Essays in Empirical Macroeconomics

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Declaration

This thesis has not previously been submitted for a degree at this or any other university or institution. To the best of my knowledge, it contains no other material previously published by another person, except where due reference is made in the text of this thesis.

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Abstract

This thesis is a collection of three self contained chapters in the area of empirical macroeconomics.

Chapter 2 examines the behaviour of the volatility of the structural shocks and the macroeconomic variables in the post-reform period in India in a time-varying framework. A time varying parameters structural vector autoregression with stochastic volatility model is used to investigate the evolving dynamics of the macroeconomy of India in the post-reform period. We detect a sharp reduction in estimated stochastic volatility during the post-reform years for all shocks and variables. In terms of the stochastic volatility, we find that the period 2001 to 2006 seems to have the lowest volatility in the whole sample and can be dubbed as the short ‘Great Moderation’ period of India. We find that the estimated stochastic volatility of supply shocks is more than the demand shocks. We also note that demand shocks rather seem to be persistent than supply shocks during the period from 2007-14.

Chapter 3 explores the role of nominal GDP as an implicitly preferred monetary policy target in the US during the Great Moderation period. Monetary policy via stabilization of inflation expectations by targeting inflation, has been argued as one of the prominent factors contributing for the Great Moderation in the U.S. Studies using Taylor rule type monetary policy reaction functions have found inflation to be the major target variable of the Federal Reserve. This study counters this view, and shows that for accomplishing its objective of stabilizing inflation expectations, the Federal Reserve was instead implicitly targeting nominal GDP. This claim is corroborated by estimating different variants of nominal GDP rules, which then is compared with Taylor rules using both ex-post revised data and real time briefing forecasts of FOMC. The results counter the conventional view, and observe that post Volcker era or during the period of Great Moderation (1984-2007), the Federal Reserve had a stronger implicit preference for nominal GDP as compared to inflation.

Chapter 4 examines whether nominal GDP can pass the forecasting test to be a monetary policy framework. Forecast targeting became an important component of central banks from 1990’s onwards as a systematic approach to monetary policy deliberations and as a good communication medium with the
public. Any robust monetary policy regime has to have good forecasting performance of its nominal anchor. Nominal GDP targeting has been suggested as a suitable alternative to the present inflation ‘targeting’ monetary policy framework. But as a good framework its nominal anchor should have good forecasting ability. This chapter tries to compare the forecast performance between the nominal anchors of inflation and nominal GDP targeting regimes for U.S. This task is undertaken by using a series of models from simple autoregressive models to state space models. U.S Inflation is hard to forecast, but it seems that NGDP is much more harder to forecast.
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Chapter 1

Introduction

India embarked on the process of major economic reforms starting in 1991 in the aftermath of a severe balance of payment crisis. These reforms included wide ranging changes in the financial sector, with a slew of measures such as dismantling of interest rate controls, introduction of capital adequacy requirements along with prudential norms for banks, and other measures for increasing competition. This transition from a closed regime to a relatively open regime must have changed the volatility of the structural shocks and macroeconomic variables. In the second chapter, we examine the volatility of three structural shocks and macroeconomic variables in the post-reform period from 1991 to 2014.

For undertaking this task we use a Bayesian time-varying parameter structural VAR with stochastic volatility, following the works of Primiceri (2005), Canova and Gambetti (2005), Gambetti, Pappa and Canova (2006) and Benati and Mumtaz (2007). We use the index of industrial production, CPI inflation and call money rate to investigate the nature of the volatility and the implications of structural shocks. The structural shocks that are identified using sign restriction techniques display different features at different points
in time. One of the issues with the Indian data is availability of short time series. We could not use a TVP-VAR-SV framework before 1991 to understand the evolution of volatility due to lack of interest rate data. For understanding the nature of volatility of variables from a longer time period, we have used a univariate AR(1) time-varying stochastic volatility model from 1970-2014. We examine the stochastic volatility of three macroeconomic variables, industrial output (IIP), consumer price index (CPI), and wholesale price index (WPI).

Results from the second chapter show that time variation is an important feature of the major macroeconomic variables in India. During the post-reform period from 1991 onwards, we detect a sharp reduction in estimated stochastic volatility for all shocks and variables. Interestingly, during the East Asian crisis the volatility surge is much higher than observed during the recent global financial crisis. We find that CPI inflation response to monetary policy shocks are somewhat consistent with industrial output. This similar response in both the variables in terms of synchronous fluctuations in volatility was also observed with the univariate stochastic volatility model for both the variables. We also note that demand shocks rather seem to be persistent than supply shocks during the period from 2007-2014. In terms of the stochastic volatility we find that the period from 2001 to 2006 seems to have the lowest volatility in the whole sample and can be dubbed the short ‘Great Moderation’ period of India. Estimated stochastic volatility of the supply shocks is more than the demand shocks.

In the third and fourth chapters, we focus on the monetary policy framework in the US economy. The ‘Great Moderation’ has been considered a period of reduction in macroeconomic volatility in the US (Stock and Watson, 2002), Bernanke (2004). Many factors have been attributed for the decline
in macroeconomic volatility including inventory dynamics (McCarthy and Zakrajsek, 2007), smaller macroeconomic shocks (Stock and Watson, 2002) and stronger preference for low inflation in the monetary policy process (Clarida, Gali and Gertler, 2000; Bernanke (2004). One of the prominent factors that has been argued for contributing to the Great Moderation in the US, is the stabilization of the inflation expectations by focusing on inflation. Monetary policy rules such as the Taylor rule (2003) embody such hypothesis.

Clarida, Gali and Gertler (2000); Stock and Watson (2002); and Bernanke (2004), have argued that post-Volcker or during the Great Moderation period, the monetary policy preferences of the Federal Reserve were much more sensitive and tuned to changes in expected inflation and overwhelmingly found it to be the preferred policy target of the Federal Reserve. But was the Federal Reserve just implicitly targeting inflation? Alan Greenspan, Federal Reserve chairman during this period, stated in one of his speeches in 1992 that the Federal Reserve should target NGDP growth rate at 4.5%. A natural question to ask is whether the Federal Reserve was implicitly targeting nominal GDP. The third chapter of this thesis, answers this question.

The third chapter estimates a forward looking nominal GDP rule for the US, spanning from 1960-2007. This study shows that for accomplishing its objective of stabilizing inflation expectations, the Federal Reserve was implicitly targeting nominal GDP. This claim is corroborated by estimating different variants of nominal GDP rules, which then is compared with Taylor rules using both ex-post revised data and real time briefing forecasts of FOMC. The results counter the conventional view, and observe that post Volcker era or during the period of Great Moderation (1984-2007), the Federal Reserve had a stronger implicit preference for nominal GDP as compared to inflation.
Chapter 4 explores whether nominal GDP can pass the forecasting test to be a good monetary policy framework. Optimal nominal GDP targeting has been found to be superior to inflation targeting frameworks such as the Taylor rule (Jensen, 2002) and also more efficient especially when the economy is hit by a cost push shock, supply shocks or shocks to country risk (Henderson and McKibbin, 1993; Jensen, 2002). Nominal GDP targeting has the operational advantage as there is no requirement for having an output gap measurement. For nominal GDP targeting to be implemented as a monetary policy regime, its nominal anchor should have good forecasting ability. Forecast targeting became an important component of central banks from the 1990s onwards as a systematic approach to monetary policy deliberations and as a good communication medium with the public. Any robust monetary policy regime has to have good forecasting performance of its nominal anchor.

The fourth chapter compares the forecast performance between the nominal anchors of inflation and nominal GDP targeting regimes for the US. This task is undertaken by using a series of models including Autoregressive models, Integrated Moving Average models, Vector Autoregression model and Unobserved Components model. The forecasting performance shows that US inflation is hard to forecast, but it seems that nominal GDP is much harder to forecast.

1.1 Thesis Outline

This thesis contains three self contained chapters. The chapters are organized as follows,

- Chapter 2 - Time-varying Macroeconomic Dynamics of the Indian Econ-
• Chapter 3 - Implicit Central Bank Targets: Nominal GDP and the Great Moderation

• Chapter 4 - Does Nominal GDP pass the forecastability test for being the future monetary policy framework?

• Chapter 5 - Conclusion.
Chapter 2

Time-varying macroeconomic dynamics of the Indian economy

2.1 Introduction

India embarked on the process of major economic reforms starting in 1991 in the aftermath of a severe balance of payment crisis. These reforms included wide-ranging changes in the financial sector, with a slew of measures such as dismantling of interest rate controls, introduction of capital adequacy requirements along with prudential norms for banks, and other measures for increasing competition. These reforms brought in more efficiency in financial intermediation and also led to a substantial reduction in the cost of banking.

During the initial phase of reforms, during the 1990s, many changes were also introduced in the monetary policy framework by the Reserve Bank of India (RBI). In terms of its liquidity management operations, the RBI shifted from direct instruments to indirect instruments, and also moved from multiple indicator regime to using the interest rate as its most important instrument for monetary policy. This transition was helped by the introduction of the
liquidity adjustment facility (LAF) in 2004. More reform measures were also unveiled, that smoothed the transition from a closed regulated regime to a more open regime. This included deregulation of interest rates, auction-based market borrowing programme of the government, the introduction of money market instruments, the phasing out of ad hoc Treasury bills, replacement of cash credits with term loans and there was a reduction in statutory reserve requirements (Mohanty, 2012).

The single policy rate was only recently introduced by the RBI in 2011 with the weighted average call money rate being explicitly recognized as the operating target. On January 2014, the RBI proposed a major overhaul of the monetary policy framework in India from the ad hoc policy framework to adopting inflation targeting as its primary policy target. Even if instruments that are targeted are known it has been found in certain episodes in India, that the mapping between the policy variables and objective variables does not appear to work well. Or in other words, the transmission channel of macroeconomic variables is somewhat weak. Studies related to India have shown that the monetary transmission mechanism has become more efficient during the post-reform years (Kalirajan and Singh, 2007; Aleem, 2010; Mohanty and John, 2015).

The transmission channel of macroeconomic variables in emerging economies have generally been found not to be that efficient. Mohanty and Klau (2001) in their comprehensive study of emerging economies using data from 1980s and 1990s found that supply factors are more dominant and especially they found inflation in these countries is driven more by supply-side factors. Regarding India, most studies examine the workings of the monetary transmission mechanism and the impact of monetary policy shocks.
Kalirajan and Singh (2007) examine the monetary transmission mechanism during the post-reform years from January 1993 to March 2005. Using cointegrated vector error correction method, they examined the effectiveness of interest rates in the monetary policy framework. As discussed earlier, during this period the liquidity adjusted facility and other major reforms had not started to show the dominance of interest rates. Kalirajan and Singh (2007) find that positive shock to industrial output (proxy for output) is followed with an increase in interest rates after a lag of two periods. They argue that a increase in interest rates from an output shock should be understood in the context of tighter credit and saving situations. In the case of India, they argue that tight credit, hence higher interest rates, exists due to overemphasis on exchange rate management. Strong capital flows coupled with capital controls make open market operation ineffective in controlling the exchange rate due to the dominant effect of sterilization. So they argue that using sterilization to control sharp nominal appreciation and increase in the interest rate to stabilize inflation, makes it difficult to establish which effect dominates output. Mohanty (2012) using a four-variable SVAR examines the monetary transmission mechanism of India. He finds that with a monetary policy shock (call money rate) RGDP decreases for a period of six to eight quarters.

Mohanty and John (2015) who wrote the first paper using time-varying VAR for India, examine inflation dynamics from 1996Q4 to 2014Q1 using five variables time-invariant SVAR and TVP-VAR-SV model. In their time-invariant case, they find the response of inflation to output gap shock to increase inflation, which lasts for around 7 quarters and then it falls. In their study they do not find output gap to be significant. In the case of inflation shock they find that interest rates (weighted average call money rates) in-
creased just for the first quarter then it sharply falls and stays below for the next 4-5 quarters. In the TVP-VAR-SV model, where the identification is based on Cholesky decomposition, the time-varying accumulated impulse response of an output gap shock to inflation shows a positive response of inflation and inflation seems to be persistently positive. They also find that one percentage point shock in the interest rates (call money rates) leads to a 120 basis points fall in inflation that lasts for around six quarters. There is a paucity of studies understanding the behaviour of the volatility of major macroeconomic variables and how the nature of the shocks have evolved in a time-varying framework after the 1991 economic reforms. This study undertakes this task.

In this chapter, we use a Bayesian time-varying parameter structural VAR with stochastic volatility following the works of Primiceri (2005), Canova and Gambetti (2005), Gambetti, Pappa and Canova (2006) and Benati and Mumtaz (2007) to understand the evolution of structural characteristics of the Indian economy in the post-reform period from 1991 to 2014. We use the Index of industrial production, CPI inflation and call money rate to investigate the nature of the volatility and the implication of the structural shocks. The structural shocks that are constructed using sign restriction technique, display different features at different points in time. One of the issues with Indian data is availability of short time series. For understanding the volatility of variables we have also used a univariate time-varying stochastic volatility model from 1970-2014. We could not use a TVP-VAR-SV framework before 1991 to understand about the evolution of volatility due to lack of interest rate data. We examine the stochastic volatility of three macroeconomic variables, Industrial output (IIP), CPI Inflation, and WPI Inflation.

The main results suggest considerable reduction in volatility from 1970s
onwards in all the structural shocks and inflation variables. Indian macroeconomic variables seem to exhibit time variation as can be noted through the TVP-VAR-SV impulse response functions. Interestingly, for the period during the East Asian crisis the volatility surge is much higher than observed during the recent Global financial crisis. In terms of the stochastic volatility we find that the period 2001 to 2006 seems to have the lowest volatility in the whole sample and can be dubbed the short ‘Great Moderation’ period of India. We observe that response of industrial output and CPI inflation are synchronous to monetary policy response. In the univariate model also we find that CPI inflation volatility fluctuations are more synchronous to CPI inflation than WPI inflation. We also note that demand shocks rather seem to be persistent than supply shocks during the period from 2007 to 2014. Estimated stochastic volatility of the supply shocks is more than the demand shocks.

The rest of the chapter is structured as follows. In section 2.2 we provide the description of the time-varying structural VAR model. Section 2.3 provides the details of the estimation procedure of the time-varying structural VAR model. Section 2.4 examines the empirical results and provides plausible inference of the results. In the last section we conclude. Appendix A.1 has the details of the estimation of the univariate stochastic volatility model.

2.2 The model

We work with the following time-varying parameters VAR($p$) model:

\[ Y_t = c_t + B_{0,t} + B_{1,t}Y_{t-1} + \ldots + B_{p,t}Y_{t-p} + \nu_t \]  

(2.2.1)
where $VAR(v_t) = \Omega_t$ and $Y_t = [y_t, \pi_t, r_t]$, and $y_t$ is the annualized growth rate of index of industrial production which has been taken as a proxy for output. $\pi_t$ is the CPI inflation which is also transformed into annualized growth rate and interest rate $r_t$ that we have used is the call money rate. The overall sample period is from 1991m4 to 2014m12. The lag used for VAR is 4, which we have taken according to Bayesian Information Criterion.

