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Analysis of monetary policy variables with stock returns using var frame work

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Abstract
In order to analyze the sources of fluctuations in stock returns, a standard complete structural macro model is probably required. Using the vector autoregressive (VAR) framework, this study empirically documents the impulse response functions of monetary policy variables and stock market The analysis is carried out by considering monthly changes of the Reserve Bank of India data of Exchange rate, Broad money, Inflation with Index values of Nifty Fifty from 2000 to 2016 .The analysis concludes that shocks of past values stock returns impacts on stock returns by itself and other monetary policy variables impact on stock returns is however less significant.

Keywords: VAR modeling, Impluse response, macroeconomic variables

Introduction
In order to analyze the sources of fluctuations in stock returns growth, a standard complete structural macro model is probably desirable. However, such a model is derived on the basis of economic theory. Thereby two major problems arise: the theory must be exact enough to identify the endogenous and exogenous variables and the functional form connecting them. The second problem concerns the identification problem of recovering structural parameters from estimated reduced form. Out of these problems another class of nonstructural models: Vector autoregressive (VAR models) have been evolved, pioneered by Sims (1980) and popularized by researchers such as Litterman (1984) and Doan(1984). VAR model does not require any explicit economic theory to estimate a model. It uses only the observed time series properties of the data to forecast economic variables.
The VAR models have many applications (see Cooley and Leory, 1985). They are used to determine how each endogenous variable responds over time to a shock in that variable and in every other endogenous variable. VAR models are useful for analysis of the effect of alternative monetary or fiscal policies (Sims, 1982). The VAR models also provide a straightforward way of predicting the values of set of economic variables at any given point in time.
In this paper, we develop and estimate an monthly macro econometric model for the impact of monetary policy on stock returns over the period 2000 to 2016 using VAR technique proposed by Litterman (1984) and Sims (1980, 1982 & 1986). The main focus of this study is to analyze empirically the strength of short-run and long-run impacts of anticipated and unanticipated macroeconomic variables and its impact on stock returns.
The paper is divided into five parts. VAR approach is outlined next, followed by a methodology and discussion on the data analysis used to estimate the model. The next part discusses the empirical results, with conclusions.

Methodology
Population and Sampling
For the population, data of two stock return indices of NSE and BSE is adapted for finite time period. The selected indices have at least 16 years of monthly values, thus providing enough number of observations to perform a time series models and for accurate estimation considering growth of IT, Banking and Infrastructure sectors in economy, respective indices namely CNX IT, CNX Banking Nifty, CNX infrastructure can also be added further,

monthly index values are collected from official website of NSE and BSE through Yahoo finance, google finance and Thomsan reuters.
Data of monthly values of one index from NSE and one index from BSE of 16 years data are considered for the study. This large and varied data sample is expected to reflect drastic changes taken place in Indian stock market.

Sampling Period
Data samples of monthly rates is considered for twenty years from Jan 2000 to Oct 2016.This period is considered as there is no much structural breaks and there is no much recession effect in india, hence it is a stable period for our data analysis

Vector Auto Regressive (Var) Method
The methodology of the VAR is briefly described here. A k-equation VAR can be represented in a matrix form as follows:

