Time-varying Trend Inflation in Large Emerging Economies.

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Abstract

We investigate the importance of time-varying trend inflation in explaining the inflation process in the five largest emerging economies: Brazil, Russia, India, China and South Africa (also known as the BRICS countries) since 1990s. Our analysis is based on a non-centered unobserved components stochastic volatility model of inflation. We decompose inflation into a permanent stochastic trend and a transitory (inflation gap) component. The level and variability of trend inflation shows the dominance of trend component on the inflation process in all these emerging economies except India. Through time-varying volatility of trend shocks, we analyze the monetary regimes in these countries to know whether inflation expectations have been well anchored or not. Using Bayesian model comparison we test whether stochastic volatility is required for modelling inflation in these emerging economies, and we find that stochastic volatility provides a better fit for modelling inflation for these economies.

Keywords : Trend-Inflation Gap Decompositions, Non-Linear State Space Models, Stochastic Volatility, Trend Inflation, Bayesian Estimation.

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Introduction

Modern central banking specifies an important role for inflation expectations with the monetary policy frameworks formulated to anchor inflation expectations. Credibility of central banks and effectiveness of monetary policy is gauged by its ability to anchor inflation expectations. Monetary policy frameworks such as inflation targeting are designed to mainly anchor inflation expectations. Anchoring of inflation expectations plays an even more pertinent role for the central bank of the emerging economies, as they have endured historically double digit inflation rates. Thus a few emerging economies have adopted inflation targeting to anchor inflation expectations much better and hence stabilize their inflation. To understand whether anchoring of inflation expectations have worked in the emerging economies, it is paramount to understand the effectiveness of the monetary policy in these economies. Estimates of the level and variability of trend inflation provides a good understanding of whether inflation expectations have remained anchored or not[1]. Volatility of trend shocks helps to capture the uncertainty in the trend of inflation expectations[2]. Trend inflation also captures the long run target of inflation set by the central bank, and thus any deviation from the target, i.e the inflation gap shows that the targets were not met.

In this paper we provide the estimates of the trend inflation and time-varying volatility of the trend shocks for the five largest emerging economies: Brazil, Russia, India, China and South Africa (also known as the BRICS countries) using a non-centered unobserved components model from 1990 onwards. In the model we decompose inflation into trend (permanent) component and transitory component (inflation gap). We estimate a modified version of an univariate unobserved components model with stochastic volatility for modelling inflation in the BRICS countries[3]. The reason for using univariate model to capture the trend inflation is due to two reasons. The unobserved components stochastic volatility (UC-SV) model has become the benchmark model for capturing the role of the permanent and transitory components for inflation especially after the seminal work of Stock

[1]There are direct measures such as survey measures which also capture inflation expectations and have been found quite useful for policy purposes. But they come in different frequencies and for emerging economies, these sort of surveys and other measures from financial data are not considered that reliable as they show much noise in the data and have measurement errors.

[2]In this model based approach, the permanent or trend component captures the long term inflation expectations. This component is considered to be determined by the behavior of the monetary policy of the central bank.

[3]Stochastic volatility models are widely used in finance to model the volatilities in asset prices. In macroeconomics these have been used to characterize the evolving variances of inflation and real variables.

and Watson (2007). From the autocorrelation functions and the unit root tests, we find that UC-SV model approximates the inflation of the BRICS countries quite well. Secondly, we find better out-of-sample fit of the UC-SV model compared to multivariate benchmark VAR models for the emerging economies in our paper[4]. As shown in Table 3, we find that the root mean square forecast error (RMSFE) for UC-SV model for all the other countries except China was much better compared to two VAR models.

For U.S., Stock and Watson (2007); Atkeson and Ohanion, 2001 and Cecchetti et. al. (2007) have found that univariate models such as UC-SV models capture the inflation process slightly better than multivariate models especially when we compare the forecasting performance. There is also a wide agreement, that the behavior of inflation with respect to its volatility and persistence has changed over time. This has led to modelling the inflation process with time-varying volatility (Cogley and Sargent 2005; Primiceri 2005, Stock and Watson 2007). Stock and Watson (2007) show for U.S inflation, that the variance in the trend shocks are much larger whereas the variance of the transitory shocks have remained constant. This dominance of trend shocks is also shown for G-7 countries by Morley et. al (2015). However (to the best of our knowledge) there is no literature which has investigated the time-varying trend inflation process and the changes in the variance of the trend and transitory shocks for the emerging economies. This paper fills this gap by estimating trend inflation for the BRICS countries.

Our paper undertakes the estimation for the BRICS countries for two important reasons. Firstly, BRICS countries are the largest emerging economies with combined GDP (PPP) of more than 30 trillion dollars. Secondly, most of these countries have adopted inflation targeting as their monetary policy framework from 1990s. One of the main objective of having an inflation targeting framework is to anchor inflation expectations. Through the estimates of the level and variance of the trend inflation for these economies, we can know whether inflation targeting has helped to anchor inflation expectations.

Brazil was one of the early large emerging economies to implement the inflation targeting framework in 1999. China doesn't have an explicit inflation targeting framework, but studies have found that during the years of 1992-2007, Chinese monetary policy framework was following a sort of an "implicit inflation targeting" framework (He and Pauwels 2008). India has recently adopted inflation targeting as its monetary policy framework in 2014, with CPI as the headline inflation to target.

[4]For the BRICS countries we did recursive psuedo out-of-sample forecasting exercise and found that the UC-SV model is a better predictor than multivariate VAR models for all the BRICS countries except China.

Before 2014, monetary policy process in India followed an implicit target range for anchoring inflation expectations. Russia also implemented inflation targeting framework in 2014 and South Africa introduced inflation targeting framework in 2000. Thus the estimation of trend inflation and the volatility of the trend is quite relevant for these emerging economies especially those which are using inflation targeting framework.

The inflation process in these emerging economies has undergone regime changes and also structural breaks were noticed after 1990s (Chang, 2010; John, 2015; Mohanty 2011; Phiri, 2017). These economies have undergone structural reforms in the financial sectors since 1990's. Eric Girardin et al (2017) constructing a monetary policy index for China, found two different regimes before and after 2002. In India, there were multiple monetary policy regimes from 1990 onwards including the multiple indicator approach in the 1990's to Liquidity Adjustment Facility (LAF) introduced in 2000 (Mohanty, 2011; Patra et al. (2014)). In Brazil and South Africa also there was monetary regime changes with the introduction of the inflation targeting regimes. With these regime changes, modelling any inflation or monetary policy process has to adhere to the Lucas critique (1976)[5]. Time invariant models or constant parameter models will be not appropriate for these economies to incorporate either the Lucas critique or to capture the changes across different monetary policy regimes. Thus we use a model with time-varying parameters.

Effectiveness of the inflation targeting framework also requires proper transmission of the monetary policy. Studies have found that monetary policy has been quite effective in the BRICS countries in countering inflation. Especially contractionary monetary policy has been found to stabilize inflation in these countries (Mallick and Sousa, 2012).

