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Uncertainty and Effectiveness of Monetary Policy: A Bayesian Markov Switching-VAR Analysis

Abstract: There is a growing body of literature examining the effectiveness of the monetary policy on the macroeconomy in different contexts for developed and developing countries. However, lately, especially after the GFC, the focus of research shifted to examine the role of uncertainty in economic activity and on the monetary policy effectiveness. Both theoretical and empirical studies suggest that uncertainty does influence monetary policy effectiveness. However, until now, empirical studies are restricted to only developed countries. To this end, the present study examines the influence of uncertainty on monetary policy effectiveness for a developing country, namely India. We applied a non-linear VAR, which allows us to examine the effect of monetary policy shocks during high and low uncertainty periods. The results exhibit that uncertainty influences the effectiveness of monetary policy shocks. We find weaker effects of the monetary policy shocks during high uncertainty regime relative to low uncertainty regime.

Keywords: Uncertainty, Monetary Policy, India

JEL Classification: E310, E320, E400

1. Introduction

Over the years, theoretical and empirical literature employing different methodology led to a consensus that monetary policy affects macroeconomy at least in the short-run (Romer and Romer, 1989; Bernanke and Blinder, 1992; Christiano, Eichenbaum, and Evans, 1994a; Christiano, Eichenbaum, and Evans, 1994b). There are many alternative channels for the transmission of monetary policy discussed in the literature. These include interest rate channel (Hicks, 1937; Taylor, 1995), credit channel (Bernanke, 1986; Bernanke and Blinder, 1992; Ben and Gertler, 1995), asset prices channel (Meltzer, 1995; Zhang and Huang, 2017), exchange rate channel (Obstfeld and Rogoff, 1995), expectation channel (Taylor, 1995; Blinder, 1998) and balance sheet channel (Mishkin, 1996).[1] These recognised channels are not mutually exclusive, and that more than one channel can work simultaneously and achieve the policy objective(s). However, the empirical studies over the years have not yet reached an agreement regarding the working and effectiveness of these channels (Ben and Gertler, 1995). Often the term "black box" is used to describe the monetary policy mechanism by the economists.

The effectiveness of the transmission channels depends on the economic structure, development of financial and capital markets, economic conditions, among other factors of an economy (Cevik and Teksoz, 2013). As these factors vary across developed and developing countries, there is no reason to believe that monetary policy mechanism would be the same for developed and developing countries (Mishra, Montiel, and Sengupta, 2016). These observations led to vast empirical literature to analyse the monetary policy operations for both developed and developing countries contingent on a specific aspect of different economies. The slowdown and dismal economic recovery in many countries after the global financial crisis (GFC) of 2007-08 (Castelnuovo, Lim, and Pellegrino, 2017) sparked the debate about the effect of uncertainty on the macroeconomy. Besides, the slow recovery following the policy actions and the seminal work by Bloom (2009), led to a rejuvenating interest among researchers and policymakers to examine the role of uncertainty in monetary policy transmission.[2] The theoretical discussion on the role of uncertainty on general policy effectiveness can be traced back to Brainard (1967). The author argues that the impact of policy actions will not be of the same scale when the assumption of certainty is relaxed. The diversion becomes more in the presence of multiple objectives and policy tools.

Furthermore, Sengupta (2014) asserted that the effects of monetary policy on real variables keep changing with time, and this can be attributed to different kinds of uncertainties. While, the empirical literature examining the dependence of monetary transmission on the structure, development and other aspects of the economy

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1 See Meltzer (1995), Mishkin (1996), and Mishkin (2001),Paramanik and Kamaiah (2014) and Cevik and Teksoz (2013) for theoretical discussions on these channels. In addition, Özlü and Yalçın (2012) investigate the trade credit channel of monetary policy transmission in Turkey by using a large panel of corporate firms.

2 The increasing importance of 'portfolio balance channel' and 'expectations' channel during global financial crisis (Yellen, 2011; Joyce, Tong, and Woods, 2011), also emphasise the need to study the effect of uncertainty on monetary policy transmission. Wu, Lim and Jeon (2016) examine the effectiveness of the monetary policy transmission mechanism from the bank-lending channel perspective during the global financial crisis of 2008–2009.

is growing, the role of uncertainty in influencing the monetary policy effectiveness has been ignored. However, after the GFC and Bloom's (2009) seminal work, there is a spurt in the empirical literature examining the role of uncertainty in influencing the monetary policy transmission.

The concept of uncertainty associated with Knight (1921) is the inability of people to forecast the likelihood of events happening in future. A closely related concept is a risk which refers to a known probability distribution over a set of events (Castelnuovo, Lim, and Pellegrino, 2017). Though, theoretically, these two concepts are different but hard to differentiate empirically or in the data analysis (Castelnuovo, Lim, and Pellegrino, 2017). To the extent of literature, the term uncertainty includes both uncertainty (Knight's definition) and risk. Moreover, there is no perfect measure of uncertainty, and a range of proxies like the volatility of the stock market or GDP has been used (Bloom, 2014). One reason to use the volatility is unavailability of perfect measure of uncertainty. Another fact is that more the series is volatile more challenging to forecast, an integral component of Knight's (1921) definition of uncertainty.

In line with the theoretical propositions by Bernanke (1983), Dixit and Pindyck (1994) and more recently by Bloom (2009) and Aastveit, Natvik, and Sola (2013), among others. There is a consensus that a heightened uncertainty dampens monetary policy effectiveness. The theoretical propositions have explained the various mechanism through which uncertainty influences the effectiveness of the monetary policy. One of the widely discussed and accepted the explanation for the role of uncertainty to dampen the effectiveness of monetary policy is based on the 'real options theory'. The theory suggests that, in the presence of some form of fixed costs and partial irreversibility associated with the investment and hiring process, a heightened uncertainty motivates agents to adopt 'wait and see' approach and postpone their decisions, thus weakening the impact of monetary policy (Bloom, 2009; Bloom, Bond, and Van Reenen, 2007). Another explanation is based on the fact that an increased uncertainty may lead to increase risk premia and thus cost of financing, which reduces micro and macro growth (Bloom, 2014). Further, during uncertain times, higher precautionary savings by risk-averse agents could also lower the effectiveness of the monetary policy on the real economy (Bloom, 2014).