The covariance matrix of the error term $v_t$, i.e., $\Omega_t$ has time-varying elements. Following Cogley and Sargent (2002), Cogley and Sargent (2005), Primiceri (2005) and Gambetti, Pappa and Canova (2006) we also assume that the time-varying parameters are stacked in the vector $\theta_t$. The time-varying parameters are postulated to evolve as:

$$P(\theta_t \mid \theta_{t-1}, Q) = I(\theta_t)F(\theta_t \mid \theta_{t-1}, Q)$$ (2.2.2)

where $I(\theta_t)$ is the function rejecting unstable draws. In this way we can enforce stationary constraint on the VAR with $F(\theta_t \mid \theta_{t-1}, Q)$ evolving according to the following law of motion:

$$\theta_t = \theta_{t-1} + \eta_t$$ (2.2.3)

where $\eta_t \sim N(0, Q)$ and the reduced-form errors of the VAR in equation 2.1.1 are posited to be zero mean normally distributed. The covariance matrix of the error terms have time-varying elements with the following structure:
$$VAR(\upsilon_t) = \Omega_t = A_t^{-1} H_t (A_t^{-1})'$$  \hspace{0.5cm} (2.2.4)$$

$A_t$ is a lower triangular matrix with elements $a_{i,j}$ and $H_t$ is a diagonal matrix with diagonal elements $h_{i,t}$. These time varying matrices $H_t$ and $A_t$ are defined as:

$$H_t = \begin{bmatrix} h_{1,t} & 0 & 0 \\ 0 & h_{2,t} & 0 \\ 0 & 0 & h_{3,t} \end{bmatrix} \hspace{0.5cm} A_t = \begin{bmatrix} 1 & 0 & 0 \\ a_{21,t} & 1 & 0 \\ a_{31,t} & a_{32,t} & 1 \end{bmatrix} \hspace{0.5cm} (2.2.5)$$

where $h_{i,t}$ evolves according to a geometric random walk:

$$\ln h_{i,t} = \ln h_{i,t-1} + z_t$$ \hspace{0.5cm} (2.2.6)$$

and non zero and non-unitary elements of matrix $A_t$ are stacked in the vector $a_t = [a_{21,t}, a_{31,t}, a_{32,t}]$, and these evolve as driftless random walk (Primiceri, 2005):

$$a_t = a_{t-1} + \tau_t$$ \hspace{0.5cm} (2.2.7)$$

and we also assume the vectors $[\upsilon'_t, \eta'_t, \tau'_t, z'_t]$ to be distributed as:
(2.2.8)

\[
\begin{bmatrix}
v_t \\
\eta_t \\
\tau_t \\
z_t
\end{bmatrix}
\sim \mathbf{N}(0, \mathbf{V})
\]

where \( V \) is a block diagonal matrix:

\[
V = \begin{bmatrix}
\Omega_t & 0 & 0 & 0 \\
0 & Q & 0 & 0 \\
0 & 0 & S & 0 \\
0 & 0 & 0 & G
\end{bmatrix}
\]

and \( G = \begin{bmatrix}
\sigma_1^2 & 0 & 0 \\
0 & \sigma_2^2 & 0 \\
0 & 0 & \sigma_3^2
\end{bmatrix} \)

As described in Primiceri (2005), there are two reasons for using a block diagonal structure for \( V_T \). First, for a heavily parameterised model like we are using, block diagonal structure provides parsimony and second, it gives proper structural interpretations of innovations. Using the relation \( A_t v_t = \tau_t \), where \( VAR(\tau_t) = S_t \). For our VAR this implies:

\[
\begin{pmatrix}
1 & 0 & 0 \\
a_{21,1} & 1 & 0 \\
a_{31,1} & a_{32,1} & 1
\end{pmatrix}
\begin{pmatrix}
v_{1,t} \\
v_{2,t} \\
v_{3,t}
\end{pmatrix} =
\begin{pmatrix}
\tau_{1,t} \\
\tau_{2,t} \\
\tau_{3,t}
\end{pmatrix}
\]

(2.2.10)

or in other way this can be written:

\[
v_{1,t} = \tau_{1,t}
\]

\[
v_{2,t} = a_{21,1} v_{1,t} + \tau_{2,t}
\]

\[
v_{3,t} = a_{31,1} v_{2,t} + a_{32,1} v_{1,t} + \tau_{3,t}
\]
where $VAR(\tau_{2,t}) = h_{2t}$ and $VAR(\tau_{3,t}) = h_{3t}$

\begin{align*}
a_{21,t} &= a_{21,t-1} + \tau_{1t} \\
\begin{pmatrix}
a_{31,t} \\
a_{32,t}
\end{pmatrix} &= \begin{pmatrix}
a_{31,t-1} \\
a_{32,t-1}
\end{pmatrix} + \begin{pmatrix}
\tau_{2t} \\
\tau_{3t}
\end{pmatrix} \\
VAR(\tau_{1t}) &= S_1 \quad \text{and} \quad \begin{pmatrix}
VAR(\tau_{2t}) \\
VAR(\tau_{3t})
\end{pmatrix} = S_2
\end{align*}

This implies that the non-zero and non-unitary elements of $A_t$ which belong to different rows will evolve independently. This structural VAR seems particularly useful for analysis of economies such as India which have undergone various structural changes in the last 25 years because the magnitude of the contemporaneous interrelations among the error terms in equation 2.1.1 are flexible to change across time. This can also be corroborated by the different monetary policy regimes with multiple targets and multiple instruments which have been used in the last 25 years which is the period of the study. Another advantage of using time varying SVAR is that it allows shifts in shock volatility which are independent from the fluctuations seen in the coefficient $\theta_t$.

### 2.3 Estimation

We estimate the above equations in the previous section using Bayesian estimations. For this we have to set up priors, which we describe next. Then we simulate the posterior distribution of the hyper parameters and the states.
conditional on the data using Markov Chain Monte Carlo (MCMC) algorithm and after that we check for the convergence of the Markov Chain.

2.3.1 Priors

The first task is to set the initial values of the states $\theta_0$, $a_0$ and $h_0$ which we assume as Normal and independent from one another and also independent from the distributions of the hyper parameters. For calibrating the prior distributions for $\theta_0$, $a_0$ and $h_0$ we first estimate a fixed coefficients VAR using a training sample which in our case is around 5 years from 1991m4 to 1996m4. So we set $\theta_0$:

$$\theta_0 \sim N(\hat{\theta}_{ols}, 12\hat{V}(\hat{\theta}_{ols}))$$  \hspace{1cm} (2.3.1)$$

For the other two states $a_0$ and $h_0$ we proceed in the following manner. From the fixed coefficient VAR, let $\hat{\Sigma}_{ols}$ be the estimated covariance matrix of $\upsilon_t$ and let $C$ be the lower triangular Cholesky factor of $\hat{\Sigma}_{ols}$, where $CC' = \hat{\Sigma}_{ols}$. The priors for the diagonal elements of the VAR covariance matrix are set as:

$$lnh_0 \sim N(ln\mu_0, 10 \times I_3)$$  \hspace{1cm} (2.3.2)$$

Prior for the off-diagonal elements $A_0$ are set:

$$a_0 \sim N(\hat{a}_{ols}, V(\hat{a}_{ols}))$$  \hspace{1cm} (2.3.3)$$
where \( \hat{a}_{ols} \) are off diagonal elements of \( \hat{\Sigma}_{ols} \) with each row scaled by corresponding elements in the diagonal. The prior on \( Q \) is postulated as an Inverse Wishart distribution:

\[
Q_0 \sim \text{IW}(\bar{Q}_0, T_0) \tag{2.3.4}
\]

where \( Q_0 \) is set equal to \( Q_0 = \lambda + \hat{\Sigma}_{ols} \). The value of \( \lambda \) is set as \( 3.5 \times 10^{-4} \) (Cogley and Sargent 2005). This prior is quite important as it influences the amount of time variation allowed in the VAR model. The prior distribution of the block of \( S \) is Inverse Wishart,

\[
S_i \sim \text{IW}(\bar{S}_i, K_i), \quad i = 1, 2. \tag{2.3.5}
\]

\( S_i \) is calibrated using \( \hat{a}_{ols} \) where we have \( \bar{S}_1 = 10^{-3} \times [\hat{a}_{0,11}] \) and \( \bar{S}_2 = 10^{-3} \times \text{diag}([|\hat{a}_{0,21}|, |\hat{a}_{0,31}|]) \).

For the variances of the stochastic volatility innovations, we assume an inverse gamma distribution for the elements of \( G \) as suggested by Cogley and Sargent (2002, 2005):

\[
\sigma_i^2 \sim \text{IG}(\frac{10^{-4}}{2}, \frac{1}{2}) \tag{2.3.6}
\]
2.3.2 Posterior Simulations

Using MCMC algorithms, we simulate the posterior distributions of the hyper parameters and states condition on data.

- **Drawing $\theta_t$:** Conditional on $A^T, H^T$ and $Y^T$, we draw $\theta_t$ using Carter and Kohn (2004) algorithm. The posterior density can be factored as:

\[
p(\theta^T|Y^T, A^T, H^T, V) = \prod_{t=1}^{T-1} p(\theta_t|\theta_{t-1}, Y^T, A^T, H^T, V)
\]

(2.3.7)

Conditional on $A^T, H^T$ and $V$, first elements on the right side $p(\theta^T|Y^T, A^T, H^T, V) = N(\theta_T, P_T)$ is worked out with Kalman Filter, where $P_T$ is the precision matrix of $\theta_T$ also calculated by Kalman Filter. Rest of the elements are computed using Backward Recursion algorithm as suggested by Cogley and Sargent (2005). So with conditional normality of $\theta_t$, we have:

\[
\theta_t|\theta_{t-1} + P_{\theta|t}P_{\theta|t+1}^{-1}(\theta_{t+1} - \theta_t)
\]

(2.3.8)

\[
P_{\theta|t+1} = P_{\theta|t} - P_{\theta|t}P_{\theta|t+1}P_{\theta|t}
\]

(2.3.9)

which provides for each $t$ from $T-1$ to 1, $p(\theta_t|\theta_{t+1}, Y^T, A^T, H^T, V) = N(\theta_t|\theta_{t+1}, p_{\theta|t+1})$.

The backward recursion starts with a draw from $N(\theta_T, P_T)$, let us denote as $\bar{\theta}_T$. 

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We can get $\theta_{T-1|T}$ and $P_{T-1|T}$ conditional on $\tilde{\theta}_T$ from equations 2.3.8 and 2.3.9. This allows us to draw $\tilde{\theta}_{T-1}$ from $N(\theta_{T-1}, p_{T-1})$ and this goes on till $t = 1$.

- **Drawing elements of $a_t$:** Elements of $a_t$ are drawn, conditional on $Y^T$, $\theta^T$ and $H^T$. The elements of $a_t$ are drawn following Primiceri (2005). We can write equation (2.2.1) as $A_t\tilde{Y}_t = A_t(Y_t - X'_t\theta_t) = A_tu_t = u_t$, with $Var(u_t) = H_t$, namely:

\[ \tilde{Y}_{2t} = -a_{21,t}\tilde{Y}_{1t} + u_{2,t} \quad (2.3.10) \]

\[ \tilde{Y}_{3t} = -a_{31,t}\tilde{Y}_{1t} + u_{2,t} - a_{32,t}\tilde{Y}_{2t} + u_{3,t} \quad (2.3.11) \]

And we have the identity $\tilde{Y}_{1t} = u_{i,1}$, where $\tilde{Y}_t = [\tilde{Y}_{1,t}, \tilde{Y}_{2,t}, \tilde{Y}_{3,t}]$. Based on the observation equations (2.3.10) and (2.3.11), and the transition equation (2.3.3), the elements of $a_t$ can be drawn using the same algorithm we used for drawing $\theta_t$. The algorithm is separately applied to the observation equations (2.3.10) and (2.3.11).

- **Drawing $H_t$:** Conditional on $Y^T, \theta^T$ and $A^T$, we can observe the orthogonal innovations, $A_t(Y_t - X'_t\theta_t) = u_t$, where $VAR(u_t) = h_{i,t}$. We draw $h_{i,t}$ by applying the Independence Metropolis Hasting algorithm for each $u_t$. Conditional on draw of $h_{i,t}$ we can draw $g_i$ from the Inverse Gamma distribution.

\[ g_i \sim IG\left(\frac{(ln.h_{i,t} - ln.\tilde{h}_{i,t-1})'(ln.h_{i,t} - ln.\tilde{h}_{i,t-1}) + g_0}{2}, \frac{T + v_0}{2}\right) \quad (2.3.12) \]
• **Drawing Hyper parameters:** Conditional on $Y^T, \theta^T, A^T$ and $H^T$, the innovations to $\theta_t, a_{i,t}$ and $h_{i,t}s$ are known. This allows us to draw the hyper parameters, basically the elements of $Q, S_1, S_2$ and $\sigma_i^2$ from their respective distributions.

Now for simulating the posterior distribution of the different states and hyper parameters (conditional on the data), we use MCMC algorithm by iterating the above four steps. The posterior results are based on 200,000 draws and after burn-in of 10,000 draws.

### 2.3.3 Identification

The structural analysis in the TVP-VAR-SV model is based on the identification of three shocks. The shocks are supply shocks, demand shocks and monetary policy shocks. For identifying these shocks we use sign restrictions as suggested in the work of Uhlig (2005) and Peersman (2005). Recent studies using structural VAR have been more inclined to use sign restrictions for identifying the structural shocks of their models. Different identification strategies have been found to be suitable for different scenarios. Sign restrictions have been found to have a number of advantages as compared to structural shocks identified by zero or long run restrictions. Contemporaneous sign restrictions have this useful feature of allowing the model to be relatively agnostic from the impact of structural shocks beyond the contemporaneous effects and it has also been found to be consistent with many theoretical models (Peersman, 2005). Sign restrictions is basically undertaken to calculate the structural impact matrix, i.e., an $A_0$ matrix from each retained draw of the covariance matrix, which gets us an impulse response function produced from a particular shock with its signs being set consistent with some theory.
For undertaking this exercise, we use the algorithm of Ramirez, Waggoner, and Zha (2010) which is an efficient algorithm for finding the structural impact matrix consistent with the impulse responses of a certain sign consistent with theory. The procedure works as follows:

- First we specify the eigenvalue-eigenvector decomposition of the VAR’s covariance matrix $\Sigma$. This can be written as $\Sigma = PD\bar{P}^\prime$ and we assume $\bar{A}_0 = PD\bar{\gamma}$.

- Then we draw an $N \times N$ matrix $K$ from a $N(0, 1)$ and after this we take the QR decomposition of $K$.

- We compute $Q$ and $R$ such that $K = QR$. $Q$ is orthonormal, i.e., $QQ^\prime = I$.

- We then compute the structural impact matrix $A_0 = \bar{A}_0 \times Q^\prime$ and keep the $A_0$ matrix which satisfies the sign restrictions provided for the particular shock.

- This algorithm is repeated for each Gibbs iteration till we get around 100 structural impact matrices that satisfy the sign restrictions.