We undertake the Bayesian model comparison described in Chan (2018) using a non-centered parameterization of the unobserved components stochastic volatility (UC-SV) model to test whether stochastic volatility is useful in capturing the inflation process in these emerging economies . The inclusion of stochastic trend in the univariate unobserved components stochastic volatility (UC-SV) model of inflation

[5]Lucas Critique(1976) argued that the parameters estimated for a model during one policy regime cannot capture the policy implications in the same way when there is a change in the policy regime. He criticized many of the Phillips curve models of the 1970's, after the inflation-growth relation had become unstable. In terms of econometric analysis it implied, that a constant parameter model cannot capture the changes properly when there are regime changes during the estimation period. Time-varying parameter models have recently become a good way to capture any policy implications with multiple regime changes and the consequent structural changes in the economy. These BRICS countries, during the last three decades have undergone series of changes in their economy and hence time-invariant models may not be appropriate for modelling any macroeconomic process.

is primarily due to the presence of unit root in the inflation process (Stock and Watson 2007). It is difficult to reject the null hypothesis of a unit root in inflation process in most of the countries. We conducted the standard unit roots tests, that is the Augmented Dickey-Fuller (ADF) tests, which confirm the presence of unit root in the inflation process for these economies except for Russia. Table 2 presents the results of the unit root test for consumer price index (CPI) inflation for each country. We cannot reject the null hypothesis of the unit root at the 5 percent level for Brazil, China, India and South Africa but not for Russia. Thus the results confirm the assumptions used in the UC-SV model.

< insert Table 2 here >

We address three important macroeconomic questions in this paper for these emerging economies : (1) Whether the trend shocks or the transitory shocks are the more prominent drivers of the inflation in these five economies (2) Does the monetary policy frameworks in these economies help to anchor inflation expectations or not (3) whether stochastic volatility provides a better fit for modelling inflation in these economies. The model is estimated using a Bayesian framework where we use Markov Chain Monte Carlo (MCMC) methods for simulating the posteriors.

In this paper, we find that trend component plays an important role in driving inflation in the case of Brazil, South Africa and China whereas for India transitory component is more dominant. This could be observed through variance decomposition where the trend shocks for Brazil, China and Russia are more dominant than the transitory shocks, whereas for India transitory shocks are more dominant. For Brazil and South Africa, we observe that inflation targeting seems to anchor inflation expectations but with a lag. In the case of India, much better anchoring of inflation expectations is observed after autonomy of the central bank is established. The results from the Bayesian model comparison using log Bayes factor shows that stochastic volatility is preferred by the data for all these emerging economies for modelling trend inflation.

The rest of the paper is organized in the following manner. Section 2 presents the details of the model description regarding the non-centered unobserved components stochastic volatility model and estimation using Bayesian techniques. Section 3 provides the posterior estimates of the time-varying trend inflation. Section 4 we present the results from the variance decomposition of the trend and transitory shocks to inflation. In section 5 we undertake model comparison to test whether adding stochastic volatility provides a better fit to capture the trend inflation in these economies. Section 6 we conclude.

2. Model Description

We investigate the trend inflation, inflation gap and trend shocks in these economies using a non-centered unobserved components stochastic volatility model (Stock and Watson 2007). Unobserved components stochastic volatility (UC-SV) models have been found to capture important features of the inflation process by decomposing inflation into a trend and transitory components. There is a large literature recently that has studied the behavior of inflation, characterizing the evolving variances of the inflation process and they observe that the persistence and volatility of inflation has changed over time(Cogley and Sargent, 2005; Primiceri 2005; Sims and Zha, 2006 and Stock and Watson, 2007, Cecchetti et al 2007; Chan, Koop and Potter 2013).

We find that the inflation process of these five emerging economies is well approximated by an unobserved component model by checking the first order autocorrelation for the first difference of inflation ($\triangle\pi_t$) as shown in Table 1. If the first-order autocorrelation is negative for the first difference of the inflation process and if there is unit root in inflation which we discussed in the last section, then the inflation process is well approximated by an integrated moving average process ($IMA(1,1)$) process which is equivalent to an unobserved components (UC) model[6].

< insert Table 1 here >

Table 1 shows the first five autocorrelations of $\triangle\pi_t$. The first order autocorrelation is negative for all these economies in the respective sample periods. The first order autocorrelation is statistically significant at 5% level for all the countries except Brazil. Higher order autocorrelations especially after fourth order are statistically insignificant for all the BRICS countries. The negative first order autocorrelation and smaller higher order autocorrelations suggest that the inflation process for the BRICS countries can be well described by an unobserved components model.

2.1 Model Specification

In this section we estimate the trend and inflation gap (cycle) model. The basic model is a version of the unobserved components stochastic volatility (UC-SV)

[6]Stock and Watson (2007) found that UC-SV process captures important features of the inflation process of U.S. Cecchetti et al (2007) show that G-7 countries inflation process can be captured well by UC-SV process.

model of Stock and Watson (2007). We modify the UC-SV model of Stock and Watson (2007) by rewriting it in a non-centered parameterization form (Chan 2018). This modification helps us to test whether stochastic volatility is useful to model the trend and inflation gap for inflation in the BRICS countries . The trend-inflation gap decomposition of inflation in an unobserved component is based on the idea that the non-stationary trend component captures the long term inflation whereas the inflation gap is the transitory component.

$$\pi_t = \tau_t + c_t \tag{1}$$

where π_t is the quarterly inflation rate, τ_t is the inflation trend and c_t is the inflation gap[7]. Trend inflation is modeled as a driftless random walk[8].

$$\tau_t = \tau_{t-1} + \epsilon_t^{\tau} \tag{2}$$

$$c_t = \epsilon_t^{\pi} exp(h_t/2)$$

$$h_t = h_{t-1} + \epsilon_t^{h} \tag{3}$$

and $\epsilon_t^{\tau} \sim N(0, \sigma_{\tau}^2)$, $\epsilon_t \sim N(0, 1)$ and $\epsilon_t^{h} \sim N(0, \sigma_h^2)$

We also capture the changes in the inflation trend at varying rates at different points in times for these economies. For introducing time-varying variance we allow stochastic volatility in the disturbance term of the inflation trend,

$$\epsilon_t^{h} \sim N(0, exp(g_t)$$

$$g_t = g_{t-1} + \epsilon_t^{g} \quad \text{where } \epsilon_t^{g} \sim N(0, \sigma_g^2) \tag{4}$$

The initial conditions τ_0, h_0 and g_0 are treated as unknown parameters.

We have $\sigma_g^2 \sim N(0, V_{\sigma_g^2})$ and $\sigma_h^2 \sim N(0, V_{\sigma_h^2})$.

The UC-SV model is estimated using a Bayesian framework. We use non-centered parameterization of Fruhwirth-Schnatter and Wagner (2010) for estimation of the UC-SV model (Chan 2018). One of the main reasons for using non-centered parameterization is to test whether stochastic volatility is useful for modelling inflation in these economies.

