bid Rate. This is the interest rate that a bank participating in the Indian interbank market would be willing to pay to attract a deposit from another participant bank. The other two variables are the Gross Domestic Product and the Inflation. Impulse response functions are obtained to see how one variable responds to a change in another variable.

Keywords: Exchange Rate, Money Market, Stock Index, Stock Market, Vector Auto-regression.

INTRODUCTION

Every economic variable has some degree of association with another economic variable. When one variable is changed by a certain amount, it may have varying amounts of changes in the variables it is associated with. While one variable might react positively, the other might react negatively; while one may undergo significant changes, the other may react feebly. Insight into this interdependence can prove to be valuable in developing efficient policies. This paper estimates the relationship between monetary policy and stock prices for the Indian economy. The literature that is present has studied the response of changes in monetary policy to asset prices in the United States of America. No significant work has been done to capture the relationship between monetary policy and stock prices for the Indian economy.
Central banks are known to keep inflation in check and decide the interest rate at which other banks accept loans known as ‘repo rate’ in the Indian economy. Interest rate and inflation are closely linked; interest rates are used by central banks to control inflation and as interest rates are lowered, more people are able to borrow more money, which results in surplus money to spend for the consumers, causing an increase in

inflation and economic growth. Basically, by lowering the interest rates, central banks attempt to increase the supply of money by making it easier to obtain.

On the other hand, if central banks increase the interest rates, it becomes more expensive for banks to borrow money from central banks. As a result, banks increase the rates that they charge their customers which leaves consumers with less money to spend. Not just individuals, but businesses also get affected because if a business is left with lower sum of money to spend and cuts back on growth or makes less profit, then future cash flows will drop, which lowers the stock price of the company. If enough companies experience declines in their stock prices, the whole market or index like NIFTY goes down.

The financial crisis of 2007-2008 saw one of the worst damages to world market caused by inflated asset price values. Asset prices fizzled out of control largely because of insufficient monitoring of asset price movements. Any crisis raises questions of why and how we got there and what lessons should be drawn to avoid repetition of past developments without laying ground for a new disaster.

The paper pans out as follows; next section gives a brief review of the previous work done on monetary policy and asset pricing. The section following that explains in detail Structural Vector Auto Regressions (SVAR) and gives other mathematical and theoretical background required. Then we summarize the data, data sources, the results of various tests employed and inferences derived from the study. Appendices collect the graphs and figures associated.

LITERATURE REVIEW

Bernanke and Gertler estimated that the goal of monetary policy should be price stability. But this notion was soon countered by Cecchetti, Genberg, Lipsky, and Wadhwani, who suggested that central banks are responsible for stock price changes. However, Cecchetti et al. suggested that asset pricing must not be a direct goal of monetary policy decided by central banks, whereas Goldhart says asset pricing contributes directly to price stability. Gilchrist & Leahy (3) recommended that asset prices and the economy as a whole can exhibit large fluctuations in response to these shocks. They did not find a strong case for including asset prices in monetary policy rules. Studies by Hilde C. Bjornland & Leitemo (1) support the idea that monetary policy making is indeed important for the stock market N.Cassola & Morana (2)found that asset prices contain information that is useful for the conduct of monetary policy in the euro area and a price stability oriented monetary policy may have a beneficial impact on the stock market as well.Ibrahim(4) analyzed the interactions between stock prices and exchange rates in Malaysia, using bivariate as well as multivariate co-integration, and Granger-causality tests. In the analysis, three exchange rate measures were used: the real effective exchange rate, the nominal effective exchange rate, and the RM/US rate. The results from the bivariate models indicate no long-run relationship between the stock market index and any of the exchange rates. Results from multivariate tests suggest that there is unidirectional causality from the stock market to the exchange rates. Secondly, both the exchange rates and the stock index are Granger caused by the money supply and the reserves.M. Khalid & Rajaguru (5) examined the dynamic linkage among exchange rate, stock prices and the money market in Pakistan. They reported no co-integration among the variables, but established the presence of causality among the variables.Pan, Fok, & Liu(6) examined dynamic linkages between exchange rates and stock prices for seven East Asian countries, including Hong Kong, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand, for the period January 1988 to October 1998 and found evidence of a causal relationship between the two markets in all the countries except for Malaysia.