The variables included in the sign restrictions are index of industrial production, consumer prices and average weighted call money rate. The sign restrictions are based on theoretical aggregate demand and supply frameworks which are consistent with most structural models. The identification strategy follows that of Peersman (2005), which is given in Table 2.1.

The sign restrictions identification strategy assumes that a positive aggregate supply shock that has a positive impact on output is assumed to not to result in an increase in consumer prices and nominal interest rates. A positive aggregate demand shock has a positive impact on output and will not result in a decrease in consumer prices and nominal interest rates. An expansionary
Table 2.1: Sign Restrictions

<table>
<thead>
<tr>
<th></th>
<th>Industrial Output (IIP)</th>
<th>CPI Inflation</th>
<th>Call Money Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supply Shock</td>
<td>≥ 0</td>
<td>≤ 0</td>
<td>≤ 0</td>
</tr>
<tr>
<td>Demand Shock</td>
<td>≥ 0</td>
<td>≥ 0</td>
<td>≥ 0</td>
</tr>
<tr>
<td>Monetary Policy Shock</td>
<td>≤ 0</td>
<td>≤ 0</td>
<td>≥ 0</td>
</tr>
</tbody>
</table>

monetary policy shock that increases the nominal interest rates is assumed to not increase output and consumer prices.

For this study we have followed the procedure of keeping the $A_0$ matrix closest to the median of the estimated distribution of the $A^0$ for each draw from its VAR posterior.

2.4 Results

The data has been obtained from the Reserve Bank of India database and IFS (IMF). We have used the index of industrial production as a proxy for output, for inflation we have used two different measures, consumer price index (CPI) and wholesale price index (WPI) inflation. Average weighted call money rate has been used as the interest rate variable. Except for the call money rate, all the data were deseasonalised using Census X-12 technique, and transformed to annualized growth rates. For the univariate model, we have used quarterly data from 1971Q2-2014Q4, and for the TVP-VAR-SV model, we have used monthly data from 1991m4 to 2014m12.

2.4.1 Univariate and multivariate stochastic volatility

To attain a perspective on the stochastic volatility of macroeconomic variables from a broader time period, we use a univariate time-varying stochastic volatil-
ity model. Due to the unavailability of interest rate data before 1991, we could not use the TVP-SVAR-SV model for the sample before 1991.

Figure 2.1(a) shows the stochastic volatility of the industrial output (IIP) from 1973 onwards along with its long run mean. The period of highest volatility for industrial output is observed around 1988-89, a period just before the balance of payment crisis in 1991. During this period, India had very high external borrowings along with massive public expenditure spending which some consider to be the seed of the 1991 crisis (Panagariya, 2003). The second sharp spurt occurred around 2009, during the recent financial crisis. It seems that the ‘decoupling’ story of Indian economy to the financial crisis does not hold while gauging at posterior median of the industrial output during this period.

Figure 2.1(b) exhibits the stochastic volatility for WPI (Wholesale Price Index) inflation, which has been the headline inflation for India before the new monetary policy framework of inflation targeting was introduced in January 2014 with CPI as its nominal anchor. Peak volatility in WPI inflation can be seen from the initial data point 1973 to 1976, and then it slides gradually before stabilizing around 1984. In the early 1970s we had the OPEC price hikes which in turn had led to high inflation levels across the globe, which seem to have percolated quite strongly also in India. India was susceptible to high pass through of high oil prices in the 1970s and 1980s, as being a closed economy with crude oil constituting the biggest chunk of its import basket the impact was substantial. After the early 1990s reforms, after which the Indian economy opened up, it was noted that changes in global commodities for a wide range of goods influenced domestic inflation as compared to the 1970s and 1980s when oil dominated (Mohanty, 2010).
Figure 2.2(a) captures the stochastic volatility for CPI inflation. As expected the sharpest spike in volatility is observed in 1975, the peak of the OPEC oil crisis, which as discussed earlier led to high inflation across the world and in India. The Reserve Bank of India seems in a slight way vindicated for introducing CPI as the headline inflation, because comparing CPI with WPI, we find that CPI captures more events/crises and it synchronizes closely with output fluctuations. Below we also find that monetary policy shocks have similar impact on industrial output and CPI inflation. CPI shows a bump unlike WPI in 1998-91, which as discussed above for industrial output volatility, was the precursor of the balance of payment crisis in 1991. The other much sharper spike is noticed around the period of the the East Asian Crisis in 1997-98, where India seems to have been affected more as compared to the recent ‘Great Recession’ of 2008.

Figure 2.3 shows the 16th and 84th percentiles of the standard deviation of the structural shocks along with the posterior median. Stochastic volatility of the supply shocks over the whole sample is more erratic compared to the other two shocks. The highest surge in volatility for all the shocks can be observed during the East Asian Crisis period. This result contradicts many studies that had found India to be mostly insulated from the East Asian crisis during 1997 (Dua 2007). During the 2008 Global Financial Crisis (GFC), we observe that volatility of supply shocks is higher than other shocks but still lower than observed during the East Asian crisis years. Monetary policy shocks have a higher surge during 2006-07, compared to the GFC period, which could be due to the high global inflation concern observed during 2006, due to the spiraling of commodity and agricultural prices around the globe. Estimated stochastic volatility of supply shocks is more than the demand shocks.
2.4.2 Impulse response to structural shocks

Supply shocks: Figure 2.4 presents results of the time-varying impulse response functions to a supply shock together with 16th and 84th percentiles of the distribution, for whole sample from 1996m4-2014m12. 3-D surface charts of the time-varying VAR helps us to show the impulse response to a supply shock at each point in time. In our case, for a shock in the first month we get the impulse response function for the variables for the whole year and with the time varying construct for every year from 1996-2014. Time-variation can be observed over the whole sample for CPI inflation and call money rate. According to the sign restrictions, we expect a positive supply shock to reduce inflation and interest rates. In the Indian case, we find the direction of response of CPI Inflation and call money rate to be overall consistent with sign restrictions.

The sharp drop in CPI inflation due to the supply shock can be observed during 2002-03. We detect for call money rate, sharp drops during the East Asian Crisis period (1997), around 2000 and just before the GFC (2007). Gauging the response of the call money rate we note especially during 2006 and GFC years a slight downward slide is observed after 8 months which persists until the 25th month\(^1\). The high global and domestic inflation observed during 2006 must have warranted the higher interest rates. With regard to supply shock

\(^1\)We also observe a slight rise in some years for call money rates before 2006. This positive response of call money rate to supply shocks has been found in studies with time invariant VAR models (Kalirajan and Singh). One reasonable argument which we have discussed earlier for the high interest rates is the existence of tighter credit conditions and low saving rates in India (Kalirajan and Singh, 2007). Tight credit conditions may exist in India during this time period due to the overemphasis on exchange rate management. Strong capital inflows coupled with capital controls make open market operation ineffective in controlling exchange rate due to dominant effect of sterilization. So Reserve Bank of India (RBI) used sterilization to control nominal appreciation and increased the interest rates for stabilizing inflation, which in turn makes it difficult to establish which effect dominates output.
to industrial output (IIP), we do not find much time variation.

Figure 2.5 shows the persistence with regard to supply shocks. We note persistence of CPI inflation to supply shocks especially during the early 2000 and during the global financial crisis period. In the case of call money rates, we detect its persistence to supply shocks mostly during the 2006-08.

**Demand shocks:** Figure 2.6 presents time-varying impulse response functions to a demand shock with 16th and 84th percentiles of the distribution, for whole sample from 1996m4 - 2014m12. Time variation can be noted both for the industrial growth and CPI inflation. For a one percent positive demand shock, we can observe on average around 0.3 percent positive response of industrial growth (IIP). From the East Asian crisis period to 2003, we note that IIP slides to the negative 0.1 percent for some months.

We note the sharpest spike in the call money rates in response to the demand shocks during the East Asian crisis period, and the second biggest spike can be noticed during 2006-07. During the global financial crisis period from 2007 onwards we observe that the call money rates falling to the negative region slightly in the 6th month and are persistently low till the 20th month. This anomaly can be due to the crisis period asymmetry in the macroeconomy.

In figure 2.7, we can observe the persistence of the variables to the demand shocks. From 2007 onwards, during the global financial crisis period, we note industrial output(IIP) to be consistently persistent to demand shocks. Call money rates are found to be persistent from 1996 to 2003.
Monetary policy shocks: Figure 2.8 presents time varying impulse response functions to a one percent monetary policy shock with 16th and 84th percentiles of the distribution. We observe a sharp drop in industrial growth (IIP) due to a positive monetary shock in 2004 and during the global financial crisis years, 2008, 2011 and 2013. In the case of CPI inflation, we note sharp drops also during the global financial crisis years, 2011 and 2013 and also a slide can be observed during 2004-05. We notice that CPI inflation response to monetary policy shocks are somewhat consistent with the industrial output. This similar response in both the variables in terms of synchronous fluctuations in volatility was also observed with the univariate stochastic volatility model for both the variables. The only difference is in the magnitude of the slide, with the sharpest drop for industrial output occurring in 2004 whereas for CPI inflation it is noted during the global financial crisis period. In figure 2.9, we also observe the call money rate to be persistent to a monetary policy shock during 2009, at the peak of the global financial crisis.

We can denote the years from 2001-2006 as the short ‘Great Moderation’ period of India. In terms of stochastic volatility we find that the period 2001 to 2006 seems to have the lowest volatility in the whole sample. First when we examine the stochastic volatility of all the three variables in the univariate model (figure 2.1, 2.2), we note that 2001-2006 has the least volatility. Next when we observe the estimated stochastic volatility of the shocks (figure 2.3), we observe the least volatility again during 2001-2006.

Figure 2.10 provides the mean of the retained MCMC draws for checking the convergence of the time varying parameters. The means are calculated for every 20 draws for $\theta_t$, $h_{i,t}$ and $a_{ij,t}$. The recursive mean show convergence for $\theta_t$ and $a_{ij,t}$, but the parameter of stochastic volatility $h_{i,t}$ seems not to have
converged properly with inconsistent fluctuations.

2.5 Conclusion

This chapter has examined the time varying evolution of structural shocks and stochastic volatility for India in the post-reform period. We used a Bayesian time varying parameter structural VAR with stochastic volatility and identified three structural shocks namely supply shocks, demand shocks and monetary policy shocks using the identification strategy of sign restrictions. For examining the stochastic volatility of the major macroeconomic variables, we used three macroeconomic variables, Industrial output (IIP), CPI Inflation, and WPI Inflation. The main results can be summarized as follows,

Time variation is an important feature of the major macroeconomic variables in India. During the post-reform period 1991 onwards, we detect sharp reduction in estimated stochastic volatility for all shocks and variables. Interestingly, during the East Asian crisis the volatility surge is much higher than observed during the recent global financial crisis. We find that CPI inflation response to monetary policy shocks are more consistent with industrial output. This similar response in both the variables in terms of synchronous fluctuations in volatility was also observed with the univariate stochastic volatility model for both the variables. We also observe that demand shocks seem to be persistent unlike supply shocks during the period from 2007-14.

A.1 Appendix

Univariate Stochastic Model Estimation
The model can be written as:

\[ Y_t = c_t + b_t Y_{t-1} + \varepsilon_t \sqrt{exp(ln h_t)} \]  \hspace{1cm} (2.5.1)

The coefficients evolve as:

\[ B_t = B_{t-1} + e_t \hspace{0.5cm} \text{where} \hspace{0.5cm} B = \{c, b\}, \hspace{0.5cm} e_t \sim N(0, Q) \]  \hspace{1cm} (2.5.2)

Variance of the error term \( h_t \) evolves as:

\[ ln h_t = ln h_{t-1} + v_t \hspace{0.5cm} \text{where} \hspace{0.5cm} v_t \sim N(0, g) \]  \hspace{1cm} (2.5.3)

The above model is estimated by combining the Carter and Kohn Algorithm with Metropolis algorithm.

- **Step 1:** Start with a setting an Inverse Wishart prior for \( Q, Q \sim IW(Q_0, T_0) \). Prior scale matrix is constructed as \( Q_0 = k \times Q_{ols} \times T_0 \). \( k \) is the scaling factor, \( Q_{ols} \) is the variance covariance matrix of \( B \) and \( T_0 \) is the length of the training sample. We get a starting value for \( h_t \) as, then set the priors for \( \bar{\mu} \) and \( \bar{\sigma} \). Then we set \( p(g) \sim IG(g_0, v_0) \) and set starting value for \( g \) and \( Q \).

- **Step 2:** Sample initial values of \( h_t \) from log normal density conditional on \( g \) and \( B_t \),

\[ f(h_0 | h_1) = h_0^{-1} \exp \left( \frac{-(ln h_0 - \mu_0)^2}{2\sigma_0} \right) \]  \hspace{1cm} (2.5.4)
Draw a new value of \( h_t \) from the candidate density:

\[
q(\Phi^{G+1}) = h_t^{-1} \exp\left(-\frac{(\ln h_0 - \mu)^2}{2\sigma_h}\right)
\]

where \( \mu = \frac{\ln h_{t+1} + \ln h_{t-1}}{2} \), \( \sigma_h = \frac{g}{T} \). Then we compute the acceptance probability:

\[
\alpha = \min\left(\frac{h_{t,\text{new}}^{-\frac{1}{2}} \exp\left(-\frac{-\epsilon_t}{2h_{t,\text{new}}}\right)}{h_{t,\text{old}}^{-\frac{1}{2}} \exp\left(-\frac{-\epsilon_t}{2h_{t,\text{old}}}\right)}, 1\right)
\]

Draw \( u \sim U(0,1) \). If \( u < \alpha \) then set \( h_t = h_{t,\text{new}} \).

- Step 3: Given \( h_t \), compute \( \upsilon_t = \ln h_t - \ln h_{t-1} \). Then draw \( g, g \sim IG\left(\frac{\upsilon_t^2 + g_0}{2}, \frac{T + g_0}{2}\right) \) which is Metropolis plus Gibbs.

- Step 4: Conditional on \( h_t \) and \( Q \) sample \( B_t \) using the Carter and Kohn algorithm. This is then incorporated into the Kalman Filter.

- Step 5: Sample \( Q \sim IW\left(\begin{pmatrix} (B_t - B_{t-1})' (B_t - B_{t-1}) + Q_0 & T_0 + T \end{pmatrix} \right) \)

- Step 6: Repeat steps 2 to 5 \( M \) times. After burn-in the last draws of \( h_t, g, B_t \) and \( Q \) gives an approximation to the marginal posterior distribution.
Figure 2.1: Univariate Stochastic Volatility of industrial output and WPI inflation

(a) Industrial Output

(b) WPI Inflation
Figure 2.2: Univariate Stochastic Volatility of CPI inflation

(a) CPI Inflation

Stochastic Volatility CPI

Estimated posterior median
16th Percentile
84th Percentile

Long Run Mean of CPI
Figure 2.3: Posterior Median, 16th and 84th percentile of the standard deviation of the structural shocks
Figure 2.4: Time-varying median impulse response functions to a supply shock
Figure 2.5: Persistence with supply shocks
Figure 2.6: Time-varying median impulse response functions to a demand shock
Figure 2.7: Persistence with demand shocks
Figure 2.8: Time-varying median impulse response functions to a monetary policy shock
Figure 2.9: Persistence with monetary policy shocks
Figure 2.10: Convergence: Recursive Mean for VAR parameters
Chapter 3

 Implicit central bank targets: nominal GDP and the Great Moderation

3.1 Introduction

Anchoring inflation expectations has come to be widely accepted goal of monetary policy (Woodford 2003). This strong preference for stabilization of inflation expectation started during Paul Volcker’s tenure as the US Federal Reserve chairman. He has been credited for starting the ‘hawkish’ era of central banking in US, with strong monetary policy reaction towards fluctuations in inflation. The supporters of this hypothesis argue that the economic fluctuations that the US encountered in the 1960s and 1970s, was the result of lack of focus of the Federal Reserve towards inflation stabilization. One of the arguments put forward for the ‘dovish’ monetary policy of the 1970s, was that there seemed to exist a long run permanent tradeoff between the level of unemployment and inflation, which was dismissed in the 1980s due to high inflation rates observed and also further economic research convinced that such a long
run tradeoff may not really exist (Sargent 1999).

