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Abstract

The research work focuses on the applicability of parametric approaches such as Time-Varying and Sign Restricted Vector Auto Regression (VAR), Structural Vector Autoregression (SVAR) models for some problems faced by the Indian Economy. The study is based on three issues, which are categorised as the following three chapters 1. Analysing Inflation in India using Time-Varying SVAR Model 2. Twin Deficit Hypothesis and its Relevance in India: Time-Varying VAR Approach 3. Oil Shocks and Its Impact On Indian Economy: Sign Restricted SVAR Model.

In the first chapter using Time-Varying SVAR Impulse Response Functions (IRFs), it is checked whether crude oil price shock has brought about changes in the inflation (p), output growth (x) and interest rate (i) of Indian economy. It is based on the procedure followed by Nakajima (2011). The results indicate that sudden oil price shock is followed by an increase in inflation. The increase in inflation is later accompanied by a decline in output growth, to which Reserve Bank of India (RBI) responds by raising the interest rate, thereby making the inflation move towards the stability level as specified by the RBI i.e. (5-5.5%).

In the second chapter, Time-Varying Vector Autoregression (VAR) has been employed to prove the existence of twin deficit hypothesis in India following the methodology by Nakajima (2011). The budget deficit and trade deficit are interrelated through the phenomena termed as twin deficit hypothesis. To understand the phenomena, the study has tried to understand the impact of the fiscal shock on macro variables in India namely current account deficit as a percentage of GDP, Real effective exchange rate of India and real GDP of India. The impact of the fiscal shock on macro variables is studied, as maintaining a sustainable level of budget deficit is considered to be a necessary condition for the maintenance of a comfortable level of current account balance. The results indicate that fiscal deficit and current account deficit are related in the Indian context, and twin deficit hypothesis holds.

In the third chapter, a Sign Restricted SVAR Model has been employed to understand

the macroeconomic impact of oil shocks on the Indian economy. Three types of shocks have been identified using sign restrictions, namely an Oil Supply Shock, Oil Demand Shock created by Global economic activity and an Oil-specific Demand Shock following the identification procedure of Baumister, Peersman and Van Robays (2012). The results indicate that output growth and inflation react very differently to the fluctuations in oil prices as the type of the shock is concerned.

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Contents

1	Analysing Inflation in India using Time-Varying SVAR Model	17
1.1	Introduction	17
1.1.1	Research Problem	18
1.2	Literature Review	19
1.2.1	Time-Varying Parameter SVAR with Stochastic Volatility	20
1.3	Methodology	22
1.3.1	The Basic Model	23
1.3.2	Analytical Framework (TV-SVAR with Stochastic Volatility)	31
1.4	Results	34
1.4.1	Stochastic Volatility Plot	35
1.4.2	Time - Varying Simultaneous Relation	37
1.4.3	Time - Varying Impulse Response Functions and Comparison with VAR Models	40
1.5	Conclusion	41
2	Twin Deficit Hypothesis and its Relevance in India: Time-Varying VAR Approach	51
2.1	Introduction	51
2.2	Research Problem	53
2.3	Literature Review	53
2.4	Basic Model	55
2.5	Data and Methodology	56
2.5.1	Time-Varying VAR Model	57
2.6	Results	62

2.6.1	Stochastic Volatility Plot	62
2.6.2	Time-Varying Simultaneous Relation	65
2.6.3	Constant Impulse Response Functions/Constant VAR and Time-Varying Impulse Response Functions	67
2.7	Conclusion	69
3	Oil Shocks and Its Impact On Indian Economy: Sign Restricted SVAR Model	77
3.1	Introduction	77
3.2	Research Problem	78
3.3	Literature Review	79
3.4	Methodology	81
3.4.1	Sign Restricted SVAR Framework	82
3.5	Results	83
3.5.1	Oil Supply shock	83
3.5.2	Oil Demand Shock-driven by global economic activity	84
3.6	Conclusion	85
A	Chapter1	89
B	Chapter2	93
C	Chapter3	97

List of Figures

1-1	Annual Rate of Inflation	18
1-2	Stochastic Volatility Plot of Inflation	35
1-3	Stochastic Volatility Plot of Output growth	36
1-4	Stochastic Volatility Plot of Interest Rate	36
1-5	Stochastic Volatility Plot of Crude Oil	36
1-6	Time Varying Simultaneous Relation of Inflation Shock to Output growth .	37
1-7	Time Varying Simultaneous Relation of Inflation Shock to Interest Rate . .	38
1-8	Time Varying Simultaneous Relation of Inflation Shock to Interest Rate . .	38
1-9	Time Varying Simultaneous Relation of Inflation Shock to Interest Rate . .	38
1-10	Time Varying Simultaneous Relation of Inflation Shock to Interest Rate . .	39
1-11	Time Varying Simultaneous Relation of Inflation Shock to Interest Rate . .	39
1-12	IRF of crude oil price shock to inflation in a Constant VAR Model	41
1-13	IRF of inflation shock to output growth in a Constant VAR Model	42
1-14	IRF of inflation shock to output growth in a Time-Varying VAR Model . . .	42
1-15	IRF of output growth to inflation in a Constant VAR Model	42
1-16	IRF of output growth to inflation in a Constant VAR Model	43
1-17	IRF of output growth to inflation in a Time-Varying VAR Model	43
1-18	IRF of crude oil price shock to interest rate in a Constant VAR Model	43
1-19	IRF of crude oil price shock to interest rate in a Time-Varying VAR Model .	44
1-20	IRF of inflation shock to interest rate in a Constant VAR Model	44
1-21	IRF of inflation shock to interest rate in a Time-Varying VAR Model	44
1-22	IRF of output growth shock to interest rate in a Time-Varying VAR Model .	45
1-23	IRF of output growth shock to interest rate in a Time-Varying VAR Model .	45

2-1	Current Account Deficit and Fiscal Deficit Trend in India.	52
2-2	Stochastic Volatility Plot of Fiscal Deficit	63
2-3	Stochastic Volatility Plot of Current Account Deficit	63
2-4	Stochastic Volatility Plot of Real Effective Exchange Rate	63
2-5	Stochastic Volatility Plot of Real GDP	64
2-6	Time-Varying Simultaneous Relation of Real GDP shock to FD	65
2-7	Time-Varying Simultaneous Relation of Real GDP shock to REER	65
2-8	Time-Varying Simultaneous Relation of FD shock to REER	65
2-9	Time-Varying Simultaneous Relation of real GDP shock to CAD	66
2-10	Time-Varying Simultaneous Relation of real FD shock to CAD	66
2-11	Time-Varying Simultaneous Relation of REER shock to CAD	66
2-12	Constant Impulse Response Functions/Constant VAR	67
2-13	Time-Varying Impulse Response Functions/Time-Varying VAR	68
3-1	Average Price of Crude Oil in India Note: based on the data of Ministry of Petroleum and Natural Gas (PPAC)	78
3-2	The impulse response functions (IRF) of the variables output growth and Inflation (WPI) to an oil supply shock	84
3-3	The impulse response functions (IRF) of the variables output growth and Inflation (WPI) to an oil demand shock driven by global economic activity	84
3-4	FEVD for India's GDP, Shock 1: oil supply shock, Shock 2: oil demand shock and Shock 3: oil-specific demand shock	85

List of Tables

3.1 Sign Restrictions	82
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List of Abbreviations

AIC	Akaike Information Criteria
ARDL	Auto Regressive Distributed Lag
BRICS	Brazil Russia India China South Africa
BVAR	Bayesian Vector Auto Regression
CAD	Current Account Deficit
CPI	Consumer Price Index
ECM	Error Correction Model
FDI	Foreign Direct Investment
FD	Fiscal Deficit
FRBM	Fiscal Responsibility and Budget Management
GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
HICP	Harmonised Index of Consumer Prices
IRF	Impulse Response Function
LAF	Liquidity Adjustment Facility

OECD	Organisation for Economic Co-operation and Development
RBI	Reserve Bank of India
REER	Real Effective Exchange Rate
REH	Ricardian Equivalence Hypothesis
STAR	Smooth Transition Threshold Auto Regression
SVAR	Structural Vector Auto Regression
TV-SVAR	Time Varying Structural Vector Auto Regression
TV-VAR	Time Varying Vector Auto Regression
US	United States
VAR	Vector Auto Regression
VECM	Vector Error Correction Model
WPI	Wholesale Price Index

Nomenclature

<i>C</i>	Consumption Expenditure
<i>c</i>	crude oil price
<i>CA</i>	Current Account
<i>cagdp</i>	current account deficit as a percentage of GDP
<i>fgdp</i>	fiscal deficit as a percentage of GDP
<i>G</i>	Government Spending

I	Investment
i	interest rate
$lgdp$	real GDP of India
M	Imports
$NFYA$	Net Factor Income from Abroad
p	inflation
R	Government transfers
$reer$	real effective exchange rate
S	Savings
Sg	Government saving
Sp	Personal disposable income
T	Taxes
X	Exports
x	output growth
G_j	GDP growth
P_j	Price level
P_{oil}	real price of crude oil
Q_{oil}	world oil production
Y_w	world economic activity

Chapter 1

Analysing Inflation in India using Time-Varying SVAR Model

1.1 Introduction

In today's world, maintaining low and stable price is essential for improving country's economic growth. Central Banks devise a framework to fuel the growth of the country. It is a major institution for maintaining economic growth and price stability in a country. Monetary Policy in India is looked after by the Reserve Bank of India (RBI). Recent Monetary Policy in India is driven by multiple objectives like maintaining price stability, ensuring an adequate credit flow to foster economic growth and financial stability. The relative emphasis on these objectives varies from time to time depending on evolving macroeconomic developments. Consumer Price Index (CPI) data show that India has suffered from chronic inflation for the past five years. In last five years, CPI persistently stayed higher than the Central Bank's limit (which is 5.0%- 5.5%) [22]. For the past decade, we see that the trend line of inflation is high, though it has moved from double digits to a single digit with 8.9% in recent period, it is still not a good sign. For a developing country like India, high inflation is not a good sign for the following reasons:

1. High inflation implies greater burden on average earning people, mainly affects poor. Uncontrolled inflation can lead to distributional inequality in the society.

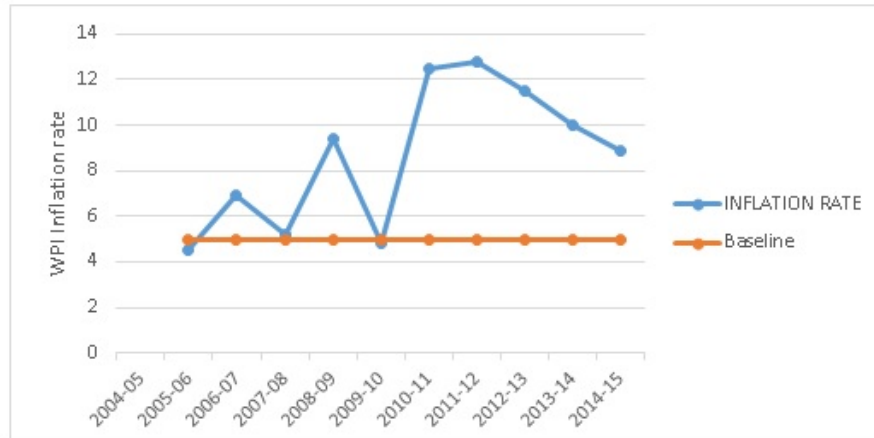


Figure 1-1: Annual Rate of Inflation

2. High inflation dries average household savings and decline in overall investment. As a result credit crunch stumbles the economic growth.
3. As inflation rises, high-risk premia in financial markets become prominent. The impact will adversely affect the nominal interest rates. The Higher nominal interest rate is a threat to the economy.
4. Higher inflation leads to the appreciation of real exchange rate. Global trade competitiveness gets affected through the fluctuations of the currency exchange rate.

1.1.1 Research Problem

Many studies have been carried out to analyse inflation using Time-Varying SVAR approach, in developed countries like Australia, USA and so forth. In recent years, Time-Varying SVAR methodology has been employed in the past studies in Gulf Cooperation Council (GCC) and Brazil Russia India China and South Africa (BRICS). However, very few studies using the applicability of the Time-Varying SVAR approach in understanding the inflation effects in India have been carried out. This approach widens the scope of this chapter. In other words, this chapter tries to check the effect of crude oil price shock on macro variables (output growth and interest rate) and to check how it produces effects in inflation. So the chapter aims to check whether oil price shock has brought

about any changes in the above-stated macro variables in India. Moreover, the study tests whether the monetary policy mechanisms adopted by the Central Bank has helped in controlling inflation in India. However, in this chapter only those models are looked into which have applied Vector Auto Regression (VAR), Structural Vector Auto Regression (SVAR) and time-varying VAR and SVAR. The chapter mainly focuses on Time Varying Structural Vector Auto Regression (TV-SVAR) approach in understanding the impact of crude oil price shock on inflation, how RBI responds to this situation and whether RBI has been effective in controlling inflation.

1.2 Literature Review

Most of the countries' Central Bank target for a low and positive inflation. Persistently high inflation can damage countries economic as well as social growth. Though various models have been employed for understanding inflation dynamics, it is only by the end of late 1990's that the Time-Varying Vector Auto Regression (TV-VAR) and Time Varying Structural Vector Auto Regression (TV- SVAR) started gaining importance. In the TV-VAR models proposed in the recent years, we can categorise it into the following three types based on its parameter specification. They are Type 1: Here the parameters are treated as latent variables and are assumed to follow random walks without drifts. The works of Cogley and Sargent [6] [7], Primiceri [19], Canova, Gambetti and Pappa [5], Nakajima, Shiratsuka and Teranishi [16] have employed this technique. Type 2: Here the parameters switch between regimes and are driven by latent state variable which follows a Markov switching process. The work of Sims and Zha [23] is a good example of this category. Type 3: Here the parameters change from one regime to another smoothly (permanently) in time and the specification is the multivariate extension of the Smooth Transition Threshold Autoregression (STAR) model. This technique was developed in the work of He, Terasvirta and Gonzalez [9]. Amongst the three types my chapter focuses on Time-varying parameter SVAR with Stochastic Volatility which falls under Type 1 category.

1.2.1 Time-Varying Parameter SVAR with Stochastic Volatility

It was Cogley and Sargent [6] who employed three variables (inflation, unemployment and interest rate) and two lags with time-varying coefficients in a VAR model to study the persistence of inflation in the US after World War II. However, this model faced a major limitation i.e. the absence of stochastic volatility. Later Cogley and Sargent [7] improved on their previous model by introducing stochastic volatility into the VAR model but with a non-varying structural shock. In other words, this model has drifting coefficients which allow for changing the variances. This model thus permits stochastic volatility of the shocks, but the contemporaneous responses to shocks do not alter over time. Later Primiceri [19] came up with a model which used three variables namely, inflation, unemployment rate and short-term nominal interest rate with a lag of two periods in time varying SVAR framework to study the Monetary Policy and the Private Sector behaviour of the US economy. In contrast to the work of Cogley and Sargent [7], the framework of his allowed all the parameters to change for the US economy. Following the work of Primiceri, many works came up employing the framework of time varying SVAR. Some of these works were like that of Canova, Gambetti and Pappa [5] who used five variables (real output, hours, inflation, federal fund rates and money supply) in time varying SVAR framework to check the dynamics of output growth and inflation in the US, euro area and U.K. Benati and Surico [2] employed a time-varying VAR model with stochastic volatility and the following variables (short-term interest rate, inflation, output growth and money growth to understand the inflation gap persistence in the US economy. Baumeister, Durinck and Peersman [1] used a TVP-VAR model for understanding the effects of excess liquidity shocks on economic activity, asset prices and inflation in the euro area. The variables used in the study were real GDP, HICP consumer prices, short-term interest rate, real asset price index and broad monetary aggregate M3. Later Cogley, Primiceri and Sargent [8] used a time-varying VAR model with drifting coefficients and stochastic volatility including three variables i.e. inflation, unemployment and the short-term interest rate to understand the inflation gap persistence in the US economy. Nakajima, Shiratsuka and Teranishi [16] employed a TVP-VAR model under-

standing the effects of monetary policy commitment in the Japanese economy. Again Nakajima, Kasuya and Watanabe [15] had used a Bayesian TVP-VAR model to study the Monetary Policy effect on the Japanese economy. Mumtaz and Sunder-Plassmann [14] used a TVP-VAR to study the time-varying properties of the real exchange rate for the U.K, Eurozone and Canada by taking into account three variables.

However, very few studies using the applicability of the Time-Varying SVAR approach in understanding inflation, through monetary policy transmission mechanism in India have been carried out. It is only by the end of the year 2000 that the applicability of VAR, SVAR and TV-VAR and TV-SVAR models started gaining importance in India. It was Bhat-tacharya and Sensharma [3] who first used SVAR model for understanding the monetary policy signals in pre and post Liquidity Adjustment Facility (LAF) period in India using SVAR model. In the pre-LAF period, they found that CRR performed better than RBI's signalling target Bank Rate. In post LAF period the repo and reverse repo rate were identified to be effective instruments of signalling in money, bond and forex market. However, it remained unaffected in the stock market. Later Biswas, Singh and Sinha [4] built a model to forecast inflation in India and also the Index of Industrial Production (IIP) growth using Bayesian Vector Autoregression (BVAR) model. Authors claim that their prediction made with BVAR framework is better than making predictions through VAR model. In a study of Patnaik [18], to identify the major causes of inflation in India using a VAR model she concludes that inflation in India could be found to be mainly demand driven. The supply side effects persist, but it is not sustainable. The author argues for a better stabilisation policy. Mallick [11] in his paper used an SVAR approach to capturing the macroeconomic effects of monetary policy in the Indian context. He found that supply shocks were the dominant source of inflation and interest rate play a better role in stabilising inflation in India than the exchange rate. Later, Mishra and Mishra [12] tried to capture the monetary transmission mechanism for Indian economy by using VAR approach. Their results suggest that demand effects of interest rate are stronger than the exchange rate effects. The paper also shows the potential conflict between exchange rate and the interest rate, which acts as a primary concern for inflation targeting in India. The work of Kumar, Srinivasan and Ramachandran [10] became significant as

they tried to build a model of inflation using time varying parameter for India. To determine the dynamics of inflation they used RBI's preferential parameters and the slope of Phillips Curve. The model is estimated using the median -unbiased estimator. They conclude that exchange rate and good luck helped in inflation reduction while monetary policy and structural change have played a non-trivial role. However, it was Mohanty and John [13] who first employed Time-varying SVAR with stochastic volatility approach to examine the factors that may have contributed to inflation in India. Crude oil prices, output gap, fiscal policy and monetary policy were taken as the variables other than inflation for their study. They conclude by saying the drivers of inflation are frequently changing in India and also comment that the role of monetary and fiscal policy to contain the inflation has failed, irrespective of the nature of the shock to inflation.