METHODOLOGY

The following subsections give the details of the methodology followed in this study. To study the interdependence of the monetary policy in India and the stock prices, we make use of the mathematical model known as Structural VAR. We estimate this model using four variables, namely, Real GDP, Inflation, Stock Market Index (NIFTY, in this case) and the MIBID, the Mumbai Interbank Bid Rate, representing the interest rate. This is the rate that banks involved in the Indian interbank market are willing to pay for the purpose of attracting deposits from other participating banks.

Vector Auto regression (VAR)

A VAR model describes a vector of *n* variables as a linear function of the specified number of lags, i.e., the number of previous values, of that variable and all the other variables in the system. A VAR (p) model is specified as

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \epsilon_t$$

where c is a $n \times 1$vector of constants, y_t is a $n \times 1$ vector of variables, Φj is a $n \times n$ matrix of autoregressive coefficients for $j = 1, 2, ..., p$, ϵ_t is a $n \times 1$ vector of error terms and p is the appropriate number of lags. For example, if we take a system of two variables with two lags, in matrix form, the VAR can be written as

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \Phi_{11}^1 & \Phi_{12}^1 \\ \Phi_{21}^1 & \Phi_{22}^1 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \Phi_{11}^2 & \Phi_{12}^2 \\ \Phi_{21}^2 & \Phi_{22}^2 \end{bmatrix} \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

For each variable, a separate equation can be obtained from the above matrix notation. Each of the equations, in turn, can be estimated by using Ordinary Least Squares (OLS), since each equation has the same regressors.

The number of suitable lags can be calculated using an Information Criterion (IC) such as the Akaike Information Criterion (AIC) or the Schwarz Criterion. An IC has the form

$$IC(p) = ln|\Sigma(p)| + c_T . \varphi(n, p)$$

where $\Sigma(p)$ is the residual covariance matrix, $c_T$is a way of indexing the time series, based on the number of observations and $\varphi(n, p)$ is a penalty function for increasing the number of lags. The aim is to minimise an IC. However, the number of appropriate lags as estimated by an IC is not sufficient. A VAR must be well specified, i.e, there must not be a correlation amongst the error terms. Lags must be increased over what is suggested by an IC until all correlation issues are resolved.

Writing the VAR in lag operator notation, we get,

$$\left[I_n - \Phi_1 L - \Phi_1 L^2 - \cdots - \Phi_p L^p\right] y_t = c + \epsilon_t$$

where

$$L y_t = y_{t-1}, L^2 y_t = y_{t-2}$$

and so on, we say that the VAR is stable if all values of z satisfying

$$\left|I_n - \Phi_1 z - \Phi_1 z^2 - \cdots - \Phi_p z^p\right| = 0$$

lie outside the unit circle.

Structural VAR

We start with an underlying structural model of the for

$$A y_t = C(L) y_t + B u_t$$

Where the “structural shocks” u_t are normally distributed and correlated. We cannot estimate this equation directly due to identification issues, but instead we can write it as a reduced-form VAR, by taking the matrix *A* to the other side of the equation, such as

$$y_t = A^{-1}C(L)y_t + A^{-1}Bu_t$$

We can now estimate this VAR, and thus obtain the corresponding coefficients, however, we cannot get our structural model back because there are more unknowns than equations, when we compare the VAR that we estimate and the structural model we started with.

A conventional VARmodel, as described above, can be seen as a particular case of the more general structural model, where the *A* matrix is identity. In a structural model, however, this matrix can have unknown coefficients instead of 0's on the non-diagonal elements, accounting for contemporaneous effect amongst the variables, i.e., a change in one variable can cause an effect in another variable at the same instant of time.