Paul Volcker during his tenure as the Federal Reserve chairman, made his priority of stabilizing inflation expectations as the major objective of the Federal Reserve and his legacy of stabilizing inflation expectations endured in successive regimes. Paul Volcker was not interested in whether inflation surged due to demand side or supply side factors. Even during the brief but rather unsuccessful experiment of introducing monetary targeting, his main objective was to influence inflation expectations (Hetzel 2004). The conventional view is that inflation expectations can be stabilized by targeting inflation.

Clarida, Gali and Gertler (2000), Stock and Watson (2002) and Bernanke (2004) have argued that post-Volcker or during the ‘Great Moderation’ period, the monetary policy preferences of the Federal Reserve were much more sensitive and tuned to changes in expected inflation and overwhelmingly found inflation to be the preferred policy target of the Federal Reserve. This is also substantiated by the proponents of inflation targeting (Bernanke (2004), Svensson (2007)) who argue that stabilizing inflation should be the single most important objective of the central bank. Monetary policy rules such as the Taylor rule (2003) embody such an hypothesis. This study counters this hypothesis, and shows that for accomplishing its objective of stabilizing inflation expectations during Great Moderation, the Federal Reserve was instead implicitly targeting nominal GDP.

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1 The ‘Great Moderation’ has been considered as a period of reduction in macroeconomic volatility in the US spanning from 1984-2007 (Stock and Watson (2002), Bernanke (2004)). Many factors have been attributed for the decline in macroeconomic volatility including inventory dynamics (McCarthy and Zakrajsek (2007)), smaller macroeconomic shocks (Stock and Watson (2002)) and stronger preference for low inflation in the monetary policy process (Clarida, Gali and Gertler (2000), Bernanke (2004)). Stabilizing inflation expectations through the monetary policy process has been argued as one of the prominent factors responsible for the Great Moderation.
Nominal GDP has not been used as an explicit target by the Federal Reserve, but gauging the minutes of the Federal Open Market Committee (FOMC) meetings during Paul Volcker’s era, it seems that nominal GNP was used as an intermediate target\(^2\). Alan Greenspan in 1992 came much closer in arguing that Federal Reserve should target NGDP growth of 4.5\(^3\)

Let me put it to you this way. If you ask whether we are confirming our view to contain the success that we’ve had to date on inflation, the answer is “yes.” I think that policy is implicit among the members of this Committee, and the specific instruments that we may be using or not using are really a quite secondary question. As I read it, there is no debate within this Committee to abandon our view that a non-inflationary environment is best for this country over the longer term. Everything else, once we’ve said that, becomes technical questions. I would say in that context that on the basis of the studies, we have seen that to drive nominal GDP, let’s assume at 4-1/2 percent, in our old philosophy we would have said that [requires] a 4-1/2 percent growth in M2. In today’s analysis, we would say it’s significantly less than that. I’m basically arguing that we are really in a sense using [unintelligible] a nominal GDP goal of which the money supply relationships are technical mechanisms to achieve that. And I don’t see any change in our view… and we will know they are convinced (about “price stability”) when we see the 30-year Treasury at 5-1/2 percent.

The above Greenspan quote can be somewhat substantiated if we look at

\(^2\)From the FOMC minutes 1982 December (20), Federal Reserve Bank of Boston President Frank Morris says, “I think we need a proxy – an independent intermediate target – for nominal GNP, or the closest thing we can come to as a proxy for nominal GNP, because that’s what the name of the game is supposed to be”.

\(^3\)Market Monetarist blog - “When US 30-year yields hit 5% the Great Recession will be over” 28th May 2013.
figures 3.1(a) and 3.1(b). Figure 3.1(a) shows the inflation gap\(^4\) with the federal funds rate, whereas in figure 3.1(b) we have the nominal GDP gap\(^5\) and the federal funds rate.

From 1989-1992, we can observe that the inflation gap increases (figure 3.1(a)). When the inflation gap increases on the positive side, we expect the central bank to try to reduce the gap by using contractionary monetary policy by raising the interest rates in an inflation targeting regime. But here we find that the Federal Reserve just did the opposite. But observing the NGDP gap during 1989-1992, the gap is approaching zero and in the negative region, and we would expect in an NGDP targeting regime for an expansionary monetary policy and the Federal Reserve is indeed using an expansionary policy. Another anomaly with regard to inflation can be found from mid-1996 to mid-1999 where we find that the inflation gap becomes negative sharply but not much movement is observed in the federal funds rate. In the case of the NGDP gap, its interaction with federal funds rate is quite synchronous till 2007.

\(^4\)For inflation we have used the GDP deflator. The inflation gap has been constructed by differencing GDP deflator from its trend, which has been constructed from a Hodrick-Prescott filter. The smoothing parameter \(\lambda = 1600\), as we have used quarterly data.

\(^5\)Nominal GDP gap has been constructed by differencing nominal GDP from its trend which has been constructed from a Hodrick-Prescott filter
Figure 3.1: Inflation Gap and NGDP Gap

(a) Inflation GAP and Federal Funds Rate

(b) NGDP Gap and Federal Funds Rate

Influential monetary policy rules such as the Taylor rule (1993) and the Henderson-McKibbin rule (1993) were formulated as an exercise to depict the behaviour of the preferences of the Federal Reserve in the US. The Taylor rule (1993) has become a standard benchmark analysis for monetary policy in US and elsewhere, with several studies corroborating that indeed the Federal
Reserve has been closely following the Taylor rule (Clarida Gali and Gertler, 2000; Gerlach and Schnabel, 2000). The original Taylor rule (1993) showed that the monetary policy process in the US can be described in terms of short term interest rates which stabilize two operational variables, inflation and the output gap, with more weightage given to inflation. The logic underlying the Taylor rule is that the Federal Reserve responds to increases in inflation by raising the interest rates more than one-for-one, which can eliminate self-fulfilling expectations and hence reduce economic fluctuations, which in turn stabilizes inflation expectations. But the Taylor rule in a series of studies has been criticized due to ‘operational’ problems for policy purposes.  

NGDP targeting has an operational advantage as there is no requirement for having an output gap measurement. Output gap has been a controversial ‘operational’ variable for the central banks as it has complications regarding modeling potential output and its measurement. Orphanides (2001) found that measurement error in output gap contributed to the excessive inflation in the 1970s. He also argued that a monetary policy based on real time output gap can deviate much more than the desired policy. Studies have shown that this uncertainty in output gap can be quite risky for the monetary policy process and thus less weight should be given to output gap (Smets, 2002; Rudebusch, 2002). There are also studies that have argued that even if output gap is measured perfectly by the central bank, strong responses to the output gap can be destabilizing by raising the probability of indeterminacy

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6 The criticism related to the operational issue of the Taylor rule was related to informational, data timing and measurement problems especially for real variable such as the output gap. If policymakers were going to use the original Taylor rule, then they would require information about unreliable indicators’ such as natural rate of interest and potential output, which studies have shown are not reliable (Laubach, 2001; Laubach and Williams, 2001; Christiano and Fitzgerald, 2001; Orphanides and Van Norden, 2002; Van Norden, 2002; Orphanides, 2003).

7 Coibion and Gorodnichenko (2011) - “We find that if the post-1982 Fed had responded as strongly to the output gap as it did before Volcker, then the likelihood of the US economy’s being in the indeterminacy region would be somewhat higher, particularly at higher rates.
and Gorodnichenko, 2011).

Table 3.6 provides coefficients for the output gap in various Taylor rule estimations. In Orphanides (2003) observing the estimation results of the Taylor rule with real time output gap data, the coefficient estimates in the period 1982-1997 is just 0.10 and in earlier periods also the coefficients are less than 0.20. Coibion and Gorodnichenko (2011) using real time data from FOMC staff meeting found somewhat bigger coefficient estimates for the output gap around 0.44 during the Post-Volcker or the Great Moderation period. But still the estimates are not that large. There seems to be less preference for the output gap given by the Federal Reserve.

Optimal nominal GDP targeting has been found to be superior to inflation targeting frameworks such as the Taylor rule (Jenson 2002). It has been found to be more efficient especially when the economy is hit by a cost push shock, supply shocks or shocks to country risk (Henderson and McKibbin, 1993; Jensen, 2002). NGDP targeting accommodates the two important components that central banks are most concerned about, inflation and output. Nominal GDP can also serve as long run anchor of monetary policy and this takes care of the concern that monetary policy cannot influence the real output in the long run (Rudebusch, 2000).

This chapter examines the monetary policy preferences of the Federal Reserve for the period 1960-2007. The main contribution of this chapter is to show that during the Great Moderation period, the US Federal Reserve was stabilizing inflation expectations, by implicitly targeting nominal GDP. This is shown by estimating different variants of nominal GDP rules, which then of inflation.”
are compared with Taylor rules using both ex-post revised data and real time briefing forecasts of FOMC. With ex-post revised data, which includes also the Volcker period along with the Great Moderation period (1979Q4 - 2006Q4), we find stronger preference to the nominal GDP variable as compared to the inflation in the Taylor rule. This stronger preference is again found in the two different sets of real time data (Greenbooks forecasts and briefing forecasts from FOMC meetings).

The plan of the chapter is as follows. In section 3.2 we derive the forward looking nominal GDP rule that will be used for estimation purposes. Section 3.3.1 provides the estimation results with ex-post revised data comparing the performances of the nominal GDP rule to the Taylor rule. In section 3.3.2 we provide our estimation results with real time data comparing the performance of nominal GDP rule to the Taylor rule. In section 3.4, identification issue in the NGDP rule. In section 3.5, we provide model comparisons and also provide some robustness analysis. And in section 3.6 we conclude.

### 3.2 Forward Looking Nominal GDP Rule

In this section we derive a forward-looking nominal GDP rule that will be used for estimation. Monetary policy rules such as the Taylor rule, were originally formulated with the federal funds rate reacting to contemporaneous data of inflation and the output gap (Taylor, 1993). There has been criticism regarding the use of contemporaneous data in formulating monetary policy rules, as it can be non-operational due to the uncertainly involving getting realized data such as real GDP even at the end of the quarter (McCallum and Nelson, 1998). This issue was rectified by Clarida, Gali and Gertler (2000) when
they proposed a forward-looking Taylor rule, in which the respective central banks respond to deviations of the expected variables from their respective targets. Thus monetary policy functions have been derived taking into consideration such that the current monetary policy reacts to future expected values of macroeconomic targets.

Below we specify a forward looking nominal GDP rule. The nominal GDP rule has been specified by first taking a baseline rule. The baseline rule constitutes of a target monetary policy rate. The target rate is a function of the deviation of future nominal GDP from period \( t \) to period \( t + k \), \( E_t Y_{t,k} \) from Federal Reserve supposed target, \( Y^* \).

The target model’s baseline equation is:

\[
r^* = r^* r^* + \beta (E | Y_{t,k} | \Omega_t) - Y^*
\]  

(3.2.1)

In the above equation (3.2.1), \( r^* \) denotes the desired interest rate when the nominal GDP is at its target level. \( Y_{t,k} \) denotes the quarter-to-quarter annualized percent change in nominal GDP between period \( t \) and \( t + k \). \( E \) is the expectation operator and \( \Omega_t \) is the information set. This sort of forward

\[\text{Nominal GDP targeting was suggested as a probable monetary policy regime in the late 1970s. The studies suggested that nominal GDP targeting would be better than other monetary policy regime in stabilizing output and employment (Meade, 1978; Tobin, 1980; Corden, 1981; and McCallum, 1985). Nominal GDP targeting can work by the following process where the objective of the Central bank is to reduce the loss function given as,}

\[L_{t+j} = (x_t - x_{t-1} + \pi_t - (\Delta x + \pi)^*)^2,\]

where \( x_t \) is the nominal GDP rate and \( \pi_t \) is the inflation rate. Here the loss function is an increasing function of the deviations of the nominal GDP growth from the target \( (\Delta x + \pi)^* \). The central bank would not raise the interest rate as long as the nominal GDP remains below a deterministic target path which would be equal to the long average growth rate of real output and target inflation rate thus keeping stabilizing inflation and also diminishing fluctuations in real cyclical aggregates (McCallum and Nelson, 1999).
looking rule has the advantage that the central bank does not require exact information about the current values of its operational variables.

Consistent with earlier studies, we assume that there is some sort of interest rate smoothing by the Federal Reserve (Clarida et al 2000). Studies have shown that policy gradualism helps in the process of convergence to rational expectations equilibrium (Clarida et al, 2000; Bullard and Mitra, 2002; Woodford, 2003). We incorporate partial adjustment of the actual federal funds rate to the target level.

\[ r_t = \rho(L)r_{t-1} + (1-\rho)r_t^* \quad (3.2.2) \]

where,

\[ \rho(L) = \rho_1 + \rho_2 L + ... + \rho_p L^p \]
\[ \rho = \sum_{i=1}^{p} \rho_i \]
\[ r_{t-i} = L^i r_t \]

Equation (3.2.2) describes the partial adjustment mechanism of the interest rate of the central bank to its target rate \( r_t^* \). Each period the central bank tries to eliminate a fraction \((1-\rho)\) of the gap between the current level and the linear combination of its past values.\(^9\) For obtaining the policy reaction function we combine the baseline equation (3.2.1) with the partial adjustment equation (3.2.2):

\(^9\) \( \rho \) denotes the degree of smoothing of interest rate changes.
\( r_t = (1 - \rho)[rr^* + \beta Y_{t,k}] + \rho(L)r_{t-1} + \varepsilon_t \)  \hspace{1cm} (3.2.3)

where, \( \varepsilon_t = -(1 - \rho)\{\beta(Y_{t,k} - E[Y_{t,k} | \Omega_t]) \}

The error term \( \varepsilon_t \) is a linear combination of the forecast errors and is thus orthogonal to any variable in the information set \( \Omega_t \). For estimation purposes let us consider a vector of variables \( Z_t \) known when policy rates are set. This implies through equation (3.2.3) that we have a set of orthogonality conditions:

\[ E(\varepsilon_t Z_t) = 0 \]  \hspace{1cm} (3.2.4)

The above condition can be used thus to estimate the parameter vectors using Generalized Method of Moments (GMM) [Hansen (1982)]. To estimate the expectations process, it can be assumed that the Federal Reserve has rational expectations which means in a sense there exists a set of moment conditions and hence Generalized Method of Moments can be used for estimation (Clarida, Gali and Gertler, 2000; Favero, 2009). Instrument variable approach has the advantage that if the orthogonality condition of the instruments and model errors are valid, then parameter estimation can be valid under quite general assumptions about the serial correlation of the variables and it is not required to be specific. In the GMM procedure an optimal weighting matrix is used that accounts for serial correlation in the error term.