Following Fruhwirth-Scnatter and Wagner(2010) and Chan(2018) , we define the following,

$$\widetilde{\tau} = (\tau_t - \tau_0)/\sigma_\tau \tag{5}$$

$$\widetilde{h} = (h_t - h_0)/\sigma_h \tag{6}$$

Thus using (5) and (6) we can rewrite the UCSV model (1) to (4) in the following way,

$$\pi_t = \tau_0 + \sigma_\tau \widetilde{\tau}_t + e^{1/2(h_0 + \sigma_h \widetilde{h_t})} \epsilon_t^\pi \tag{7}$$

$$\tau_t = \tau_{t-1} + e^{1/2(g_0 + \sigma_g \widetilde{g_t})} \epsilon_t^\tau$$

$$\widetilde{h_t} = \tilde{h}_{t-1} + \epsilon_t^h$$

$$\widetilde{g_t} = \tilde{g}_{t-1} + \epsilon_t^g$$

We have ϵ_t^π, ϵ_t^τ , ϵ_t^h and ϵ_t^g which are *iid* $N(0,1)$, where $\widetilde{h_0}$ and $\widetilde{g_0}$ are set values of zero. We can run this model without considering stochastic volatility with the permanent/trend component and transitory component assigned values of $\sigma_h = 0$ and $\sigma_g = 0$. In the later section we will test whether addition of the stochastic volatility process in the unobserved component model captures the inflation process in these economies.

Morley et al (2015) use the corresponding values as $\omega_g^2 = \omega_h^2 = 0.5$ for G-7 countries whereas Stock and Watson (2007) use $\omega_h^2 = 0.2$ and $\omega_g^2 = 0.2$ for the U.S. economy. We estimated these parameters using a relatively loose prior and we used for the estimation values of $\omega_g^2 = \omega_h^2 = 0.1$ in these economies. But we also did some robustness checks by setting different values for theses hyperparameters. We checked for $\omega_g^2 = \omega_h^2 = 0.2, 0.3, 0.5, 0.05$ but didn't find much change in the results.

2.2 Bayesian Estimation

We estimate our model using these three types of states,

$\tau = (\tau_1, ..., \tau_T)'$;
$\tilde{h} = (\tilde{h}_1, ..., \tilde{h}_T)$
$\tilde{g} = \tilde{g}_1, ..., \tilde{g}_T)$

We initialize the state equations with,

[7] Inflation gap is defined following this property, $lim_{j\to\infty} E_t[c_{t+j}] = 0$ with probability 1

[8] The trend inflation component approximates long horizon forecasts of inflation, which is equivalent to core inflation (Bryan and Cecchetti 1994). Thus we can assume that trend inflation has the following property, $lim_{h\to\infty} E_t[\pi_{t+h}] = E_t[\tau_{t+h}]$ with probability 1.

$$\tau_1 \sim N(\tau_0, V_\tau exp(g_0 + \sigma_g \widetilde{g_1})),$$

$$\widetilde{h_1} \sim N(0, V_h)$$

$$\widetilde{g_1} \sim N(0, V_g).$$

We assume normal priors for σ_h and σ_g , thus we have $\sigma_g \sim N(0, V_{\sigma_g})$ and $\sigma_h \sim N(0, V_{\sigma_h})$.

First we set the values for $V_{\sigma_g} = V_{\sigma_h} = 0.1$. We also assume that $h_0 \sim N(a_{h_0}, b_{h_o})$, $g_0 \sim N(a_{g_0}, b_{g_o})$ and $\tau_o \sim N(a_{\tau_0}, b_{\tau_o})$. We will have following values for, $a_{h_o} = a_{g_0} = a_{\tau_0} = 0$, whereas for $b_{h_0} = b_{g_0} = b_{\tau_0} = 10$.

For sampling of the states, instead of using traditional Kalman filter based methods, we use the more efficient Precision Samplers which is based on band matrix routines. Precision samplers are computationally more efficient as compared to Kalman filter.

We use four block Gibbs sampler for simulating from the joint posterior,

$$(\tau|\ y, \tilde{h}, \tilde{g}, \sigma_h, \sigma_g, \tau_0, h_0, g_0)$$
$$(\tilde{h} \mid y, \tau , \sigma_h , h_0)$$
$$(\tilde{g}|\ y, \tau , \sigma_g , g_0)$$
$$(\tau_0 \mid y, \tau, \tilde{g}, \sigma_g)$$

For sampling of τ we use precision sampler (Chan and Jeliazkov, 2009), to sample $\widetilde{h}$ we use auxiliary mixture sampler. The joint conditional density of the states is nonlinear so we approximate the nonlinear stochastic volatility model using mixture of linear Gaussian models. For estimating the above stochastic volatility nonlinear model we use auxiliary mixture sampler of Kim, Shephard and Chib (1998) [Kroese and Chan (2014)].

3. Data and Empirical Results

The data that we use for estimating the non-centered UC-SV model for all the BRICS countries: Brazil, Russia, India, China and South Africa is CPI inflation. We used CPI inflation only, as CPI is the headline inflation for all these economies. We obtain the quarterly data from Federal Reserve Bank of St. Louis - FRED database. As the data was not seasonally adjusted, we applied the X-12-ARIMA seasonal adjustment filter to each inflation series. The respective time series data that we use for the estimation are based on data availability. We use split-sample results as it helps to understand the changing behavior of inflation accross years. For Brazil, data used is from first quarter of 1994 to second quarter of 2018, for China from first quarter of 1993 to first quarter of 2018, India data used is from first quarter of 1990 to first quarter of 2018, Russia from first quarter of 1992 to fourth quarter of 2018 and for South Africa the data used is from first quarter of 1990 to fourth quarter of 2018. As all the data that were used were quarterly so we transformed the data by using this following standard formula, $y_t = 400ln(z_t/z_{t-1})$. All the results are based on 1,10,000 draws after an initial 10,000 draws were discarded.

As there were outliers is most of the countries, so for proper estimation we Winsorize all the series. For Brazil, China, India and South Africa we set the upper bound at 90th percentile whereas the lower bound was set at 10th percentile. For Russia, due to large outliers, we took the upper bound at 84th percentile and lower bound at 16th percentile.

Inflation in the BRICS Economies

3.1 Trend Estimates

In this section we present the trend estimates and in the next sub-section we present the variance decomposition of the time-varying variance of the trend and transitory shocks. Figure 1 shows the trend (left panel) and transitory (inflation gap) estimates which is shown on the right panel. The solid line shows the CPI inflation whereas the dashed line shows the trend estimates on the left panel. The shaded grey area in the right panel shows the 10 and 90 percent quantiles of the posterior distribution.