1.3 Methodology

The paper focuses on the usage of Time-Varying SVAR model for the following reasons:

1. A large number of studies have been carried out on the transmission of monetary policy shocks using SVAR models. The role played by changes in the volatility of these shocks has been ignored in the existing SVAR model. The studies do allow time-varying shock volatility, but do not incorporate a direct impact of the shock variance on the endogenous variables. But, Time-Varying SVAR model helps to overcome this problem. (Mumtaz and Sunder-Plassmann, [14]).
2. The model must include time variations of the variance and covariance matrix of the innovations, to make changes in policy, structure and their interactions. This reflects both time variation of the simultaneous relations among variables of the model and heteroscedasticity of the innovations. This could be done by developing a multivariate stochastic volatility modelling strategy for the law of motion of the variance and covariance matrix. This could also be stated as the advantage of the Time-Varying SVAR model compared to the other models (Primiceri E Giorgio, [19]).

3. TV-SVAR models are faster in capturing the structural changes in inflation than the rolling VAR models. The TV- VAR models are far superior to the VAR models (K. Triantafyllopoulos, [24]).

1.3.1 The Basic Model

Let us consider a simple VAR model with constant parameters and with no restriction on the AR lag structure.

$$\mathbf{A}\mathbf{y}_t = \mathbf{F}_1\mathbf{y}_{t-1} + \dots + \mathbf{F}_s\mathbf{y}_{t-s} + u_t \quad (1.1)$$

where \mathbf{y}_t denotes a $k \times 1$ vector of variables with a lag length of 's', \mathbf{A} is the matrix of contemporaneous coefficients while $\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_s$ are the matrices of coefficients, u_t is assumed to have mean 0 and fixed variance-covariance matrix Σ . The structure of the matrix \mathbf{A} is

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \alpha_{k1} & \alpha_{k2} & \dots & 0 \end{bmatrix}$$

In other words, the equation could be rewritten as

$$y_{i,t} = \mathbf{x}'_{i,t}\boldsymbol{\beta}_t + u_{i,t} \quad i = 1, \dots, n \quad t = 1, \dots, T \quad (1.2)$$

where $y_{i,t}$ denotes the observation on the variable i at time t , $\mathbf{x}_{i,t}$ is a k -vector of lagged dependent explanatory variables. Considering all the endogenous variables jointly Eq.(1.2) looks like

$$\mathbf{y}_t = \mathbf{X}'_t\boldsymbol{\beta} + u_t \quad (1.3)$$

where $\mathbf{y}_t = [y_{1t}, y_{2t}, \dots, y_{nt}]'$ is the n -vector of endogenous variables,

$$\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \quad \mathbf{X}'_t = \begin{bmatrix} \mathbf{x}'_{1,t} & 0 & \cdots & 0 \\ 0 & \mathbf{x}'_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{x}'_{n,t} \end{bmatrix} \quad \boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_n \end{bmatrix} \quad \mathbf{u}_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{bmatrix}$$

Now considering a model with time-varying parameters and no restriction on the AR lag structure Eq.(1.2) can be written as:

$$y_{i,t} = \mathbf{x}'_{i,t} \boldsymbol{\beta}_{i,t} + u_{i,t} \quad i = 1, \dots, n \quad t = 1, \dots, T \quad (1.4)$$

Here $y_{i,t}$ denote the observation of variable i at time t . Let $\mathbf{x}_{i,t}$ be a k -vector of explanatory variables in equation Eq.(1.4). Now considering all the $y_{i,t}$'s jointly Eq.(1.3) looks like:

$$y_t = \mathbf{X}'_t \boldsymbol{\beta}_t + u_t \quad (1.5)$$

Here $y_{i,t}$ denote the observation of variable i at time t . Let $\mathbf{x}_{i,t}$ be a k -vector of explanatory variables in Eq.(1.5). Now considering all the $y_{i,t}$'s jointly in Eq.(1.5) looks like¹:

$$\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \quad \mathbf{X}'_t = \begin{bmatrix} \mathbf{x}'_{1,t} & \mathbf{0}_{1 \times k_2} & \cdots & \mathbf{0}_{1 \times k_n} \\ \mathbf{0}_{1 \times k_1} & \mathbf{x}'_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_{1 \times k_n} \\ \mathbf{0}_{1 \times k_1} & \cdots & \mathbf{0}_{1 \times k_{n-1}} & \mathbf{x}'_{n,t} \end{bmatrix} \quad \boldsymbol{\beta}_t = \begin{bmatrix} \boldsymbol{\beta}_{1,t} \\ \boldsymbol{\beta}_{2,t} \\ \vdots \\ \boldsymbol{\beta}_{n,t} \end{bmatrix} \quad \mathbf{u}_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{bmatrix}$$

The vector of innovations u_t is assumed to have a multivariate normal distribution with mean zero and a covariance $\boldsymbol{\Omega}_t$ i.e. $u_t \sim (0, \boldsymbol{\Omega}_t)$. This matrix can be decomposed using a triangular factorization i.e. $\mathbf{A}_t \boldsymbol{\Omega}_t \mathbf{A}'_t = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}'_t$ ² where \mathbf{A}_t and $\boldsymbol{\Sigma}_t$ are $n \times n$ matrices having the following structure.

¹for better explanation see Appendix A

²See the Appendix A for explanation

$$\mathbf{A}_t = \begin{bmatrix} 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \ddots & \vdots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix} \quad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}$$

Assuming $u_t = \mathbf{A}_t^{-1} \Sigma_t \boldsymbol{\varepsilon}_t$, $\boldsymbol{\varepsilon}_t$ where is a n -vector whose components have independent univariate normal distribution. Thus Eq.(1.5) can be rewritten as:

$$y_t = c_t + \mathbf{B}_{1,t} y_{t-1} + \dots + \mathbf{B}_{k,t} y_{t-k} + u_t \quad (1.6)$$

This model was employed in the work of Primeceri [19], Cogley and Sargent [6], [7] and Nakajima [17]. However, these models had some differences which are explained below briefly by comparing each of these models.

COGLEY AND SARGENT [6]

The aim of this paper was to provide evidence for the evolution of measures of the persistence of inflation, prospective long-horizon forecasts (means) of inflation and unemployment. The model has also employed three variables. (Inflation, unemployment and the real interest rate) Moreover, two lags for estimation. The data for the sample spans from 1948: Q1 to 2000: Q4. The primary results were that there was a long run mean, persistence and variance of inflation have changed. The Taylor principle was violated before Volcker (pre-1980) and the monetary policy was too loose. The model could be explained as follows: The measurement equation used is similar to Eq.(1.5) stated above i.e.

$$y_t = \mathbf{X}'_t \boldsymbol{\theta}_t + \varepsilon_t \quad (1.7)$$

Here \mathbf{y}_t is a n -vector of endogenous variables. $\boldsymbol{\theta}_t$ is a k vector of coefficients. \mathbf{X}'_t is a $n \times k$ matrix of predetermined/exogenous variables and ε_t is a $n \times 1$ vector of prediction errors. The vector \mathbf{y}_t includes inflation and other variables that are useful for predicting inflation. The coefficients of VAR are considered as a hidden state vector and the state vector $\boldsymbol{\theta}_t$ are postulated to evolve according to:

$$\rho(\theta_{t+1} | \theta_t, V) \propto I(\theta_{t+1})f(\theta_{t+1} | \theta_t, V) \quad (1.8)$$

With $I(\theta_t) = 0$, if the roots of the associated VAR polynomial are inside the unit circle and 1 otherwise. V is the covariance matrix defined as:

$$f(\theta_{t+1} | \theta_t, V) \sim N(\theta_t, Q) \quad (1.9)$$

Eq.(1.9) is represented as the driftless random walk, which becomes the transition equation such as

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{v}_t \quad (1.10)$$

Here \boldsymbol{v}_t is an i.i.d Gaussian process with mean 0 and covariance Q . the innovations $(\boldsymbol{\varepsilon}'_t, \boldsymbol{v}'_t)$ are assumed to be i.i.d with zero mean and covariance matrix.

$$\mathbf{E}_t = \begin{pmatrix} \boldsymbol{\varepsilon}'_t \\ \boldsymbol{v}'_t \end{pmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}'_t & \boldsymbol{v}'_t \end{bmatrix} = V = \begin{pmatrix} \mathbf{R} & \mathbf{C}' \\ \mathbf{C} & \mathbf{Q} \end{pmatrix}$$

\mathbf{R} is a $n \times k$ covariance matrix for the measurement innovations, and \mathbf{Q} is the $k \times k$ covariance matrix for the state innovations, and \mathbf{C} is a $k \times n$ covariance matrix. The authors use Bayesian methodology so θ_t 's are parameters, and the elements \mathbf{R} , \mathbf{Q} and \mathbf{C} are treated as hyperparameters.

PRIMICERI [19]

The paper studies the changes in the monetary policy in the US over the post-world war period. There are three variables employed namely inflation, unemployment and real interest rate and two lags have been used for estimation. The data is from 1953: I to 2001: III. The main results were that the systematic responses of the interest rate to inflation and unemployment trend toward a more aggressive behaviour and this had a negligible effect on the rest of the economy. The model could be explained as follows:

The model follows Eq.(1.6) and is written as:

$$y_t = c_t + \mathbf{B}_{1,t}y_{t-1} + \dots + \mathbf{B}_{k,t}y_{t-k} + u_t \quad (1.11)$$

The VAR's time-varying parameters collected in the vector \mathbf{y}_t are postulated to evolve according to

$$\rho(\theta_t | \theta_{t-1}, Q) \propto I(\theta_t) f(\theta_t | \theta_{t-1}, Q) \quad (1.12)$$

with $I(y_t)$ being an indicator function rejecting unstable draws thus enforcing a stationarity constraint on the VAR and with $f(\theta_t | \theta_{t-1}, Q)$ given by:

$$\theta_t = \theta_{t-1} + \eta_t \quad \eta_t \sim N(0, Q) \quad (1.13)$$

The time-varying matrices \mathbf{H}_t and \mathbf{A}_t are defined as

$$\mathbf{H}_t = \begin{bmatrix} h_{1t} & 0 & 0 \\ 0 & h_{2t} & 0 \\ 0 & 0 & h_{3t} \end{bmatrix} \quad \mathbf{A}_t = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 \\ \alpha_{31,t} & 0 & 1 \end{bmatrix} \quad (1.14)$$

With $h_{i,t}$ evolving as geometric random walks, $\ln h_{i,t} = \ln h_{i,t-1} + v_{i,t}$.

h_t is defined as $\mathbf{h}_t = [h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}]'$ the non zero and non-one elements of the matrix \mathbf{A}_t , are postulated by collecting in the vector $\boldsymbol{\alpha}_t = [\alpha_{21,t}, \dots, \alpha_{n1,t}, \dots, \alpha_{nn-1,t}]'$ to evolve as driftless random walks. This model has drifting coefficients and a fully varying covariance matrix. It permits changes in the contemporaneous responses to standard shocks, which is in accordance with the lower triangular structural VAR. To compute the specification, the elements below the main diagonal of \mathbf{A}_t are stacked by rows into an $n(n-1)/2 \times 1$. Vector $\boldsymbol{\alpha}_t = [\alpha_{21,t}, \dots, \alpha_{n1,t}, \dots, \alpha_{nn-1,t}]'$. Vector $\boldsymbol{\omega}_t = [\log \sigma_{1,t}, \dots, \log \sigma_{n,t}]'$.

Thus the dynamics of the time varying parameters are determined by the following state of equations:

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\gamma}_t \quad \boldsymbol{\gamma}_t \sim N(0, Q) \quad (1.15)$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\zeta}_t \quad \boldsymbol{\zeta}_t \sim N(0, Q) \quad (1.16)$$

$$\boldsymbol{\omega}_t = \boldsymbol{\omega}_{t-1} + \boldsymbol{\eta}_t \quad \boldsymbol{\eta}_t \sim N(0, Q) \quad (1.17)$$

Eq.(1.15)-Eq.(1.17) clearly explains the random walk structure of the TV Parameter. Here the covariance matrices \mathbf{Q} and \mathbf{W} of the vectors of state innovation $\boldsymbol{\gamma}_t$ and $\boldsymbol{\eta}$ are left unrestricted but the covariance matrix \mathbf{S} of the vector of state innovations $\boldsymbol{\zeta}_t$ is assumed to be block diagonal with blocks corresponding to different rows of \mathbf{A}_t . The joint distribution of the innovations is postulated as $[\log\sigma_{1,t}, \dots, \log\sigma_{n,t}]' [\boldsymbol{\varepsilon}_t, \boldsymbol{\gamma}_t, \boldsymbol{\zeta}_t, \boldsymbol{\eta}_t]' \sim N(0, \mathbf{V}_A)$ where \mathbf{V}_A is assumed to be block diagonal with blocks \mathbf{I}_n , \mathbf{Q} , \mathbf{S} and \mathbf{W} .

Thus when a comparison is made between Cogley and Sargent [6] and Primecери [19], we find that in the former there are drifting coefficients but a fixed covariance matrix of the innovations. This rules out any changes in the variances or contemporaneous responses to the shocks. It is based on Eq.(1.2). The coefficients are assumed to follow Eq.(1.12), but the covariance matrix of the observation innovations is constant i.e. $\boldsymbol{\Omega}_t = \boldsymbol{\Omega}, t = 1 \dots T$. The joint distribution of innovations is postulated $[\mathbf{u}_t, \boldsymbol{\gamma}_t]' \sim N(0, \mathbf{V}_C)$ where the matrix \mathbf{V}_C is assumed to be block diagonal with blocks $\boldsymbol{\Omega}$ and \mathbf{Q} .

COGLEY AND SARGENT [7]

This paper was an improvement over the paper of Cogley and Sargent [6]. The previous model faced a major limitation of the absence of stochastic volatility. This paper improved on this by introducing stochastic volatility into the VAR model, but with a non-varying structural shock. The model is based on Eq.(1.6). The model could be explained as follows:

The measurement equation used is Eq.(1.7) and the transition equation used is Eq.(1.10). In Eq.(1.7) y_t is a vector of endogenous variables, \mathbf{X}_t includes a constant plus lags of y_t and $\boldsymbol{\theta}_t$ is a vector of VAR parameters. In the measurement equation $\mathbf{X}_t = \mathbf{I}_n \otimes \mathbf{x}_t$ and x_t includes all the regressors (i.e. lags of y_t as well as the constant). Thus the measurement equation could be rewritten as:

$$y_t = \boldsymbol{\Theta}_t x_t + \varepsilon_t \quad (1.18)$$

Here the relationship between $\boldsymbol{\Theta}_t$ and $\boldsymbol{\theta}_t$ is given by $\boldsymbol{\Theta}_t = \text{vec } \boldsymbol{\theta}_t'$. The innovations v_t are normally distributed with covariance matrix \mathbf{Q} . The innovations ε_t are also normally

distributed with the variance that evolves over time:

$$\boldsymbol{\varepsilon}_t \sim N(0, \mathbf{R}_t) \quad (1.19)$$

With

$$\mathbf{R}_t = \mathbf{B}^{-1} \mathbf{H}_t^{-1'} \quad (1.20)$$

Here \mathbf{B} is lower triangular matrix with ones on the diagonal and \mathbf{H}_t is a diagonal with elements that vary over time according to drift less, geometric random walk.

$$\ln h_{i,t} = \ln h_{i,t-1} + \sigma_i \eta_{i,t} \quad (1.21)$$

Now when the Eq.(1.15) is pre-multiplied by \mathbf{B} we obtain

$$\mathbf{B}y_t = \mathbf{B}_t x_t + u_t \quad (1.22)$$

Where $\mathbf{B}_t = \mathbf{B}\boldsymbol{\Theta}_t$ which are the structural form coefficients and $u_t = \mathbf{B}\boldsymbol{\varepsilon}_t$ is a vector of uncorrelated errors. Let \mathbf{a}_t be defined as $\text{vec}(\mathbf{B}'_t) = (\mathbf{B} \otimes \mathbf{I}_p)^{\theta_t}$ where p is the number of regressors in each equation. Pre multiplying Eq.(1.7) by $\mathbf{B} \otimes \mathbf{I}_p$ gives the transition equation for structural parameters which is also a random walk:

$\mathbf{a}_t = \mathbf{a}_{t-1} + \tilde{v}_t$, $\tilde{v}_t \sim N(0, \tilde{Q})$ with $\tilde{Q} = (\mathbf{B} \otimes \mathbf{I}_p) \mathbf{Q} (\mathbf{B} \otimes \mathbf{I}_p)$. Since \mathbf{Q} is unrestricted in this work of Cogley and Sargent this transformation does not alter any assumption. Thus, this model has drifting coefficients but only allows for changing the variances. This model thus permits stochastic volatility of the shocks but the, contemporaneous responses to shocks do not change over time. The coefficients and the log standard deviations are assumed to follow Eq.(1.15)-(1.17), but it is assumed that $\mathbf{A}_t = \mathbf{A}$, $t = 1 \dots T$. The joint distribution of innovations is postulated as $[\boldsymbol{\varepsilon}_t, \boldsymbol{\gamma}_t, \boldsymbol{\eta}_t]' \sim N(0, \mathbf{V}_B)$ where matrix \mathbf{V}_B is assumed to block diagonal with blocks \mathbf{I}_n , \mathbf{Q} and \mathbf{W} .