For real time data, we define \( \alpha = rr^* \) and we can rewrite equation (3.2.3) as:
\[ r_t = (1 - \rho) [\alpha + \beta Y_{t,k}] + \rho(L)r_{t-1} + \varepsilon_t \] (3.2.5)

We proxy the unobserved forecasts of nominal GDP by the Greenbook forecasts which were released in \( t + n \), so we can rewrite (3.2.5) as:

\[ r_t = (1 - \rho) [\alpha + \beta Y_{t+n} | \Omega_{t+n}] + \rho(L)r_{t-1} + \upsilon_t \] (3.2.6)

And the forecast errors are defined in (3.2.7) where they are subsumed into error term \( \upsilon_t \).

\[ E\{Y_{t+n} | \Omega_{t+n}\} - E\{Y_{t+n} | \Omega_t\} = \sum_{i=1}^{n} \xi_{t+1} \] (3.2.7)

The estimates are robust and valid only if forecast errors are unbiased and serially uncorrelated. Due to less time span between real time data and the first estimates, the unbiasedness and serial correlation is much weaker than white noise forecast error with respect to ex-post revised data (Gerberding, Seitz and Worms, 2005; Kozicki and Tinsley, 2009).

\[ E\{Y_{t+n} | \Omega_t\} - E\{Y_{t+n} | \Omega_t\} = \sum_{i=1}^{n} \xi_t \] (3.2.8)
3.3 Estimation

3.3.1 Estimation results using ex-post revised data

In this section results are provided of estimation of the monetary policy reaction function defined by equation (3.2.3). The data are of quarterly frequency and taken from the website of the Federal Reserve Bank of St. Louis FRED. The interest rate that is used is the effective Federal Funds rate. The results show that there exists a significant relationship between the federal funds rate and nominal GDP.

<table>
<thead>
<tr>
<th></th>
<th>Estimation sample</th>
<th>$\beta_{y_{gdp}}$</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960Q3- 1979Q2</td>
<td>0.79</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>1979Q3 - 2006Q4</td>
<td>3.72</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.91)</td>
<td>(0.02)</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Estimation sample</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1960Q3- 1979Q2</td>
<td>0.83</td>
<td>0.48</td>
<td>0.64</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.06)</td>
<td>(0.04)</td>
<td></td>
</tr>
<tr>
<td>1979Q3 - 2006Q4</td>
<td>2.32</td>
<td>0.79</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.26)</td>
<td>(0.04)</td>
<td></td>
</tr>
</tbody>
</table>

NGDP Rule: $r_t = (1 - \sum_{i=1}^{p} \rho_i)(\alpha + \beta Y_{t,k}) + \sum_{i=1}^{p} \rho_i r_{t-i} + \epsilon_{t,i}$

Taylor Rule: $r_t = (1 - \sum_{i=1}^{p} \rho_i)(\alpha + \beta \pi_{t,k} + \gamma \pi_{t,q}) + \sum_{i=1}^{p} \rho_i r_{t-i} + \epsilon_{t,i}$
In table 3.1, the results reported are based on estimation using the Generalised Method of Moments. Instruments used for estimation are growth rate of nominal GDP, M2 growth rate, term structure spread (10 year Government Security - 3 month Treasury Bill) and growth rate of commodity price index. Quarterly data was used so the instruments consist of four lags each. Nominal GDP coefficient is $\beta_{ngdp}$ and $\rho$ is the coefficient of the interest rate smoothing term. The Taylor rule in table 3.1 is based on the estimation results from Consolo and Favero (2009). The policy reaction function that is estimated in Favero (2009) is the following:

$$r_t = (1 - \sum_{i=1}^{p} \rho_i)(\alpha + \beta \pi_{t,k} + \gamma_{t,q}) + \sum_{i=1}^{p} \rho_i r_{t-i} + \varepsilon_{t,i} \quad (3.3.1)$$

For comparability both the rules have estimation results with the same set of time periods. As in Clarida, Gali and Gertler (2000), the first period of the sample has been divided into 1960Q3-1979Q2, and the second is from 1979Q4-2006Q4 for estimation purposes. As in the literature, we call the first period as the pre-Volcker era (1960Q3-1979Q2), and the second is a combination of the Volcker era and the Great Moderation period (1979Q4-2006Q4). Both models are not rejected at any conventional significance levels and are significant in most of the cases. First gauging at the pre-Volcker era (1960Q3-1979Q2), we note that both the coefficients of the Taylor and NGDP rules are less than

---

$\pi_t$ the annualized inflation quarterly inflation rate of the GDP chain weighted price index, $x_t$ the output gap and $r_t$ the effective federal funds rate. The sets of instruments are lags of inflation rate, the output gap, the M2 growth rate, the term structure spread and growth rate of the commodity price index.

$\varepsilon_{t,i}$ This period consists the tenures of William Martin, Arthur Burns and William Miller as chairman of the Federal Reserve. Whereas the second period encompasses the tenure of Volcker and Greenspan, considered the era of stability and moderation in the macroeconomic literature.
unity. Comparing the estimates in both the models we find that coefficient of inflation in the Taylor rule (0.83) is slightly more preferred than the coefficient of nominal GDP (0.79) in the nominal GDP rule.

In the second sample period (1979Q4-2006Q4), we find that the results are completely the opposite with coefficient of nominal GDP (3.72) being more than that of inflation (2.32). With ex-post revised data, our model shows that the US Federal Reserve in the Great Moderation period seemed to have an implicit preference for nominal GDP as compared to inflation, contrary to which is reported in most of the macroeconomic literature.

So the main conclusion that comes from the estimation results of the ex-post revised data is that inflation is the more preferred variable of the US Federal Reserve during 1960-79 but from 1979 to 2006, nominal GDP seems to be the variable implicitly preferred by the US Federal Reserve.

### 3.3.2 Estimation Results using Real Time Data

Analysis with real time data, especially for historical evaluation of the monetary policy process, is considered more efficient as it has been observed that ex-post revised data does not provide the real information of what policy makers may know and sometimes this discrepancy may be large. Orphanides (2001) found that the Taylor rule provides a good description of monetary policy when ex-post revised data is used but with real time data the scenario does not seem to be that perfect. Basically, he found that the better fit of the Taylor rule was questionable when estimated using real time data.

Orphanides (2001) notes that “Interpretation of historical policy based on
revised data instead of the data available to policy makers when policy decisions were made appears to be of questionable value. Estimated policy reaction functions obtained using the ex post revised data yield misleading descriptions of historical policy. The presence of noise results in biased estimates and potentially obscures the appropriate specification of the policy reaction function. Needless to say, identification of monetary policy shocks under such circumstances becomes a haphazard enterprise.” In another study, Rudebusch (1998) using real time data found the optimal coefficients in the Taylor rule that he estimated were much bigger than the original one estimated by John Taylor.

Real time data for the study has been obtained from the Federal Reserve of Philadelphia from its Greenbook forecasts\(^{12}\). Romer and Romer (1996) observed that Greenbook forecasts were better forecasts than any other private forecasts\(^{13}\).

Greenbook forecasts have this good feature that rational expectations does not require to be imposed on the central bank to estimate the policy reaction function. Greenbook forecasts has been used as a proxy for the Fed’s expectations (Orphanides 2002; 2003). The monetary policy reaction function can be estimated using Least Squares as long as the orthogonality condition is satisfied, which basically means that current forecasts are uncorrelated with monetary policy shocks. This basically means that in a given period, the

\(^{12}\)It might be argued that as these forecasts are prepared by the staff at the Federal Reserve so it might be argued that it may not provide a truly objective view and might have forecasts endogenous to policy assumptions. But as Kozicki and Tinsley (2009) have argued, that for short term projections such endogeniety may not matter.

\(^{13}\)They noted that, “information the Federal Reserve has about the economy that is not known to market participants is likely to be reflected in the Federal Reserve’s internal forecasts. Because the Federal Reserve makes its forecasts public only after five years, the forecasts can contain information that is not known contemporaneously to market participants...We also find that the Federal Reserve possesses equally important private information about the path of future output. Thus our results provide powerful evidence that the Federal Reserve has important information about the path of the economy beyond that available to market participants.”
changes in the policy settings prescribed by the rule has no relation to the forecasts. This case can be argued for Greenbook forecasts as the actual decision taken during the FOMC meeting is independent of the forecasts that is prepared by the staff before the meeting (Boivin 2006).

For estimation purposes we have utilized two different types of real time data sets. Firstly, we have taken the quarterly data directly provided in the Federal Reserve of Philadelphia and then we have extracted Greenbook forecasts from individual FOMC meetings which range from 6-12 data points in a year, as shown in Orphanides (2003; 2004) and Coibion and Gorodnichenko (2011). We utilize the data from 1969 to 2006 and divide into different samples based on estimation of various monetary policy rules.

Table 3.2 provides the estimation results comparing the contemporaneous nominal GDP rule and the Taylor rule. In the contemporaneous rule, we use the Greenbook forecast values for the current quarter. We also provide point estimates, standard errors, which are in parenthesis and selected statistics provide information regarding the fit of the models.
Table 3.2: Real time data from FOMC staff meetings

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.38</td>
<td>2.01</td>
<td>1.96</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(0.707)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.98</td>
<td>0.94</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.019)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.94</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>s.e.e.</td>
<td>0.50</td>
<td>0.33</td>
<td>0.341</td>
</tr>
<tr>
<td>AIC</td>
<td>1.49</td>
<td>0.67</td>
<td>0.70</td>
</tr>
<tr>
<td>BIC</td>
<td>1.56</td>
<td>0.72</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Heteroskedastic Robust Standard Errors & Covariance with (lag truncation=4)

Based on quarterly data of the Greenbook forecasts from the Federal Reserve of Philadelphia.

For estimation with real time data, we are considering just the Great Moderation period which is relevant for the central analysis. Considering the Great Moderation period from 1983-2006, we find that the coefficient of inflation (1.96) which is the main target variable in the Taylor rule is less than the main target variable (i.e., nominal GDP (2.01)) in the NGDP rule. It might be argued that the difference is not that much and especially the $R^2$ are the same. But if we observe the Information Criterions for comparing which model has the better fit, we find that the NGDP rule has the better fit with lesser AIC and BIC than does the Taylor rule. Thus from real time data estimation also, we find that federal funds rate responds more to nominal GDP than inflation, or in other words, nominal GDP was more implicitly preferred variable by the Federal Reserve during the Great Moderation.
3.4 Identification issue in the nominal GDP rule

As nominal GDP growth is a summation of real GDP growth and producer\price inflation, there may be an identification issue that needs to be resolved. It can be argued that one variable, say inflation, has been driving the growth and the composite NGDP rule may be providing a misleading picture to policymakers. One way of resolving this issue is to put inflation, nominal GDP and the output gap in a single rule and check whether the coefficients are significant and have reasonable values.

For resolving this issue we estimate two monetary policy rules. Rule 1 that we take is a Generalized Taylor rule (Coibion and Gorodnichenko, 2011) which has CPI inflation, real GDP growth and output gap as the main variables. The second rule is a modified generalized Taylor rule also with nominal GDP.

- **Rule 1**: Generalized Taylor rule with real GDP:

  \[ r_t = c + (1 - \rho_1 - \rho_2)(\phi_\pi E_t \pi_{t+j} + \phi_y E_t Y_{t+j} + \phi_x E_t x_{t+j}) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \varepsilon_t \]  
  \quad (3.4.1)

- **Rule 2**: Generalised Taylor rule with nominal GDP:

  \[ r_t = (1 - \rho_1)(\phi_\pi E_t \pi_{t+j} + \phi_y E_t NY_{t+j} + \phi_x E_t x_{t+j}) + \rho_1 r_{t-1} + \varepsilon_t \]  
  \quad (3.4.2)

---

14In Rule 1, \( r_t \) is the target federal funds rate set, \( \pi_t \) is the rate of change of the output deflator and \( x_t \) is the output gap based on Greenbook forecasts as found in Orphanides (2003 ; 2004). Rule 1 is estimated for a period from 1983-2002.

15In Rule 2, \( NY_t \) is the nominal GDP, where the data for nominal GDP has been taken from Greenbook forecasts from the FOMC meetings which have somewhat varied frequencies but post 1982 there were six FOMC meetings so we get six data points in a year. \( x_t \) is the output gap which are also based on Orphanides (2003; 2004). Rule 2 is estimated for a period from 1983-2006.
Both rules have been found to be significant and as shown in table 3.3, the standard errors are also reasonable. In both the monetary policy rules we find that the coefficients of the real variables, nominal GDP and real GDP have values larger than the coefficient for inflation. Observing at Rule 1, we note that real GDP has a larger coefficient than inflation, whereas output gap seems to be the least preferred. Observing Rule 2, we find that nominal GDP has bigger magnitude of its coefficient and can be inferred to be more preferred variable than inflation, whereas output gap is the least preferred variable.

<table>
<thead>
<tr>
<th>Table 3.3: Identification Issue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule 1</td>
</tr>
<tr>
<td>( \phi_\pi )</td>
</tr>
<tr>
<td>1.58</td>
</tr>
<tr>
<td>(0.51)</td>
</tr>
<tr>
<td>( \phi_y )</td>
</tr>
<tr>
<td>2.21</td>
</tr>
<tr>
<td>(0.82)</td>
</tr>
<tr>
<td>( \phi_x )</td>
</tr>
<tr>
<td>0.44</td>
</tr>
<tr>
<td>(0.16)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3.4: NGDP rule with output gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983-2007</td>
</tr>
<tr>
<td>( \sigma )</td>
</tr>
<tr>
<td>0.94</td>
</tr>
<tr>
<td>(0.01)</td>
</tr>
<tr>
<td>( \beta )</td>
</tr>
<tr>
<td>2.55</td>
</tr>
<tr>
<td>(0.60)</td>
</tr>
<tr>
<td>( \lambda )</td>
</tr>
<tr>
<td>0.69</td>
</tr>
<tr>
<td>(0.19)</td>
</tr>
<tr>
<td>( R^2 )</td>
</tr>
<tr>
<td>0.98</td>
</tr>
</tbody>
</table>
In both the rules, the coefficient of inflation is less than the coefficient for the main real (output) variables showing the preference for output than inflation in the post-Volcker era or during the Great Moderation period. The output gap is the least preferred in both the monetary rules in confirmation with the standard results in the literature.

We also estimate a nominal GDP rule with an output gap (table 3.4), \( r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E\text{NY}_{t+k} + \phi E\text{x}_{t+j} + \varepsilon_t) \). We find that the magnitude of the output gap is just 0.69 compared to nominal GDP which is 2.55.