To correctly identify our structural model, we need to impose some restrictions on the *A* matrix, and consequently on theA^{-1} matrix. Effectively, we are structuring the effect of a shock based on some economic theory. If one variable does not contemporaneously affect another variable, we impose a restriction by setting that coefficient equal to zero, in the following way,

$$\begin{bmatrix} \boldsymbol{y_t} \\ \boldsymbol{\pi_t} \\ \boldsymbol{s_t} \\ \boldsymbol{r_t} \end{bmatrix} = \boldsymbol{A(L)} \begin{bmatrix} \boldsymbol{D_{11}} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{D_{21}} & \boldsymbol{D_{22}} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{D_{31}} & \boldsymbol{D_{32}} & \boldsymbol{D_{33}} & \boldsymbol{0} \\ \boldsymbol{D_{41}} & \boldsymbol{D_{42}} & \boldsymbol{D_{43}} & \boldsymbol{D_{44}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon_t}^{\boldsymbol{y}} \\ \boldsymbol{\varepsilon_t}^{\boldsymbol{\pi}} \\ \boldsymbol{\varepsilon_t}^{\boldsymbol{s}} \\ \boldsymbol{\varepsilon_t}^{\boldsymbol{r}} \end{bmatrix}$$

Here $y_t, \pi_t, s_t$and$r_t$signify the GDP, inflation, stock prices and the interest rate, respectively. We have followed a recursive ordering of the variables. One can easily verify how a shock will travel and what variables it will affect at what time period, by looking at this model. Here we make the assumption that the Real GDP and Inflation can respond with a lag to monetary policy and stock price shocks while stock prices and monetary policy can respond to each other contemporaneously. We can identify the monetary policy shock by putting output and inflation before interest rates and stock prices in the VAR and impose two zero restrictions on the relevant coefficients in the third and fourth columns of the *A* matrix above. This is why the order of the variables in the vector is paramount. Changing the order changes the interdependence of the variables and hence the structural shocks of the model.

For *K* variables in y_t, the symmetry property of $E(\varepsilon_t \varepsilon_t')$imposes $K(K+1)/2$ restrictions on the $2K^2$ unknown elements in *A* and *B*. Thus, an additional $K(3K-1)/2$ restrictions must be imposed on *A* and *B* to identify the full model. Such restriction schemes must be of the form: $A\varepsilon_t = Bu_t$. This is also known as the A-B model. We use an A-model, where $B = I$, in which case $A\varepsilon_t = u_t$. For example, the restrictions may be imposed as follows:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix}$$

Since there is a recursive ordering, the matrix A^{-1} can be identified by using Cholesky Decomposition. We follow Bjornland & Leitemo [1] by imposing the so called “short run” restrictions. These restrictions can be applied by Cholesky decomposition of the variance-covariance matrix where A^{-1} is the Cholesky factor. The relationship is represented as

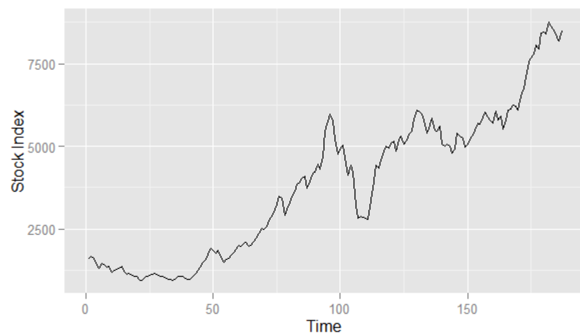
$$\Sigma = A^{-1}(A^{-1})'$$

Unit Root Testing

Before we can use a time series in a VAR model, we need to first make sure that the series is stationary. A stationary series is one that has constant mean and variance over time. If the series is not stationary, we need to transform it to a stationary series before using it for modelling.