Nakajima [17]

The work carried out by Nakajima to analyse the monetary policy commitment in Japan using three variables namely inflation, output and interest rates³. In the previous

³The study used two types of interest rates, namely short-term interest rates and medium-term interest rates. Using these two interest rates, two sets of data were generated and evaluated.

works, it is noticed that the time-varying coefficients were only capturing temporary shifts in the coefficients. However, in the methodology employed by Nakajima the time-varying coefficients α_t captures both the temporary and permanent shifts in the coefficients. In other words, a structural break is also being captured in this methodology. The TVP model is as follows:

$$y_t = x_t' \beta + z_t' \alpha_t + \varepsilon_t, \quad \varepsilon_t \sim \mathbf{N}(0, \sigma_t^2), \quad t = 1, \dots, n \quad (1.23)$$

$$\alpha_{t+1} = \alpha_t + u_t, \quad u_t \sim \mathbf{N}(0, \Sigma) \quad (1.24)$$

$$\sigma_t^2 = \gamma \exp(h_t), \quad h_{t+1} = \phi h_t + \eta_t, \quad \eta_t \sim \mathbf{N}(0, \sigma_t^2), \quad t = 1, \dots, n-1 \quad (1.25)$$

Here Eq.(1.23) is a regression equation where y_t is a scalar of response, x_t' and z_t' are $k \times 1$ and $p \times 1$ vectors of covariances respectively. In this equation there is a constant co-efficient and time-varying co-efficient. The constant co-efficient is β which is a k vector and the time-varying co-efficient is α_t which is a p vector. The effects of x_t on y_t are assumed to be time-invariant, while the regression relations of z_t to y_t are assumed to change over time.

In Eq.(1.24) the time-varying coefficients α_t are assumed to follow first-order random walk process. In other words, we can say that α_t captures both the temporary and permanent shifts in the coefficients. Eq.(1.25) captures the stochastic volatility. Here the log-volatility, h_t is modelled to follow AR(1) process in the equation. This has been done to avoid the spurious movements of α_t . In other words, it can be said that the stationary condition is assumed in the following equation as $\eta_t \sim \mathbf{N}(0, \sigma_t^2)$. Moreover, ϕ is also assumed as $|\phi| < 1$. The disturbance of the regression is ε_t , which follows a normal distribution with time-varying variances σ_t^2 as shown in Eq.(1.23). In crux Eq.(1.23)-Eq.(1.25) are assumed to follow the following assumptions:

1. $\alpha_0 = 0$
2. $u_0 \sim \mathbf{N}(0, \Sigma)$

3. $\gamma > 0$

4. $h_t = 0$

After having a survey of all the works employing time-varying VAR, the analytical framework of the proposed study would be based on the methodology followed by Nakajima [17]. The analytical framework is explained in the next section.

1.3.2 Analytical Framework (TV-SVAR with Stochastic Volatility)

To understand the impact of crude oil price shock on macro variables and to check how it produces dynamic effects in inflation in India, the study employs a four-variable VAR. It includes inflation (p), output growth (x), interest rate (i)⁴ and crude oil prices (c)⁵ [25]. Here inflation is calculated based on Whole Sale Price Index (WPI). The data on inflation and output growth is obtained from the Reserve Bank of India (R.B.I) website [20]. The data for crude oil is obtained from the World Bank data on international commodities [23]. The data employed is quarterly data Q1:1996 to Q4: 2013. The lag of 2 periods is taken based on Akaike information criteria(AIC). Hence there is a possibility of seasonality in the data set. This issue is tackled by using cubic spline methodology. The data uses WPI, as the measure of inflation for the following reasons:(i) WPI has a wider coverage of items compared to CPI and is much more directly affected by international commodity prices in comparison to CPI. This study tries to understand whether oil price shock has brought about any change in the macro variables and crude oil price is an international commodity. (ii) Data on WPI is available on a weekly basis in comparison to CPI data. Thus the data on WPI helps us to capture the impact of shocks better. (iii) During the present study period, the RBI did not change the inflation measure from WPI to CPI. Thus to capture the effectiveness of the policy decisions taken the study resort to WPI as a measure. Thus, Time-Varying Impulse Response Function (IRF) is used to check whether oil price shock has brought about changes in the macro variables stated above. Using the Time-Varying IRF we check the following:

⁴Here interest rate refers to nominal interest rate

⁵Here crude oil prices refer to the World Brent Oil Prices

1. Impact of crude oil price shock to inflation.
2. Impact of crude oil price shock to output growth.
3. Impact of inflation shock to output growth.
4. Impact of crude oil price shock on the interest rate.
5. Impact inflation shock on the interest rate.
6. Impact of output growth shock to the interest rate.

The Structural identification restriction for SVAR are estimated as follows:

1. Crude oil price is considered to be exogenous to the framework.
2. Inflation is said to respond immediately to the crude oil prices and with output growth and interest rate with a lag of one period.
3. Output growth is sensitive to interest rate and inflation.
4. Interest rate is sensitive to output growth and inflation.

\mathbf{Y}_t is a n -vector of the following 3 variables $[\pi_t, x_t, i_t]$ at time t with crude oil prices (c_t) considered to be exogenous to the system. The structural identifications are incorporated into Eq.(1.1)⁶. Following Eq.(1.1) - (1.6), the TVP -VAR is formulated on Nakajima's work [17] as follows⁷:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t}y_{t-1} + \mathbf{B}_{2t}y_{t-2} + \mathbf{B}_{3t}y_{t-3} + u_t \quad (1.26)$$

Here $\mathbf{u}_t = \mathbf{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t$. Thus the equation could also be rewritten as follows:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t}y_{t-1} + \mathbf{B}_{2t}y_{t-2} + \mathbf{B}_{3t}y_{t-3} + \mathbf{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t \quad (1.27)$$

Here $y_t = \mathbf{X}_t' \boldsymbol{\beta}_t$ where in the case of \mathbf{B}_{1t} the expansion will be as follows:

⁶See the Appendix A for the structural identification imposed on the variables.

⁷Refer Appendix A for the software and package information

$$\mathbf{B}_{1t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{1t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{1t} = \begin{bmatrix} b'_{1,1t} \\ b'_{2,1t} \\ \vdots \\ b'_{n,1t} \end{bmatrix}$$

$$\mathbf{X}_t = \begin{bmatrix} 1y'_{t-1} & 0 & 0 & \cdots & 0 \\ 0 & 1y'_{t-1} & 0 & \cdots & 0 \\ 0 & 0 & 1y_{t-1} & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1y_{t-1} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} c_1 \\ b_{1,1t} \\ c_2 \\ b_{2,1t} \\ \vdots \\ c_n \\ b_{n,1t} \end{bmatrix}$$

In this similar manner B_{2t} and B_{3t} will be formulated. Thus we can say that $B_t = [vec(B1, t)', vec(B2, t)', \dots, vec(Bn, t)']$. Other than these the parameters in Eq.(1.27) follow a random walk process as follows:

$$\boldsymbol{\beta}_{t+1} = \boldsymbol{\beta}_t + u\boldsymbol{\beta}_t, \quad \mathbf{a}_{t+1} = \mathbf{a}_t + u_{at}, \quad \mathbf{h}_{t+1} = \mathbf{h} + u_{ht} \quad (1.28)$$

$$\begin{bmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{bmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_{ht} \end{pmatrix} \right)$$

for $t=s+1, \dots, n$, where $\boldsymbol{\beta}_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0})$, $\mathbf{a}_{s+1} \sim N(\mu_{a0}, \Sigma_{a0})$ and $\mathbf{h}_{s+1}(\mu_{h0}, \Sigma_{h0})$.

Other than this the TVP-VAR model has the following properties

1. In the model we assume a lower triangular matrix \mathbf{A} where \mathbf{a}_t is the stacked vector

of lower-triangular elements in A_t and $\mathbf{h}_{t+1}=(h_{1t},\dots,h_{kt})'$ with $h_{jt}=\log \sigma_{jt}^2$ for $j = 1, \dots, k, t = s + 1$.

2. The parameters are not assumed to follow a stationary process such as AR(1), but the random walk process.
3. The variance and covariance structure for the innovations of the time-varying parameters are governed by the parameters, Σ_β, Σ_a and Σ_h .
4. Prior is set for the random walks. The prior distribution of the variance-covariance matrix is assumed to follow inverse-Wishart. The prior distribution of the initial states of time varying coefficients is assumed to be normally distributed. This is estimated using Gibbs sampling in (Markov Chain Monte Carlo) algorithm.

1.4 Results

The study focuses on the usage of time-varying Impulse Response Function(TV-IRF) with stochastic volatility following the methodology of Nakajima [17] to analyse the impact of crude oil price (c) shock on inflation (p), output growth (x) and the interest rate (i). First, the stochastic volatility is plotted for all the variables. The stochastic volatility helps in understanding the significant spike periods. Secondly, the Time- Varying Simultaneous Relations of all the variables are plotted. The Time- Varying Simultaneous Relations helps in understanding the relationship between the different variables employed. Next, the impulse response functions are calculated. Here IRFs is estimated by fixing the initial shock as the average of stochastic volatility measure for each variable and using the simultaneous relations at each point. The estimated time varying coefficients are used to compute the IRFs from the current to future periods. Finally, the impact of the variables in a VAR and Time-Varying SVAR model are compared using an Impulse Response Function (IRF). This comparison is made to understand the significance of using a TV-SVAR model to understand the impact of an oil shock on the specified macro variables.

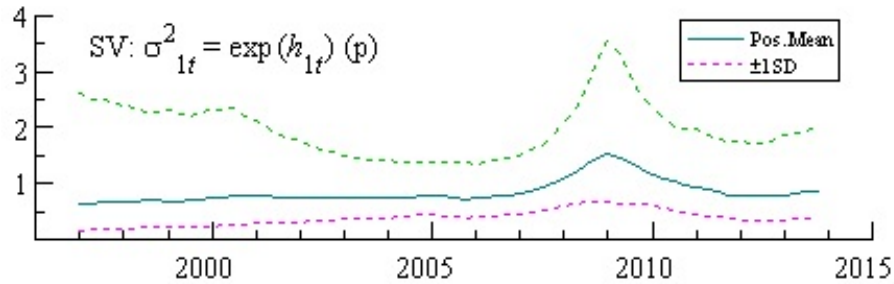


Figure 1-2: Stochastic Volatility Plot of Inflation

1.4.1 Stochastic Volatility Plot

In figure 1.2 the stochastic volatility plot of inflation is considered. Here the spike could be seen in the year 2009. The reason for the spike could be attributed to the global financial crises of 2008, as a result of which the prices are said to increase. In figure 1.3 the stochastic volatility plot of output growth is considered. Here we see two spikes, one in the year 2006 and the other in the year 2009. The spike in 2006 is a positive output growth spike as the Foreign Direct Investment (FDI) inflows stood at 5.5\$ billion in 2004 [25]. This made India be the 10th largest regarding overseas investment received. However, the spike in 2009 is for a negative output growth which happened gain due to the global financial crises. In the case of interest rate, we see two spikes which are seen increasing from the year 2000 with a huge fluctuation in 2009. Here again, the severe impact of the global financial crisis could be found. According to the Monetary Policy Report of 2013 [21] the interest rate recorded it's highest and lowest interest rates in the following years were the spikes are depicted. This could be observed from figure 1.4. In figure 1.5 we find that there are two stochastic volatility spikes for crude oil price. Around 2001, the spike could be attributed to multiple issues such as the 9/11 attacks and the uncertainties surrounding major economies. Further, the collapse of the dot com bubble may be also taken into consideration. The spike around 2009 could be attributed to the oil price collapse after the 2008 financial crisis.

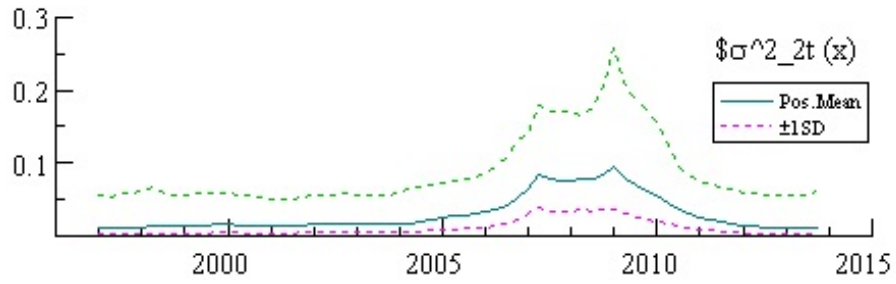


Figure 1-3: Stochastic Volatility Plot of Output growth

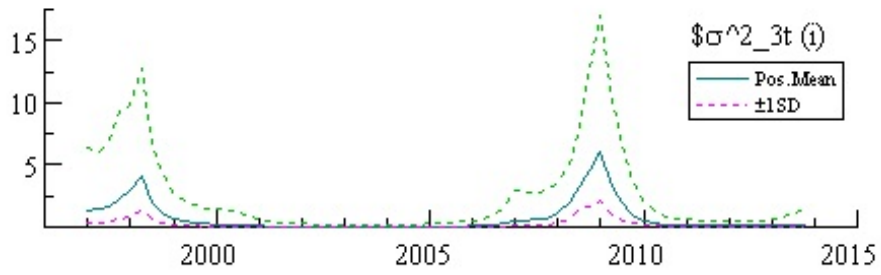


Figure 1-4: Stochastic Volatility Plot of Interest Rate

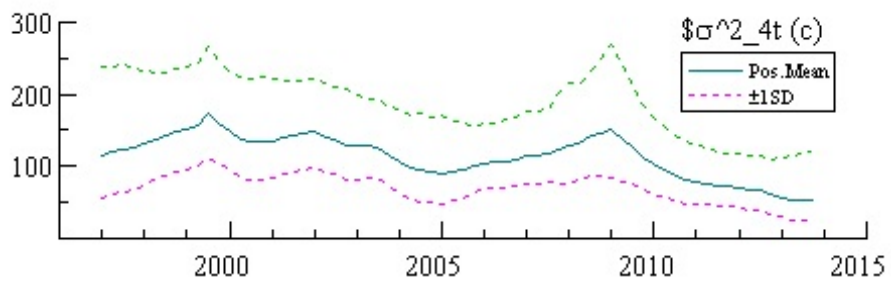


Figure 1-5: Stochastic Volatility Plot of Crude Oil

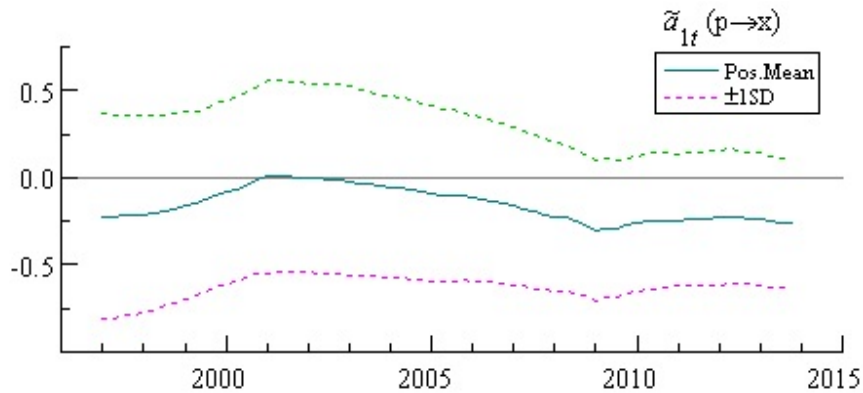


Figure 1-6: Time Varying Simultaneous Relation of Inflation Shock to Output growth

1.4.2 Time - Varying Simultaneous Relation

Next, the time varying simultaneous relation, a salient feature of TVP-VAR is analysed. In figure 1.6 the time varying simultaneous relation of inflation shock to output growth is observed. Here it is noted that the simultaneous relation of the shock of inflation to output growth remains negative throughout the period. In figure 1.7 the time varying simultaneous relation of inflation shock to interest is observed. It is found that interest rates remain positive throughout the period. In figure 1.8 the shock of output growth to interest rate is considered. It is found that the shock of output growth to interest rate remains positive till 2004 later fluctuates and becomes positive after 2005. In other words, the simultaneous relation of the interest rates to output growth shock vary over time. This is similar to the shock of inflation to crude oil remains as it varies throughout the period of analysis. This is seen in figure 1.9. The shock of output growth to crude oil price remains negative till 2008 and becomes positive after 2008 in response to the global financial crises. In other words, we can say that in figures 1.10 the simultaneous relation of output growth to crude oil price vary over time. While the shock of an interest rate to crude oil price is positive with fluctuations and making it at a high positive rate after 2008, in responses to the global financial crises. This could be observed in figure 1.11.