### 3.5 Model Comparison and Robustness Analysis

We can compare two different rules or models by the fit of both the models. Figures 3.2 (a) and 3.2 (b) provides the actual Federal Funds rate (FFR) fitted with predictions of the nominal GDP rule, and figure 3.3 shows actual FFR fitted with predictions of the Taylor rule.
Observing the figures we can note that during the Great Moderation period,
the fit with predicted nominal GDP rule matches the actual FFR better than
the Taylor rule.

Table 4 provides the model comparison for both the rules with the rules
estimated for different time horizons \((t = 0, 1, 2)\).\(^{16}\) The estimation is again
based on real time data from the Greenbook forecasts of the Federal Reserve
of Philadelphia. As can be seen in table 3.4, for model comparison and for
comparing the fit of the models we have provided the respective \(R^2\), Akaike
Information Criterion (AIC) and Bayesian Information criterion (BIC). Both
the rules have been estimated for the period from 1983-2006. As we know
the lesser the value of the information criterion the better is the fit. Table 4
shows that AIC and BIC values for the nominal GDP rule is much smaller
than the corresponding values for the Taylor rule, showing clearly that the
nominal GDP rule has a better fit than the Taylor rule.

Table 3.5 shows the relevant nominal GDP rule \((t - 1, t, t + 1,t + 2)\) which
can be used for policy purposes. We can note from the table that a forward
looking nominal GDP rule with horizon \(t + 1\) has the largest coefficient which
has been used for estimations. Thus the forward looking NGDP rule of the
form \(r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t Y_{t+1})\) is the most relevant rule.

3.6 Conclusion

Stabilization of inflation expectations by implicitly or explicitly targeting in-
flation has been argued as one of the major factors that contributed for the
Great Moderation in the US. This study counters this view, and shows that
for accomplishing its objective of stabilizing inflation expectations, the Federal

\(^{16}\)Following rules have been estimated. For Nominal GDP rule: \(r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t Y_{t+k}\) and for Taylor rule \(r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t \pi_{t+k} + \phi E_t x_{t+j})\)
Reserve was instead implicitly targeting nominal GDP. This claim has been corroborated by estimating different variants of nominal GDP rules and compared with Taylor rules using both ex-post revised data and real time briefing forecasts of FOMC.

With ex-post revised data, which includes also the Volcker period along with the Great Moderation period (1979Q4-2006Q4) we find a stronger preference for nominal GDP variable as compared to the inflation in the Taylor rule. This stronger preference is again found in the two different sets of real time data (Greenbooks forecasts and briefing forecasts from FOMC meetings). We have also illustrated that during the Great Moderation period, the fit with predicted nominal GDP rule matches the actual federal funds rate better than does the Taylor rule. The overall results counter the conventional view, and observe that post Volcker era or during the period of Great Moderation (1984-2007), the Federal Reserve had a stronger implicit preference for nominal GDP as compared to inflation.
### Table 3.5: Model Comparison

Nominal GDP Rule: \( r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t Y_{t+k}) \)

1983-2006 (Great Moderation Period)

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>t + 1</th>
<th>t + 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>0.986</td>
<td>0.983</td>
<td>0.981</td>
</tr>
<tr>
<td>( AIC )</td>
<td>0.341</td>
<td>0.520</td>
<td>0.656</td>
</tr>
<tr>
<td>( BIC )</td>
<td>0.391</td>
<td>0.570</td>
<td>0.705</td>
</tr>
</tbody>
</table>

Taylor Rule: \( r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t \pi_{t+k} + \phi E_t x_{t+j}) \)

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>t + 1</th>
<th>t + 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>0.981</td>
<td>0.970</td>
<td>0.982</td>
</tr>
<tr>
<td>( AIC )</td>
<td>0.702</td>
<td>0.682</td>
<td>0.662</td>
</tr>
<tr>
<td>( BIC )</td>
<td>0.753</td>
<td>0.733</td>
<td>0.713</td>
</tr>
</tbody>
</table>

### Table 3.6: Relevant NGDP Policy Rule

\( r_t = \rho r_{t-1} + (1 - \rho)(\alpha + \beta E_t Y_{t+k}) \)

1983-2007

<table>
<thead>
<tr>
<th></th>
<th>t - 1</th>
<th>t</th>
<th>t + 1</th>
<th>t + 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta )</td>
<td>1.62</td>
<td>1.92</td>
<td>2.21</td>
<td>1.94</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.50)</td>
<td>(0.82)</td>
<td>(1.50)</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.96</td>
<td>0.94</td>
<td>0.95</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.98</td>
<td>0.98</td>
<td>.98</td>
<td>0.98</td>
</tr>
<tr>
<td>( BIC )</td>
<td>0.61</td>
<td>0.39</td>
<td>0.57</td>
<td>0.70</td>
</tr>
</tbody>
</table>
Table 3.7: Irrelevance of Output Gap

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1969:1997</td>
<td>0.14 (0.03)</td>
</tr>
<tr>
<td>1969:1979</td>
<td>0.19 (0.04)</td>
</tr>
<tr>
<td>1982:1997</td>
<td>0.10 (0.03)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre -Volcker (1960-79)</td>
<td>0.27 (0.08)</td>
</tr>
<tr>
<td>Volcker-Greenspan (1979-96)</td>
<td>0.93 (0.42)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coibion and Gorodnichenko (2011)</th>
<th>Coefficient of Output gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-1979</td>
<td>0.48 (0.12)</td>
</tr>
<tr>
<td>Post 1982</td>
<td>0.44 (0.16)</td>
</tr>
</tbody>
</table>


Chapter 4

Does nominal GDP pass the forecastability test for being a future monetary policy framework?

4.1 Introduction

The recent financial crisis has cast doubts on inflation targeting as an optimal monetary policy framework. Some have even argued for the death of inflation targeting during the recent financial crisis (Frankel 2012). Inflation targeting as a monetary policy framework seems to work better in an economy dominated with demand side shocks, but with supply side shocks it seems to have problems. This can be a severe constraint during any crisis period which has large supply shocks. Nominal GDP targeting has been suggested to rectify this problem as it has been argued to perform better with supply shocks (Woodford 2012).
Forecast targeting became an important part of the central banking decision making process especially after inflation targeting became a predominant monetary policy regime in many countries (Svensson, 1999). Woodford, 2007) stresses this point succinctly, “In my view, the most important recent development with regard to the practical use of policy rules has been the development, at several central banks since the early 1990s, of methods of forecast targeting, both as a systematic approach to monetary policy deliberations and as a basis for communication with the public”.

Inflation targeting is one of the most influential and widespread monetary policy frameworks that has come to dominate central banking. In this framework, there is an announced numerical target with major emphasis on monetary policy making for inflation forecasts with high degrees of transparency and accountability. The explicit monetary policy objective of the central banks in inflation targeting is in the form of a unique numerical target that can be in the form of levels or a range for annual inflation. Some central banks have set up a certain horizon during which the inflation target shall meet. However, having a fixed horizon has its own problems. Some studies have shown that having a fixed horizon is not appropriate for most circumstances. Therefore, for resolving such ambiguities an explicit intertemporal loss function as the operational objective of the central bank has been specified (Svensson 1999).

The quadratic intertemporal loss function is of the following form:

\[
L_t = (1 - \delta)E_t \sum_{\tau=0}^{\infty} \delta^\tau [(\pi_{t+\tau} - \pi^*)^2 + \lambda y_{t+\tau}^2] \tag{4.1.1}
\]
where \( \delta(0 < \delta < 1) \) is the discount factor, \( \pi_t \) is the inflation rate whereas \( \pi^* \) is the inflation target, \( y_t \) is the output gap and \( \lambda \) is the relative weight to stabilize the output gap. When \( \lambda = 0 \), then we have strict inflation targeting, whereas when we have \( \lambda > 0 \), the output gap enters the loss function and we have flexible inflation targeting. When the discount factor reaches one, then the intertemporal loss function becomes the weighted sum of the unconditional variances of inflation and output gap:

\[
\lim_{\delta \to 1} L_t = Var[\pi_t] + \lambda Var[y_t]
\]

This happens when \( E[\pi_t] = \pi^* \) and \( E[y_t] = 0 \).

Price stability has been the primary concern of the central banks but nowadays there has been explicit concern not only about inflation but also about the stability of the real economy. Hence the target variables have been expanded to include both inflation and output gap. The inclusion of the stability of real economy has been called “flexible inflation targeting”\(^1\). However, it has been observed that central banks have not been that transparent about the relative weights attached to the stability of variables apart from inflation.

The second major concern is related to forecasting inflation for a medium horizon. Since inflation is partially predetermined in the short run due to sticky prices and wage contracts, monetary policy can only influence expected future inflation. So the mainly de facto intermediate target of the policy is forecasting inflation which has also been called in the literature “inflation

\(^1\)Strict inflation targeting happens when the central bank is exclusively concerned about inflation, which is a rarity. The monetary framework can also be classified into three different regimes: (i) full-fledged inflation targeting, (ii) implicit price stability anchor, and (iii) inflation targeting lite. The regimes are differentiated by the clarity and credibility of the commitment to the inflation target.(Carare and Stone 2006).
forecast targeting” (Svensson 1999). For carrying this out the central bank sets the instrument rate such that forecasts of target variables seem consistent.

In comparison to non-inflation targeting countries, studies have found that economies have benefited by inflation targeting, especially emerging economies where the inflation levels, persistence, and volatility have reduced (Roger and Stone, 2005). In a comprehensive study (Goncalves and Salles, 2008) of 36 emerging economies in which 13 were inflation targeters from 1980 to 2005, it was found that there was greater fall in inflation and a greater reduction in growth volatility experienced by emerging market inflation targeting countries. The study also found that adoption of inflation targeting by emerging economies did contribute towards the attainment of superior outcomes in terms of economic performance.

Another monetary policy framework which was suggested as a probable monetary policy regime in the late 1970s was Nominal GDP targeting. Nominal GDP targeting was suggested to be better than other monetary policy regimes in stabilizing output and employment (Meade (1978), Tobin (1980), Corden (1981) and McCallum (1985)). Nominal GDP targeting can be described by the following process where the objective of the central bank is to reduce the loss function given as:

\[
L_{t+j} = (x_t - x_{t-1} + \pi_t - (\Delta x + \pi^*)^2,
\]

where \(x_t\) is the nominal GDP rate and \(\pi_t\) is the inflation rate. Here the loss function is an increasing function of the deviations of the nominal GDP growth from the target \((\Delta x + \pi^*)\). The central bank would not raise the interest rate
as long as the nominal GDP remains below a deterministic target path which would be equal to the long average growth rate of real output and target inflation rate thus keeping stabilizing inflation and also diminishing fluctuations in real cyclical aggregates (McCallum and Nelson 1999). Woodford (2012) argues that nominal GDP targeting would have performed better than inflation targeting during the recent financial crisis comparing US nominal GDP growth with a log-linear trend line. Woodford argued that if inflation or real GDP increased, then according to the Taylor rule the Federal Reserve would have raised the interest rate. Whereas, if the Federal Reserve follows a nominal GDP target, then it would not raise the rates until inflation and real growth reached back to the trend line.

Another desirable property of nominal GDP targeting is that the objective of the central bank can be expressed entirely in nominal terms (i.e., monetary terms). It may be better than inflation targeting as the movements in nominal spending growth may be more closely and reliably related to central bank policy actions (open market sales and purchases) and also it would not have to rely on concepts such as the Phillip curve which have weak consensus in the profession (McCallum 2011).

Compared to the inflation targeting framework it may have less fluctuations as it can respond to very high and very low growth rates of output (McCallum and Nelson, 1999). McCallum (1999) has also argued that using growth rate of nominal GDP also avoids estimating the potential or the natural rate of output, which has got mismeasurement problems involved. It has also been argued that nominal GDP targeting dominates not only monetary targets due to velocity shocks but also an exchange rate target when exchange rate shocks are large and also dominates a price level target when the supply shocks are large (Frankel 2012). Henderson and McKibbin (1993), comparing
monetary targeting, inflation targeting and nominal income targeting for open economies with different degrees of instrument adjustment and wage persistence also found theoretically and empirically that nominal GDP targeting dominates pure inflation targeting in the case of supply shocks or shocks to country risks. Frisch and Staudinger (2002) also find that if the parameters at the unemployment rate in the central bank’s loss function exceeds a certain level, then regardless of whether a supply or a demand shock occurs, nominal GDP targeting is better than inflation targeting.

The debate regarding the efficacy of ‘instrument rules’ and ‘target rules’ has been a much debated issue in monetary policy literature (Svensson, (2003,2004); McCallum and Nelson, 2005). An instrument rule is a sort of a formula that portrays a relation of the monetary instrument as a function of current observed variables (McCallum and Nelson 2005). Famous examples include the Taylor rule (1993), Henderson - McKibbin rule (1993) and the McCallum rule (1988) etc.

Forecast targeting became an important component of central banks from the 1990s onwards as a systematic approach to monetary policy deliberations and as a good communication medium with the public. Inflation targeting is a classic example of forecast targeting with the term coined as a substitute by Svensson(1997) for inflation targeting. Forecast targeting involves a commitment by the central bank to adhere to a certain policy objective and adjust the main monetary policy instrument in such a way that target criterion is satisfied. This helps in making monetary policy decisions much more effective. But this effective dissemination procedure has to be backed by good forecasts. If the forecasts are way off mark, then it tarnishes the credibility of the central bank. In this chapter, following the standard tenets of ‘targeting’ based mon-
etary policy framework, we undertake an exercise of comparing the inflation targeting and nominal GDP targeting regime, on the basis of their forecast performance for the US, using a series of models from simple autoregressive models to standard state space models.

The plan of the chapter is as follows. In section 4.2 we provide details of the data. Section 4.3 describes the methodology for evaluating the forecasting models. Section 4.4 provides the details about the forecasting models. Section 4.5 presents the results. Section 4.6 we present some robustness check. Section 4.7 concludes.

4.2 Data

The data constitutes of quarterly time series of the US economy. The data has been taken from St. Louis Federal Reserve database (Fred). The series has been divided into three different samples. The first is the full sample which consists of the period from 1970Q2:2014Q2, and the other two samples are from 1970Q2:1983Q4 (the great inflation era) and 1984Q2 to 2007Q4 (the great moderation era). The variables that have been used in the different forecasting exercises include nominal GDP, real GDP, implicit GDP deflator, consumer price index (CPI), PCE (Personal consumption expenditure) and federal funds rate (FFR).

The data were transformed by first taking the log difference and then taking the growth rates, except for the federal funds rate which was not transformed and kept at levels. The transformation was done in the following manner, 

\[ y_t = 400 \ln \left( \frac{y_t}{y_{t-1}} \right)^2. \]

\(^2\)400 has been used due to quarterly series.
All the variables that are used for forecasting are stationary. Two standard unit root tests, ADF (Augmented Dickey Fuller) test and PP (Phillips-Perron) test were conducted for the variables used for forecasting. The results are provided in the Appendix A.1. All the variables except the federal funds rate were tested all the variables were found to be I(1) so were transformed to make them I(0).