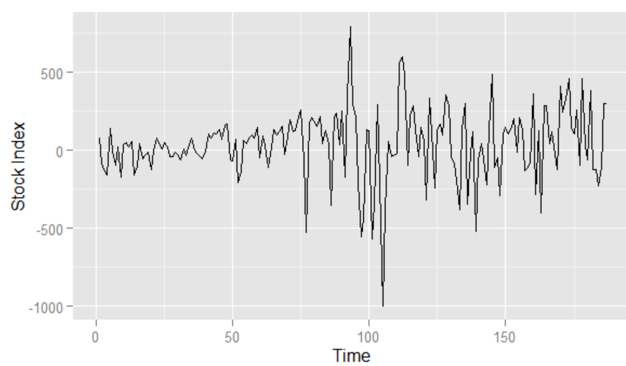
As can be seen from the graph below, the NIFTY Index has a definite upward trend, which implies non-stationarity of the data,

Figure I: NIFTY Index with Upward Trend



This trend can be removed by constructing an OLS regression line and shifting the graph so that the regression line is parallel to the horizontal axis, which, for example, gives the following data

Figure II: Detrended NIFTY Index



This is one way of removing the trend; this does not guarantee stationarity. To guarantee stationarity, we need to recognise the presence of a unit root and test the series for a unit root. An equation of the form

$$y_t = \alpha y_{t-1} + \epsilon_t$$

where ϵ_t is i.i.d ~ (0, σ^2), is said to have a unit root when

$$\alpha = 1$$

Presence of a unit root implies that the series is non-stationary. There are number of reasons why non-stationary series are not suitable for modelling. One reason is that in a non-stationary series, any ”shock” will have infinite persistence. If $|\alpha| > 1$, the series is non-stationary as well as explosive, then the shocks will not only have infinite persistence, but will have an increasingly large influence. But $|\alpha| > 1$ does not describe many series in economics, so we characterise non-stationarity by the presence of a unit root. Another reason is the problem of spurious regression. When two series are non-stationary, a regression of one on the other could have a high R^2 (the coefficient of determination), which may imply that there is a strong correlation between the two, even though the two may actually be uncorrelated. Stationarity can be induced by differencing the series. In the above equation, let's say there is a unit root, i.e, $\alpha = 1$. Subtract y_{t-1} from both sides, i.e,

$$y_t - y_{t-1} = \epsilon_t$$

This implies

$$\Delta y_t = \epsilon_t$$

Thus, we say we have induced stationarity by differencing once. The number of such differences required to induce stationarity is called the order of integration, specified by I(k), where k is the number of differences required. A number of different tests can be used to test whether a series is stationary or non-stationary, such as the Augmented Dickey Fuller Test (ADF), Phillips-Perron Test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. ADF and PP tests test for the null hypothesis that the series is non-stationary, whereas the KPSS test tests for the null hypothesis that the series is stationary. These tests can be applied after each differencing for the determination of the order of integration. The ADF test specifies and tests the following equation for non-stationarity

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \epsilon_t$$

where p is the appropriate number of lags so that t is uncorrelated and homoskedastic and $\delta = \alpha - 1$, under the null hypothesis that the series is non-stationary, i.e.,

$H_0 : \delta = 0$
$H_A : \delta < 0$

Here the null hypothesis is $\delta = 0$ because we first difference the series, which implies that a unit root will have $\delta = 0$. The ADF t-statistic is based on the least squares estimates of the specified ADF equation and are given by

$$ADF_t = t_{\delta=0} = \frac{\hat{\delta}}{SE(\delta)}$$

RESULTS AND DATA

Data

The data that has been used is of monthly frequency, because of lack of availability of more frequent data, from January, 2000 to January, 2015. The graphs of the variables with respect to time are given below. Here $t = 0$ represents the starting date, i.e., January, 2000 in this case. Some basic statistical analysis of each of the variables is also given.

Figure III: Graph of NIFTY closing price vs. time. The graph shows an upward trend

Table 1: Statistical Analysis of Variables

Variable Name	Mean	Standard Deviation	Skewness	Kurtosis
Stock Price	3822.027	2207.47	0.301	2.0543
G.D.P.	1254.111	616.8213	0.1761	1.6467
M.I.B.I.D.	7.115	1.7557	-0.3476	1.6468
Inflation	6.8163	2.8716	0.4939	1.9707

The statistical analysis gives the mean of the NIFTY closing price, GDP, MIBID and Inflation as 3800, 1254, 7.1% and 6.8% respectively. Stock Price, GDP and Inflation are slightly positively skewed, while MIBID is slightly negatively skewed. All the variables have positive kurtosis, which suggests that they are slightly flatter relative to a normal distribution.