$$A(L)Y_t=A+U_t \quad (1)$$

And

$$A(L)=I–H_1L_1–H_2L^2-\ldots..H_kL^n \quad (2)$$

Y_t is an kx1 vector of variables, A is an kx1 vector of constants, and U_t is an kx1 vector of random variables. Equation (2) is a kxk matrix of normalized polynomial in lag operator L (L^m $Y_t=Y_{t-1}$) with the first entry of each polynomial on A's being unity.
VAR model is a system of autoregressive equations. Theoretically, regressands can be taken in the form of infinite lags of other cointegrated variables. As the central limit theory plays key role in the study of heteroscedasticity, without innovation of VAR, cointegration theory is no different than a regular high-degree AMAR model. Traditional MA and AMAR model is confined by the number of autogressive variables. In other words, MA and AMAR models exclude the possibility to simultaneously disclose the autogression among various variables. Although, in 1960s and 1970s, some statisticians and economists have already shed light on this problem, complete solution is developed by Sims (1980) [17] . Johnston and Dinardo (2004) offer a laconic summary of the essential ideas of VAR model.
Hence, each equation in the system can be estimated using OLS. Moreover, OLS estimates are consistent and asymptotically efficient. Even though the error terms are correlated across equations, Seemingly Unrelated Regression (SUR) do not add to the efficiency of the estimation procedure since all regressions have identical right-hand-side variables. However, before estimating the model, the lag length must be chosen. If L is the lag length, number of coefficients to be estimated is k (kL + c), where c is the number of constants. The VAR model presented above indicates that the current innovations (U_t) are unanticipated but becomes part of the information set in the next period. The implication is that the anticipated impact of a variable is captured in the coefficients of lagged polynomials while the residuals capture unforeseen contemporaneously events. A joint F-test on the lagged polynomials provides information regarding the impact of the anticipated portion of the right-hand side variables. The impact of the unanticipated policy shocks (i.e. the policy variables such as changes in money supply and government expenditures) on other economic variables can be analyzed by employing the "impulse response functions" (IRFs) and "variance decompositions" (VDCs) that are obtained from a moving average representation of the VAR model given below[equations (3) & (4)]:

$$Y_t=Constant+H(L)U \quad (3)$$

And

$$H (L)=I+H_1L+H_2L+\ldots.. \quad (4)$$

Where H is the coefficient matrix of the moving average representation, which can be obtained by successive substitution in equations (1) and (2). The elements of the H matrix trace the response over time of a variable i due to a unit shock given to a variable j.
The impulse response functions make it possible to analyze the dynamic behavior of the target variables due to unanticipated shocks in the policy variables. Variance decompositions show the portion of variance in the prediction for each variable in the system that is attributable to its own innovations and to shocks to other variables in the system.

Granger Causality/Block Exogeneity Wald Tests
VAR Granger Causality/Block Exogeneity Wald Tests (GCBEW) examines whether the lags of excluded variable affects the endogenous variable. The present study contains two variables such as return and trading volume. The GCBEW test helps to investigate the causality between these two variables. It helps to identify whether the lags of one variable cause the lags of another variable in a VAR model. It never explains when the change will take place because of the change in the other lagged variable. It provides simple causality among the variable not the time of change or the effect of change.

Impulse Response and Variance Decomposition
Impulse Response Analysis
Impulse response traces out the responsiveness of the dependent variable in the VAR to shocks to each of the variable (Brooks, 2008). It plots the response of a variable against the shock during a particular period of time. It identifies the response of other variable due to a shock during a particular period of time.

Variance decomposition analysis.
Variance decomposition or forecast error variance decomposition shows the amount of information each variable contribute the other variable in a VAR model. Variance decomposition gives the proportion of movements in the dependent variables that are due to their own shock and shock to the other variables in the system (Brooks, 2008). The study also conducts the Hasbrouck (1995) information share to understand the proportional contribution of that market to price innovation variance.

Results and Discussions
Data Analysis
The data for the study is obtained from various publications of RBI portal and other portal like NSE and BSE. In order to

maintain uniformity among variables data, the model is estimated using monthly data from 2000 to 2016. The variables included in the VAR model are Nifty Fifty stock index, Bank rate, consumer price index (CPI), Exchange rate, Broad money (M3). The objective here is to study the dynamics of the variables or the inter-relationship between these key macroeconomic variables and stock returns, in particular, the influence of policy variables. All the variables are in logarithms. It is important to note that in order to capture the finer details of the economy, a larger model with more variables would be desirable. However, with VAR models, one runs into serious degrees of freedom problems when the variables are many, especially with monthly data

As a pre-requisite certain properties of the variables in the model must be checked in order to determine the appropriate specification for VAR estimation. The order of integration for each variable is determined using Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) [15] tests. The results of these tests are reported in table I. With the exception of ADF test with constant for NIFTY FIFTY & CPI and with constant and PP test with constant for Bank rate, CPI, Currency circulation, exchange rate, all other ADF and PP tests for variables in log levels indicate that they are non-stationary. When first differenced in log, we find the evidence that the variables are stationary. Since the results, overall, tend to suggest non-stationary in log levels of the variables but stationarity in their log first differences, we proceed by contending that the variables belong to the I (1) process.