4.3 Methodology Used for Evaluating Forecasts

4.3.1 Pseudo out-of-sample forecasts

The chapter uses pseudo out-of-sampling measures of predictive content to undertake the forecasting exercise. For undertaking the pseudo out-of-sample forecasts, we use a part of the dataset starting from date T=1 to T0. We estimate the parameters of the model using data to T0 and make the forecast of the data \( Y_{T_0+h/T_0} \), conditional upon the data till T0. This forecast data is then compared with the actual data. This exercise is then taken one step ahead and repeated recursively, and hence in a sense we produce a series of pseudo out of sample forecasts. Henceforth we quantify and summarize the forecast errors of this pseudo out of sample forecasting procedure, and then can find the model that shows the least forecast error. Most studies computing pseudo out-of-sample forecasting exercise use mean squared forecast errors (MSFE), which are scale-dependent errors but as we are comparing between the two different variables, we would require a scale independent error measure so we use mean absolute percentage error (MAPE). The MAPE is estimated as:

\[
MAPE = \frac{1}{T - h - T_0 + 1} \sum_{t=T_0}^{T-h} |y_{t+h} - \hat{y}_{t+h|t}|/|y_{t+h}| \tag{4.3.1}
\]
where $T$ is the last observed value and $T_0$ is the starting observed value for which pseudo out of sample forecasts are undertaken. $y_{t+h}$ is the starting value observed at the time $t+h$, whereas $\hat{y}_{t+h|t}$ is the $h$ step ahead forecast given the information upto time $t$. In this chapter, we have used two different $T_0$ values for the three samples. For the full sample from 1970Q2-2014Q2 we have used $T_0 = 40$, whereas for the other two samples we have used $T_0 = 18$, as total number of observations are much less in these samples.

**4.3.2 Direct Forecasts**

In this chapter, most of the forecasts are estimated with direct multi-step ahead forecasts. Direct forecasts for univariate variables $y_{t+h}$ can be written as:

$$\hat{y}_{t+h}^{D,h} = \beta + \sum_{i=1}^{p} \hat{\rho}_i y_{t+i-1}$$

(4.3.2)

where we can construct direct forecasts by using $\mathbf{E}(\hat{y}_{t+h}^{D,h} | I_t, \theta)$. In the case when the model is misspecified, the direct multi-step approach has been found to provide more accurate forecasts than the iterated multi-step approach (Marcellino, Stock and Watson 2006). Point forecast using the iterated multi-step approach has been found to be a more complicated function of the parameter estimates than using the direct multi-step approach.
4.4 Forecasting Methods

For the forecasting exercise, several models were constructed. The forecasts were undertaken at different forecast horizons such as one, two and four quarters for the quarterly data. The forecasting model follows this general form:

\[ y_{t+h} = \mu + \alpha(L)y_t + \beta(L)'Z_t + \varepsilon_{t+h} \]  

(4.4.1)

where \( \alpha(L) \) is scalar lag polynomial, \( \mu \) is a constant, \( \beta(L) \) denotes lag polynomial and \( Z_t \) is a vector of predictor variables.

There are some advantages of using h-step ahead projections. If we require to simultaneously forecast \( Z_t \), with h-step ahead forecasts we are not required to estimate additional equations. It can reduce the impact of specification error in one step ahead models by using the same horizon for estimation as well as for forecasting.

4.4.1 Autoregressive (AR) models

AR models are one of the simple but standard forecasting models in macroeconomics time series forecasting. AR models can generally be written as:

\[ (1 - \phi_p L)y_t = u_t, \text{ where } u_t \sim N(0, \sigma^2) \]  

(4.4.2)

Estimation of AR models is reasonably simple as they can be written in the form of the linear regression model. The AR forecasts can be recursively calculated in the following form:
\[ \hat{\Delta}y_{t+h|T} - \hat{\mu} = \hat{\alpha}_1(\hat{\Delta}y_{T+h-1|T} - \hat{\mu}) + \ldots + \hat{\alpha}_p(\hat{\Delta}y_{T+p|T} - \hat{\mu}) \] (4.4.3)

### 4.4.2 Integrated Moving Average (IMA) models

Unlike AR(q) models which simply require estimating past observations, MA(q) models require estimation of unobserved error terms. Typically estimating MA(q) models requires the Kalman filter, which for evaluating the likelihood requires a system of recursive equations. Here we follow a different approach to evaluate the likelihood (Kroese and Chan 2014).

We know that under MA(q) models, \( Y_1, \ldots, Y_T \) are linear combinations of \( T \) normal random variables \( \varepsilon_1, \ldots, \varepsilon_T \) and thus \( Y = (Y_1, \ldots, Y_T) \) has multivariate normal distribution. This process would require manipulating large matrices for estimation which can be time consuming. One way to resolve this issue is to utilize the information that MA(q) can be written as sparse matrices which in turn makes the computation easier.

For evaluating the MA(2) model, we can write the model in matrix form:

\[ y = \mu + H_\psi \] (4.4.4)

where \( \mu = (\mu_1, \ldots, \mu_T)' \), \( u = (u_1, \ldots, u_T)' \) \( \sim N(0, \sigma^2) \). \( H_\psi \) is a banded \( T \times T \) matrix that contains only 3(T-1) non zero elements. For MA(2) we have:
\[
H_\psi = \begin{pmatrix}
1 & 0 & 0 & 0 & 0 & \ldots & 0 \\
\psi_1 & 1 & 0 & 0 & 0 & \ldots & 0 \\
\psi_2 & \psi_1 & 1 & 0 & 0 & \ldots & 0 \\
0 & \psi_2 & \psi_1 & 1 & 0 & \ldots & 0 \\
0 & 0 & \psi_2 & \psi_1 & 1 & 0 & \ldots \\
. & 0 & 0 & \psi_2 & \ldots & \ldots & \ldots \\
. & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
. & \ldots & \ldots & 0 & \ldots & 0 \\
0 & . & . & . & 0 & \psi_2 & \psi_1 & 1
\end{pmatrix}
\] (4.4.5)

Hence after few changes we have \((y|\psi, \sigma^2) \sim N(0, \sigma^2 H_\psi H_\psi')\). Hence the loglikelihood can be written:

\[
l(\theta|\sigma^2, y) = -\frac{T}{2} \log(2\pi \sigma^2) - \frac{1}{2} \log|H_\psi H_\psi'| - \frac{1}{2\sigma^2} y' (H_\psi H_\psi')^{-1} y
\] (4.4.6)

For evaluating the \(l(\theta|\sigma^2, y)\) it is not necessary to compute the inverse \((H_\psi H_\psi')^{-1}\) which can be time consuming. Instead we can obtain the product \((H_\psi H_\psi')^{-1} y\) which can be computed by solving the system \(H H_\psi' z = y\) for \(z\). Integrated moving average models provide a slight variation of MA models with the dependent variable written in its first difference.

### 4.4.3 Unobserved component (UC) model

Unobserved component models are type of state space models which have this feature of decomposing a time series into trend, seasonal, cyclical and irregular components and where each process stochastically evolves through
time. In the basic form, the unobserved component model constitutes two components, the observed variable $y_t$ which is modeled on the state $\tau_t$, also called the measurement equation as shown in (4.4.7) below:

$$y_t = \tau_t + \varepsilon_t, \varepsilon_t \sim iid N(0, \sigma^2)$$

(4.4.7)

$$\tau_t = \tau_{t-1} + u_t, u_t \sim iid N(0, \omega^2)$$

(4.4.8)

whereas equation (4.4.8) is the transition equation. One of the issues with unobserved component models is that there can be overfitting of data\(^3\). To resolve such an issue and also to show the evolution of the unobserved variable over time transition equation can be useful. For understanding the dynamic properties of a time series this sort of a decomposition is quite useful and provides good information also of how the components have evolved over time. In forecasting we are concerned with a single variable but understanding the dynamic properties and knowing the time series decomposition can be useful in forecasting. For modeling the evolution of univariate time series such as inflation and nominal GDP, the component $\tau_t$ can be interpreted as the stochastic trend or underlying inflation or nominal GDP.

4.4.3.1 Estimation

For estimation we would be fixing the values of $\omega^2$ and try to obtain the value of $\sigma^2$ using the Expectation Maximizing algorithm (EM) (Kroese and Chan, \footnote{If we just use measurement equation, then maximum likelihood estimator for the state variable $\tau_t$ and parameters $\sigma^2$ may not be defined. This situation can arise due to the sum of state variables and parameters being greater than the observables. Thus we can have a unbounded likelihood function and hence perfectly fitting of data. Having a transition equation is one of the ways to resolve such an issue.}}
We would be maximizing the likelihood function in the following way:

\[ L(\sigma^2; y) = \int f(y|\tau, \sigma^2)f(\tau|\omega^2)d\tau \]  \hspace{1cm} (4.4.9)

To estimate with EM algorithm we can write (4.4.7) and (4.4.8) in matrix form and derive expressions for \( \ln f(y|\tau, \sigma^2) \) and \( f(\tau|\omega^2) \)

\[ y = \tau + \epsilon, \text{where} \ \epsilon \sim N(0, \sigma^2 I) \]  \hspace{1cm} (4.4.10)

where \( \epsilon = (\epsilon_1, ..., \epsilon_T) \), \( I \) is \( T \times T \) identity matrix. Now we can have a expression for \( f(y|\tau, \sigma^2) \) using (4.4.10):

\[ f(y|\tau, \sigma^2) = -\frac{T}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}(y - \tau)'(y - \tau) \]  \hspace{1cm} (4.4.11)

For deriving an expression for \( f(\tau|\omega^2) \), we can write the transition equation as, \( H\tau = u \), where \( u \sim N(0, \Omega) \) and \( \Omega = \text{diag}(\omega_0^2, \omega^2, ..., \omega^2) \)is a diagonal matrix. Here we have \( |\text{det}(H)| = 1 \) and hence H is invertible, so we get:

\[ \tau = H^{-1}u \sim N(0, (H'\Omega^{-1}H)^{-1}) \]  \hspace{1cm} (4.4.12)

where \( \Omega^{-1} \)is a diagonal matrix. Thus (4.4.11) can be rewritten as:

\[ f(y|\tau, \sigma^2) = -\frac{T}{2} \ln(2\pi) - \frac{T}{2} \ln\omega^2 - \frac{1}{2} \tau'(H'\Omega^{-1}H)\tau \]  \hspace{1cm} (4.4.13)
Now we implement the expectation process of the EM algorithm, for which we have to derive the conditional density of the states given y,

$$g_i(\tau) = f(\tau|y, \sigma_{i-1}^2, \omega^2) \quad (4.4.14)$$

where $$\sigma_{i-1}^2$$ is the current value of $$\sigma^2$$ in iteration i. For further evaluation we will show that $$(\tau|y, \sigma_{i-1}^2, \omega^2)$$ has multivariate normal density. Using (4.4.11) and (4.4.12) we get:

$$\ln f(\tau|y, \sigma_{i-1}^2, \omega^2) = f(y, \tau|\sigma_{i-1}^2, \omega^2) + c \quad (4.4.15)$$

where c is a constant (ignoring constants terms not involving $$\tau$$). Solving this we get:

$$-\frac{1}{2}(\tau'K_i\tau - \frac{2}{\sigma_{i-1}^2}y'\tau) + c \quad (4.4.16)$$

where $$K_i = H'\Omega^{-1}H + \sigma_{i-1}^{-2}I$$ and shows probability distribution of the normal distribution. And resolving further we get,

$$f(\tau|y, \sigma_{i-1}^2, \omega^2) \sim N(\hat{\tau}_i, K_i^{-1}) \quad (4.4.17)$$

where $$\hat{\tau}_i = \sigma_{i-1}^{-2}K_i^{-1}y.$$
Now we compute the expectation using EM algorithm, E-Step of EM algorithm can be written:

\[ Q_i(\sigma^2) = \mathbb{E}_{y|\tau, \sigma^2} \ln f(y|\tau, \sigma^2) + c \]  
(4.4.18)

\[ = -\frac{T}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} [\text{tr}(K_i^{-1}) + (y - \hat{\tau}_i)'(y - \hat{\tau}_i)] + c \]  
(4.4.19)

Here we have used the assumption \( \mathbb{E}(z'z) = \text{tr}(\Sigma) + \mu'\mu \), where \( z \) is a random vector with mean vector \( \mu \) and covariance matrix \( \Sigma \).

For getting the M-Step we differentiate \( Q_i(\sigma^2) \) w.r.t \( \sigma^2 \),

\[ \sigma_i^2 = Q_i(\sigma^2) = \frac{1}{T} [\text{tr}(K_i^{-1}) + (y - \hat{\tau}_i)'(y - \hat{\tau}_i)] \]  
(4.4.20)

Thus given \( K_i \) and \( \hat{\tau}_i \) from the expectation process and updating using (4.12) we get the estimate of \( \hat{\sigma}^2 \).

### 4.4.4 VAR models

VAR models are one of the most versatile and efficient tools for out of sample forecasting. Doan, Litterman and Sims (1984), Litterman (1986) were some of the seminal works in this area. The VAR in lag order notation takes the form:

\[ Y_t = C + A(L)Y_{t-1} + \varepsilon_t \]  
(4.4.21)
where $Y = (y_1....y_n)'$, $\varepsilon = (\varepsilon_1....\varepsilon_n)'$and $A(L) = \sum_{j=1}^{m} A_j L^j$. $C$ and $A_j$ are $n \times 1$ and $n \times n$ parameter matrices respectively. The above equation can be further written as:

$$Y_t = \Lambda x_{t-1} + u_t, \quad (4.4.22)$$

$$= (x_{t-1}' \otimes I_n)\beta + \varepsilon_t \quad (4.4.23)$$

where $x_t = (1, Y_t', ...., Y_{t-m+1}'), \beta = \text{vec}(\Lambda)$ and $\Lambda = (C, A_1, ......., A_m)$.