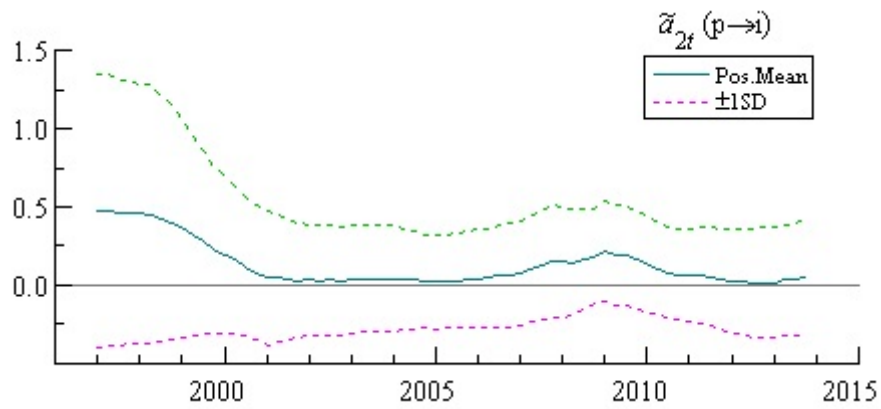


Figure 1-7: Time Varying Simultaneous Relation of Inflation Shock to Interest Rate

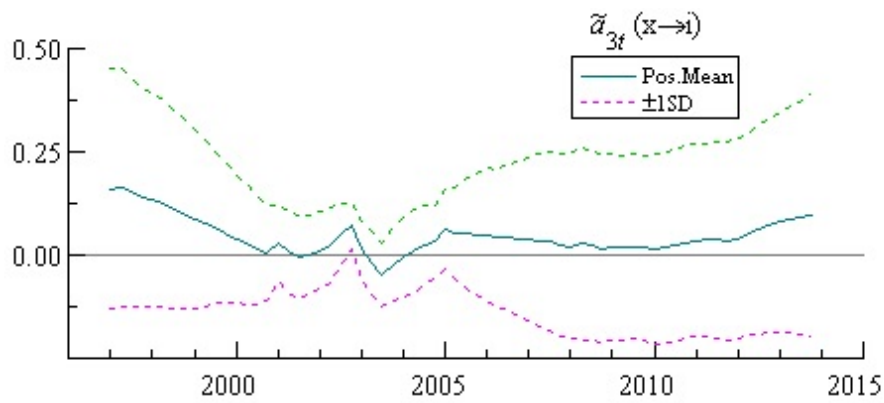


Figure 1-8: Time Varying Simultaneous Relation of Inflation Shock to Interest Rate

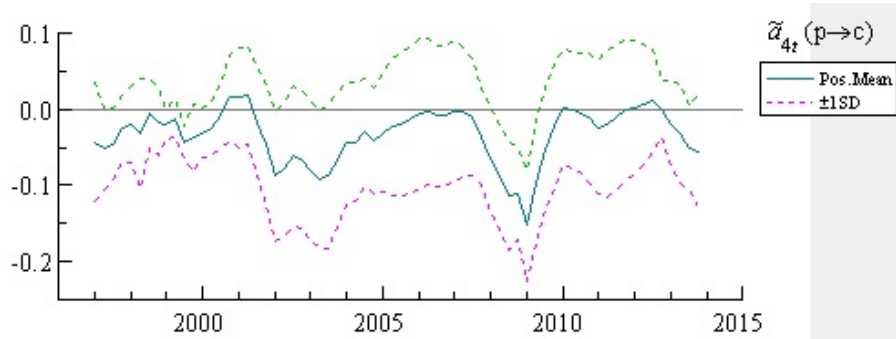


Figure 1-9: Time Varying Simultaneous Relation of Inflation Shock to Interest Rate

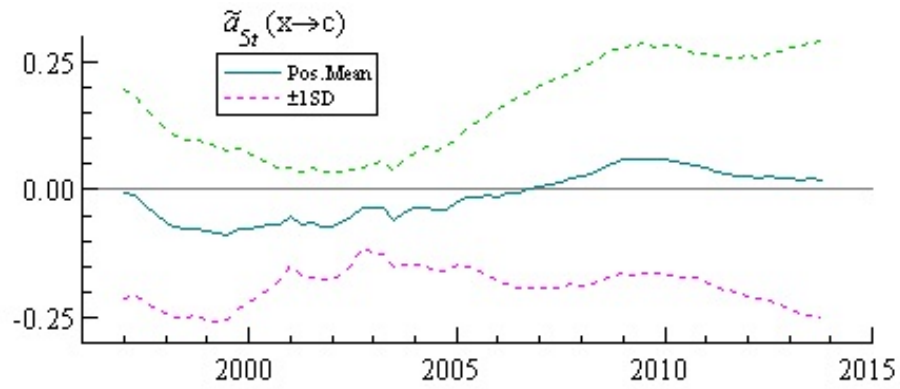


Figure 1-10: Time Varying Simultaneous Relation of Inflation Shock to Interest Rate

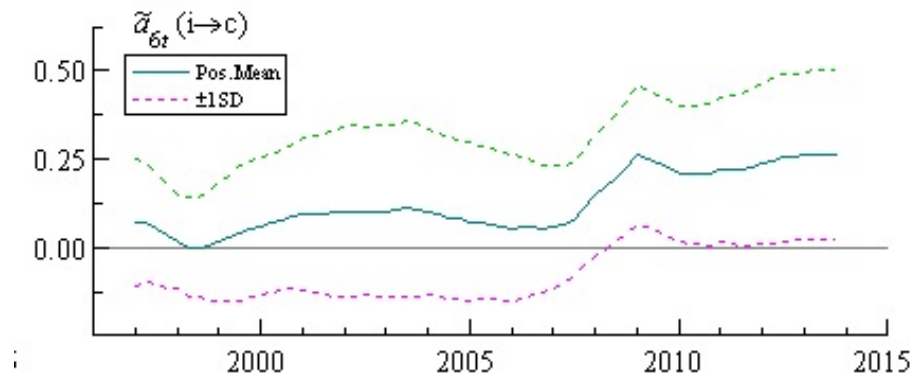


Figure 1-11: Time Varying Simultaneous Relation of Inflation Shock to Interest Rate

1.4.3 Time - Varying Impulse Response Functions and Comparison with VAR Models

Next, the impulse response functions are calculated. Here IRFs is estimated by fixing the initial shock as the average of stochastic volatility measure for each variable and using the simultaneous relations at each point. The estimated time varying coefficients are used to compute the IRFs from the current to future periods. The time-varying IRFs will also be compared with the constant VAR models to understand the advantage of a time-varying model. In time-varying IRF we have a short, medium and long-term forecast. The short term is for four quarters. The medium term is for eight quarters ahead, and the long term impact is for 12 quarters ahead period.

The time varying IRFs are estimated by showing the size of responses from a four period ahead of the horizon for a 12 period ahead of the horizon. Firstly the IRF of a crude oil price shock to inflation in a VAR and Time-Varying VAR model is analysed. In figure 1.12 it is found that the impact of crude oil price shock to inflation is negative throughout the period of study in a constant VAR Model. However, the impact of crude oil price shock to inflation is initially positive but becomes negative during the third period varying VAR Model. This is clearly seen in figure 1.13. But the impact of inflation shock to output growth is same in both the VAR and time-varying VAR Model. This is clearly evident from figure 1.14 and figure 1.15. In other words, when the response of output growth to one SD shock in inflation is analysed in time varying IRE, initially in the first period, it is positive while it continues to become negative from the second to the third period. Similarly, in a constant VAR Model, it could be found that the result obtained is similar, i.e., Initially, it is positive but comes negative at a later period. When the impact of output growth to inflation is made, the results obtained in a constant VAR Model and time- varying VAR Model differ. In a constant VAR Model, the response is found to be negative throughout the period, as seen in figure 1.16. However in time-varying VAR Model, initially in the first period, it is positive while it continues to become negative from the second to the third period as seen in figure 1.17. When the impact of Crude oil price shock to interest rate is analysed in time-varying VAR Model, we find

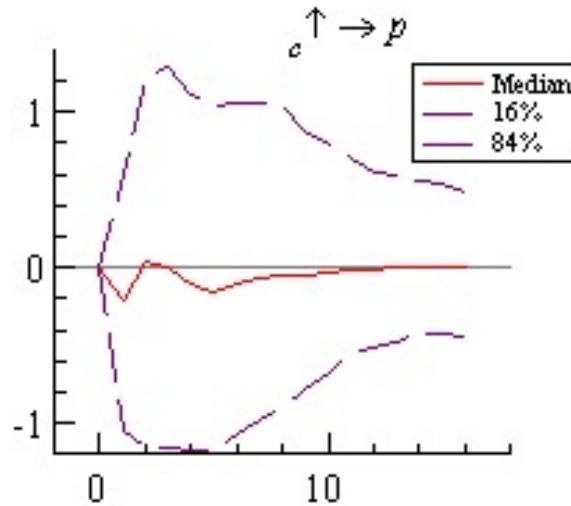


Figure 1-12: IRF of crude oil price shock to inflation in a Constant VAR Model

that initially the interest rate responds immediately by increasing and later increasing at a declining rate. In other words, it becomes negative from the four years ahead of the horizon as seen in figure 1.19. This is similar to the result obtained in a constant VAR Model as seen in figure 1.18 where the response is seen increasing at a declining rate. However, the impact of inflation shock to interest rate is initially negative and tends to be positive for the next two periods as seen in figure 1.21 for a time-varying VAR. But, in the constant VAR Model, the impact is found to be positive throughout the period, as seen in figure 1.20. In figure 1.23 the impact of output growth shock to interest rate is analysed. The impact of the output growth shock to interest rate is positive for the first two periods but tends to be negative by the end of the third period in a time-varying model. But for a constant VAR model the impact is found to be negative as seen in figure 1.22.

1.5 Conclusion

From the results obtained above, we could clearly see the difference in using a time - varying VAR model in comparison with a constant VAR Model. It is evident from the results that time - varying VAR Model is more sensitive in capturing results compared to a constant VAR Model. When the policy initiative is analysed, we find that the imme-

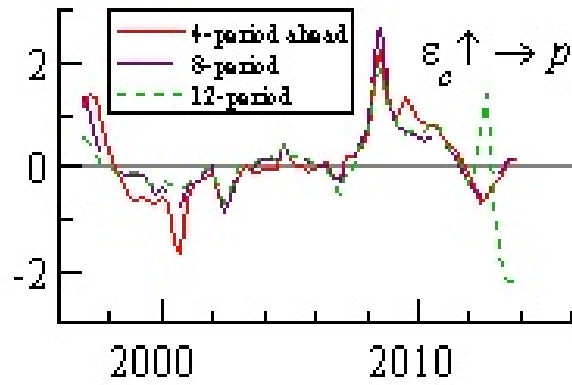


Figure 1-13: IRF of inflation shock to output growth in a Constant VAR Model

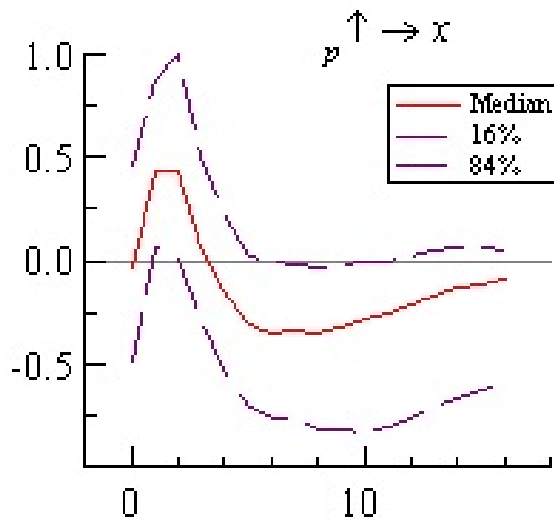


Figure 1-14: IRF of inflation shock to output growth in a Time-Varying VAR Model

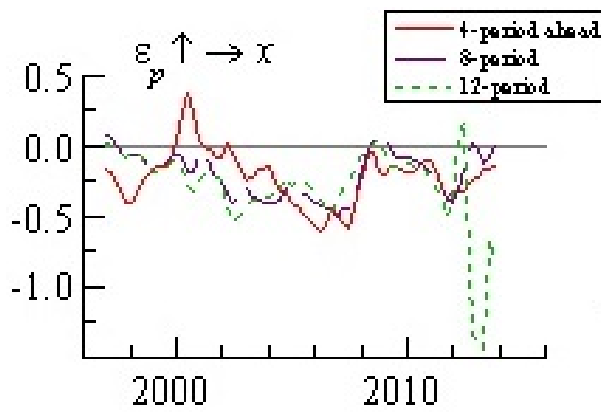


Figure 1-15: IRF of output growth to inflation in a Constant VAR Model

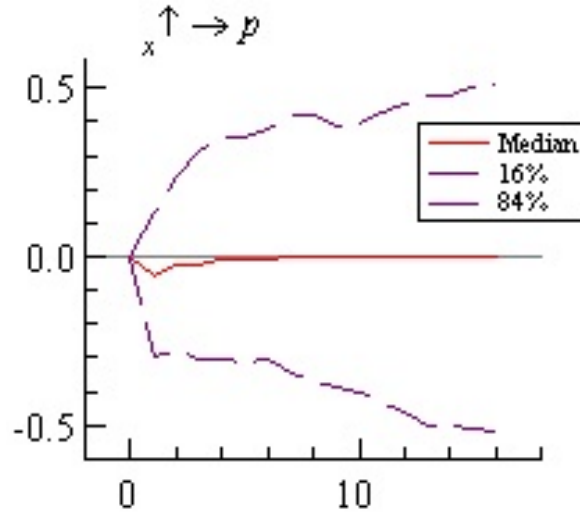


Figure 1-16: IRF of output growth to inflation in a Constant VAR Model

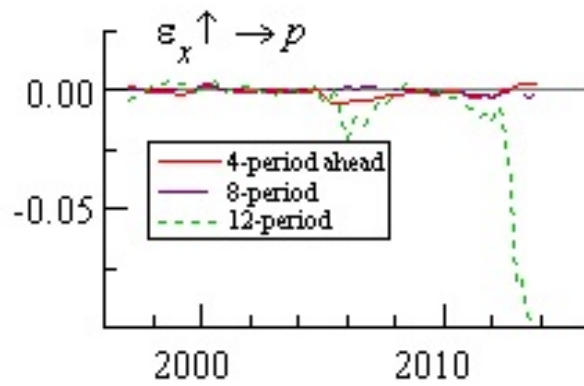


Figure 1-17: IRF of output growth to inflation in a Time-Varying VAR Model

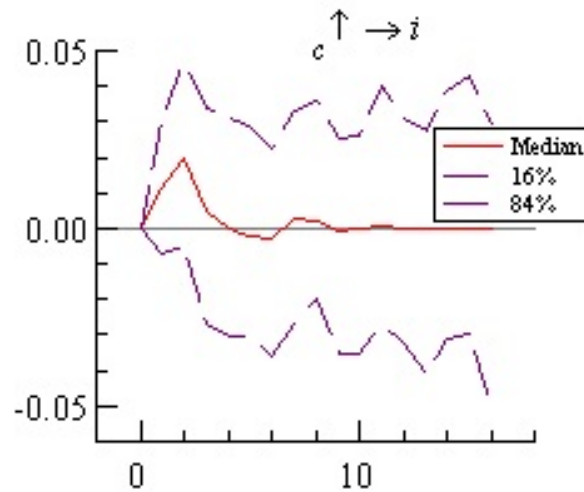


Figure 1-18: IRF of crude oil price shock to interest rate in a Constant VAR Model

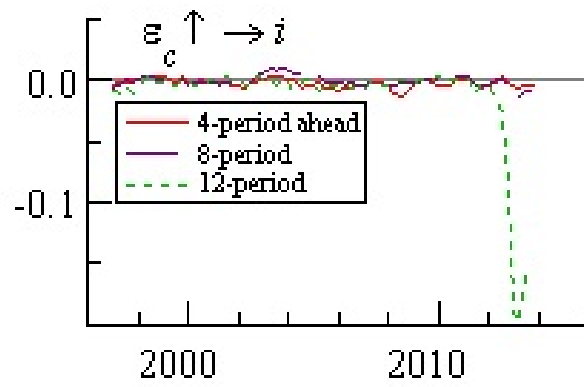


Figure 1-19: IRF of crude oil price shock to interest rate in a Time-Varying VAR Model

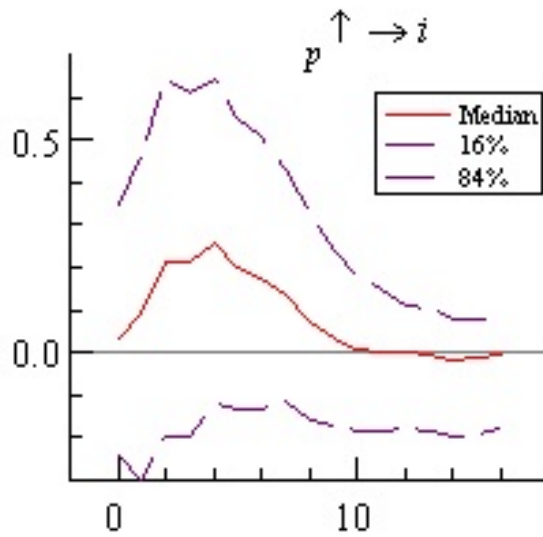


Figure 1-20: IRF of inflation shock to interest rate in a Constant VAR Model

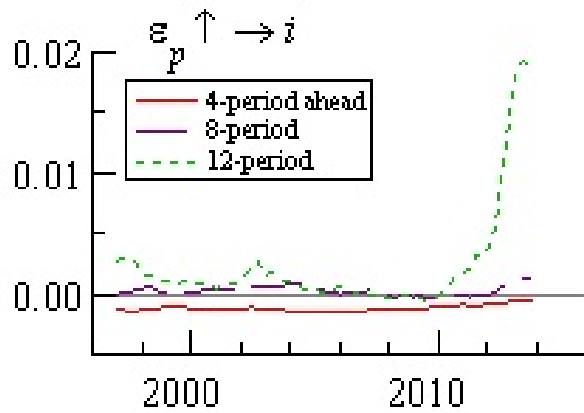


Figure 1-21: IRF of inflation shock to interest rate in a Time-Varying VAR Model

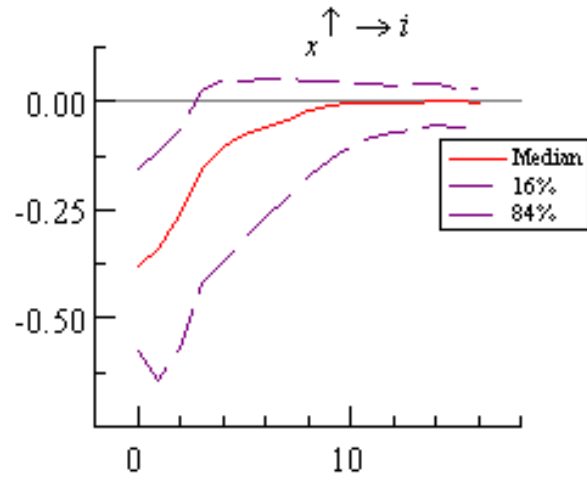


Figure 1-22: IRF of output growth shock to interest rate in a Time-Varying VAR Model