The level and variability of trend inflation suggests whether inflation expectations are well anchored or not. We can observe from Figure 1, that the trend component has a better fit for the BRICS economies except India. In UC-SV model, if the trend inflation is exactly moving along with actual inflation, it is consistent with the notion that actual inflation resembled that of a random walk in those years (Mertens 2011). For Brazil, China, Russia and South Africa we observe that most of the changes in inflation is captured by the trend component. For India and Brazil in the years before inflation targeting, we observe persistent deviation of the trend inflation from the actual inflation and hence the transitory component plays an more important role in driving the inflation process compared to the trend component. After 2011, the year when there was a global slowdown due to the Global financial crisis, the transitory component was more persistent especially in Russia and South Africa, with larger inflation gaps. The dominance of the trend component in these economies is similar to U.S and other advanced economies (Stock and Watson 2007;

Garnier et al. 2015; Cecchetti et al. 2007) where also the primary driving force for inflation was trend inflation.

< insert Figure 1 here >

Table 4 presents the trend estimates (median estimates of the posterior distribution of the trend inflation) in four different sample periods. The fluctuations in trend inflation has not been consistent across the BRICS economies. For China and India there is a sharp increase in trend inflation during the period of the recent global financial crisis from 2007Q1 to 2013Q4. Brazil introduced inflation targeting in 1999, and we notice that the trend inflation has reduced in the years after inflation targeting is introduced than before.

< insert Table 4 here >

4. Variance Decomposition of Trend and Transitory Component

Table 5 presents the variance decomposition of the time-varying permanent and transitory component. This is captured by the posterior estimates of the time-varying standard deviation of the trend component σ_g and transitory component σ_h. Figure 2 and Figure 3 displays the posterior estimates of the time-varying trend shocks and transitory shocks respectively. The shaded grey colored area represents 90 percent credible intervals in both the Figures.

Uncertainty in the trend of inflation expectations is captured by the volatility of the trend shocks (σ_g). If the volatility of the trend shocks are high, that shows that inflation expectations are not properly anchored. Whereas, a low volatility of the trend shocks suggests that inflation expectations have been well anchored. Monetary policy is considered credible and effective if the inflation expectation have remained anchored.

< insert Table 5 here >

From Figure 2, we notice a marked reduction in the trend shocks (posterior estimates of the standard deviation of the trend component) for all these economies compared to the early years. Brazil and South Africa were the first countries to introduce inflation targeting. Brazil introduced inflation targeting in 1999 but due to the financial crisis in 2002, inflation targeting regime could be properly implemented only from 2003. From 2003, there is a reduction in volatility of the trend shocks showing that inflation targeting did indeed help to anchor inflation expectations especially after 2003 due to stable inflation targeting regime. In the case of South Africa, which introduced inflation targeting in 2000, we notice sharp reduction in the uncertainty due to trend shocks from 2002 onwards. In 2001, there was a sharp currency depreciation in South Africa of around 37 percent which made monetary policy ineffective till 2002. From 2003 inflation targeting regime was stable and well anchored inflation expectations can be observed after 2003 till the global financial crisis of 2008 which increased the uncertainty of trend shocks.

In the case of China, the inflation expectations are not well anchored till 2011. But after 2011, we observe sharp reduction in the uncertainty of trend shocks and hence better anchored inflation expectations. From 2002 onwards, China adopted anti-inflation monetary policy stance and became much more proactive after the years of 2008 (Girardin et al. 2017). Thus we can notice with better effectiveness of monetary policy from 2011, inflation expectations are much better anchored due to the reduction in the uncertainty in the trend shocks.

< insert Figure 2 here >

India introduced inflation targeting in 2014 but there is not much anchoring of inflation expectations we notice till 2018. Rather we observe from 1997, a noticeable lowering of the uncertainty of trend inflation for India. This perhaps was the outcome of the central bank of India gaining its autonomy from the government. Before 1997, one of main functions of the central bank of India was automatic monetisation of India's fiscal deficit and thus inflation stabilization was not a priority. With substantial independence of the central bank in India from 1997, we notice considerable lowering of the volatility of trend shocks, and hence better anchoring of inflation expectations. For Russia, inflation expectations are not well anchored till 2015. Only after 2015, we notice reduction in the uncertainty of trend shocks.

From Figure 3, captures the transitory shocks for these economies. In China, we observe highly persistent transitory shocks due to high fluctuations in the uncertainty of the transitory shocks. For India and South Africa, after 2010 we can observe increase in the uncertainty of transitory shocks. For Brazil, around 2002 when it faced a financial crisis, there is increase in the uncertainty of transitory shocks. For Russia, there is not much persistence compared to the other economies.

From the third column of Table 5, we can observe the ratios of trend shocks to transitory shocks. A ratio greater than one shows the dominance of trend shocks in the inflation process, whereas a ratio less than 1 shows the dominance of transitory shocks on the inflation process. For Brazil, Russia and South Africa, we notice a complete dominance of trend shocks in the all the four split sample years. Whereas for China we notice that trend shocks had the dominant influence on the inflation process till 2013, but after from 2014 transitory shocks are more dominant. In the case of India, we clearly observe that transitory shocks have been dominating the inflation process for the all the four sample periods. Hence for India, dominance of transitory shocks show the ineffectiveness of the monetary policy compared to other BRICS economies.

Significant time-variation can be observed in both the trend and transitory shocks. From Figure 2 we observe much more time-variation in the volatility of trend shocks for Brazil, China and South Africa. For India and Russia, there is much less time variation in the trend component. From Figure 3 we observe more time-variation in the volatility of transitory shocks of China and India. Not much of time-variation is noticed in the volatility of transitory shocks for Brazil and South Africa. Overall we find that there is time variation in the trend component or transitory component for these economies. There is not a single country for which time-variation is not noticed. The credible intervals are much wider for the estimates for China and Brazil which may imply more uncertainty in the estimates.

< insert Figure 3 here >

5. Model Comparison

In this section we undertake bayesian model comparison to understand whether the data matches a model with stochastic volatility for modelling trend inflation or without stochastic volatility in these five large emerging economies. Model comparison in Bayesian setting is be conducted by a widely used criterion such as the Bayes factor, where in Model 1 we may not include stochastic volatility or in other words it's a constant variance model ($h_0 = h_1 = ... = h_T$) which is then compared with another Model 2 which has stochastic volatility.

Bayes factor is written as $BF_{12} = \frac{p(y|Model\ 1)}{p(y|Model\ 2)}$, where $p(y|Model\ 1)$ is the marginal likelihood for model 1 and denominator is the marginal likelihood for model 2. If the BF_{12} has a value greater than one, then model 1 is considered the better model given the data. Bayes factor requires us to estimate the marginal likelihood of both the models for comparing it . Estimation of the marginal likelihood of the models with time-varying parameters and stochastic volatility estimation is not a trivial task. We use a method proposed by Chan(2018) using non-centered parameterization for state space models for evaluating the in-sample fit and to test whether stochastic volatility is required for modelling trend inflation in these countries. Chan(2018) uses non-centered parameterization to overcome issues related to usage of error variances and instead uses standard deviation for constructing the Bayes factor[9].