For estimating $\Lambda$ we use the least square estimator:

$$\hat{\Lambda}_t = (t^{-1} \sum_{s=1}^{t-1} Y_{s+1}'x_s)(t^{-1} \sum_{s=1}^{t-1} x_s x_s')^{-1} \quad (4.4.24)$$

And the covariance matrix $\Sigma$ can be estimated by:

$$\hat{\Sigma} = \frac{1}{T} \sum_{t=1}^{T} (Y_t - \hat{\Lambda}x_{t-1})((Y_t - \hat{\Lambda}x_{t-1})' \quad (4.4.25)$$

Now having known the parameters, the forecasts can be constructed. The $h$-step ahead recursive VAR forecast can be written as

$$\hat{Y}_{t+h} = C + A_1\hat{Y}_{t+h-1} + .... + A_m\hat{Y}_{t+h-m}. \quad (4.4.26)$$
4.5 Results

4.5.1 AR models

AR models have been found in many cases to be better than the benchmark random walk forecasts. This section summarizes the results of the univariate autoregressive models with four different lags. Forecasts were made with different horizons, which includes one, two and four ahead inflation and NGDP growth (h= 1, 2 and 4). In tables 4.1, 4.2 and 4.3 the forecast performance in the form of MAPE is provided with all the three different samples. In the first sample which constitutes the full sample from 1970Q2 to 2014Q2 (Table 4.1), GDP deflator forecast performance is better than all the other variables. The percentage errors of the NGDP is greater than as compared to the other three inflation measures. The percentage errors of the NGDP is greater than as compared to the other three inflation measures. In terms of the three inflation measures, GDP deflator has the lowest MAPE followed by PCE and the worst forecast performance is of CPI. In the sample from 1970Q2 to 1983Q4, which was a period of high inflation in the US, the MAPE values were much higher as compared to the other two samples. Here also the mean absolute percentage errors of GDP deflator are the least and hence have the best forecast performance. NGDP has the highest percentage errors as compared to all the three variables and hence its has the worst forecast performance again in terms of the autoregressive models. In the third sample also the results are same as compared to the other two samples with NGDP forecast performance being the worst in the sample. In the case of AR models for NGDP, for the sample 1970Q2-2014Q2 and 1984Q1-2007Q4 we find especially for one quarter ahead forecasts the AR(4) model seems to perform better as compared to the other AR models.
4.5.2 IMA models

Stock and Watson (2007) found that for forecasting inflation in the US especially the IMA (1,1) model performs quite well. The reason was due to the apparent unit root in the inflation and also due to the negative auto-correlation in the time series data. We here also use the IMA (1,1) model along with the IMA (1,2) model to compare the forecast performance of NGDP with the three different inflation variables. First we start comparing the results for the IMA (1,1) model shown in table 4.4. For the sample from 1970Q2-2014Q2 we find that NGDP forecasts in terms of mean absolute percentage errors do not perform better in terms of MAPE for all the three inflation measures. For one step ahead forecasts the IMA(1,1) seems to model NGDP better than AR(1), AR(2), AR(3) except AR(4) where the percentage errors are the same, whereas with h = 2, 4 we find that AR(4) performs worse than IMA(1,1). For the other two samples from 1970Q1-1983Q4 and 1984Q1-2007Q4, we find the same pattern of results with NGDP performing worse than all three inflation measures. In table 4.5 are provided the mean absolute percentage errors for the IMA(1,2) model. For the IMA(1,2) model also we find that for all the samples NGDP seem to perform worse than all the three inflation measures.

4.5.3 UC models

UC models seem to fit the NGDP data quite well as compared to earlier AR models and IMA(1,1) models for the full sample 1970Q2-2014Q2. In the UC model, the unobserved component $\tau_t$ can be assumed to modeled as inflation and NGDP separately in our case. The mean absolute percentage errors of NGDP are much closer to the other inflation measures as compared to earlier models during 1970Q2-2014Q2, but still NGDP performs worse than all the three inflation measures.


4.5.4 VAR models

VAR models have become standard benchmark models for any forecasting exercise. Most of the central bank projections around the world use VAR models. We have used a small VAR with three variables and lag of three. We also tried the results in VAR(2) but was not that different and VAR(3) results were better. The variables used in all the six VAR models were NGDP and federal funds rate. For the three NGDP VAR we used different inflation measures as shown in the parenthesis in table 4.9.

The results in the VAR models are also not different from the above models as we had expected. For the full sample, 1970Q2-2014Q2, compared to all three inflation VAR models show better forecast performance than all the three NGDP VAR models. As in the above models, GDP deflator has the best forecast performance as shown with the least mean absolute percentage error. For the second sample from 1970Q2-1983Q4 we again find the same set of results with NGDP forecasts having the higher values of percentage error. This pattern also continues for the third sample from 1983Q2-2007Q4.

4.6 Robustness check

One of the issues with using a percentage error for forecast accuracy such as MAPE is that it has been found to have a bias favoring estimates that are below the actual values. So when the forecast or the actual values used in the denominator have values closer to zero percent, the value would be undefined as it is bounded on the lower end but is unbounded on the upper end. So as a robustness check we have tried to compare the results using another standard forecast accuracy measure, root mean squared error (RMSFE). Another issue that we have dealt in this section is comparing the forecast accuracy of real
GDP with the earlier nominal GDP and the three inflation measures. The robustness check is performed for the full sample size from 1970Q2 to 2014Q3.

The RMSFE results for the various models are provided in table 4.10. As can be gauged from the table, the RMSFE seems to synchronous with MAPE measures. The forecasting performance of the inflation measures seem to be again better than both real GDP and nominal GDP. GDP deflator has the best forecasting performance as compared to all the other variables and nominal GDP seems to perform the worst.

4.7 Conclusion

In this chapter we have compared the forecastability of two monetary policy regimes by comparing the forecasting performance of its nominal anchors. For undertaking such a task we have employed different sets of models with multi step ahead forecasts in three different samples for US. Our forecasting results finds that in all the models used, inflation as a nominal anchor has better forecasting performance as compared to NGDP for the US. This study does not imply that nominal GDP targeting is not a preferable monetary policy framework, as it has been found to be superior in many other aspects for being a good monetary policy framework. This study finds that in terms of standard forecast performance nominal GDP as a potential monetary policy anchor does not seem to outperform inflation.
Figure 4.1: CPI, GDP Deflator and PCE

- CPI
- Def
- PCE

- NGDP
- CPI
Table 4.1: AR Models - 1970Q2:2014Q2

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Figure 4.2: AR Models: One step ahead forecasts for PCE - 1970Q2:2014Q2
Figure 4.3: AR Models: One step ahead forecasts for NGDP - 1970Q2:2014Q2
Figure 4.4: One step ahead forecast for IMA(1,1) Models
Table 4.4: IMA(1,1) Model

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<td>5.83</td>
<td>5.84</td>
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<tr>
<td></td>
<td>CPI</td>
<td>2.17</td>
<td>2.22</td>
</tr>
<tr>
<td></td>
<td>PCE</td>
<td>2.29</td>
<td>2.41</td>
</tr>
<tr>
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<td>GDP Deflator</td>
<td>1.35</td>
<td>1.41</td>
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<tbody>
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<td>5.66</td>
<td>5.44</td>
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<tr>
<td></td>
<td>CPI</td>
<td>2.16</td>
<td>2.26</td>
</tr>
<tr>
<td></td>
<td>PCE</td>
<td>2.30</td>
<td>2.35</td>
</tr>
<tr>
<td></td>
<td>GDP Deflator</td>
<td>1.35</td>
<td>1.41</td>
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<td>5.30</td>
</tr>
<tr>
<td></td>
<td>CPI</td>
<td>2.17</td>
<td>2.27</td>
</tr>
<tr>
<td></td>
<td>PCE</td>
<td>2.30</td>
<td>2.35</td>
</tr>
<tr>
<td></td>
<td>GDP Deflator</td>
<td>1.35</td>
<td>1.41</td>
</tr>
</tbody>
</table>
Figure 4.5: One step ahead forecasts of PCE (upper) and NGDP (lower) with UC models

UC Model with \( \omega = 0.25 \), PCE

UC Model with \( \omega = 0.25 \), NGDP
Table 4.9: VAR(3) Forecasts (MAPE)

<table>
<thead>
<tr>
<th>Horizon</th>
<th>CPI</th>
<th>PCE</th>
<th>GDP Deflator</th>
<th>NGDP(Deflator)</th>
<th>NGDP(PCE)</th>
<th>NGDP(CPI)</th>
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<tbody>
<tr>
<td>1970:1 – 2014:2</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>h=1</td>
<td>2.83</td>
<td>2.38</td>
<td>1.52</td>
<td>5.95</td>
<td>5.91</td>
<td>5.89</td>
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<tr>
<td>h=2</td>
<td>3.01</td>
<td>2.45</td>
<td>1.62</td>
<td>5.75</td>
<td>5.60</td>
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<tr>
<td>h=4</td>
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<td>1.63</td>
<td>5.72</td>
<td>5.77</td>
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<tr>
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<td>6.82</td>
<td>5.75</td>
<td>5.43</td>
<td>9.40</td>
<td>9.50</td>
<td>9.47</td>
</tr>
<tr>
<td>h=2</td>
<td>7.09</td>
<td>5.83</td>
<td>5.50</td>
<td>9.33</td>
<td>9.37</td>
<td>9.51</td>
</tr>
<tr>
<td>h=4</td>
<td>7.50</td>
<td>5.91</td>
<td>5.55</td>
<td>9.32</td>
<td>9.35</td>
<td>9.37</td>
</tr>
<tr>
<td>1984:1 - 2007:4</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>h=1</td>
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<td>2.62</td>
<td>1.32</td>
<td>6.09</td>
<td>6.08</td>
<td>6.01</td>
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<td>h=2</td>
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<td>5.87</td>
<td>5.92</td>
<td>5.85</td>
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<tr>
<td>h=4</td>
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<td>2.54</td>
<td>1.75</td>
<td>5.61</td>
<td>5.12</td>
<td>5.34</td>
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### Table 4.10: Robustness Check: RMSFE

<table>
<thead>
<tr>
<th></th>
<th>NGDP</th>
<th>RGDP</th>
<th>Deflator</th>
<th>CPI</th>
<th>PCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1)</td>
<td>3.09</td>
<td>2.61</td>
<td>0.89</td>
<td>2.22</td>
<td>1.53</td>
</tr>
<tr>
<td>AR(2)</td>
<td>2.96</td>
<td>2.58</td>
<td>0.85</td>
<td>2.20</td>
<td>1.51</td>
</tr>
<tr>
<td>AR(3)</td>
<td>2.03</td>
<td>2.60</td>
<td>0.84</td>
<td>2.10</td>
<td>1.46</td>
</tr>
<tr>
<td>AR(4)</td>
<td>3.02</td>
<td>2.64</td>
<td>0.84</td>
<td>2.17</td>
<td>1.48</td>
</tr>
<tr>
<td>UC(ω =0.25)</td>
<td>2.78</td>
<td>2.71</td>
<td>0.86</td>
<td>2.13</td>
<td>1.46</td>
</tr>
<tr>
<td>UC(ω =1)</td>
<td>2.72</td>
<td>2.69</td>
<td>0.88</td>
<td>2.30</td>
<td>1.58</td>
</tr>
<tr>
<td>IMA(1,1)</td>
<td>2.74</td>
<td>2.65</td>
<td>0.83</td>
<td>2.16</td>
<td>1.48</td>
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<tr>
<td>IMA(1,2)</td>
<td>2.73</td>
<td>2.66</td>
<td>0.82</td>
<td>2.14</td>
<td>1.46</td>
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</tbody>
</table>

### Table 4.11: Unit Root Tests

<table>
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<tr>
<th>Variables</th>
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<th>Lags</th>
<th>Test Statistic</th>
<th>McKinnon P-Values</th>
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</thead>
<tbody>
<tr>
<td>△GDP Deflator</td>
<td>ADF</td>
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<td>-4.07***</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>PP</td>
<td></td>
<td>-5.87***</td>
<td>0.000</td>
</tr>
<tr>
<td>△CPI</td>
<td>ADF</td>
<td>0</td>
<td>-9.35***</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>PP</td>
<td></td>
<td>-4.27***</td>
<td>0.000</td>
</tr>
<tr>
<td>△PCE</td>
<td>ADF</td>
<td>1</td>
<td>-4.63***</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>PP</td>
<td></td>
<td>-3.21***</td>
<td>0.001</td>
</tr>
<tr>
<td>△NGDP</td>
<td>ADF</td>
<td>0</td>
<td>-6.43***</td>
<td>0.000</td>
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<tr>
<td></td>
<td>PP</td>
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<td>-2.80***</td>
<td>0.005</td>
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</tbody>
</table>

4) All the variables were found to be first difference stationary
5) *** indicate 1 percent level of significance
Chapter 5

Conclusion

The thesis has presented three self-contained chapters on empirical macroeconomics. The thesis has contributed to the literature on exploring the nature of the volatility of the structural shocks and the macroeconomic variables in the post-reform period in India. It has also contributed to the literature for examining the forecasting performance of a new monetary policy regime for the US economy, and has also contributed to a larger literature of the factors contributing to the Great Moderation in the US.

5.1 What have we learned?

Chapter 2 has examined the evolution of the volatility of the structural shocks and macroeconomic variables in a time-varying framework. We found that time variation is an important feature of the major macroeconomic variables in India. During the post-reform period 1991 onwards, we detect a sharp reduction in estimated stochastic volatility for all shocks and variables. Interestingly, during the East Asian crisis the volatility surge is much higher than observed during the recent global financial crisis. We found that CPI inflation response to monetary policy shocks are more consistent with industrial output. This similar response in both the variables in terms of synchronous fluctua-
tions in volatility was also observed with the univariate stochastic volatility model for both the variables. We also observed that demand shocks seem to be persistent unlike supply shocks during the period from 2007-2014.

Chapter 3 explored the role nominal GDP as a monetary policy framework during the Great Moderation period in the US, and showed that for accomplishing its objective of stabilizing inflation expectations, the Federal Reserve was implicitly targeting nominal GDP. This claim has been corroborated by estimating different variants of nominal GDP rules and compared with Taylor rules using both ex-post revised data and real time briefing forecasts of FOMC. With ex-post revised data, which included also the Volcker period along with the Great Moderation period (1979Q4-2006Q4), we find a stronger preference for nominal GDP variable as compared to the inflation in the Taylor rule. This stronger preference was again found in the two different sets of real time data (Greenbooks forecasts and briefing forecasts from FOMC meetings). We have also illustrated that during the Great Moderation period, the fit with the predicted nominal GDP rule matches the actual federal funds rate better than does the Taylor rule. The overall results counter the conventional view, and observe that post-Volcker era or during the period of Great Moderation (1984-2007), the Federal Reserve had a stronger implicit preference for nominal GDP as compared to inflation.

Chapter 4 explored whether nominal GDP can pass the forecasting test to be a monetary policy framework. We examined the forecastability of the NGDP regime with the inflation targeting framework by comparing the forecasting performance of its nominal anchors. This task was undertaken by using a series of models including Autoregressive models, Integrated Moving Average models, Vector Autoregression model and Unobserved Components
Our forecasting results found that in all the models used, inflation as a nominal anchor has better forecasting performance as compared to NGDP for the US. Thus we find that the US inflation is hard to forecast, but it seems that nominal GDP is much harder to forecast.

5.2 Future research possibilities

This thesis has opened up a number of avenues for future research. Chapter 2 explored the issue of volatility in the post reform period in India with a three variable TVP-VAR-SV model. An interesting area of research in the future would be to explore the transmission of shocks in the economy with a larger number of variables using a time-varying FAVAR model, and explore whether there are asymmetries in the propagation mechanism in the good and bad times.

Chapter 3 explored the role of the nominal GDP as a monetary policy framework during the Great Moderation, by comparing it with the Taylor rule in an empirical setup. It can be argued for the sake of robustness, that this comparison in a DSGE setup should be explored. This can be an interesting future research area which can also examine the welfare gains from the two monetary policy frameworks.

Chapter 4 examined the forecastability of the NGDP regime with the inflation targeting framework by comparing the forecasting performance of its nominal anchors for the US economy. This forecasting exercise can be explored in the case of India, which has recently introduced inflation targeting as its explicit monetary policy framework.
Bibliography


[45] Panagariya, Arvind., 2003, India’s Economic Reforms: What has been accomplished and What Remains to be done, International Trade 0309013, EconWPA.