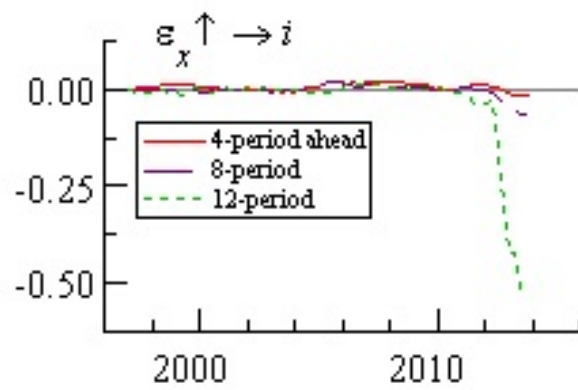


Figure 1-23: IRF of output growth shock to interest rate in a Time-Varying VAR Model

mediate response of crude oil price shock to inflation is that inflation rises in one-quarter period ahead, followed by a decline in inflation after four quarter period. The output growth immediately responds by becoming negative and later becomes negative at a lesser rate during the four quarter period ahead. The inflation shock makes output growth to respond quickly by becoming positive and subsequently becomes negative after four quarter period. The interest rate responds immediately by increasing at a positive rate, which continues even after 4 quarters. From the results obtained we could conclude that a crude oil prices shock is followed by an increase in inflation. Later the inflation shocks respond to output growth with a decline in output growth. The R.B.I responds to this situation by raising the interest rate, and we see inflation reaching stability rates after this. Thus we can conclude that the monetary policy is effective in controlling inflation in India, to some extent.

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Chapter 2

Twin Deficit Hypothesis and its Relevance in India: Time-Varying VAR Approach

2.1 Introduction

The impact of the budget deficit in developing countries, is a topic that is highly debated nowadays, as the effect of it depends on the response of trade deficit to changes in the fiscal shocks. In other words, we can say that budget deficit and trade deficit are interrelated, through the phenomena called twin deficit hypothesis. Maintaining a sustainable budget deficit is thus considered as a necessary condition for the maintenance of a comfortable level of current account balance. However, there exist views that are supporting as well as rejecting twin deficit hypothesis. The view supporting twin deficit hypothesis states that budget deficit leads to a trade deficit. Studies conducted by Abell [1], Zietz and Pemberton [43], Bachman [10], Kasa [19], Vamvoukas [40], Cavallo [12] and Erceg *et al.*[16] confirms this claim. Moreover, they also found that the budget deficit is a significant cause of the trade deficit. However, the Ricardian Equivalence Hypothesis (REH) denies this claim. In other words, REH argues that the two deficits are not twins. Studies conducted by Enders and Lee [15], Boucher [11], Winner [41], and Kaufmann,

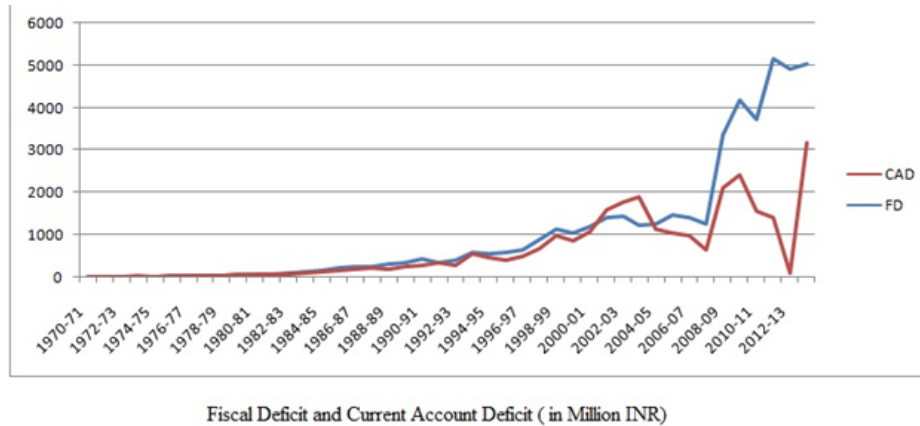


Figure 2-1: Current Account Deficit and Fiscal Deficit Trend in India.

Johan and Georg [20], are some examples that validate this claim. In the Indian context, it is noticeable that there is a direct relationship between fiscal deficit and current account deficit. This could be clearly seen in figure 2.1.

When the fiscal deficit was high, the current account deficit was also high and vice versa. For example, India experienced a fiscal deficit (FD) of 6% of GDP for the year 2008-09, and that Current Account Deficit (CAD) was -2.3%. Similarly, the Fiscal deficit was 6.5% of GDP during 2009-10, and Current Account Deficit (CAD) was -2.8%. In the year 2011-12 fiscal deficit was 5.7%, in 2012-13; 5.1% and in 2013-14, it was 4.8%. Subsequently, the CAD were -4.2% and -4.6%(Economic Survey 2016, [14]). Thus we can say that both the CAD and fiscal deficit are increasing magnitude which proves the existence of twin deficit hypothesis in the Indian context. Other than the relationship we can also learn certain information about FD and CAD for the last four decades from figure 1. First of all, there is an overall increasing trend in both FD and CAD. Further, Till 1990's, both FD and CAD we see small in magnitude.

Post-1990-1991, we can see that both of these increase hand in hand, and the magnitude increases over time. Between 2004-2008, there is a drop in FD and CAD; this could be attributed to the introduction of the Fiscal Responsibility and Budget Management (FRBM) Act in 2003 as well as the performance of the Indian economy over that period. However, in the post-2008 crisis period, both FD and CAD were increasing in values due to the impact of the crisis on the Indian economy. However, the question that

whether fiscal deficit leads to current account deficit or vice versa needs to be analysed. According to the twin deficit framework, an increase in the fiscal deficit in a country will make the domestic interest rate to rise which leads to increased capital inflows into the domestic economy. Thus, the exchange rate gets appreciated which paves the way for trade and current account deficit. As stated earlier, there are circumstances where Current account deficit could lead to a fiscal deficit. High magnitude CAD could result in the occurrence of financial crises and to resolve the situation the government could implement expansionary fiscal policy. This could lead to current account deficit in the country. Thus the chapter also aims to check whether it is a fiscal deficit that leads to current account deficit or it the other way around.

2.2 Research Problem

There have been several methodologies employed to understand the relevance of Twin Deficit Hypothesis. The methods include Granger causality tests, Vector Error Correction Models (VECM), Vector Autoregression (VAR) Models and Structural Vector Autoregression (SVAR) Models. However, there has been no study conducted yet employing a time-varying VAR approach in the Indian context to analyse twin deficit hypothesis. Time-Varying VAR helps us to predict the results with greater sensitivity, hence making our work significant in this domain. The chapter also checks whether the fiscal deficit leads to current account deficit or vice - versa.

2.3 Literature Review

Works focusing on twin deficit hypothesis gained importance by the end of 1980's. This happened after increase in trade deficit and budget deficit simultaneously in the US economy. This section focusses on those works which discusses of twin deficit hypothesis. One of the first studies conducted was by Darrat [13]. The study focussed on the causality between fiscal deficit and trade deficit from 1960-1984. The granger causality test confirmed the relationship between the two variables. Later in 1990, Enders [15] analysed

the relation between budget deficit and current account deficit from 1947-1987 employing a VAR Model. This study also confirmed the relation. Even Abell [1] and Bahmani [8] examined the relationship for U.S economy and using an autoregressive model confirmed the relation like others. We find that till the end of 1990's the focus was primarily on the U.S economy. However the observation of this phenomena started gaining importance in European countries like Greece such as the works of Vamvoukas [40]. In this work he employed an Error Correction Model and found a short and long run relationship between the variables. A similar work was done later by Georgantopoulos [17]. The importance of the relationship between CAD and fiscal deficit only started gaining importance in developing countries by the year 2000. Turkey was one among the first developing countries to study twin deficit problems. Works carried out by Zengin [42], Kutlar [35], Akbostanci [3], Utkulu [39], Ata *et al.* [7], Aksu [4], Ahmet *et al.* [2] and Sever [34]. All the studies confirmed a long run relationship between the variables though the methodologies differed. The work of Zengin employed an impulse response function while others used Granger causality and Error Correction Model for analysis. Even countries like Saudi Arabia [5], Malaysia [30], Kuwait [22], Brazil [18], Pakistan [24], [33] have carried out works to confirm the phenomena. As our study concentrates on Indian economy the chapter now focuses on the works carried in Indian economy. The number of studies conducted to address the issue of twin deficit hypothesis in India is limited. It was Anoruo, E. and Ramchander [6] who first tried to address the issue of twin deficit hypothesis in India using a VAR model. The study confirmed the relation from CAD to Fiscal deficit for the short run but not for the long period. The work of Parikh, A. and Rao, B. [27] also supported the causality relationship even for the long run. However the results obtained by Basu, S. and Datta, D. [9] were contradictory. They did not support twin deficit hypothesis. Ratha, A. [32] confirmed the relation in the short run. Recent works of Kumar, P.K.S. [21] and K.G.Suresh and Tiwari [37] also confirmed the existence of the phenomenon. However the techniques employed were different. The former employed a autoregressive distributed lag (ARDL) cointegration technique for long run and error correction mechanism (ECM) for short run. The later work used a Structural Vector Autoregression (SVAR) model for analysis.

However, in all these studies we find that a time varying methodology has not yet been employed and our work focuses on the application of this methodology to analyse twin deficit hypothesis in India.

2.4 Basic Model

The Current Account Balance could be defined as follows:

$$CA = (X - M) + NFYA \quad (2.1)$$

Here X stand for Exports and M stand for Imports and (X-M) is net exports. NFYA stand for Net Factor Income from Abroad.

The national saving in an open economy can be expressed as

$$S = I + CA \quad (2.2)$$

Here $I = Y - C - G$. I stands for investment spending, C for consumption expenditure and G for Government Spending. In Savings again a classification can be made i.e. private sector savings (Sp) and saving decisions made by the government (Sg). Thus the equation becomes as follows:

$$S = Sp + Sg \quad (2.3)$$

Sp could also be described as the Personal disposable income that is saved, and thus the equation could be rewritten as:

$$Sp = Yd - C = (Y - T) - C \quad (2.4)$$

Yd is disposable personal income, and T is tax collected by the government. Similarly, government saving (Sg) could be defined as the difference between government revenue collected in the form of taxes (T) and expenditures in the form of government purchases

(G) and government transfers (R) and hence, the equation becomes:

$$Sg = T - (G + R) = T - G - R \quad (2.5)$$

Therefore, Equation (4) in an identity form can be written as:

$$S = Sp + Sg = (Y - T - C) + (T - G - R) = I = CA \quad (2.6)$$

Further, we can modify Equation (7) as follows if we allow the effects of government saving decisions in an open economy:

$$Sp = I + CA - Sg = I + CA - (T - G - R) \quad (2.7)$$

This equation could be rewritten as:

$$CA = Sp - I - (G + R - T) \quad (2.8)$$

Here (G + R - T) stands for consolidated public sector budget deficit. In eq (8) we can find two possibilities. The first possibility is that twin deficit hypothesis exists. In other words we can say that if a difference between private savings and investment remains stable over time, then the fluctuations in the public sector deficit will be fully translated to current account making the twin deficits hypothesis to exist. The second possibility assumes that a change in the budget deficit will be fully offset by a change in savings and budget deficit known as Ricardian Equivalence Hypothesis. The chapter focuses on the first possibility i.e. twin deficit hypothesis holds.

2.5 Data and Methodology

The chapter focusses on the usage of Time-Varying SVAR model for the following reasons:

1. A large number of studies have been carried out on the transmission of mone-

tary policy shocks using SVAR models. The role played by changes in the volatility of these shocks has been ignored in the existing SVAR model. The studies do allow time-varying shock volatility but do not incorporate a direct impact of the shock variance on the endogenous variables. But, Time-Varying VAR model helps to overcome this problem.(Mumtaz and Zanetti, [25]).

2. The model must include time variation of the variance and covariance matrix of the innovations, to make changes in policy, structure and their interactions. This rejects both time variation of the simultaneous relations among variables of the model and heteroscedasticity of the innovations. This could be done by developing a multivariate stochastic volatility modelling strategy for the law of motion of the variance and covariance matrix. This could also be stated as the advantage of the Time-Varying VAR model compared to the other models (Primiceri E Giorgio, [29]).
3. TV-SVAR models are faster in capturing the structural changes in a variable than the rolling VAR models. The TV- SVAR models are far superior to the VAR models (K.Triantafyllopoulos, [38]).

2.5.1 Time-Varying VAR Model

Let us consider a simple VAR model with constant parameters and with no restriction on the AR lag structure.

$$\mathbf{A}\mathbf{y}_t = \mathbf{F}_1\mathbf{y}_{t-1} + \dots + \mathbf{F}_s\mathbf{y}_{t-s} + u_t \quad (2.9)$$

where \mathbf{y}_t denotes a $k \times 1$ vector of variables with a lag length of 's', \mathbf{A} is the matrix of contemporaneous coefficients while $\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_s$ are the matrices of coefficients, u_t is assumed to have mean 0 and fixed variance-covariance matrix $\mathbf{\Sigma}$. The structure of the matrix \mathbf{A} is

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \alpha_{k1} & \alpha_{k2} & \cdots & 0 \end{bmatrix}$$

In other words, the equation could be rewritten as

$$y_{i,t} = \mathbf{x}'_{i,t} \boldsymbol{\beta}_t + u_{i,t} \quad i = 1, \dots, n \quad t = 1, \dots, T \quad (2.10)$$

where $y_{i,t}$ denotes the observation on the variable i at time t , $\mathbf{x}_{i,t}$ is a k -vector of lagged dependent explanatory variables. Considering all the endogenous variables jointly Eq.(2.10) looks like

$$\mathbf{y}_t = \mathbf{X}'_t \boldsymbol{\beta} + u_t \quad (2.11)$$

where $\mathbf{y}_t = [y_{1t}, y_{2t}, \dots, y_{nt}]'$ is the n -vector of endogenous variables,

$$\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \quad \mathbf{X}'_t = \begin{bmatrix} \mathbf{x}'_{1,t} & 0 & \cdots & 0 \\ 0 & \mathbf{x}'_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{x}'_{n,t} \end{bmatrix} \quad \boldsymbol{\beta} = \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_n \end{bmatrix} \quad u_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{bmatrix}$$

Now considering a model with time-varying parameters and no restriction on the AR lag structure Eq.(2.11) can be written as:

$$y_{i,t} = \mathbf{x}'_{i,t} \boldsymbol{\beta}_{i,t} + u_{i,t} \quad i = 1, \dots, n \quad t = 1, \dots, T \quad (2.12)$$

Here $y_{i,t}$ denote the observation of variable i at time t . Let $\mathbf{x}_{i,t}$ be a k -vector of explanatory variables in equation Eq.(2.12). Now considering all the $y_{i,t}$'s jointly Eq.(2.11) looks like:

$$y_t = \mathbf{X}'_t \boldsymbol{\beta}_t + u_t \quad (2.13)$$

Here $y_{i,t}$ denote the observation of variable i at time t . Let $\mathbf{x}_{i,t}$ be a k -vector of ex-

planatory variables in Eq.(1.5)¹. Now considering all the $y_{i,t}$'s jointly in Eq.(1.3) looks like:

$$\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \quad \mathbf{X}'_t = \begin{bmatrix} \mathbf{x}'_{1,t} & \mathbf{0}_{1 \times k_2} & \cdots & \mathbf{0}_{1 \times kn} \\ \mathbf{0}_{1 \times k_1} & \mathbf{x}'_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \mathbf{0}_{1 \times kn} \\ \mathbf{0}_{1 \times k_1} & \cdots & \mathbf{0}_{1 \times kn-1} & \mathbf{x}'_{n,t} \end{bmatrix} \quad \boldsymbol{\beta}_t = \begin{bmatrix} \boldsymbol{\beta}_{1,t} \\ \boldsymbol{\beta}_{2,t} \\ \vdots \\ \boldsymbol{\beta}_{n,t} \end{bmatrix} \quad \mathbf{u}_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{bmatrix}$$

The vector of innovations \mathbf{u}_t is assumed to have a multivariate normal distribution with mean zero and a covariance $\boldsymbol{\Omega}_t$ i.e. $\mathbf{u}_t \sim (0, \boldsymbol{\Omega}_t)$. This matrix can be decomposed using a triangular factorization i.e. $\mathbf{A}_t \boldsymbol{\Omega}_t \mathbf{A}'_t = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}'_t$ matrices having the following structure.