< insert Table 7 here >

Chan (2018) constructs the Bayes factor using Savage-Dickey density ratio $p(\sigma_h = 0)/p(\sigma_h = 0|y)$ in favor of stochastic volatility model comparing against the constant variance model. Savage-Dickey density ratio in the non-centered parameterized approach becomes a nested model when $p(\sigma_h = 0)$ is shown as the restricted version of $p(\sigma_h = 0|y)$ with $\sigma_h = 0$. Where $p(\sigma_h = 0)$ is the marginal prior density of σ_h estimated at zero and $p(\sigma_h = 0|y)$ is the marginal posterior evaluated at zero. Following Chan (2018), we approximate $p(\sigma_h = 0|y)$ using Monte Carlo estimator. The results of the model comparison are shown in Table 7.

< insert Figure 4 and Figure 5 here >

Figure 4 and Figure 5 shows the posterior and prior densities of σ_h and σ_g. The symmetry of the posterior density can be observed as the sign of both σ_h and σ_g is not identified. If the posterior density is bimodal with little mass around zero then the Bayes factor is large and model with stochastic volatility is preferred. This can be understood by the construction of our Bayes factor which is in favor of the unrestricted model against the restricted model where σ_g or σ_h = 0. The posterior density for σ_g is bimodal for all the BRICS countries and Brazil, China, Russia and South Africa also have posterior densities with little mass around 0 suggesting the importance of stochastic volatility for modelling trend inflation. The posterior density of σ_h for India is only bimodal with little mass around zero whereas for the other countries it's unimodal.

We formally test to know whether stochastic volatility is required in modelling inflation by constructing Bayes factor as discussed earlier using Savage-Dickey density ratio (Chan 2018). If the Bayes factor is positive, then we can infer that stochastic volatility is preferred as the Bayes factor is constructed in support of the unrestricted model against the restricted model.

[9]The conventional inverse-gamma prior for σ_τ^2 has zero density at zero values. So following Chan(2016) we use non-centered parameterization and work with the standard deviation σ_τ that is defined to have its support on whole real line. Following Kroese and Chan (2014) by some change of variable we can show that prior of σ and σ_h^2 is gamma. Compared to conventional inverse gamma prior for shock variances, this gamma prior has more mass concentrated around small values and it also facilitates in computation.

< insert Table 6 here >

Table 7 presents the results of the log Bayes factor for three set of specifications. $logBF_{trend}$ represents log Bayes factor for the trend component, $logBF_{transitory}$ represents log Bayes factor for the transitory component and $logBF_{trend/transitory}$ represents the log Bayes factor in favor of having stochastic volatility processes against the restricted version without any stochastic volatility. $logBF_{trend/transitory}$ for all the countries are positive and large suggesting that at-least one stochastic volatility is preferred by the data while modelling inflation in the BRICS countries[10]. More specifically, we can observe that $logBF_{trend}$ which represents the log Bayes factor for the trend component favors stochastic volatility for all the countries. In the case of $logBF_{transitory}$ we find that Brazil has negative value which suggests that the data prefers not to have stochastic volatility for the transitory component but we find that log Bayes factor with transitory component is positive for China, India, Russia and South Africa which supports that stochastic volatility is preferred. So overwhelmingly the results from the log Bayes factor shows that stochastic volatility is preferred by the data for all these BRICS countries for modelling trend inflation.

Table 6 presents the posterior means of σ_g and σ_h . The estimated posterior means of σ_g for Brazil, India, Russia and South Africa are less than 0.2 whereas for China is around 0.33. Posterior means of σ_h are greater for India and Russia compared to σ_g. For estimation we have used values of 0.1 for both σ_g and σ_h. There was not much change in values using different values.

Conclusions

In this paper we estimate a non-centered univariate unobserved components stochastic volatility model for the five largest emerging economies from 1990 onwards. We focus on understanding the relative importance of trend inflation and inflation gap (transitory component) for influencing the variation in the actual CPI inflation for the BRICS economies.

We address three important macroeconomic questions in this paper for these emerging economies : (1) Whether the trend shocks or the transitory shocks are the more prominent drivers of the inflation in these five economies (2) Does the monetary policy frameworks in these economies help to anchor inflation expectations (3) whether stochastic volatility provides a better fit for modelling inflation in these economies.

[10]Numerical standard errors were significant for all the countries

For the first question we find that the trend component was the main driver for inflation in the case of Brazil, China, Russia and South Africa. For India, however we find that there is a persistent deviation of the trend inflation from the actual inflation, showing the importance of inflation gap (transitory component) in capturing the inflation process much better as compared to the trend component. For Brazil, Russia and South Africa, we notice a complete dominance of trend shocks in the all the four split sample years. Whereas for China we notice that trend shocks had the dominant influence on the inflation process till 2013, but after from 2014 transitory shocks are more dominant. In the case of India, we clearly observe that transitory shocks have been dominating the inflation process for the all the four sample periods.

For the second question, we find that Inflation targeting regimes for Brazil and South Africa were mostly effective in stabilizing inflation and hence anchoring of their inflation expectations due to the dominance of the trend shocks in their inflation process. In the case of India, where transitory shocks have the dominant influence on the inflation process, we find that monetary policy has been ineffective in anchoring inflation expectations in the inflation targeting years. For China, after 2011once the monetary policy becomes more independent, with anti-inflationary stance we notice better anchoring of inflation expectations . For Russia, inflation expectations are not well anchored till 2015. Only after 2015, we notice reduction in the uncertainty of trend shocks.

Finally regarding the third question whether to include stochastic volatility in modelling trend inflation, we observe that the log Bayes factor for the trend component favors stochastic volatility for each of the countries whereas we find that log Bayes factor with transitory component is positive for China, India, Russia and South Africa which supports that stochastic volatility is preferred. So overwhelmingly the results from the log Bayes factor show that stochastic volatility provides a better fit for the data for the BRICS economies for modelling trend inflation.

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Table 1: Autocorrelation of $\triangle\pi_t$

Lags	Brazil	Russia	India	China	South Africa
1	-0.09	**-0.22**	**-0.39**	**-0.34**	**-0.19**
2	**-0.19**	**-0.24**	0.13	0.15	**-0.24**
3	0.00	**0.21**	0.14	-0.01	0.04
4	-0.01	**-0.26**	**-0.18**	**-0.19**	-0.01
5	0.01	0.04	-0.01	0.01	-0.14

Note : Bold entries are statistically significant at the 5% significance levels using Bartlett standard errors.

Table 2: Augmented Dickey–Fuller tests

Country	CPI Inflation
Brazil	0.67
Russia	0.01
India	0.82
China	0.83
South Africa	0.34

Note: The table contains the MacKinnon p-values for the ADF tests for a unit root for CPI inflation. We selected the lag lengths based on Akaike Information Criterion(AIC) with a maximum lags of 12 quarters. The ADF test regression included an intercept for all the BRICS countries.