In this backdrop, the main goal of the present study is to empirically examine the impact of monetary policy contingent on the prevailing uncertainty in the Indian economy. In other words, we examine how different the effect of monetary policy will be in low and high uncertainty regimes in India. To conduct the empirical exercise, we chose the class of Markov-switching model, which allows us to divide the sample into high and low uncertainty regimes endogenously. Moreover, it efficiently captures the dynamics of the process in a co-integration space. To this end, we make use of two-state Bayesian Markov Switching Vector Auto-regression (BMSVAR) to the monthly data for April 1991 to December 2016. Our model includes a standard set of macroeconomic indicators, like output growth (Index of industrial production), inflation(Wholesale price index) and weighted call money rate (indicator for monetary policy). The two-state MSVAR allows us to separate the economy into low and high uncertainty regimes. The regime-dependent impulse response functions due to Ehrmann, Ellison, and Valla (2003) enable us to examine the differential effect of the monetary policy during high and low uncertainty regimes.

The present study fills the void in the literature as previous studies are confined to developed countries only. Further, the findings of the study are relevant to both modelling and policy perspectives. From the policy perspectives, our analysis is in consonance of the previous empirical literature and suggests for more aggressive and pro-active policy actions by policymakers during high uncertainty regimes (Bloom, 2014; Pellegrino, 2017).

Rest of the paper is structured as follows. Section 2 describes theoretical propositions and empirical literature on the effect of uncertainty on monetary policy effectiveness. Section 3 describes BMSVAR approach, followed by a description of our data in section 4. Findings are discussed in section 5, and section 6 concludes the study.

2. Theoretical background and literature review

Oliver Blanchard, chief economist IMF wrote back in 2009, “Uncertainty is largely behind the dramatic collapse in demand. Given the uncertainty, why build the new plant, or introduce a new product? Better to pause until the smoke clears.” Whereas, Christina Romer, the Chair of the Council of Economic Advisers, said, “Uncertainty has almost surely contributed to a decline in spending.” In 2012, Christine Lagarde, Managing director, IMF, said, “There is a level of uncertainty which is hampering decision-makers from investing and from creating jobs.” These statements, objectively show that uncertainty plays a dynamic role to shape the real economy by affecting investment, consumption and employment. A heightened uncertainty hampers investment-decisions and optimal resource allocation needed for economic development (Fatima and Waheed, 2011). The above-explained behaviour is consistent with the observed stylised facts (Castelnuovo, Lim, and Pellegrino, 2017). That is i) Consumption and investments move together with uncertainty but in opposite direction and ii) a jump in uncertainty leads to a severe drop in consumption and investment. Moreover, several empirical studies (See, Alessandri and Mumtaz, 2014; Balcilar et al., 2017; Castelnuovo, Lim, and Pellegrino, 2017, among others and references therein) have found shreds of evidence that increased uncertainty hurts real aggregate variables. However, the slowdown observed in many economies as a result of the global financial crisis of 2007, and the seminal work of Bloom (2009), rejuvenated the research examining the effect of uncertainty on the effectiveness of the monetary policy.

Many theoretical explanations point to lower the effectiveness of monetary policy in the presence of high uncertainty. One of the well-accepted explanation is "real options theory", which works due to the fixed costs and partial irreversibility associated with investment and hiring process. The hypothesis states that firms see their investment and hiring opportunities as a series of options and a heightened uncertainty can increase the firms' option value of delay to hire and invest (Bloom, 2014; Bloom, 2009). That is, when uncertainty is high, firms adopt 'wait and see' approach and postpone the investment and thus making the real economy less sensitive to monetary policy (Pellegrino, 2017). An analogous mechanism works in " precautionary savings approach" for consumptions. In the presence of heightened uncertainty, risk-averse agents may postpone their consumption (Bloom, 2014), that is higher precautionary savings are preferred in uncertain times. They hence could also be the reason for the less effectiveness of monetary policy (Pellegrino, 2017). In another explanation, Bloom (2014) also argues that uncertainty may reduce the effectiveness of monetary policy through productivity and risk premia channel. He argues that when uncertainty is high, more-productive and, unproductive firms are less aggressive to expand and contract their capacity, respectively, thus dampening the effect of monetary policy.

Further, greater uncertainty leads to increased risk premia and thus raising the cost of borrowing and lessening the effect of monetary policy. Another explanation for the lower effect of monetary policy in the presence of increased uncertainty is based on the price-setting behaviour of firms. In a general equilibrium price-setting menu costs model, Vavra (2013) argues that increased uncertainty induces a frequent price change which reduces the effectiveness of monetary policy shocks up to 50 per cent relative to the tranquil period (Pellegrino, 2017)[3]. Baley and Blanco (2016) by including information friction in addition to menu costs, also showed that in uncertain times, nominal shocks have significantly smaller effects on output.

There are few empirical studies, which examined the effect of uncertainty on monetary policy effectiveness. Aastveit, Natvik, and Sola (2013) by employing Interacted VAR methodology due to Towbin and Weber (2013) examined the effectiveness of monetary policy contingent on high and low uncertainty. They used different measures of uncertainty for the US economy, and conclude that the effect of monetary policy shocks on economic activity is considerably weaker during high uncertain times. The difference in the effect of monetary policy is more for GDP and investment. Further, they observe, consistent with "real-options" effects; investment responds two to five times lower to the monetary policy shocks when uncertainty is high.

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3 Using firm level data, (Bachmann et al., 2013), showed that firms change prices more frequently in uncertain times relative to tranquil times, a finding consistent to Vavra's (2013) model

Moreover, they find that US uncertainty weakens not only monetary policy effects on economic activity in the domestic economy, but also for the Canadian economy. Pellegrino (2017), using a non-linear interacted VAR and non-linear generalised impulse response functions due to Koop, Pesaran, and Potter (1996), examined the effect of uncertainty on monetary policy effectiveness for the US economy. They find that consistent with the "real options effects" and "precautionary savings" approach, the effect of monetary policy shocks is weaker during uncertain times. Further, they observe, the effectiveness of monetary policy shocks reduces more for GDP during uncertain times relative to tranquil times. In another study following a similar methodological approach, Pellegrino (2018) examined the effect of uncertainty on monetary policy effectiveness of the Euro area. They reached on the similar conclusion that the effects of monetary policy shocks are significantly lower during uncertain times relative to tranquil times. A study by Castelnuovo and Pellegrino (2016), using non-linear VAR and DSGE models, find conclusion consistent to the above studies.[4] They observe that real effects of monetary policy shocks are substantially weaker in the presence of high uncertainty.

However, these studies used different measures for uncertainty to segregate the economy into high and low uncertainty regimes and examine the effectiveness of monetary policy contingent on the high and low value of such measures. Whereas, we endogenously defined the high and low uncertainty regimes of the economy. A study by Eickmeier, Metiu, and Prieto (2016) is close to our study. By employing the regime-switching threshold vector auto-regression model, they examined the effect of monetary policy on economic activity during high and low volatility regimes. They conclude that monetary policy shocks have a differential effect in the high and low volatility regimes.