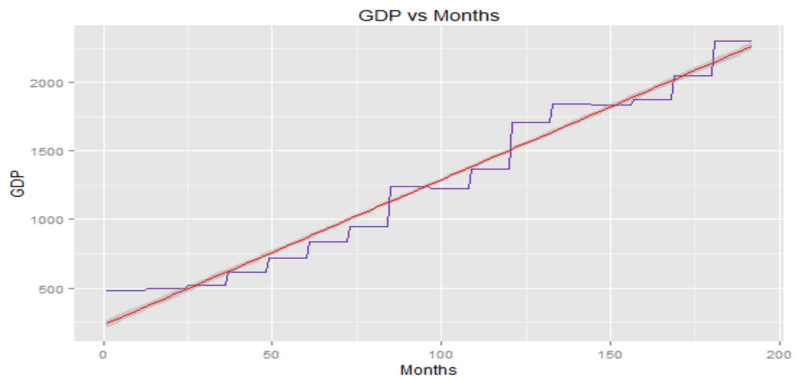


Figure IV: Graph of GDP vs. time. The graph clearly shows an upward trend

All the variables were found to be non-stationary, and hence they were differenced to achieve stationarity.

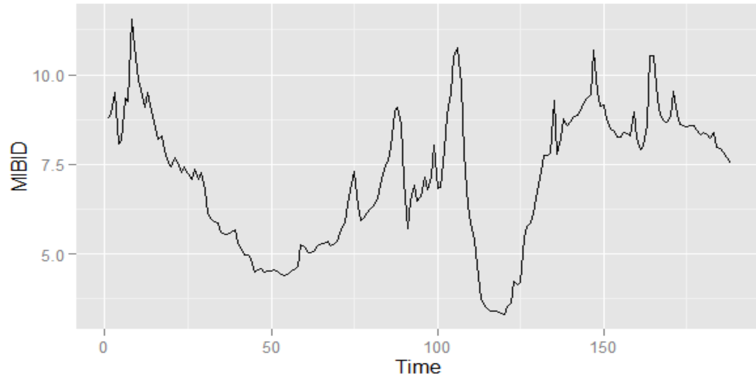


Figure V: Graph of MIBID vs. time. The graph does not show any clear trends.

The Augmented Dickey Fuller, Phillips Perron and the KPSS unit root tests were used to ensure that the variables are stationary after first differencing.
The appropriate lag lengths were chosen according to the Akaike Info Criterion, Final Prediction Error, Hannan-Quinn Criterion and the Schwarz Information Criterion. GDP and Inflation data were monthly, whereas the NIFTY index and MIBID were averaged over a month. The estimated value of the coefficients of the SVAR model is given in Appendix I

RESULTS

The analysis in this section is done through the Impulse Response Functions (IRFs) that were obtained from the estimated SVAR model. The impulse response estimates are given in AppendixI and their corresponding graphs are given below. To look at the changes in the variables according to monetary policy shocks, we look at the graphs where the impulses are MIBID and to look at the changes in the variables in response to a stock price shock, we look at the graphs where the impulse variable is NIFTY. Here the values of the coefficients depict the percentage change in that variable corresponding to an impulse. (Figures VI (a)), (Figure VI (b)) and (Figure VI(c)) graph the responses to monetary policy shocks. A monetary policy shock first increases the output, which then eventually dies down, and it approaches its mean again. However, the response of the output to stock price shocks though similar in behaviour is smaller in comparison and approaches its mean quicker. The stock prices respond to monetary policy shocks with an initial increase, after which it moves back to its mean. This is different from the results obtained in the USA (see Bjornland & Leitemo (1)); a positive monetary policy shock causes stock prices to fall in the short run and increase in the long run in the USA. Even though the short-run effect is different, the long-run effect is similar. A monetary policy shock also decreases the inflation, but in the long run the inflation slowly approaches its mean.
The red dotted lines indicate the acceptable error band. The black line in the middle gives us the actual