Table 3: Forecast Evaluation

Country	RW	AR(1)	AR(2)	AR(3)	AR(4)	VAR(3)	VAR(2)	UCSV
Brazil	1	0.79	0.74	0.80	0.80	6.07	1.26	0.82
China	1	0.93	0.95	0.96	0.92	0.93	0.80	1.01
India	1	0.83	0.79	0.83	0.84	1.2	1.14	0.66
Russia	1	1.37	2.19	1.90	2.32	4.61	4.40	1.06
South Africa	1	0.91	0.96	1.02	1.05	1.51	1.26	0.97

Note: Entries in the table are RMSFEs, relative to Random Walk (RW) forecasts.

Table 4: Trend Estimates

Country	1994Q1 -1998Q4	1999Q1 - 2006Q4	2007Q1 - 2013Q4	2014Q1 - 2018Q4
Brazil	6.86	6.48	5.18	6.15
China	6.28	1.04	3.05	1.85
India	5.62	4.46	8.59	4.73
Russia	14.58	12.16	7.72	5.55
South Africa	11.28	5.71	4.97	5.31

Note : The table contains the median of the posterior distribution of the trend inflation for four different periods.

Table 5: Variance Decomposition

Country	1994Q1 -1998Q4	1999Q1 - 2006Q4	2007Q1 - 2013Q4	2014Q1 - 2018Q4
		Median of σ_g		
Brazil	1.61	1.79	1.32	1.49
China	1.27	1.30	1.73	0.32
India	1.73	0.78	0.79	0.76
Russia	2.65	1.97	2.54	0.18
South Africa	2.27	2.73	1.66	0.68
		Median of σ_h		
Brazil	0.79	1.52	0.69	0.66
China	0.42	0.61	0.73	0.90
India	3.02	2.24	2.68	2.69
Russia	0.62	0.66	0.31	0.04
South Africa	0.57	0.56	0.47	1.28
		Ratio of $\frac{\sigma_g}{\sigma_h}$		
Brazil	2.08	1.20	1.88	2.25
China	3.04	2.28	2.41	0.36
India	0.34	0.36	0.28	0.29
Russia	4.22	2.94	7.91	3.88
South Africa	3.99	4.88	3.53	0.54

Note: We used different values for both the hyperparameters but there was not much change in the results.

Table 6: Posterior means and posterior standard errors of σ_g and σ_h

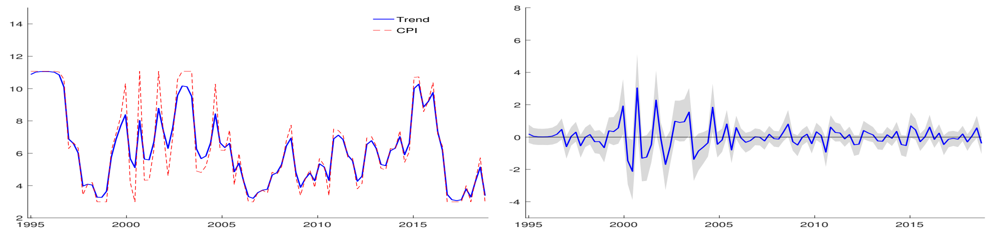
	σ_g	σ_h
Brazil	0.17 (0.11)	0.07 (0.10)
China	0.33 (0.18)	0.16 (0.20)
India	0.10 (0.11)	0.16 (0.09)
Russia	0.15 (0.15)	0.52 (0.35)
South Africa	0.16 (0.12)	0.10 (0.11)

Note : The posterior standard errors are in the parentheses.

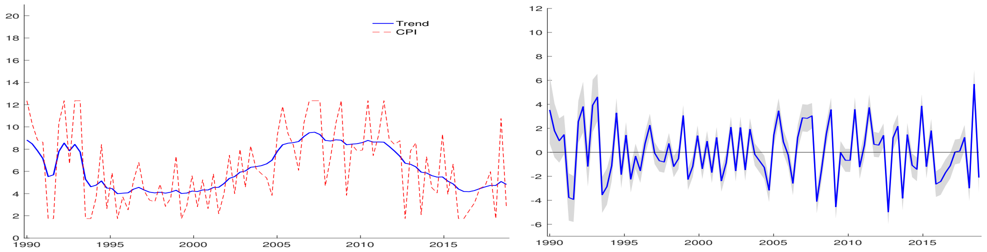
Table 7: Model Comparison

	Brazil	China	India	Russia	South Africa
$log\ BF_{trend}$	5.7	41.7	1.4	3.0	4.8
$log\ BF_{transitory}$	- 0.4	0.6	4.0	2.6	0.4
$log\ BF_{trend/transitory}$	40.5	53.5	18.7	40.2	11.0

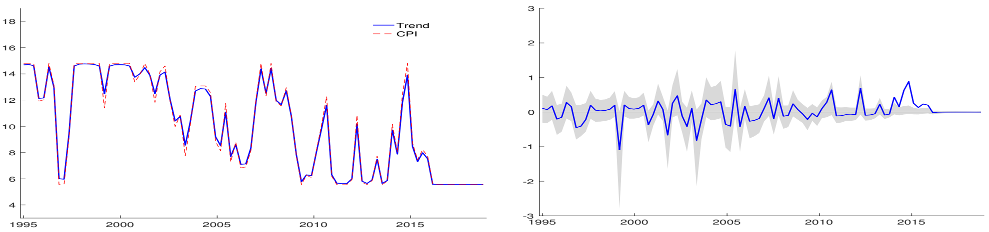
Note : $log\ BF_{trend}$ denoted the log Bayes factors for the trend component whereas $logBF_{transitory}$ is the log Bayes factor for the transitory component. From these Bayes factors we test whether to have stochastic volatility in the trend and transitory component. $log\ BF_{trend/transitory}$ is the Bayes factor comparing in favor of having both stochastic volatility processes against the restricted version without any stochastic volatility.