Moreover, they observe that the differential effect of monetary policy contingent on high and low volatility periods works through balance sheet management of financial intermediaries. That is, the magnitude of the differential effect of monetary policy during high and low volatility regimes would depend on the development of the financial system of an economy. The present study differs from the previous studies, as we endogenously segregated the economy into high and low uncertainty regimes using the Markov-switching model. Further, we applied the regime dependent impulse response functions to find the differential effect of monetary policy shocks during high and low uncertainty regimes. Our study also contributes to the vast and growing monetary policy transmission empirical literature, which over the years has reached to a general conclusion that monetary policy affects real variables at least in shot-run (See for detailed review Christiano, Eichenbaum, and Evans, 1999; Romer

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4 See for instance, Elbourne and Haan (2009) use VAR and structural VAR models to estimate the monetary transmission and they conclude that the structural VAR yields much better results.

and Romer, 2004; Bernanke, Boivin, and Eliasz, 2005; Mishra and Montiel, 2012; Paramanik and Kamaiah, 2014; Mohan, 2008; Prabheesh and Rahman, 2019; Mayandy, 2019; Juhro and Iyke, 2019; Nwosu et.al, 2019; Warjiyo, 2016). Another stream of literature related to our study is the literature debating the differential effect of monetary policy contingent to the state of the economy that is an expansion (good) and recession (bad) times. This is based on the fact that during the recessionary period, there would be more uncertainty (See Bloom, 2014, for details). There seems to be an agreement that monetary policy shocks are less effective during recessionary periods from the vast literature.

3. Methodology

The development of MSVAR (Markov switching vector auto-regression) models allowed macroeconomists to accommodate one of the critical challenges that are structural change or regime shifts in macroeconomic modelling.[5] The origin of the MSVAR approach may be traced to Goldfeld and Quandt (1973), in the form of switching regressions. Later, Hamilton (1989) and Krolzig (1998) made outstanding contributions, respectively, to develop univariate and multivariate MSVAR. The MSVAR model is well equipped to characterise the macroeconomic variables in the presence of structural breaks or regime shifts. The Markov switching model falls into the category of non-linear models as it captures the non-linear dynamic properties of the variables such as asymmetric and time-varying cycles, breaks or jumps in the variables (Fan and Yao, 2005; Balcilar et al., 2017). To fulfil the primary goal of the present study that is examining the effectiveness of monetary policy shocks during high and low uncertainty regimes, MSVAR is, therefore, an appropriate modelling approach.

3.1. Markov Switching Vector Autoregression (MS-VAR) model

The MS(m)-VAR(p) model for K endogenous variables X_t may be represented in Equation 1 as follows

$$X_t = \begin{Bmatrix} \alpha_1 + \beta_{11} X_{t-1} + \cdots + \beta_{p1} X_{t-p} + A_1 v_t \text{ if } s_t = 1 \\ \vdots \\ \alpha_m + \beta_{1m} X_{t-1} + \cdots + \beta_{pm} X_{t-p} + A_m v_t \text{ if } s_t = m \end{Bmatrix} \tag{1}$$

$$v_t \sim N(0; I_k)$$

[5] See Granger (1996), Hansen (2001), Perron (2006) for the importance of structural or regime shifts in macro-modelling.

Here, variables of the vector X_t are explained by the intercepts α_i, autoregressive terms of order p and residuals $A_i v_t$. Within the above general framework, wherein either or some specific parameters may be allowed to switch between the m regimes.[6] v_t is a K dimensional vector of normally distributed standard residuals with *zero* mean. The variance of the standard residuals are normalised to unity. However, the vector v_t is pre-multiplied by matrix A_i, which is regime dependent. Thus, the variance-covariance matrix Σ_i of the residuals $A_i v_t$ are also regime dependent; represented as follows

$$\Sigma_i = E\left(A_i v_t v_t' A_i'\right) = A_i E\left(v_t v_t'\right) A_i' = A_i I_K A_i' = A_i A_i' \tag{2}$$

S_t a regime variable is unobserved, independent of past X_s and, conditional on S_{t-1}, assumed to follow a hidden Markov process that is

$$Pr(S_t = j | S_{t-1} = i) = p_{ij}$$

for all t and regimes $i, j = 1,2,3,\cdots, m$. For, m regime, S_t follows an m-state Markov process with following transition probability matrix

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \tag{3}$$

P_{ij} is the probability of the economy for being in regime j at time t, given that at the time $t-1$, the economy was in regime i, where $i,j \in \{1,2,\cdots,m\}$.

The MSVAR specified in equations 1-3 is a general framework. Our methodology is based on the above framework, where X_t includes $\{OG_t, INF_t, IR_t\}$[7]. Given our objective, all parameters of the model including variance matrix Σ_i are allowed to switch according to the latent regime variable S_t. Here, variation in parameters directly reflects regime-switching. Thus, regime changes treated as random events are governed by exogenous Markov process. The probability value P_{ij} associated with latent Markov process based on the sample information determines the state of the economy. That is, inference about the regime can be made based on the estimated probability for each observation that it is coming from a particular regime. For our study, we assume that $m = 2$ that is two regimes. Studies by Diebold, Lee, and Weinbach (1994) and Filardo and Gordon (1998) among others show that two regime markov switching model sufficiently captures the behaviour of the macroeconomic variables. Two regimes are consistent with the notion of crisis-recovery or recession-expansion periods for an economy and high and low uncertainty regimes. We adopt Bayesian

6 See Krolzig (1997) for special cases and their properties.

7 Description of the Data is given in section 4.

Markov-Chain Monte Carlo (MCMC) integration method of Gibbs sampling for estimation. This approach allows for regime dependent impulse (RDI) response analysis and also allows to calculate the possible confidence intervals of the RDI responses.

The MS-VAR model specified in equations 1-3 has many exciting features to analyse the dynamic relationships among the study variables. First, the classification of regimes based on the parameter switching in the full sample is possible and therefore, changes in the dynamic interactions among the variables are recognised. Second, dynamic changes in the relationship among the variables are allowed to change at an unknown time. Third, inferences about the regime dependent impact of a particular variable on other variables of the system is possible through regime dependent impulse response functions.