$$\mathbf{A}_t = \begin{bmatrix} & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \ddots & \vdots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix} \quad \boldsymbol{\Sigma}_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}$$

Assuming $\mathbf{u}_t = \mathbf{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t$, $\boldsymbol{\varepsilon}_t$ where is a n -vector whose components have independent univariate normal distribution. Thus Eq.(1.5) can be rewritten as:

$$y_t = c_t + \mathbf{B}_{1,t} y_{t-1} + \dots + \mathbf{B}_{k,t} y_{t-k} + u_t \quad (2.14)$$

This model was employed in the work of Nakajima [26]³ which we use to understand the impact of fiscal policy shock on macro variables and to check how it produces dynamic effects in twin deficit hypothesis in India. The variables include current account deficit as a percentage of GDP (*cagdp*), fiscal deficit as a percentage of GDP (*fgdp*), Real effective exchange rate of India (*reer*) and real GDP of India (*lgdp*)⁴. The data is obtained from the Handbook of Statistics, Reserve Bank of India(RBI) [32]. The data employed is yearly data 1970-71 to 2013-14. The lag of 1 period is taken, and the Time-Varying IRF

¹See Appendix B for the explanation of the equation

²See the Appendix B for explanation where \mathbf{A}_t and $\boldsymbol{\Sigma}_t$ are $n \times n$

³This model has been described in detail in the first chapter, page no.26

⁴all the variables were stationary except real GDP. Real GDP was made stationary.

is used to check whether fiscal shock has brought about changes in the macro variables. Using the Time-Varying IRF we check the following:

1. The Impact of fiscal deficit shock to GDP
2. The Impact of fiscal deficit shock to real effective exchange rate
3. The Impact of fiscal deficit shock to current account deficit as a percentage of GDP
4. The Impact of current account deficit shock to fiscal deficit
5. The Impact of current account deficit shock to real effective exchange rate
6. The Impact of current account deficit shock to GDP

\mathbf{Y}_t is a n -vector of the following 4 variables [$lgdp_t, fgdp, reer, cagdp$] at time t ⁵. Following Eq.(2.9) - (2.14), the TVP -VAR is formulated on Nakajima's work [26] as follows:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t}y_{t-1} + \mathbf{B}_{2t}y_{t-2} + \mathbf{B}_{3t}y_{t-3} + \mathbf{B}_{4t}y_{t-4} + u_t \quad (2.15)$$

Here $\mathbf{u}_t = \mathbf{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t$. Thus the equation could also be rewritten as follows:

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t}y_{t-1} + \mathbf{B}_{2t}y_{t-2} + \mathbf{B}_{3t}y_{t-3} + \mathbf{B}_{4t}y_{t-4} + \mathbf{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\varepsilon}_t \quad (2.16)$$

Here $y_t = \mathbf{X}'_t \boldsymbol{\beta}_t$ where in the case of \mathbf{B}_{1t} the expansion will be as follows:

$$\mathbf{B}_{1t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{1t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{1t} = \begin{bmatrix} b'_1, 1t \\ b'_2, 1t \\ \vdots \\ b'_n, 1t \end{bmatrix}$$

⁵lgdp stands for real GDP of India, fgdp stands for fiscal deficit as a percentage of GDP, reer stands for Real effective exchange rate of India and cgdp stands for current account deficit as a percentage of GDP

$$\mathbf{X}_t = \begin{bmatrix} 1y'_{t-1} & 0 & 0 & 0 & \cdots & 0 \\ 0 & 1y'_{t-1} & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1y'_{t-1} & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1y'_{t-1} & \cdots & 0 \\ 0 & 0 & 0 & 0 & \cdots & 1y_{t-1} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} c_1 \\ b_{1,1t} \\ c_2 \\ b_{2,1t} \\ \vdots \\ c_n \\ b_{n,1t} \end{bmatrix}$$

In this similar manner B_{2t} , B_{3t} and B_{4t} will be formulated. Thus we can say that $B_t = [vec(B1, t)', vec(B2, t)', \dots, vec(Bn, t)']$.

Other than this the parameters in Eq.(2.14) follow a random walk process as follows:

$$\boldsymbol{\beta}_{t+1} = \boldsymbol{\beta}_t + u_{\beta t}, \quad \mathbf{a}_{t+1} = \mathbf{a}_t + u_{at}, \quad \mathbf{h}_{t+1} = \mathbf{h} + u_{ht} \quad (2.17)$$

$$\begin{bmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{bmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_{ht} \end{pmatrix} \right)$$

for $t=s+1, \dots, n$, where $\boldsymbol{\beta}_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0})$, $\mathbf{a}_{s+1} \sim N(\mu_{a0}, \Sigma_{a0})$ and $\mathbf{h}_{s+1}(\mu_{h0}, \Sigma_{h0})$.

In the model we assume a lower triangular matrix \mathbf{A} where \mathbf{a}_t is the stacked vector of lower-triangular elements in \mathbf{A}_t and $\mathbf{h}_{t+1} = (h_{1t}, \dots, h_{kt})'$ with $h_{jt} = \log \sigma_{jt}^2$ for $j = 1, \dots, k, t = s+1$. The parameters are not assumed to follow a stationary process such as AR(1), but the random walk process. The variance and covariance structure for the innovations of the time-varying parameters are governed by the parameters, Σ_{β}, Σ_a and Σ_h . Prior is

set for the random walks. The prior distribution of the variance-covariance matrix is assumed to follow inverse-Wishart. The prior distribution of the initial states of time varying coefficients is assumed to be normally distributed. This is estimated using Gibbs sampling in (Markov Chain Monte Carlo) algorithm.

2.6 Results

The study focuses on the usage of time-varying Impulse Response Function(TV-IRF) following the methodology of Nakajima [26]² to analyse the impact of variables namely real GDP(lgdp), fiscal deficit(fgdp), real effective exchange rate(reer) and current account deficit(cagdp) according to the specifications stated above. First, the stochastic volatility is plotted for all the variables. The stochastic volatility helps in understanding the significant spike periods. Secondly, the Time- Varying Simultaneous Relations of all the variables are plotted. The Time- Varying Simultaneous Relations helps in understanding the relationship between the different variables employed. Next, the impulse response functions are calculated. Here IRFs is estimated by fixing the initial shock as the average of stochastic volatility measure for each variable and using the simultaneous relations at each point. The estimated time varying coefficients are used to compute the IRFs from the current to future periods. Finally, the impact of the variables in a VAR and Time-Varying SVAR model are compared using an Impulse Response Function (IRF). This comparison is made to understand the significance of using a TV-SVAR model to understand the impact of an oil shock on the specified macro variables.

2.6.1 Stochastic Volatility Plot

In figure 2.2 the stochastic volatility plot of fiscal deficit is considered. It could be observed that the fiscal deficit is in an increasing magnitude. Especially in the 1990's the debt burden increased to 50 percent in comparison to the previous decades. Thus the fiscal deficit got driven by revenue deficit in 90's. However, we see a decrease from 2000 especially around 2003-2004. This could be attributed to the introduction of Fiscal Re-

²Refer Appendix B for the software and package information

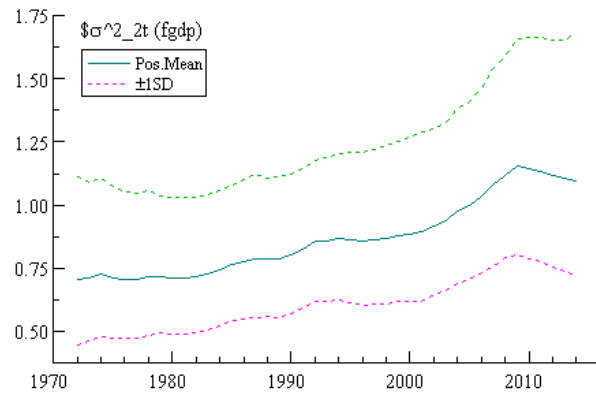


Figure 2-2: Stochastic Volatility Plot of Fiscal Deficit

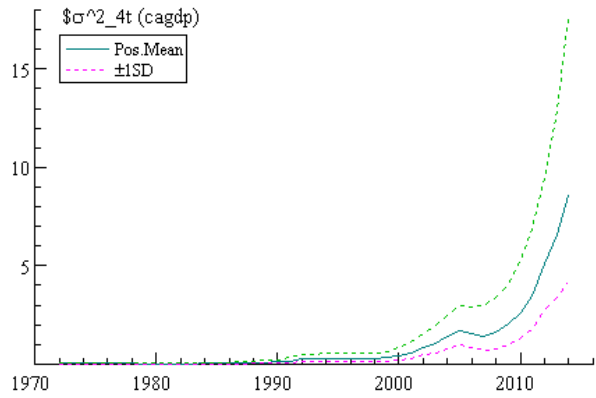


Figure 2-3: Stochastic Volatility Plot of Current Account Deficit

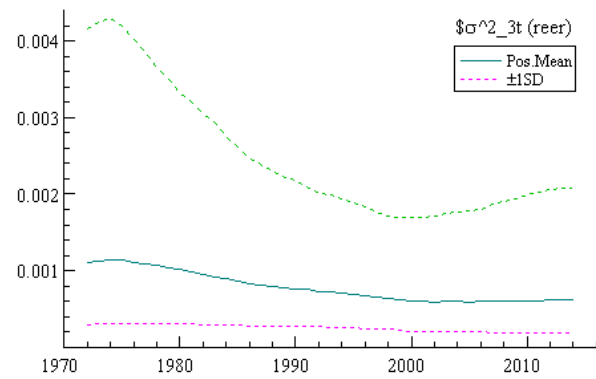


Figure 2-4: Stochastic Volatility Plot of Real Effective Exchange Rate

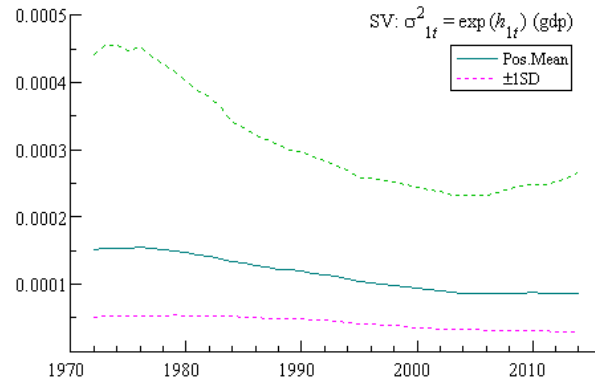


Figure 2-5: Stochastic Volatility Plot of Real GDP

sponsibility and Budget Management Act (FRBM). The Act made the fiscal deficit fall by 0.3 percent per year which finally made the fiscal deficit fall by 4.2 percent in 2007-08. But we can see a spike in 2010. In other words, we can say that there is a rising trend for the following two years. The reason for this spike could be attributed to the 2008 global financial crisis. In figure 2.3 the stochastic volatility plot of current account deficit is found. It could be observed that there is a spike in the CAD around 2003 and increased fluctuation post the 2008 crisis. The widening of the CAD could be attributed to the volatile nature of global crude oil markets and India's dependence on crude oil imports. In other words, it could be said the negative net export is making India suffer a high CAD. Other than the import of oil and gold, even NFYA is a major contributor. Government grants made to the foreigners, direct investment outflow and bank loans to the residents of the country all become part of CAD. In the figure, we can find the volatility from 1991 because CAD widened from 1991 compared to the post-reform period. This happened due to the increasing debt and equity flows which occurred following the 1991 financial crises. Moreover, the structural reforms adopted by the Indian government made the current account surplus from 2001-2004. But from 2004-05 the CAD experienced a deficit in high magnitude due to the increase in merchandise trade deficit. This could be seen as the spike increasing from 2004 to become volatile from 2008 global financial crises. However, in figure 2.4 and 2.5 the stochastic volatility plots of REER and real GDP is found stable throughout the period. Next, analysing the time varying simultaneous relation, a salient feature of TVP-VAR is carried out.

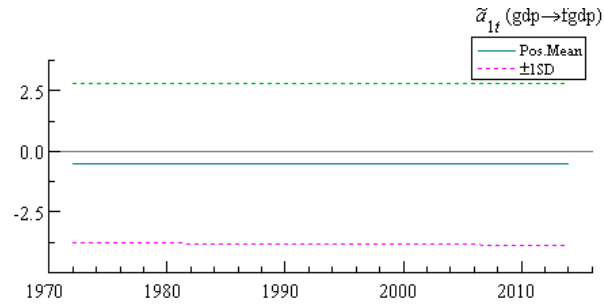


Figure 2-6: Time-Varying Simultaneous Relation of Real GDP shock to FD

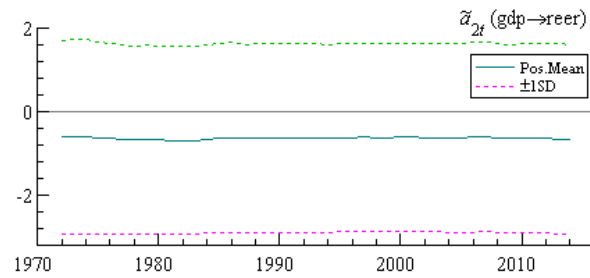


Figure 2-7: Time-Varying Simultaneous Relation of Real GDP shock to REER

2.6.2 Time-Varying Simultaneous Relation

Next, the time varying simultaneous relation, a salient feature of TVP-VAR is analysed. It could be observed from figure 2.6 and figure 2.7 that the time varying simultaneous relation of the real GDP shock to FD and real GDP shock to REER remain negative throughout the period. However, the time-varying simultaneous relation of FD shock to REER is found to be volatile throughout the period of study. This is found in figure 2.8. In figure 2.9 the time varying simultaneous relation of GDP shock to CAD is observed. It is found to be negative throughout the period. The shock of FD to CAD remains negative during the period of analysis. This is observed in figure 2.10. The shock of REER to CAD remains

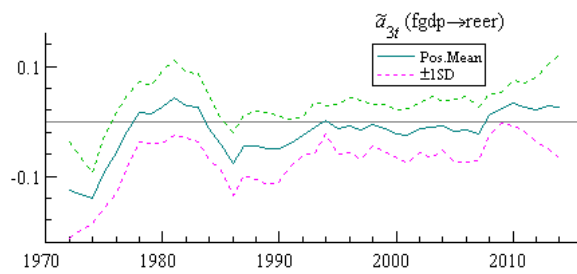


Figure 2-8: Time-Varying Simultaneous Relation of FD shock to REER

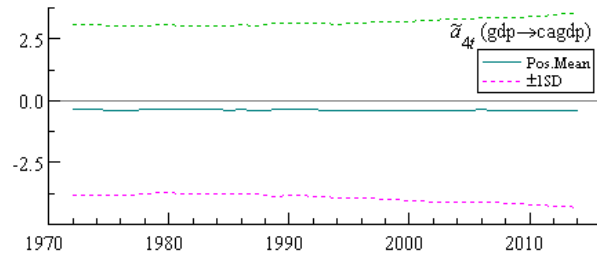


Figure 2-9: Time-Varying Simultaneous Relation of real GDP shock to CAD

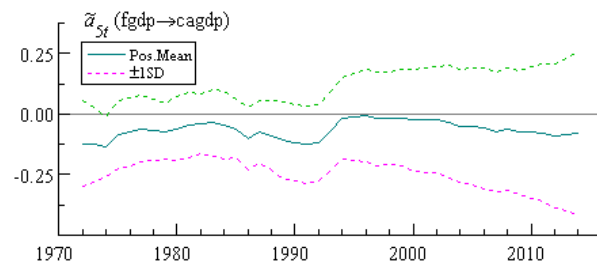


Figure 2-10: Time-Varying Simultaneous Relation of real FD shock to CAD

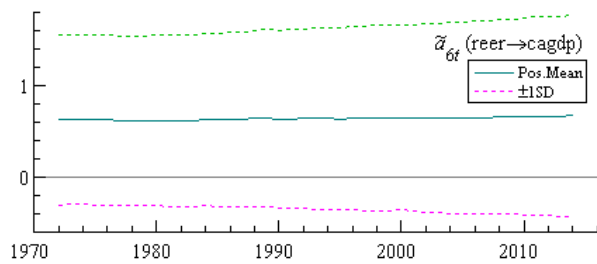


Figure 2-11: Time-Varying Simultaneous Relation of REER shock to CAD

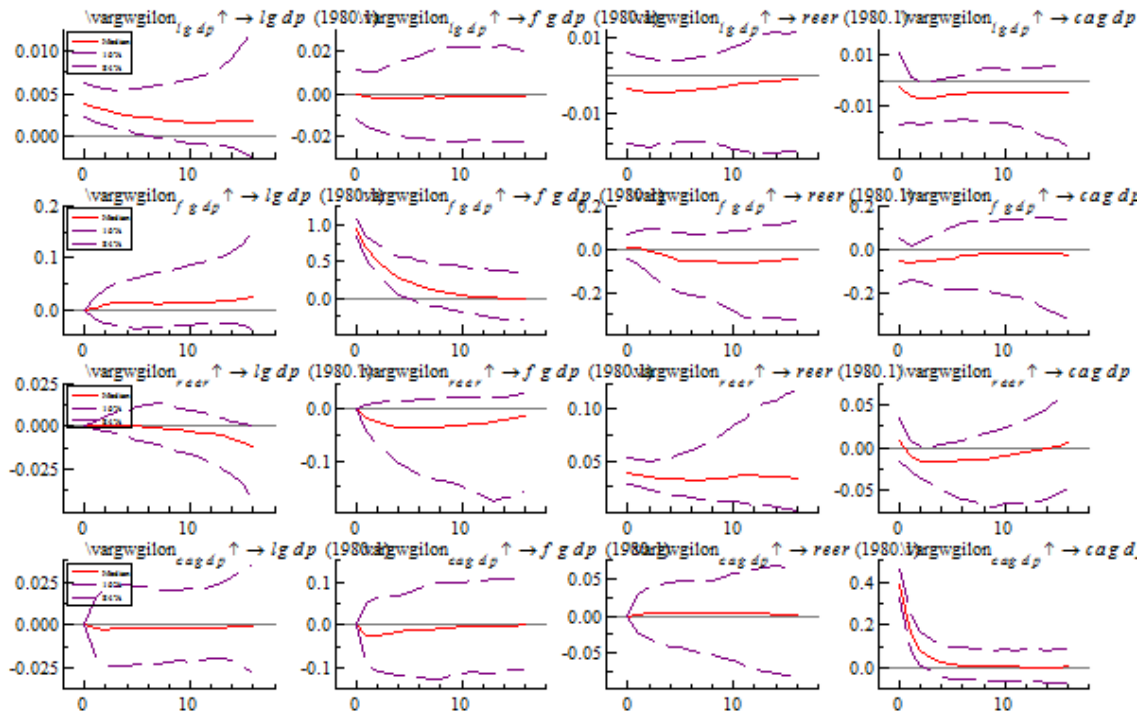


Figure 2-12: Constant Impulse Response Functions/Constant VAR

constant and positive throughout the period of analysis; this is found in figure 2.11.