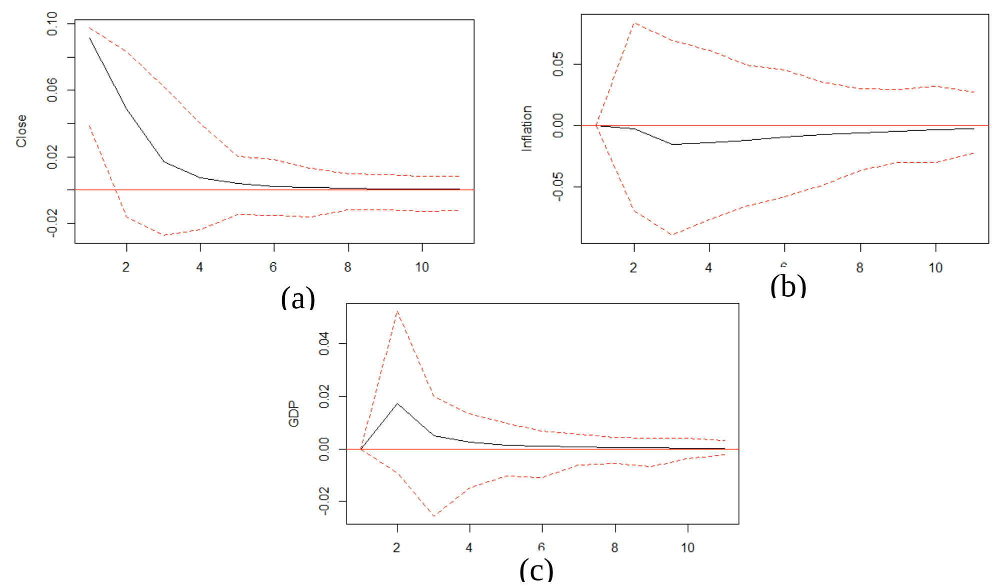


Figure VI: Response of GDP, Stock Price and Inflation when impulse is given on MIBID

forecast line. On the x-axis, we have plotted time (t) and on the y-axis, we have the values forecasted for various response variables.

(Figures VII (a)),(Figure VII (b)) and(Figure VII(c))graph the responses to stock price shocks. The output behaves much like it behaves to monetary policy shocks. Since NIFTY is smaller Index, the percentage change compared to monetary policy shock is also smaller. Inflation increases initially with a stock price shock and then approaches the mean in the long run, which is expected because positive changes in the stock prices have a chain effect which ultimately causes inflation to rise, but this increase in the inflation wears out over time. A shock in the stock prices decreases the interest rate, which is an expected result, consistent with the findings in the USA (see Bjornland & Leitemo (1)).This is an inverse result of the one found out as the response of stock price to an interest rate impulse.Response graphs of remaining variables when impulse is given on GDP and inflation are given below