3.2. Estimation

For estimating the parameters of a Markov Switching model, three methods, namely maximum likelihood (ML), expectation-maximization (EM) algorithm and Bayesian MCMC estimation approach based on Gibbs sampling, are commonly used. One of the simplest estimation methods for MS models is ML. However, it may be computationally demanding, and there would be slow convergence (Balcilar et al., 2017)[8]. Whereas, EM algorithm is a commonly used method for estimation of MS models. This method follows a two-step procedure. In the first step, it computes the conditional expectation of log-likelihood, conditioned to the specified current parameter estimates and the data known as E-step. While, parameters are computed based on the maximisation of log-likelihood of the complete data in the second step, known as M-step. However, standard errors of the parameters from the EM algorithm directly cannot be obtained. Moreover, the EM algorithm may have slow convergence (Balcilar et al., 2017). The third method for estimation of parameters of MS models is Bayesian MCMC based on Gibbs sampling. We have used the last method for estimation that is a Bayesian MCMC method. The Bayesian MCMC estimation approach assumes one sample path for the regimes and therefore, does not face the problem like ML and EM methods (See Balcilar et al., 2017). We follow Balcilar et al. (2017) to implement the bayesian MCMC estimation approach and adopt the following steps

a. Draw the parameters given the regimes
b. Draw the regimes given transitional probabilities and parameters of the model.
c. Draw the transitional probabilities given regimes. Here we do not include model parameters like excluding transition probabilities in the first step.
d. Draw Σ_i, given regimes, transitional probabilities and parameters using a hierarchical prior.

[8] For review of ML method see Redner and Walker (1984).

In the second step above, we put a threshold level for a draw to be accepted that is at least 5 per cent of the observations must fall in the regimes associated with the particular draw. In step (c), we use Dirichlet distribution to draw unconditional probabilities P, given the regimes. We set the priors for the Dirichlet distribution as 80 and 20 per cent probability respectively of staying in the same regime and switching to the other regime. We perform the MCMC integration with 60,000 posterior draws with 30,000 burn-in draws.

3.3. Regime dependent impulse response function

One major attraction of VAR modelling has been its ability to analyse the dynamic interactions among the variables through impulse response functions (IRF). Moreover, for non-linear models like Markov Switching-VAR, it is difficult to interpret the dynamic interactions of the variables only through parameters. However, for non-linear models, computation of IRF is complicated in comparison of a linear VAR. As, the IRF in MS-VAR model depend on the regime of the system in every time t and there is no simple method to compute the future path of the regime process (Balcilar et al., 2017).

We follow Ehrmann, Ellison, and Valla (2003) to construct regime-dependent impulse response function (RDIRF), assuming regimes do not switch beyond the shock horizon. The RDIRF traces the expected path of the endogenous variable at time $t + h$ following a shock of a given size (say one standard deviation) to the k^{th} standard disturbance at time t condition to regime i. The RDIRF can be defined as in equation for regime i.

$$\frac{\partial E_t X_{t+h}}{\partial v_{k,t}} \Big| s_t = \cdots = s_{t+h} = i = \theta_{ki,h} \; for \; h \geq 0 \tag{4}$$

Where $\theta_{ki,h} = \{\theta_{ki,1}, \theta_{ki,2}, \cdots, \theta_{ki,m}\}$ is the vector of the responses of the endogenous variables to a specific shock conditional to regime i. $v_{k,t}$ is the structural shock to the kth variable.

However, within the MS-VAR framework, we can estimate the variance-covariance matrix Σ_i, but not the matrix A_i for all $i \in \{1, 2, \cdots, m\}$. Which leads to the well-known problem of identification. One of the possible ways to identify the matrix A_i is to impose sufficient restrictions on the parameters obtained from reduced VAR. We follow Sims's (1980) recursive identification scheme, following the Cholesky decomposition of the variance-covariance matrix Σ_i. The order of the variables is $\{OG_t, INF_t, IR_t\}$.

4. Data

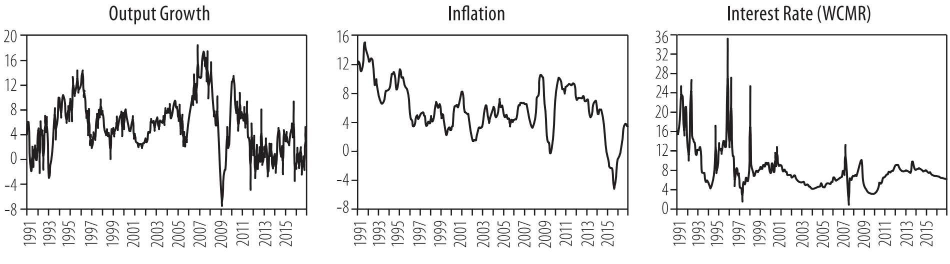
We have used the Index of Industrial Production (IIP), Wholesale Price Index (WPI) and Weighted Call Money Rate (WCMR) of monthly frequency. The data has been obtained from the EPW time-series database for the period of April 1991 to December 2016. The choice of the sample period is justified by the fact that before the 1990s, monetary policy was subjected to financial repression and fiscal dominance (Ghate and Kletzer, 2016). In fact, during 1951-1970 and 1971-90, monetary policy was guided by the plan financing and credit planning, respectively. Only after the implementation of structural reform and financial liberalisation in the 1990s, monetary policy became market-oriented (Mohanty, 2013). IIP and WPI have been seasonally adjusted as the tests exhibit the presence of a seasonal effect, using X-13 ARIMA-SEATS of U.S. Census Bureau[9]. We transformed the IIP and WPI data following Equations 5-6. The growth rate of IIP and WPI in percentage terms are used as the proxies for output growth and inflation, respectively.

$$y_t = 100 * \ln(iip_t / iip_{t-1}) \quad (5)$$

$$\pi_t = 100 * \ln(wpi_t / wpi_{t-1}) \quad (6)$$

During the sample period, there have been many changes in the monetary policy framework of RBI, from monetary targeting changed to multiple indicators approach and recently resorted to flexible inflation targeting (Bhoi, Mitra, and Singh, 2017). The changes in the monetary policy framework creates a challenge to select an appropriate variable as a proxy for the monetary policy instrument. In agreement of monetary policy literature, we chose WCMR as the indicator of the policy variable. Moreover, Bhoi, Mitra, and Singh (2017) through two different approaches, also show that WCMR is most appropriate variable. The selected variables output growth (growth of IIP), Inflation (Growth of WPI) and Interest rate (WCMR) are henceforth represented as *OG*, *INF* and *IR*, respectively.

Figure 1. Time-series plots of Variables



[9] Results for the seasonal effects are presented in Table 6. There is no seasonal effect in WCMR.

5. Empirical Findings and Discussions

Before estimating our MSVAR model, we discuss some basic descriptive statistics and time-series properties of study variables and model selection and estimation strategy employed.