2.6.3 Constant Impulse Response Functions/Constant VAR and Time-Varying Impulse Response Functions

Next, the impulse response functions are calculated. Here IRFs are estimated by fixing the initial shock as the average of stochastic volatility measure for each variable and using the simultaneous relations at each point. The estimated time varying coefficients are used to compute the IRFs from the current to future periods. Figure 2.12 shows the constant IRFs/ Constant VAR whereas figure 2.13 shows the time-varying VAR. This helps in giving a comparative evaluation of a Constant VAR model with a time-varying VAR model. In figure 2.12 the impulse response of the GDP to a positive shock of FD is significantly shown as positive, while the shock of FD to CAD results in a negative impact. A unit shock in CAD results in a negative response in both GDP as well as FD. REER registers a positive impulse response to a shock in CAD while a negative IRF to a shock in

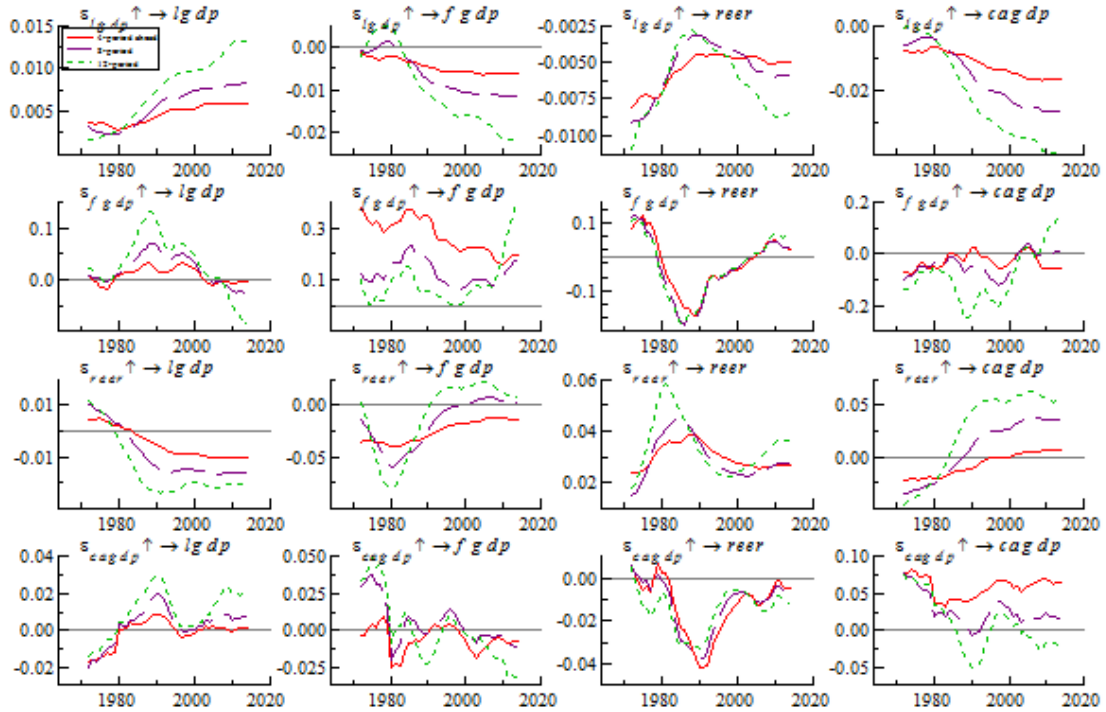


Figure 2-13: Time-Varying Impulse Response Functions/Time-Varying VAR

FD. Next, the time varying IRFs are analysed, which is depicted in figure 2.13. The time varying IRFs are estimated by showing the size of responses from a four-year ahead the horizon to a 12 year ahead of the horizon. From the Time-Varying IRF impulses, the following inferences could be made. Firstly the impact of fiscal deficit shock to GDP is initially positive but becomes negative by the third period, but the impact of fiscal deficit shock to REER is positive in nature. However when the response of REER to one SD shock in Fiscal Deficit is analysed, initially in the first two periods it is positive while it becomes negative by the third period. When the impact of Fiscal Deficit shock to Current Account Deficit is analysed we find that initially in the two periods, it is negative while it tends to positive from the third period onwards. However, the impact of Current Account deficit shock to fiscal deficit looks cyclical in nature. The response of CAD to one S.D shock in REER is negative. Again the impact of CAD on GDP is positive in nature.

The Time-Varying VAR result shows that Fiscal deficit has the positive and significant impact on current account deficit and current account deficit has an impact on

REER. The impulse response results in VAR model indicate that fiscal deficit has a positive impact on current account deficit. The response of GDP to a shock in fiscal deficit is positive in the initial years and becomes negative after the third year. Fiscal deficit's effect on current account deficit and REER is also positive. Current account deficit positively influences GDP and REER negatively. Thus we can see that the results are more clear and precise in a time-varying VAR model in comparison to a constant VAR model.

2.7 Conclusion

Despite the fact that India introduced policies like Fiscal Responsibility and Budget Management Act (FRBM) in 2004, budget deficit did not make any progressive change. As a result, the existence of twin deficit hypothesis becomes inevitable, due to the strong interrelation between budget deficit and trade deficit. By employing a Time-Varying Vector Autoregression (VAR) Model, this chapter has tried to justify the existence of twin deficit hypothesis in the Indian context, by analysing the impact of fiscal shocks on Current Account in India from 1970-71 to 2013-14. The results are interpreted from the time varying IRF obtained. From the results, it could be concluded that Fiscal deficit has a positive and significant impact on current account deficit, followed by an impact on REER. Fiscal Deficit shock makes GDP respond positively in the initial years and turns out to be negative at a later stage. The effect of Fiscal deficit shock to Current account deficit is positive. Similarly, the impact of Fiscal deficit shock to REER is positive. Thus, through this chapter it has been proved that fiscal deficit and current account deficit are related, and twin deficit hypothesis is applicable in the Indian scenario. As a policy solution, the suggestion to the Indian government is that they should try to reduce its budget deficit. If only the budget deficit decreases there would be a reduction in current account deficit, making the economy attain stability.

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Chapter 3

Oil Shocks and Its Impact On Indian Economy: Sign Restricted SVAR Model

3.1 Introduction

Fluctuations in crude oil price are one thing that economists all over the world closely monitor, as it has serious implications for the economy. Not only does it affect the global economy, but also the domestic economy depending on whether they export or import oil. India is currently the fourth largest economy in the world to import crude oil and other petroleum products following U.S.A, China and Japan [20]. Thus crude oil price shocks will affect a developing economy like India as the economic activity, and overall price level in the country would get affected. Crude oil prices could impact the economic activity and inflation in India through the channels of real income, input cost, and current account deficit and market sentiment. Even when we look at the average crude oil prices from 2000 -01 to 2015-16 in India, we see that there is a decline in the crude oil price from 2014-15 onwards. The decrease in crude oil prices has further increased India's dependence on Crude oil import by 81% in 2015-16 compared to 78.5% in 2014-2015 [15].

According to the Annual Monetary Policy Report of India [13], there has been a 50% decline in the crude oil price since June 2015. This is considered as favourable external shock for the following reasons:

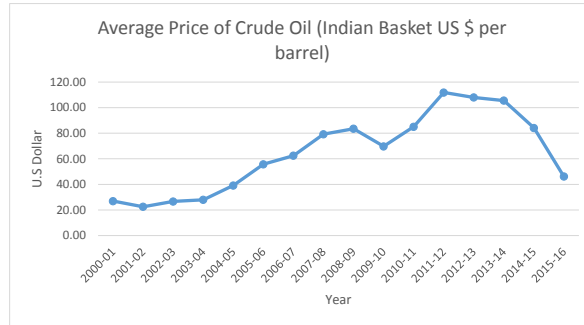


Figure 3-1: Average Price of Crude Oil in India Note: based on the data of Ministry of Petroleum and Natural Gas (PPAC)

1. Lower crude oil prices would help in raising the real income for consumers.
2. The input costs would get lowered thereby increasing the corporate profitability and inducing investment.
3. The Current Account Deficit (CAD) would get lowered, making the trade imbalance problem to get resolved.
4. The market expectations also get improved with a lower crude oil price.

But all these favourable effects could be offset by a weak global demand. Thus it becomes necessary to understand the macroeconomic impact of the crude oil price shock on the Indian economy, as it affects the economic activity and inflation in the country.

3.2 Research Problem

It becomes necessary to identify the type of shocks; to analyse the macroeconomic impact of crude oil price shock on the economy. In other words, the economic activity and price level in an economy could get affected depending on the type of shock namely oil supply shock, oil demand shock created by Global Economic activity and an oil specific Demand shock. Various methodologies have been employed across the world to address this issue. However the usage of Sign Restricted Structural Vector Autoregression (SVAR) the model started gaining importance since 2009 with the work of Kilian [10]. The application of sign restricted SVAR models have been employed in developed countries like

USA, Europe, etc., but the use of such models in developing countries are very limited. Though studies have been carried in India in comparison with other developing and developed countries, the application of a Sign Restricted SVAR model in the Indian context is very limited. The first work using a Sign Restricted SVAR framework was carried by Goyal & Singh [8], but a Bayesian estimation procedure was not employed in their estimation.

Thus this chapter becomes significant, as it tries to fill in this gap by applying a Sign Restricted SVAR model using Bayesian estimation method with Normal-Wishart prior in the Indian context and seeks to understand the macroeconomic impact of oil shocks on Indian Economy.

3.3 Literature Review

The vast amount of literature could be found relating to the impact of oil price on the economy since 1983 by Hamilton [9]. There are various approaches carried out to understand the impact of oil price shock. This chapter only focuses on Vector Autoregression (VAR), Structural Vector Autoregression (SVAR) and Sign Restricted Structural Vector Autoregression (SVAR) Models that are used to understand the relationship between oil price and economic activity. The first application of a Vector Auto Regression (VAR) Model in understanding the effect of oil price was by Burbidge and Harrison [6] on the American economy. They identified a causal relationship between oil price changes and variations in macroeconomic indicators such as GNP and the unemployment rate in the USA, with causality running from the former to the latter. Till the 1990's studies were only carried out in the American economy. Later Mork *et al.* [14] tried to understand the macroeconomic response to oil price increase and a decrease in seven OECD countries. The impact of oil price shocks on the stock market, economic activity and employment in the Greece economy was carried out by Papapetrou, E [16]. Bernanke *et al.* [3] first introduced an SVAR framework with oil shocks in USA's economy to understand the role of monetary policy after Post World War. A similar framework for understanding dynamic oil price shock using industry level data was done on US economy

by Lee & Ni [12]. Peersman [17] also introduced a similar framework. But Kilian [10] introduced SVAR Model differentiating between Oil Supply Shock, Oil demand shock created by global activity and Oil specific Demand Shock. In his paper identification methodology was triangular decomposition of the of the global real economic activity index. This model was extended using a Bayesian estimation procedure by Peersman & Robays [18][19] in understanding the Oil price shock on the Euro economy. But this model differed as the identification scheme introduces sign restrictions. Later Baumeister *et al.* [2] extended the Bayesian estimation procedure using sign restricted SVAR in understanding the economic consequences of oil price shocks on different developed and developing economies. Cunado *et al.* [7] analysed the macroeconomic impact of Oil shocks in Asian Economies using the sign restricted SVAR Approach(Bayesian) and came up with the conclusion that economic activity and prices respond very differently depending on the type of the oil price shock.

As noticed most of the studies focused on the USA and developed Economies in the World. It is only from the year 2000 that studies relating to the developing countries were carried out and were given importance. Though studies relating to the Impact of petroleum products on other sectors of the Indian economy was conducted using an Input Output Technique by Rangarajan *et al.* [20], the first work carried out using VAR to understand the impact of crude oil price shock on Indian economy was done by Battacharya and Battacharya [6]. From the Impulse Response Function generated from their VAR model they concluded that the oil price shock has it's impact on inflation. Kumar.S [11] used a VAR model and found that Oil price shocks negatively affects the growth of industrial production. The variance decomposition analysis showed that the oil price shocks combined with the monetary shocks are the largest source of variation in industrial production growth other than the variable itself. Goyal and Singh [8] introduced an SVAR Model with a horizontal and vertical long-run supply curve identification to understand the impact of oil price shocks. They came to the conclusion that both the identification strategies suggest that policy demand squeezes aggravated international oil price shocks. Aparna [1] tried to understand the impact of the crude oil shock in India using a VAR model and came to the conclusion that oil shock has an im-

mediate adverse effect on industrial production and also has a spurt in inflation. Thus by looking at these studies, we find that the works carried solely in the Indian context is limited and widens the scope of our work.

3.4 Methodology

In this chapter, an SVAR Model with sign restrictions has been used. An SVAR framework has been chosen as it helps in better evaluation of the global oil market and also help to group oil price innovations into three different types as stated by Baumeister, Peersman and Van Robays[2]. The three types of oil shocks are as follows:

1. *Oil Supply Shock*: It represents an exogenous disruption of the supply curve caused by geopolitical turmoil such as military conflicts or changes in production quotas of the Organization of Petroleum Exporting Countries. As a result, the oil supply shock tends to move oil production and oil prices in opposite directions, with no potential gain in global economic activity.
2. *Oil Demand Shock-driven by Economic Activity*: This refers to oil shocks driven by the current fundamental economic demand. This type of shock generates a shift of oil production and oil prices in the same positive direction, accompanied by an unexpected boost in economic activity; higher global economic activity would lead subsequently to increase in oil prices and oil production. However, some increase in the oil price may not be directly related to a current increase in fundamental economic activity, but are rather due to heightened concerns regarding the availability of oil in the future.
3. *Oil Specific Demand Shock*: These shocks are also referred to as the other demand shock or even speculative demand shock. These shocks arise from changes in perception or economic sentiment (i.e., forward-looking behaviours of agents) that further result in an increased demand for oil.

For the identification of the types mentioned above of oil shocks, we use sign restrictions that are imposed on the first group of endogenous variables, as in Baumeister,

Table 3.1: Sign Restrictions

Structural Shocks	Q_{oil}	P_{oil}	Y_w	G_j	P_j
Oil Supply Shocks	<0	>0		-	-
Oil Demand Shocks driven by economic activity	>0	>0	>0	-	-
Oil specific demand shock	>0	>0		-	-

Peersman and Van Robays[2].

3.4.1 Sign Restricted SVAR Framework

Our SVAR model is formulated based on Baumeister, Peersman and Van Robays[2] model as follows:

$$\begin{pmatrix} X_t \\ Y_t \end{pmatrix} = c + A(L) + \begin{pmatrix} X_{t-1} \\ Y_{t-1} \end{pmatrix} + B \begin{pmatrix} \sum X_t \\ \sum Y_{j,t} \end{pmatrix} \quad (3.1)$$

Where the vector of endogenous variables can be divided into two larger groups. In the first group, the 3 - by - 1 vector X_t captures the dynamics in the world oil market, with world oil production (Q_{oil}), the real price of crude oil expressed in U.S. dollars (P_{oil}), and a proxy variable of world economic activity (Y_w). In the second group of variables, $Y_{j,t}$ is a 2-by-1 vector containing variables such as GDPgrowth (G_j) and inflation ie price level (P_j) for India. Finally, c is a vector of constants, and (L) is a matrix polynomial with the lag operator L , which is set to be 2. The sign restrictions are as follows:

Each restriction is imposed for four subsequent periods after the impact period. This allows sufficient time for the shock to propagate. Also, we impose zero restrictions on the impact matrix for the local variables, while shocks arising from the dynamic changes in the world oil market are free to affect an individual country during the same period. Hence, the direction of responses of the local variables will be purely determined by the data. In sum, the shocks are identified in the world crude oil market.

We estimate the above VAR for each Indian economy, via Bayesian estimation with uninformative natural conjugate priors i.e. with Normal-Wishart prior. The sample period is from 1996 Q1 – 2013 Q4. The Bayesian approach has been used, as it has advan-

tages in imposing sign restrictions and computing error bands for impulse responses. There are five variables in our baseline VAR. We use the real world oil price, defined as the U.S. crude oil composite acquisition cost by refiners, deflated by the U.S. CPI. The oil production series is obtained from the U.S. Energy Information Administration (EIA) [21]. The world economic activity is proxied by the seasonally adjusted total IP index of OECD member countries¹. The GDP growth (Gj) and inflation i.e. price level (Pj) are obtained from Reserve Bank of India². All the variables are in quarterly estimates with log difference of order one taken.