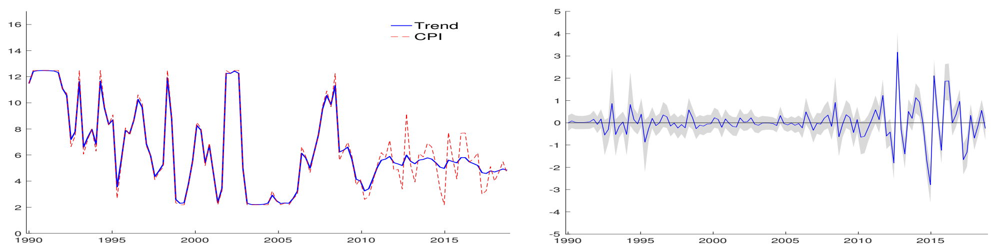
(a) Brazil



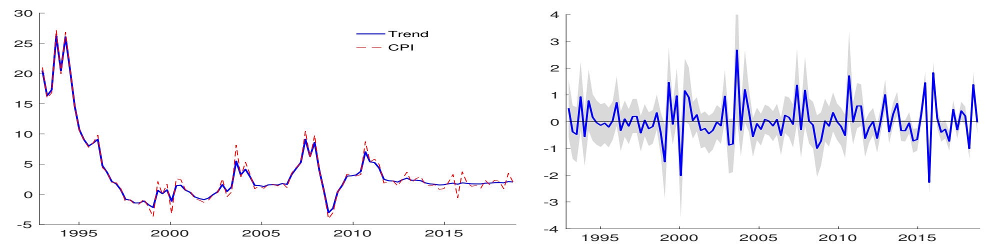
(b) India



(c) Russia

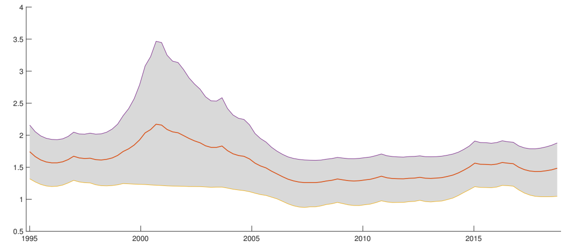


(d) South Africa

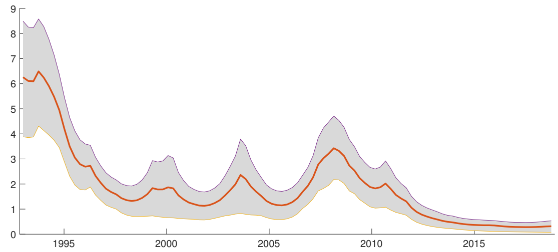


(e) China

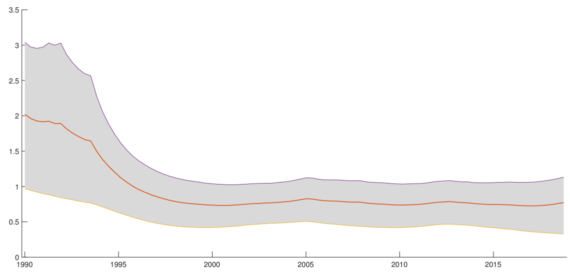
Figure 1 : Estimates of the inflation and estimated trend inflation (left panel) and transitory/inflation gap component. The inflation is measured using CPI, and the trend inflation estimates are the median of the posterior distribution. The transitory component is the inflation gap measured by taking the difference of CPI inflation with trend estimates. The shaded region represents the 10% and 90% quantiles of the posterior distribution.



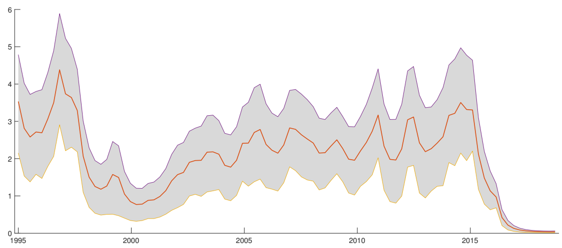
(f) Brazil



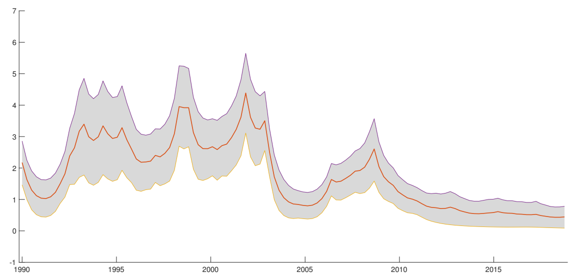
(g) China



(h) India

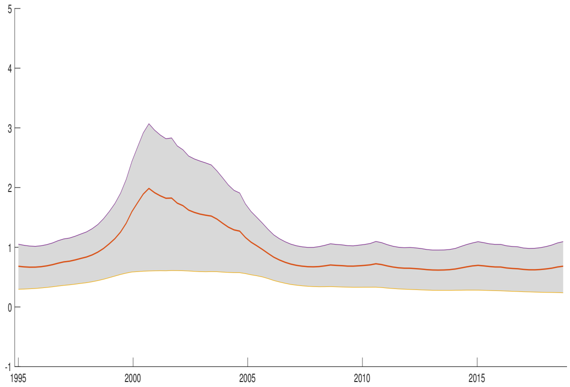


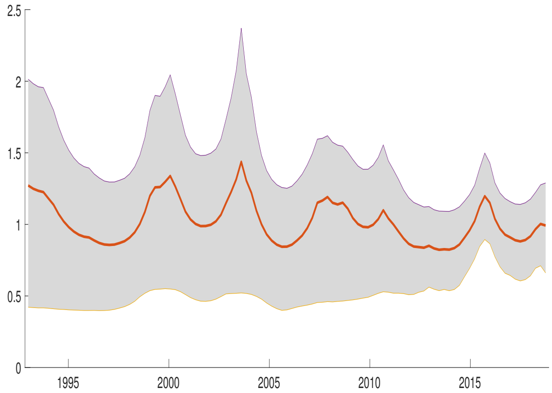
(i) Russia



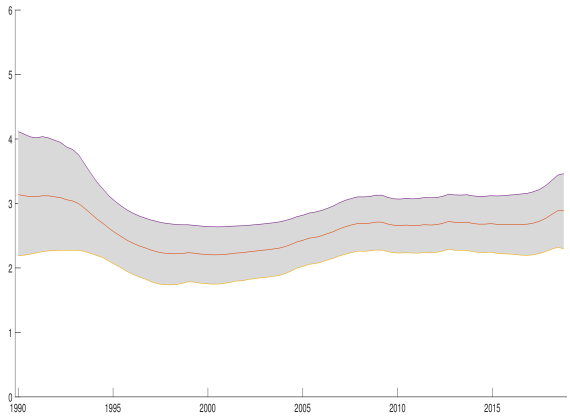
(j) South Africa

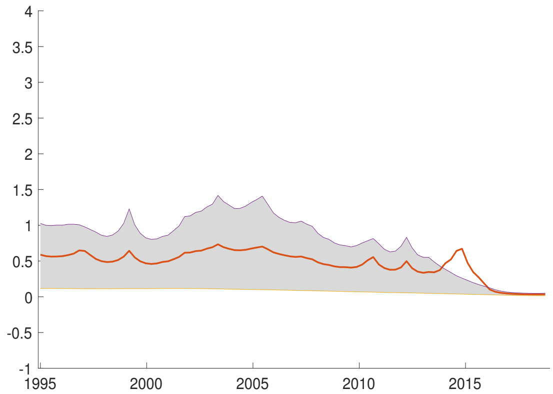
Figure 2: Posterior estimates of the time-varying permanent shocks. The shaded regions represents 90% credible intervals.