5.1. Summary Statistics

The summary statistics and time series plots of the variables are presented in Table 1 and Figure 1, respectively. The average output growth and inflation over the sample period are about 5 and 6 per cent respectively, whereas the average interest rate is more than 6 per cent. The Jarque-Bera tests show inflation and interest rate follow a non-normal distribution. However, output growth is normally distributed. The results of the Ljung-Box tests for autocorrelation at lag one[LB(Q1)] and four [LB(Q4)] of all variables reveal the presence of autocorrelation with their respective lags. The LM statistics for autoregressive conditional heteroscedasticity (ARCH) at lag one [ARCH(1)] and four [ARCH(4)] show that the variance of the variables is time-varying. The coefficient of variation (COV) statistics shows that the output growth is relatively more volatile than inflation and interest rate. Figure 1 reveals that after opening up the economy in 1991, there has been a more or less upward trend in the output growth but with fluctuations. The impact of the Asian crisis of 1997 can be observed from the Figure, after which there has been a stable performance until the Global financial crises (GFC) 2007. The impact of GFC is quite visible in 2009-10. After GFC, the output growth has been more volatile. For inflation, we observe a gradual decrease in level as well in volatility. Though from 2002 to 2014, the persistent behaviour of inflation can be observed except low inflation during 2009-10. High inflation during 1991-92 may be attributed to the drought and large fiscal deficit of government and during 2008, inflation was fuelled by the high global commodity prices and credit expansion[10]. Despite a rising policy rate, during 2010, inflation was rising due to the high global commodity prices after GFC[11]. One interesting fact about the interest rate is that there has been a fluctuation in the policy rate, whenever, there is a shock in the economy for example balance of payment crises in 1991, the Asian crisis in 1997, Dot.com bubble in 2000-2001 and GFC in 2007-08. One common observation about output growth and inflation is that both have become more stable over the study period (Mohanty, 2010).

[10] See Mohanty for detailed events related to inflation

[11] This points also highlights the effect of external factors

Table 1. Descriptive Statistics

Variables/Statistics	GIIP	INF	CMR
Mean	5.306	5.885	8.176
Prob.(Mean=0)	0.000	0.000	0.000
Std Dev	4.525	3.439	4.339
Minimun	-7.648	-5.263	0.762
Maximum	18.594	15.133	35.313
Skew	0.186	-0.231	2.516
Kurtosis	0.179	0.663	8.900
Jarque-Bera	2.212	8.488	1358.923
Prob.(JB=0)	0.331	0.014	0.000
Ljung-Box(Q1)	186.217	299.180	183.170
Prob	0.000	0.000	0.000
Ljung-Box(Q4)	634.722	1028.227	576.931
Prob	0.000	0.000	0.000
ARCH(1)	181.371	291.045	101.989
Prob	0.000	0.000	0.000
ARCH(4)	208.958	290.506	128.941
Prob	0.000	0.000	0.000
COV	1.964	1.418	1.517

Notes: SD and CV denote standard and coefficient of variation, respectively. JB denotes Jarque-Bera test for normality. LB(Q1) and LB(Q4) refer Ljung-Box q-statistics for autocorrelation tests at lag one and lag four, respectively. While ARCH(1) and ARCH(4) reports LM tests for the autoregressive conditional heteroscedasticity (ARCH) at lag one and lag four, respectively.

5.2. Time series Properties

To examine the stationarity property of the variables, we used the battery of unit root tests. Results are reported in Tables 2-3. Tests are performed with two alternative specifications. In the first specification, we include only constant in the test equation, while another specification includes both constant and trend in the test equation. Results of unit root tests show that output growth is stationary except the DF-GLS test, with constant and trend specification. For, inflation ADF, DF-GLS and Ng and Perron (2001) test results exhibit the presence of unit root opposite to the conclusion of other tests. The result showing the presence of unit root is counter-intuitive as mostly macro-variables like inflation found to be stationary.

Similarly, the KPSS and Ng and Perron (2001) test results for the interest rate show the presence of unit root. However, variation in the results may be due to the presence of structural break(s) in the variables. Perron (1989) pointed that unaccounted breaks in data generation process may reduce power of tests and results may be misleading. Therefore, in presence of structural breaks in the stationary variables, unit root tests not accounting for structural break(s) may incorrectly show non-stationarity property in the variables.

To overcome the above-stated issue, we used Zivot and Andrews (1992) and Lee and Strazicich (2003) unit root tests. Both these tests accommodate the structural breaks in the data generation process. ZA test assumes one break, while LS assumes two structural breaks and in both tests, breaks are endogenously determined.[12] Table 4 reports the results of both ZA and LS unit root tests. The results of both tests for all variables reveal that variables are

Table 2. Unit Root Tests

Tests/ Variables		Growth	Inflation	CMR	Critical Values		
		Test-stat	Test-stat	Test-stat	1%	5%	10%
ADF	C	-3.354	-2.244	-3.505	-3.454	-2.871	-2.572
	C+T	-3.605	-2.283	-3.722	-3.992	-3.426	-3.136
DFGLS	C	-2.554	-0.385	-1.895	-2.573	-1.942	-1.616
	C+T	-2.601	-1.927	-2.964	-3.470	-2.910	-2.606
PP	C	-6.968	-3.143	-6.638	-3.45121	-2.871	-2.572
	C+T	-7.139	-3.382	-7.920	-3.988	-3.424	-3.135
KPSS	C	0.277	0.607	0.860	0.739	0.463	0.347
	C+T	0.169	0.179	0.255	0.216	0.146	0.119

Notes: C and C + T refer two alternative specifications, with constant and with constant and a linear trend in test equations, respectively. ADF is the Augmented Dickey-Fuller test (Dickey and Fuller, 1979), DFGLS is the augmented Dickey-Fuller test (Elliott, Rothenberg, and Stock, 1992) with generalised least squares de-trending, PP is the Phillips-Perron test (Phillips and Perron, 1988) and KPSS is the Kwiatkowski et al. (1992) stationary test. Lag lengths for ADF and DFGLS tests are selected using the Bayesian Information Criterion (BIC). For the PP and KPSS tests, bandwidths are based on Newey-West automatic selection.

5.3. Selection and Estimation of MSVAR Model

We applied a Markov Switching model to take account of regime changes (high and low uncertainty) and structural breaks in the relationship among the study variables. Table 5 reports model selection criteria and estimates of MSVAR. We used the lag order chosen in case of linear VAR that is two ($p = 2$). The number of regimes ($m = 2$)

[12] For limitations of these type of structural break unit root tests, see Narayan and Popp (2010, 2013).

and variance specification may differ for alternative MSVAR specifications. We chose $m = 2$ that is two regimes using Akaike information criterion (AIC) as suggested by Krolzig (1997) and Psaradakis and Spagnolo (2003). We estimate the specified MS(2) VAR model using the Bayesian MCMC method utilising the Gibbs sampling.