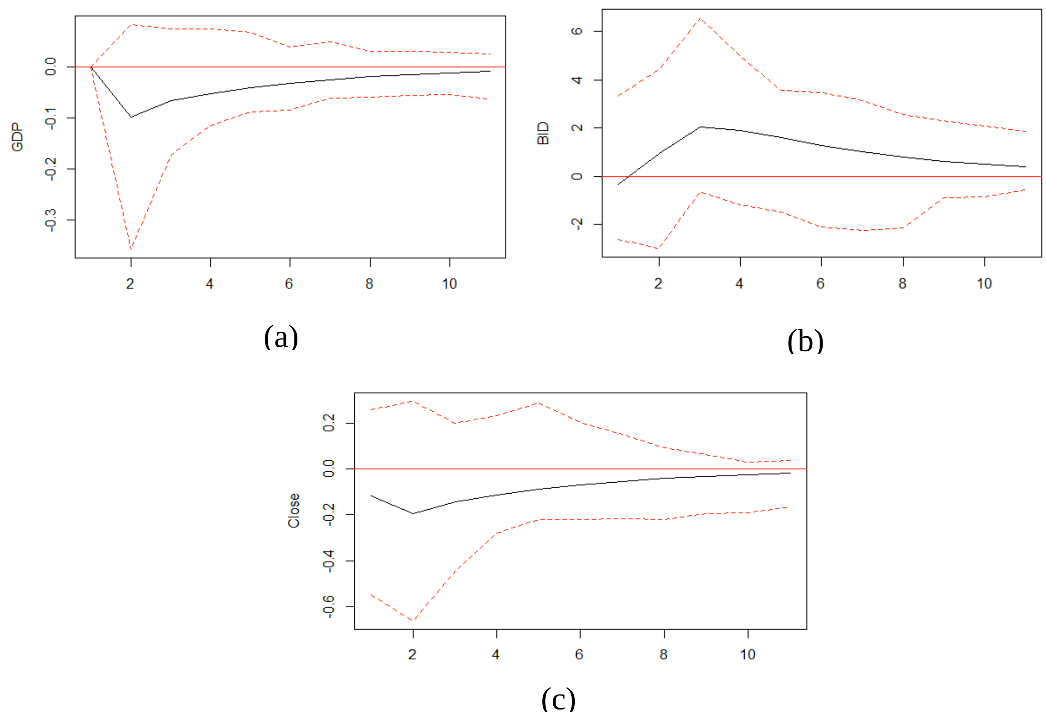
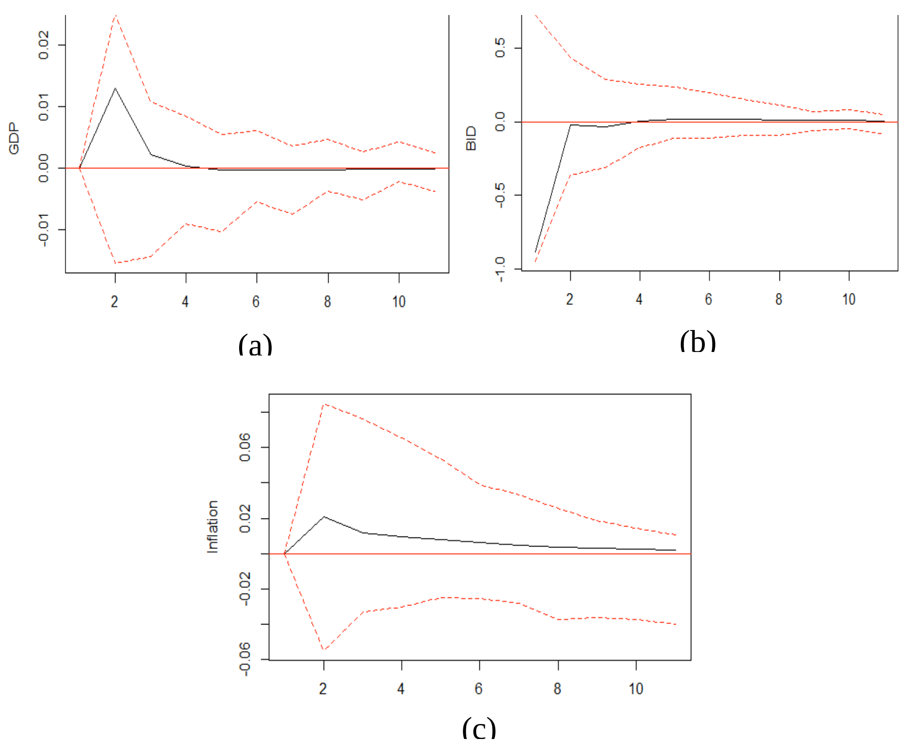


Figure VII: Impulse response coefficients for 10 days

Figure VIII: Response of GDP, MIBID and Inflation other when impulse is given on Stock Price