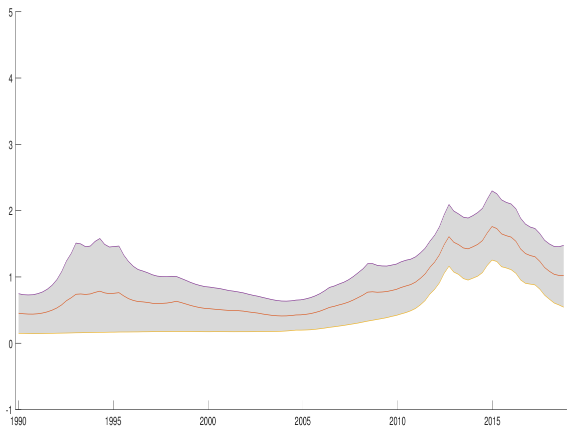


(k) Brazil China



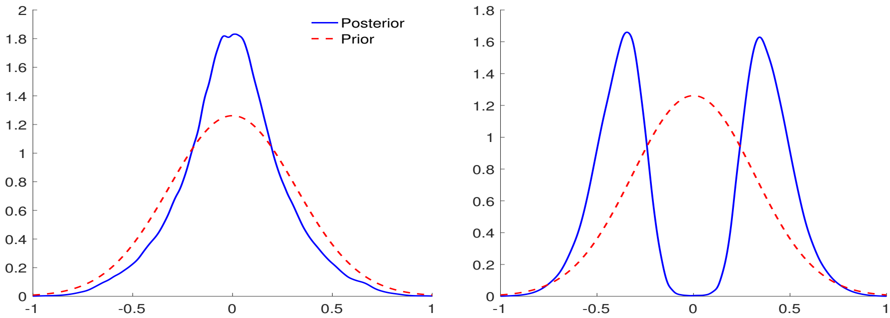


(l) India Russia

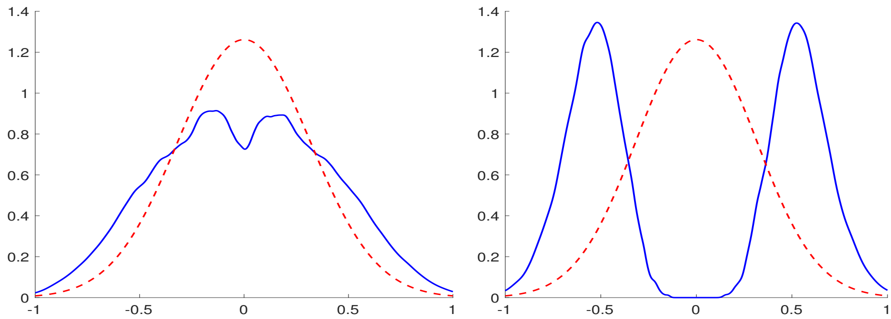


(m) South Africa

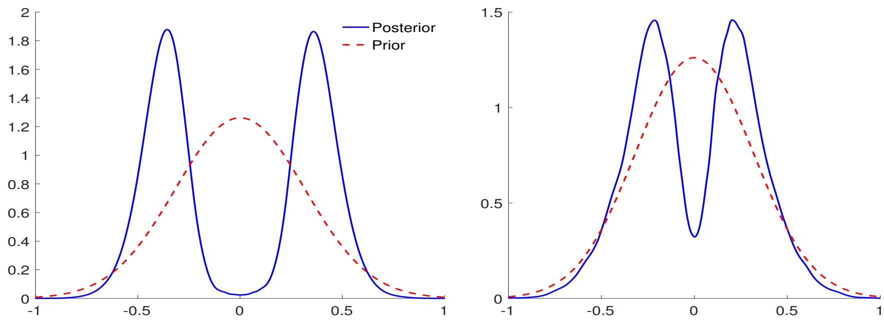
Figure 3: Posterior estimates of the time-varying transitory shocks. The shaded regions represents 90% credible intervals.



(n) Brazil : Prior and Posterior densities of σ_h (left) and $\sigma_g(right)$

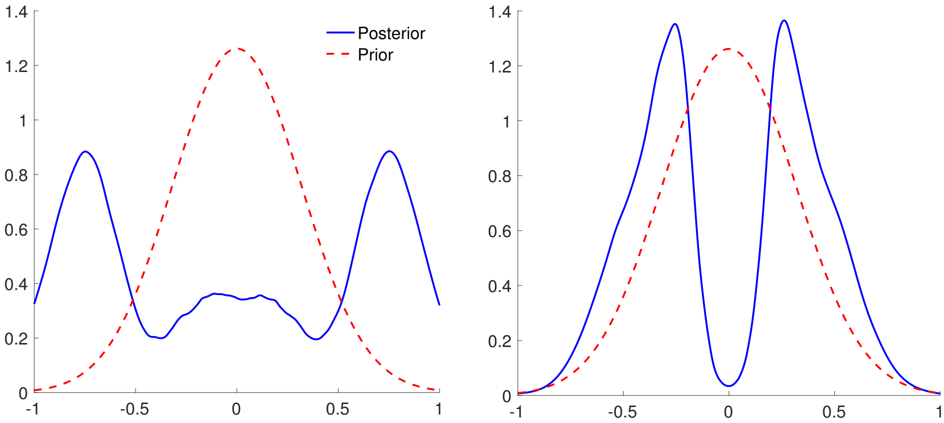


(o) China : Prior and Posterior densities of σ_h (left) and $\sigma_g(right)$

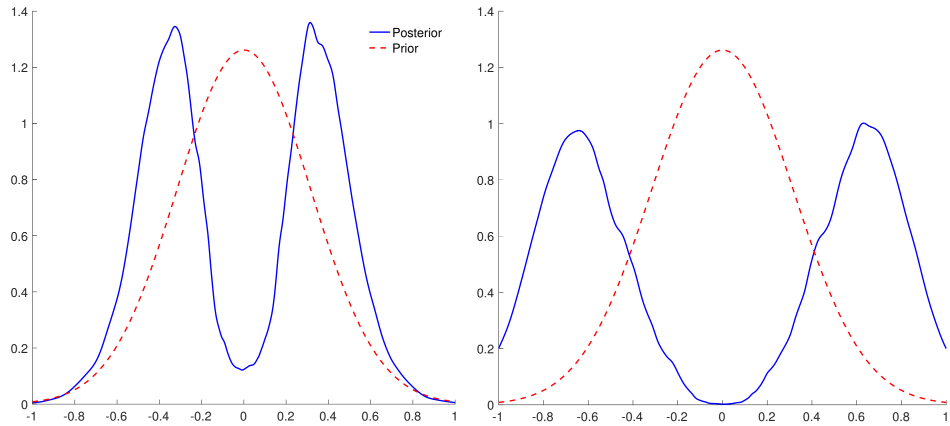


(p) India : Prior and Posterior densities of σ_h (left) and $\sigma_g(right)$

Figure 4: The prior and posterior densities are shown of σ_h (left) and $\sigma_g(right)$



(q) Russia : Prior and Posterior densities of σ_h (left) and $\sigma_g(right)$



(r) South Africa : Prior and Posterior densities of σ_h (left) and $\sigma_g(right)$

Figure 5: The prior and posterior densities are shown of σ_h (left) and $\sigma_g(right)$