Table 3. Ng-Perron Unit Root Tests

Variables/Statistics	Constant			
	MZ_a	MZ_t	MSB	MPT
GIIP	-16.149	-2.802	0.174	1.667
INF	-1.065	-0.563	0.529	16.515
CMR	-3.740	-1.270	0.340	6.609
Level of Sig	Critical Values			
1%	-13.800	-2.580	0.174	1.780
5%	-8.100	-1.980	0.233	3.170
10%	-5.700	-1.620	0.275	4.450
Variables/Statistics	Constant and trend			
	MZ_a	MZ_t	MSB	MPT
GIIP	-16.687	-2.857	0.171	5.656
INF	-7.896	-1.973	0.250	11.582
CMR	-15.772	-2.792	0.177	5.879
Level of Sig	Critical Values			
1%	-23.800	-3.420	0.143	4.030
5%	-17.300	-2.910	0.168	5.480
10%	-14.200	-2.620	0.185	6.670

Notes: The lag length or the bandwidth for the MZα, MZt, MSB and MPT tests are based on the modified Bayesian Information Criterion of Ng-Perron (2001) stationary with structural breaks at different dates.

Table 4. Unit Root Tests with Structural Breaks

Variables	ZA test			LS unit Root test		
	Statistics	P-value	Break Date	Statistics	Break Dates	
GIIP	-4.882	0.004	2005:12	-5.593	1996:03	2006:09
INF	-3.734	0.000	2010:09	-4.391	2003:07	2014:07
CMR	-4.488	0.000	1996:04	-5.536	1996:02	1998:11

Notes: ZA and LS tests are the endogenous structural break unit root tests due to Zivot and Andrews (1992) and Lee and Strazicich (2003) respectively, with breaks in both intercepts and linear trend. For the ZA test, the lag order is selected using BIC. While for the LS test lag length is based on the general to specific approach using a 10% significance level. * and ** denote the level of significance of 1% and 5% respectively.

Table 5. Model selection criteria

	MS(2)-VAR		Linear VAR(1)
Log-Likelihood			-1814.609
AIC criterion	7.810		13.542
BIC criterion	8.369		13.759
HQ criterion	8.031		13.629
log(FPE)	7.812		13.542
Transition Probability	P	**0.922**	**0.086**
		0.078	**0.914**
Regime Properties	Probability	Observations	Duration(Months)
Regime 1	0.722	225	12.84
Regime 2	0.278	87	11.68

5.4. Regime Identification and Properties

First, we discuss the relevance of identified regimes by the MSVAR model employed in the study. The smoothed probability of regime one (Low uncertainty) and regime two (high uncertainty) are shown in Figures 2-3, respectively. In Figure 3, we can observe that high uncertainty regime (regime two) has frequently occurred at the beginning of the study period relative to the later phase. It is also worthy to note that the high uncertainty regime (regime two) coincides with the different crises and shocks observed in the economy. High uncertainty regime observed during 1991-92 coincides with the balance of payment crisis(1991), while the period 1995-97 of regime two coincides with the Asian financial crisis (1997), high inflation due to shortfall in production, large fiscal deficit and monetary expansion during 1994-95. The dot.com bubble (2000) and GFC(2007) also falls in the region observed in high uncertainty regime.

Further, we plot high uncertainty regime (regime two) overlaying on output growth, inflation and interest rates as shown in Figures 4-6 respectively. These figures quite clearly exhibit that our specified model MSVAR identifies two regimes that are of low and high uncertainty based on the volatility and shocks of output growth, or of inflation, or interest rate or all of these. We observe that low uncertainty regime (regime one) and high uncertainty regime (regime two) are associated with high and low output growth, respectively. Thus from the above observations, we may conclude that results suggest two distinct regimes, regime one associated with low uncertainty and high output growth and regime two, associated with high uncertainty and low output growth.

The transition probabilities shown in Table 5 reveal that both regime one and two are persistent. Assuming that, the economy was in regime one at time *t*, the likelihood for the economy to remain in the same regime that is in regime one at time $t + 1$ is 0.922. Similarly, the probability for the economy being in regime two at time $t + 1$, assuming that the economy was in regime two at time t is 0.914. The long-run average probability for the regime one that is low uncertainty and high output growth is 0.722, while for the regime two that is for high uncertainty and low output growth regime is 0.278. Furthermore, low(high) uncertainty high(low) output growth regime found to have a high correlation with expansion(recession) periods (See Bloom, 2014, among others). Also, it is generally accepted that the probability for recessionary periods should be lesser than expansionary periods (Du Plessis, 2006). Our results suggest that on the average expected duration, of the low uncertainty-high output growth regime (regime one) is 12.84 months and 11.68 months for the high uncertainty-low output growth regime (regime two). After identifying the regimes and its appropriateness, we move to discuss the effect of monetary policy contingent on the two different regimes.

5.5. Impulse Response Functions

We analyse the results of our empirical exercise using the regime dependent impulse response function (RDIRF) due to Ehrmann, Ellison, and Valla (2003). Making inference with economic reasoning based on autoregressive coefficients of the MSVAR model is difficult and might be misleading. As the model is essentially an *atheoretical* representation of the dynamic relationship among the endogenous variables. The results of the impulse response shown in Figures 7 are obtained from the MSVAR model specified in equations 1-3. The Figure reports the impulse response with a 95% confidence interval for the response of endogenous variables to the shock given to monetary policy variable that is the interest rate. It is to be noted that, identification of the MSVAR model specified in equations 1-3 is obtained through Cholesky decomposition.