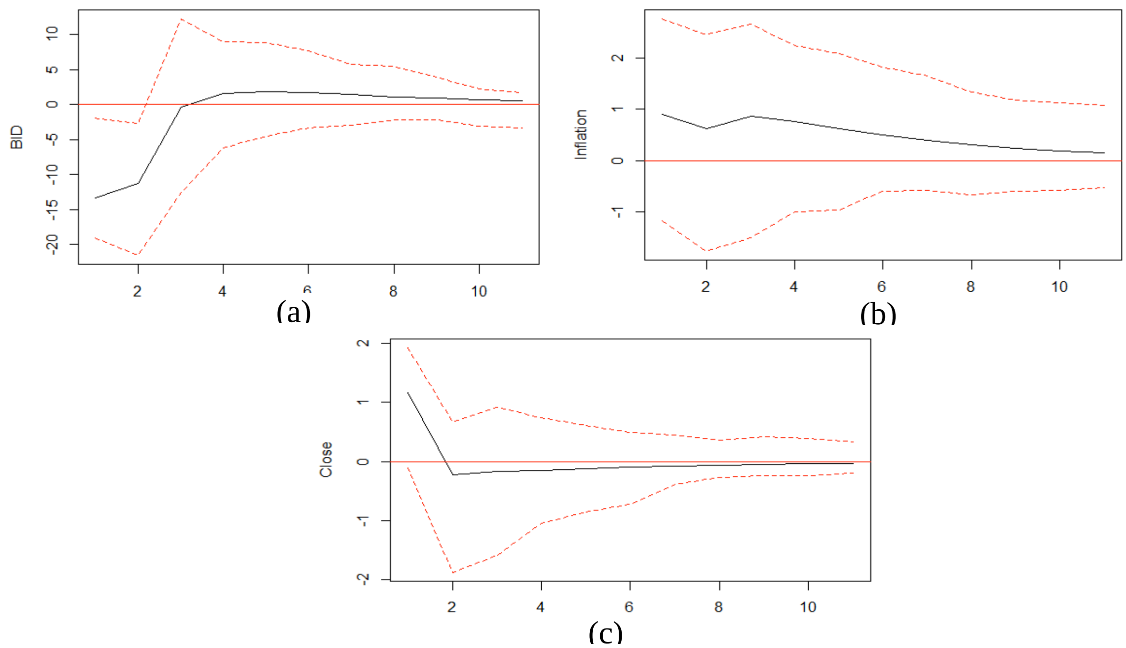


Figure IX: Response of Stock Price, MIBID and Inflation when impulse is given on GDP

ACKNOWLEDGEMENTS

We are highly indebted to our mentor Dr Mandira Sarma, Associate Professor, CITD, School of International Studies, Jawaharlal Nehru University, for her guidance.We would also like to express our gratitude to Cluster Innovation Centre, University of Delhi for providing us state of the art technological support. We also extend our gratitude to Dr. Shobha Bagai, who helped us revise the initial draft of the paper with her valuable suggestions.

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APPENDIX – I

The graphs and the estimates have been calculated using R. The scripts and the methodology are available at the following Github repository:
https://github.com/ronitkishore/MonetaryPolicy-StructuralVARs-R

APPENDIX II: Estimates and Tables

Table 2: SVAR Estimate: A Matrix

	GDP	Inflation	NIFTY	BID
GDP	1.0000	0.0000	0.000	0.000
Inflation	-0.9015	1.0000	0.000	0.000
C1ose	-14.7821	-0.2288	1.000	1.031
BID	0.4747	1.5221	9.949	1.000

Table 3: SVAR: B Matrix

	GDP	Inflation	NIFTY	MIBID
GDP	1	0	0	0
Inflation	0	1	0	0
C1ose	0	0	1	0
BID	0	0	0	1

Table 4: Impulse response coefficients for 10 days

GDP	Inflation	NIFTY	MIBID
2.816468e-18	0.000000000	0.0915796974	0.08884060
1.722310e-02	-0.002362302	0.0487613257	0.23304819
5.115968e-03	-0.015275791	0.0168867898	-0.03208166
2.659279e-03	-0.014233149	0.0074680056	-0.04919990
1.485979e-03	-0.011842516	0.0037877842	-0.04521877
9.819273e-04	-0.009421356	0.0022984003	-0.03582653
7.077087e-04	-0.007407304	0.0015785068	-0.02777323
5.343840e-04	-0.005803772	0.0011638276	-0.02151064
4.120369e-04	-0.004544091	0.0008878641	-0.01672308
3.206018e-04	-0.003557716	0.0006876958	-0.01304252