Results of Unit Root Test

Variables	ADF		PP	
	t-stastics	Prob	Adjust-stat	Prob
Log Levels				
FOR NIFTY FIFTY	-0.5569	0.8758	-0.5569	0.8758
Inflation	-13.478	0	-13.478	0
For Bank Rate	-1.4338	0.5649	-1.4338	0.5649
For Broad Money (M3)	-0.904	0.7854	-3.2778	0.0173
For Credit To Commercial Sector	-1.2612	0.6473	-1.3998	0.5817
For Us Dollar Exchange Rate	-0.2865	0.9232	0.135	0.9676
Log First Differences				
Cpi	-13.62	0	-13.62	0
For Bank Rate	-13.478	0	-13.478	0`
For Broad Money (M3)	-11.695	0	-181.65	0.0001
For Credit To Commercial Sector	-15.967	0	-15.985	0

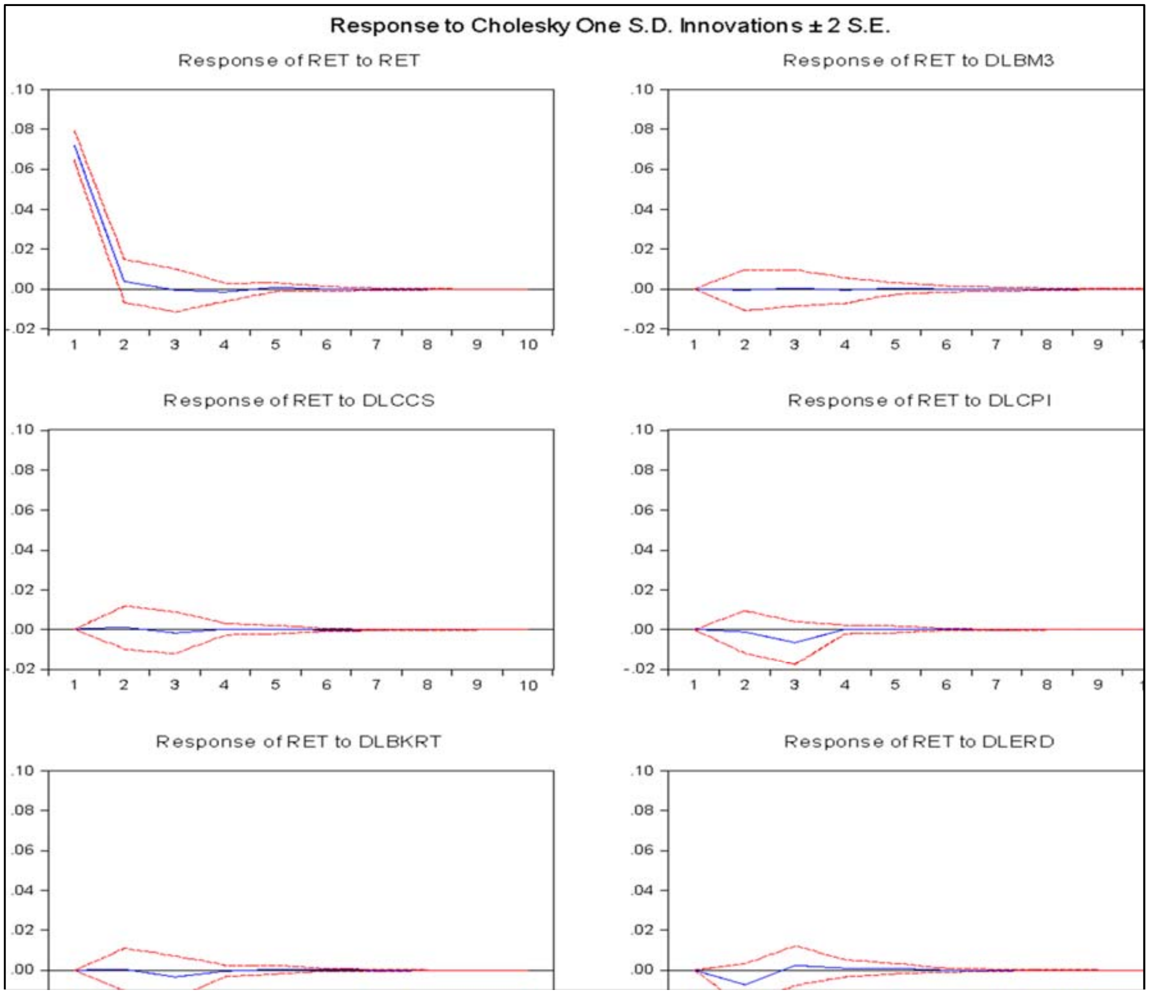
Var Granger Causality/Block Exogeneity Wald Tests