Figure 2. Smoothed probability of low uncertainty regime (Regime 1)

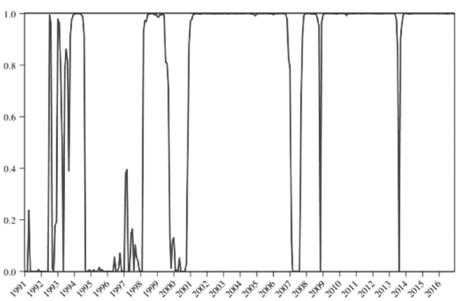


Figure 3. Smoothed probability of high uncertainty regime (Regime 2)

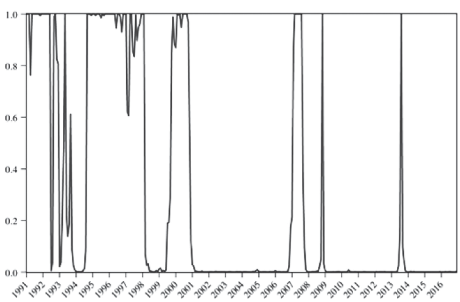


Figure 4. Output Growth and Smoothed Probability of Regime 2

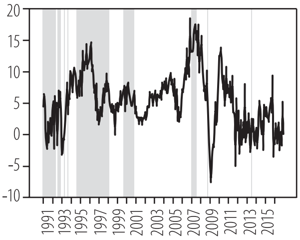


Figure 5. Inflation and Smoothed Probability of Regime 2

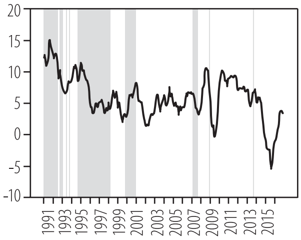
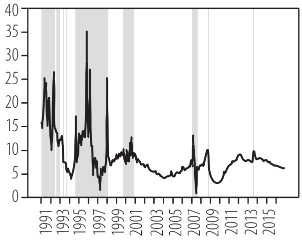


Figure 6. Interest Rate (WCMR) and Smoothed Probability of Regime 2



Orthogonalisation of the original residuals in Cholesky decomposition depends on how the variables of the model are ordered; in result, it also affects impulse response. In the line of monetary policy literature, we order the variables as "Output growth(OG)", "Inflation (INF)" and "Interest Rate(IR)"[13]. As real variables respond with a time lag to the monetary policy shocks, whereas, monetary policy responds contemporaneously to the real sector shocks (Chiu and Hacioglu Hoke, 2016). It is more apt in case of the Indian economy where structural bottlenecks still exist. Results are reported in Figure 7. Figure 7 shows regime dependent impulse response of output growth and inflation to one standard deviation positive shock to interest rate, an indicator of monetary policy over a horizon of 36 months for both low and high uncertainty regimes.

We see that the responses of output growth and inflation facing a positive shock in monetary policy(tight monetary policy) are significant and in line with the conventional economic theory in both regimes. However, in high uncertainty regime, responses are less compared to the responses in low uncertainty regime. Output growth falls by at most by approximately 0.61% in low uncertainty regime, while in high uncertainty regime it falls by at most approximately 0.30%. In both the regimes, however, the effects become zero after about 36 months following the shock.

A similar pattern is observed for the response of inflation following the shock in monetary policy. However, the difference between the peak response of inflation in low and high uncertainty regimes is less than output growth. Inflation falls by at most 0.46 per cent in low uncertainty regime following the shock in monetary policy, while in high uncertainty regime, the peak response of inflation is at most a fall by 0.31 per cent.

[13] As the sensitivity check, we have also exercised with different orders

As a sensitivity analysis, we changed the order of variables to "Output growth(OG)", "Interest Rate(IR)" and "Inflation (INF)". The resultant impulse response function is exhibited in Figure 8. In low uncertainty regime, the decline in output remains the same; however, there is more reduction in uncertain times by 10 percentage points. In the case of inflation, there is more or less the same similar response. However, the difference in responses across the two regimes are significant, and our earlier qualitative conclusion holds. That is, monetary policy is more effective in tranquil times than uncertain times.

The results are in line with the general conclusion that uncertainty dampens the effect of monetary policy (See Bloom, 2014; Aastveit, Natvik, and Sola, 2013; Pellegrino, 2018). The differential response or state-dependent effectiveness of monetary policy could be explained by the proposition of real options value theory (Bloom, 2009; Bloom et al., 2012). The real options effects could be the result of fixed cost and/or partial irreversibility (Pindyck, 1991). During high uncertainty phase, since the real options value of waiting increases, "wait and see" behaviour becomes the norm of firms; as a result firm becomes unresponsive to changes in interest rate (Bloom, 2009; Bloom et al., 2012). On the other hand, in low uncertainty phase, the response will be larger as firms are more reactive to changes in factor prices (Caggiano, Castelnuovo, and Nodari, 2017).

Through the price adjustment mechanism, Vavra (2013) also shows that during high uncertainty period, monetary policy shocks are less effective. Despite price adjustment costs, in high uncertainty phase, firms frequently adjust their prices. This frequent price adjustment results in higher aggregate price flexibility, which reduces the effect of monetary policy shocks.

Moreover, the high correlation between recessionary period and high uncertainty regime also validates the explanation given by Berger and Vavra (2015). Within the partial and general equilibrium models, and focussing on aggregate durable expenditure, authors show that during the recession, macroeconomic policies are less effective.

Overall, our empirical results with the relevant theoretical explanation show that the effect of monetary policy is sensitive to the regime prevailing in the economy.

6. Conclusion and Policy Recommendations

There is a growing body of literature examining the effectiveness of the monetary policy on the macroeconomy in different contexts for developed and developing countries. However, lately, especially after the GFC, the focus of research shifted to examine the role of uncertainty in economic activity and on the monetary policy effectiveness. There are ample empirical studies, which found evidence that uncertainty affects economic activity. Further, several theoretical studies like Bernanke (1983), Dixit and Pindyck (1994), Bloom (2009) and Bloom (2014), Aastveit, Natvik, and Sola (2013), Vavra (2013) suggest that uncertainty does influence the monetary policy effectiveness. Many empirical studies show that heightened uncertainty dampens the effectiveness of the monetary policy. However, until now, empirical studies are restricted to only developed countries.

To this end, the present study examines the influence of uncertainty on monetary policy effectiveness for a developing country namely India using the monthly data on output growth, inflation and interest rate for the period April 1991 to December 2016. We applied a non-linear VAR, which allows us to examine the effect of monetary policy shocks during high and low uncertainty periods. The results exhibit that uncertainty influences the effectiveness of monetary policy shocks. We find weaker effects of the monetary policy shocks during high uncertainty regime relative to low uncertainty regime. More specifically, we find that an increase in interest rate (tight monetary policy) leads to a fall of output growth in high uncertainty regime by about half of the fall in output growth when uncertainty is low. A similar pattern of effects of tight monetary policy is observed for inflation as well. Overall the results are in line with the theoretical propositions that uncertainty dampens the effectiveness of monetary policy shocks.

The findings have a number of relevant policy implications. The policy should be framed to avoid "wait and see" attitude among the agents such as by creating incentives to spend and invest. Incentives may be in the form of tax rates or interest rates. The influence of uncertainty on the effectiveness of monetary policy shocks could also be lessened by implementing more aggressive policies during high uncertainty regime like by reducing the nominal short-term interest rate or resorting to "quantitative easing". Moreover, there should be clear policy communications to reduce systemic risk and hence increase the effectiveness of the monetary policy. Finally, the findings suggest for a state-dependent policy response, that is to implement different policy stances in high and low uncertainty regimes.