3.5 Results

Based on Baumister, Peersman and Van Robays [2] sign restricted SVAR model, we identify three shocks 1. Oil Supply Shock 2. Oil Demand Shock created by Global Economic Activity 3. Oil Specific Demand Shock³. The results generated from Oil Specific Demand Shock are less pronounced. In other words, the impact of Oil Specific Demand Shock on the economic growth and inflation of India does not show any significant changes. Hence we display only the results generated from Oil Supply Shock and Oil Demand Shock caused by Global Economic Activity.

3.5.1 Oil Supply shock

Figure 3-2 shows the Impulse Response Functions (IRF's) of GDP growth and Inflation (WPI) to an oil supply shock. We find that the output growth of Indian economy does not respond much to the oil supply shock while the price level responds positively to an oil supply shock.

¹The data is obtained from OECD site which gives Industrial Production values for it's member states.<https://data.oecd.org/industry/industrial-production.htm>

²Data is obtained from the Reserve Bank of India, Handbook of Statistics on the Indian Economy.<https://dbie.rbi.org.in/DBIE/dbie.rbi?site=publications>

³Refer Appendix C for the software and package information

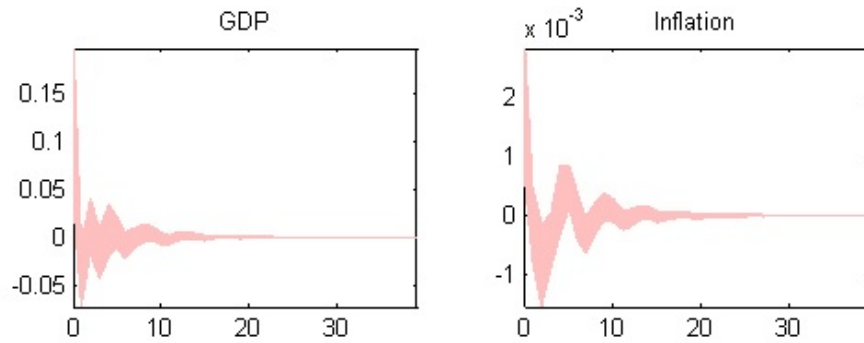


Figure 3-2: The impulse response functions (IRF) of the variables output growth and Inflation (WPI) to an oil supply shock

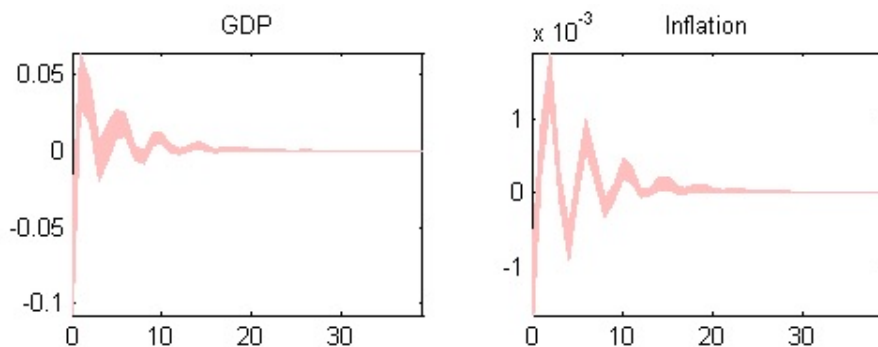


Figure 3-3: The impulse response functions (IRF) of the variables output growth and Inflation (WPI) to an oil demand shock driven by global economic activity

3.5.2 Oil Demand Shock-driven by global economic activity

Figure 3-3 shows the Impulse Response Functions (IRF's) of GDP growth and Inflation (WPI) to an oil demand shock driven by global economic activity. We find that the output growth of India responds positively to an oil demand shock driven by global economic activity while the response of price level is not much clear. India is heavily import dependent for its economic growth, and this is a positive thing for India. In other words with a positive oil shock, the trade imbalances could be solved, as a reduction in oil price would help in the reduction of the oil import bill. It would also lead to an increase in the real GDP and also help in the reducing inflation through its pass-through effect. This could be the possible reason why the output growth of India responded positively.

Figure 3-4 gives the Factor Error Variance Decomposition of the shock in GDP of India which clearly shows that the responses depend on the type of oil price shock. In

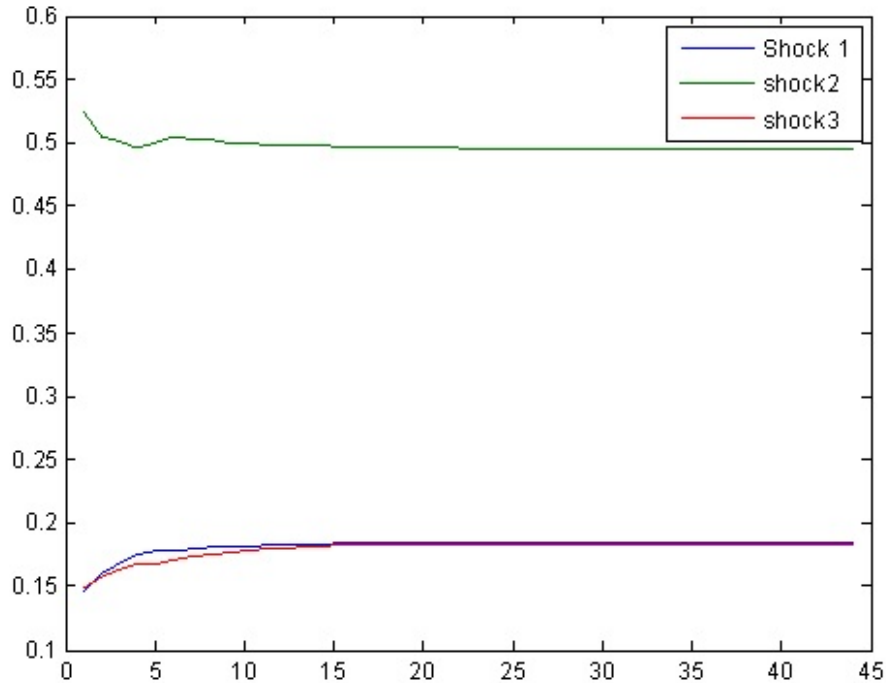


Figure 3-4: FEVD for India's GDP, Shock 1: oil supply shock, Shock 2: oil demand shock and Shock 3: oil-specific demand shock

India's case the oil demand shock driven by global economic activity is the most significant one.

3.6 Conclusion

In this chapter, the impact of structural oil price shocks on Indian economy between 1996 Q1- 2013 Q4 have been analysed. I have applied Baumeister, Peersman and Van Robays [2] sign restricted SVAR model to develop the current findings. The VAR model is estimated using a Bayesian estimation method with Normal-Wishart prior. The first shock i.e. oil supply shock did not make the economic activity (GDP Growth) of India respond much, but the price level responded positively. In the case of oil demand shock driven by Global Economic Activity the output growth responded positively, but its impact on price level was not much clear. Finally the effect of oil-specific demand shock on the economic activity and inflation of Indian economy is less pronounced which is clearly evident from the Factor Error Variance Decomposition (FEVD) of GDP. In short

oil demand shock driven by global economic activity has a significant impact on Indian economy compared to the two other structural shocks. Thus it could be summarised that the responses depend on the type of structural shock and India being a major oil importing country should be careful whereby stronger world economic activity can lead to an unexpected rise in oil prices which would have more powerful consequences on the Indian economy.

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Appendix A

Chapter 1

1. 1.3.1 The Basic Model

Equation (1.5)

(Page 20)

$$y_t = \mathbf{X}'_t \boldsymbol{\beta}_t + u_t$$

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t} y_{t-1} + u_t$$

$$\mathbf{B}_{1t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{1t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{1t} = \begin{bmatrix} b'_{1,1t} \\ b'_{2,1t} \\ \vdots \\ b'_{n,1t} \end{bmatrix}_{1t}$$

$$\mathbf{X}_t = \begin{bmatrix} 1y'_{t-1} & 0 & 0 & \cdots & 0 \\ 0 & 1y'_{t-1} & 0 & \cdots & 0 \\ 0 & 0 & 1y_{t-1} & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1y_{t-1} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} c_1 \\ b_{1,1t} \\ c_2 \\ b_{2,1t} \\ \vdots \\ c_n \\ b_{n,1t} \end{bmatrix}$$

$$\mathbf{B}_{2t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{2t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{2t} = \begin{bmatrix} b'_{1,2t} \\ b'_{2,2t} \\ \vdots \\ b'_{n,2t} \end{bmatrix}$$

With the number of k changes with the change in the value of \mathbf{B} that is $\mathbf{B}_{2,t} \quad y_{t-2}$ then it finally turns $1 + 2n$

2. 1.3.1 The Basic Model

(Page 22)

Triangular Factorisation is done through Cholesky Decomposition

$$\mathbf{A}_t \boldsymbol{\Omega}_t \mathbf{A}'_t = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}'_t$$

$$\mathbf{A} \boldsymbol{\Omega} \mathbf{A}' = \mathbf{A} \boldsymbol{\Omega}$$

inverse of a lower triangular matrix \mathbf{A} is a lower triangular matrix.

$$\begin{bmatrix} \sigma_{11} & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22} & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn} \end{bmatrix} \begin{bmatrix} \sigma_{11} & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22} & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn} \end{bmatrix}$$

$$\begin{bmatrix} \sigma_{11,t}^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22,t}^2 & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33,t}^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn,t}^2 \end{bmatrix}$$

3. 1.3.2 Analytical Framework (TV-SVAR with Stochastic Volatility)

(Page 28)

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t}y_{t-1} + \mathbf{B}_{2t}y_{t-2} + \mathbf{B}_{3t}y_{t-3} + \mathbf{B}_{4t}y_{t-4} + \mathbf{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\varepsilon}_t$$

\mathbf{B}_1 , \mathbf{B}_2 , \mathbf{B}_3 and \mathbf{B}_4 have the same structures.

$$\mathbf{B}_1 = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ 0 & 0 & 0 & b_{44} \end{bmatrix}$$

1st row is for inflation, 2nd row is for output growth, third row is for interest rate and 4th row is for crude oil price.

b_{11} stands for the effect of last period of inflation on 1st period of inflation. b_{14} stands for the effect of last period of oil price on first period of inflation. b_{34} stands for the effect of last period of oil price on the 1st period of interest rate.

4. Software and Package

For obtaining the results, the software Oxmetrics and the code used is of Nakajima(2011) with slight modifications.

Files in TVP-VAR package are:

1. TVPVAR.ox - the main source file of TVPVAR class;
2. tvpvar ex*.ox - example for use of TVP-VAR package;
3. tvpvar ex.xls - Indian data for tvpvar ex*.ox.

The following steps are involved in the model formulation:

1. Create a TVPVAR object with restrictions
2. Use `SetData(my, nlag)` to load $y = (y_1; \dots; y_n)'$ and to set the number of lags.
3. Use `SetVarName(asvar)` to set variable names
4. Use `SetPeriod(iyear, iperiod, ifreq)`: sets the starting time point of data with frequency (iyear: year of the first observation, iperiod: period of the first observation, ifreq: the number of periods in a year)
5. Code `MCMC(N)` to implement the MCMC algorithm with N iterations.
6. Use `SetFastImp(fl)` to compute time-varying impulse responses using the posterior mean of time-varying parameters as $fl = 1$ (default)
7. use `SetSigB(fl)` to compute diagonal covariance matrix for Σ_h
8. `SetImpulse(imax)`: sets the maximum length (default:12) of impulse responses (if $fl = 0$, imax smaller, computation faster); Note that imax should be larger than or equal to all the values in `vt` of `DrawImp(vt, 1)`.
9. `SetRanseed(j)`: the j-th ranseed is set.

The TVP-VAR package sets the default prior specification as:

$$(\Sigma_\beta)_i^{-2} \text{Gamma}(20, 0.01), (\Sigma_\alpha)_i^{-2} \text{Gamma}(2, 0.01), (\Sigma_h) \text{Gamma}(2, 0.01)$$

where IW denotes the invert Wishart distribution, $(\Sigma_\alpha)_i$ and (Σ_h) denote the i-th diagonal element of the matrices. In the TVP-VAR package, the hyperparameters in the prior distribution can be set by coding `SetPrior(par, arg1, arg2)`. The first argument `par` is input as the string of either "b", "a", or "h". If `SetSigB(1)`, the default prior is $\Sigma_\beta \text{IW}(25, 0.01I)$; coding `SetPrior` corresponds to $\text{IW}(arg1, arg2 \times I)$.

Appendix B

Chapter 2

1. Equation (2.3)

(page 54)

$$y_t = \mathbf{X}'_t \boldsymbol{\beta}_t + u_t$$

$$\mathbf{y}_t = \mathbf{c}_t + \mathbf{B}_{1t} y_{t-1} + u_t$$

$$\mathbf{B}_{1t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{1t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{1t} = \begin{bmatrix} b'_1, 1t \\ b'_2, 1t \\ \vdots \\ b'_n, 1t \end{bmatrix}_{1t}$$

$$\mathbf{X}_t = \begin{bmatrix} 1y'_{t-1} & 0 & 0 & \cdots & 0 \\ 0 & 1y'_{t-1} & 0 & \cdots & 0 \\ 0 & 0 & 1y_{t-1} & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1y_{t-1} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} c_1 \\ b_{1,1t} \\ c_2 \\ b_{2,1t} \\ \vdots \\ c_n \\ b_{n,1t} \end{bmatrix}$$

$$\mathbf{B}_{2t} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{1n} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ b_{n1} & b_{n2} & b_{n3} & \cdots & b_{nn} \end{bmatrix}_{2t} = \begin{bmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_n \end{bmatrix}_{2t} = \begin{bmatrix} b'_{1,2t} \\ b'_{2,2t} \\ \vdots \\ b'_{n,2t} \end{bmatrix}$$

With the number of k changes with the change in the value of \mathbf{B} that is $\mathbf{B}_{2,t} \quad y_{t-2}$ then it finally turns $1 + 2n$

2. Time-Varying VAR Model

(Page 55)

Triangular Factorisation is done through Cholesky Decomposition

$$\mathbf{A}_t \boldsymbol{\Omega}_t \mathbf{A}'_t = \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}'_t$$

$$\mathbf{A} \boldsymbol{\Omega} \mathbf{A}' = \mathbf{A} \boldsymbol{\Omega}$$

inverse of a lower triangular matrix \mathbf{A} is a lower triangular matrix.

$$\begin{bmatrix} \sigma_{11} & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22} & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn} \end{bmatrix} \begin{bmatrix} \sigma_{11} & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22} & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn} \end{bmatrix}$$

$$\begin{bmatrix} \sigma_{11,t}^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{22,t}^2 & 0 & \cdots & 0 \\ 0 & 0 & \sigma_{33,t}^2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{nn,t}^2 \end{bmatrix}$$

3. Software and Package

For obtaining the results, the software Oxmetrics and the code used is of Nakajima(2011) with slight modifications.

Files in TVP-VAR package are:

1. TVPVAR.ox - the main source file of TVPVAR class;
2. tvpvar ex*.ox - example for use of TVP-VAR package;
3. tvpvar ex.xls - Indian data for tvpvar ex*.ox.

The following steps are involved in the model formulation:

1. Create a TVPVAR object without restrictions
2. Use SetData(my, nlag) to load $y = (y_1; \dots; y_n)'$ and to set the number of lags.
3. Use SetVarName(asvar) to set variable names
4. Use SetPeriod(iyear, iperiod, ifreq): sets the starting time point of data with frequency (iyear: year of the first observation, iperiod: period of the first observation, ifreq: the number of periods in a year)
5. Code MCMC(N) to implement the MCMC algorithm with N iterations.
6. Use SetFastImp(fl) to compute time-varying impulse responses using the posterior mean of time-varying parameters as $fl = 1$ (default)
7. use SetSigB(fl) to compute diagonal covariance matrix for Σ_h

8. SetImpulse(imax): sets the maximum length (default:12) of impulse responses (if fl = 0,imax smaller, computation faster); Note that imax should be larger than or equal to all the values in vt of DrawImp(vt, 1).
9. SetRanseed(j): the j-th ranseed is set.

The TVP-VAR package sets the default prior specification as:

$$(\Sigma_{\beta})_i^{-2} \text{Gamma}(20,0.01), (\Sigma_{\alpha})_i^{-2} \text{Gamma}(2, 0.01), (\Sigma_h) \text{Gamma}(2,0.01)$$

where IW denotes the invert Wishart distribution, $(\Sigma_{\alpha})_i$ and (Σ_h) denote the i-th diagonal element of the matrices. In the TVP-VAR package, the hyperparameters in the prior distribution can be set by coding SetPrior(par, arg1, arg2). The first argument par is input as the string of either "b", "a", or "h". If SetSigB(1), the default prior is $\Sigma_{\beta} \text{IW}(25,0.01I)$; coding SetPrior corresponds to $\text{IW}(arg1, arg2 \times I)$.

Appendix C

Chapter3

1. Software and Package

For obtaining the results, the software MATLAB and the code used is of Baumeister *et al.*(2011) with the identification process of Kilian(2010).

The following files have been employed to run the results.

1. ASYBC.m - This functions sets the eigenvalues by construction
2. BOOT.m - This function sets the start up of bootstrap simulation
3. irfvar.m - This function sets the impulse response functions.
4. olsvarc.m - This function sets the sign restrictions and identifies the different types of shocks.
5. point.m - This function sets the VAR lag order, Impulse response horizon and VAR with intercept
6. vec.m - This function vectorizes an $(a \times b)$ matrix y .

Based on these functions the results as shown in Chapter 3 are obtained.