VAR Granger Causality/Block Exogeneity Wald Tests examine the bidirectional causal relationship between monetary policy variants and stock returns

Monetary policy variants	Chi-sq	Df	Prob.
DLBM3	0.123078	2	0.9403
DLCCS	0.19766	2	0.9059
DLCPI	1.709443	2	0.4254
DLBKRT	0.136867	2	0.9339
DLERD	2.281311	2	0.3196
All	4.501179	10	0.9219

From the above table, Consumer price index and Dollar exchange rates probability values are less than 0.5 meaning those variables are significant for stock returns as a dependent variable.

Impulse Re Sponse Function of Returns to Various Impulses



Impulse response gives out responses of the dependent variable in the VAR to shocks to each of the variable (Brooks, 2008). It plots the response of a variable against the shock during a particular period of time. Since CPI and Dollor exchange rate is significant ,for a strong observation impulse response is plotted for all macro-economic variables with stock returns by making stock returns as dependent variable, it is evident from the above plot that stock return has a burst impact on its own previous index values(Lag) compared to other macro-economic variables such as inflation, bank rate, exchange rate, currency circulation.

Variance Decomposition of Returns

Variance Decomposition of RET					
Period	S.E.	RET	DLERD	DLCPI	DLCCS
1	0.0721	100	0	0	0
2	0.0727	98.86	1.1069	0.001867	0.005
3	0.0731	97.655	1.1658	0.926019	0.0429
4	0.0731	97.628	1.1832	0.92526	0.0453
5	0.0731	97.614	1.1927	0.924974	0.0455
6	0.0731	97.612	1.1927	0.925186	0.0459
7	0.0731	97.611	1.1928	0.925494	0.0461
8	0.0731	97.611	1.1928	0.925493	0.0461
9	0.0731	97.611	1.1928	0.925493	0.0461
10	0.0731	97.611	1.1928	0.925493	0.0461

Variance decomposition or forecast error variance decomposition shows the amount of information each variable contribute the other variable in a VAR model. Variance decomposition gives the proportion of movements in the dependent variables that are due to their own shock and shock to the other variables in the system. From the above table we can notice that stock returns is composed with maximum values over a particular period of time meaning which the shocks of the returns is impacting on stock returns itself (but on previous data), however other variables has less effect on stock returns.

Conclusion

The purpose of this study is to empirically document how monetary policy variables effects to stock market and to test the causal link between Monetary policy variants and stock market in the India. The analysis of the monthly changes of the Reserve Bank of India data of exchange rate, broad money, inflation with index values of nifty fifty from 2000 to 2016 concludes that shocks of past values stock returns is an impact on stock returns by itself and other variables impact on stock returns is however less significant. The limitation in our study is that we have considered Consumer price index as variables, for effective analysis it is suggested to consider Whole sale price index value and also daily data for above said variables.

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