Figure 7. Impulse response to interest rate shock

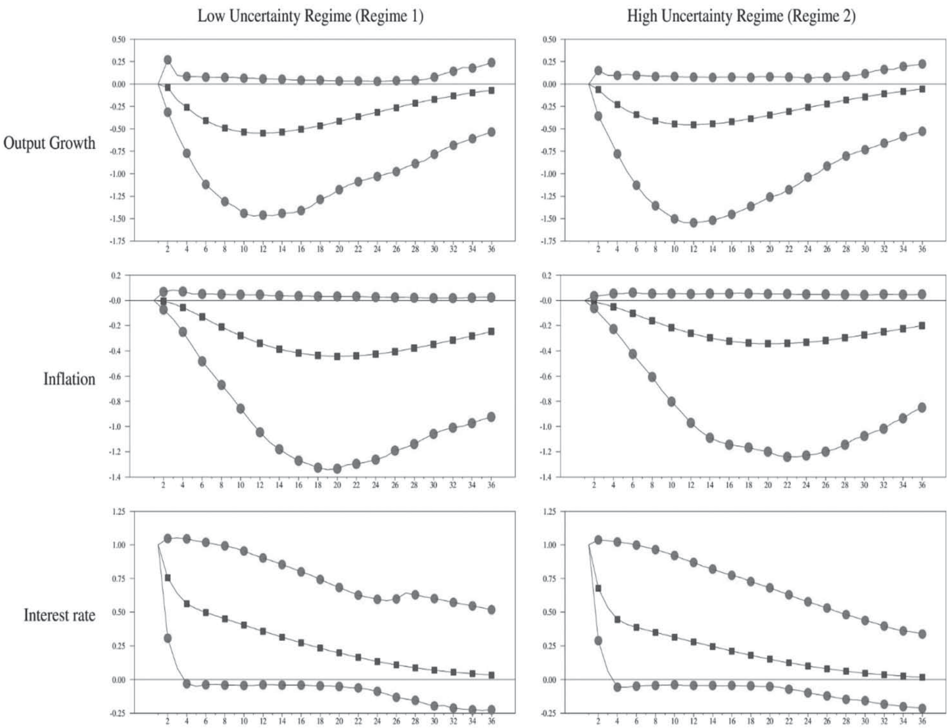
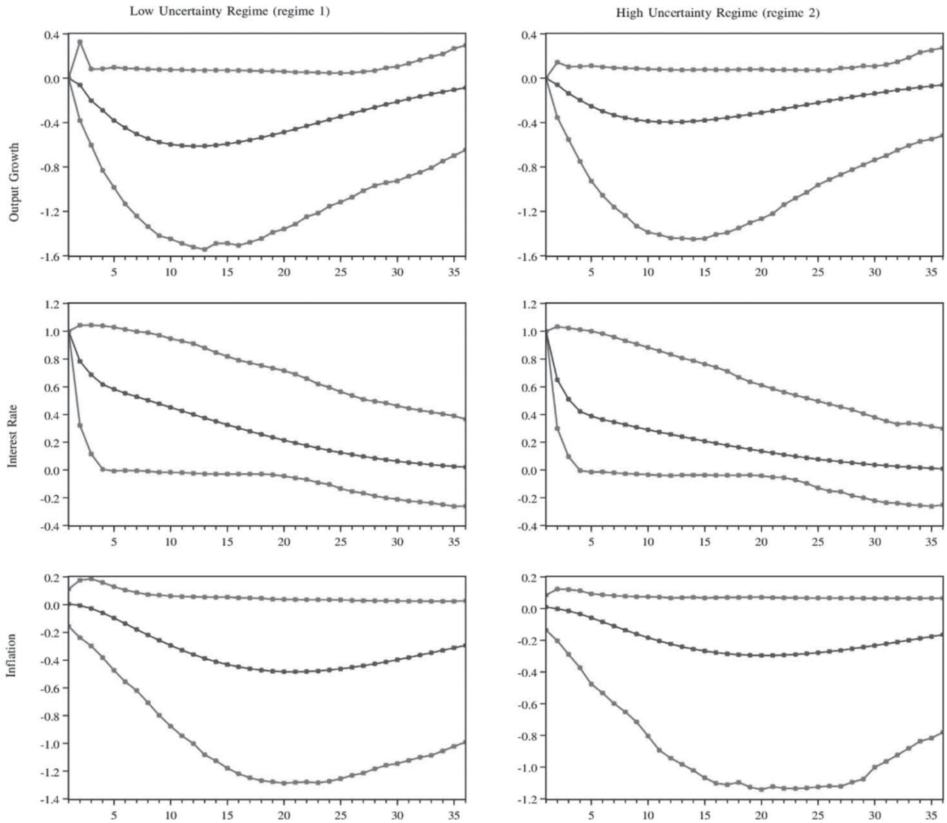


Figure 8. Impulse response to interest rate shock



A. Tables

Table 6. Seasonality Tests

Variables	Tests	Statistics	DF
IIP	BM	139.762*	11
	NT	212.700*	11
	MV	3.358*	24
WPI	BM	49.137*	11
	NT	212.749*	11
	MV	5.479*	24
WCMR	BM	2.12	11
	NT	5.064	11
	MV	1.981	24

Notes: BM refers between months test for the presence of seasonality assuming stability.NT refers non-parametric (Kruskal-Wallis) test of seasonality assuming stability. MV refers moving seasonality test. * indicates significance at 1 % or better.

B. Figures

Figure 9. Output Growth and Smoothed Probability of Regime 1

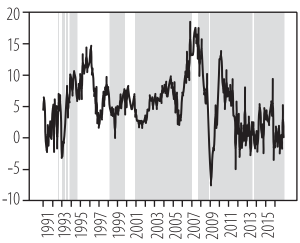


Figure 10. Inflation and Smoothed Probability of Regime 1

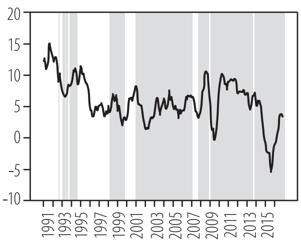
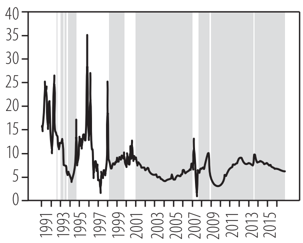


Figure 11. Interest Rate (WCMR) and Smoothed Probability of Regime 1



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