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Inflation targeting and the changing transmission mechanism of monetary policy in India☆

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ABSTRACT

We examine shifts in the conduct of monetary policy in India, before and after the adoption of inflation targeting (IT), while also accounting for the impact of COVID-19. Unlike existing studies that pre-date COVID-19, we employ a unified framework using a time-varying BVAR model with data spanning 1998 to 2024. We find that, prior to IT, contractionary monetary policy had a limited impact on inflation with presence of a price puzzle. In contrast, the IT period exhibits improved monetary policy transmission, with policy shocks exerting a stronger influence on inflation with the price puzzle disappearing, reflecting enhanced policy credibility. However, this effect weakens during the COVID-19 years. Interestingly, monetary policy had greater influence on the output gap and exchange rate in the pre-IT period, with diminished effects during IT and COVID-19 period. These findings underscore the effectiveness of inflation targeting in improving the transmission of monetary policy in India, though it shows limitations during COVID-19.

1. Introduction

Expansionary monetary policy was a key tool deployed by central banks to counter the economic disruption caused by COVID-19. However, this pandemic-era shift towards a more accommodative monetary policy stance challenged the credibility of established frameworks, such as inflation targeting (Coleman and Nautz, 2023). In many advanced economies, this shift led to de-anchoring of inflation expectations (Cecchetti et al., 2021; Galati et al., 2023). While numerous studies have investigated monetary policy across regimes in advanced economies using nonlinear frameworks (Belongia and Ireland, 2016; Canova and Gambetti, 2009; Creel and Hubert, 2015), but much of this literature predates the COVID-19 pandemic. Moreover, there are fundamental differences in how advanced and emerging economies conducted monetary policy during the COVID-19 pandemic (Serletis and Dery, 2025).

While a few studies have examined monetary policy in emerging economies during the COVID-19 period, primarily focusing on whether inflation expectations have remained anchored (Robitaille et al., 2024; Mishkin and Kiley, 2025). The broader literature on inflation targeting (IT) versus alternative monetary regimes for emerging economies, has concentrated on outcomes such as inflation volatility, exchange rate pass-through, output fluctuations, fiscal discipline, and private investment (Minea and Tapsoba, 2014; López-Villavicencio and Pourroy, 2019; Fratzscher et al., 2020; Bambe, 2023). However, to the best of our knowledge, no study has systematically examined how central banks in emerging economies recalibrate their monetary reaction functions across different regimes. Specifically, it remains unclear whether they adjust the intensity of their systematic responses to inflation, output, and the exchange rate, or whether they deviate from their policy mandates. Importantly, most existing studies exclude the COVID-19 period from their analysis. This omission represents a critical gap in the literature.

This paper addresses this key gap in the literature by analyzing the conduct of monetary policy in a large emerging economy, India, within a unified non-linear framework using time-varying Bayesian structural VAR model with stochastic volatility (TVP-BVAR-SV). It examines three distinct policy regimes: the pre-inflation targeting years (1998–2015), the inflation targeting regime (2016 onward) and the COVID-19 era (2020–2024). Building on the interest rate rule literature, particularly the Taylor (1993) rule, the analysis incorporates time-varying parameters to capture the central bank's evolving response to inflation, the output gap, and the exchange rate. While influential studies (Boivin, 2006; Kim and Nelson, 2006; Canova and Gambetti, 2009; Liu and Morley, 2014; Belongia and Ireland, 2016) have employed similar approaches, they focus exclusively on advanced economies and do not account for the impact of the COVID-19 shock on monetary policy reaction functions.

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This paper also contributes to the literature on the monetary policy transmission mechanism in India, by examining structural shifts and policy framework changes from 1998 to 2024. During this period, India moved to multiple regimes. From 1985 to 1998, the central bank (Reserve Bank of India) followed a monetary targeting regime with feedback. This was replaced by the Multiple Indicator Approach (MIA) from 1998 to 2015. Since 2016, India has adopted an inflation targeting framework.[1] Each regime employed different instruments and pursued distinct objectives, implying that the transmission mechanism has evolved across these periods and resulting in variations in the coefficients of the models used by both the central bank and private agents.[2] A substantial body of research has explored India's monetary policy transmission, but their findings remain mixed. Studies employing constant-coefficient VAR frameworks during the pre-IT period typically find that monetary policy exerts a muted or statistically insignificant effect on inflation (Mallick and Sousa, 2012; Mishra et al., 2016). Many of these studies document a "price puzzle" whereby a surprise tightening of monetary policy is paradoxically followed by rising prices (Aleem, 2010; Mishra et al., 2016; Khundrakpam and Jain, 2012). However, these studies do not capture regime shifts, particularly the transition from the MIA to inflation targeting. While Kumar and Dash (2020) incorporate time-varying dynamics, but their analysis is limited to the pre-COVID period, and the robustness of their results is unclear due to the absence of confidence intervals for the IRFs. Moreover to capture the effects of COVID-19, we require a model that can accommodate significant shifts in the variance of macroeconomic shocks from March 2020 onward (Lenza and Primiceri, 2022). The time-varying variance–covariance matrix used in this paper, effectively captures these dynamic changes. We advance this literature by examining transmission dynamics across the MIA, inflation-targeting (IT), and COVID-19 periods within a unified nonlinear framework, bolstered by extensive robustness checks and model comparison.

The main findings of this paper are as follows. In the pre-inflation-targeting (pre-IT) era, our analysis uncovers a pronounced price puzzle alongside elevated volatility in the real effective exchange rate, monetary policy and the output gap. Common explanations for the price puzzle include misidentification of policy shocks or misspecification of the monetary rule (Sims, 1992; Ramey, 2016) or a deeper credibility deficit arising from unanchored inflation expectations (Hanson, 2004). However, for India, our robustness checks (see Section 6.2) rule out misspecification, and instead indicate to lower monetary policy credibility in the pre-IT era.

We also find that the price puzzle disappears after the adoption of inflation targeting in 2016, consistent with Florio (2018), who links its disappearance in the EU to more active monetary policy and better-anchored expectations. Also the volatility of the exchange rate, monetary policy and output gap declined sharply, reflecting a marked increase in the Reserve Bank of India's credibility. Variance decompositions reveal that, under inflation targeting, monetary policy shocks explain a substantially larger share of inflation variability, suggesting a more prominent role for systematic monetary policy in shaping inflation dynamics. This parallels the U.S. experience during the Great Moderation (1985–2000), when contribution of monetary policy shocks to inflation variance was markedly greater than in the high-volatility, low-credibility era of the 1970s (Canova and Gambetti, 2009).

During the COVID-19 era, we find that the Reserve Bank of India shifted its emphasis marginally toward exchange-rate management and output stabilization. As a result, the direct impact of monetary policy shocks on inflation weakened. Notably, contractionary monetary policy shocks in this period induced a sharp decline in the output gap that persisted for three quarters. Collectively, these results demonstrate that inflation targeting in India has substantially improved the effectiveness and credibility of monetary policy relative to the earlier regime.

The structure of the paper is as follows: Section 2 outlines the methodology and identification strategy, while Section 3 presents the data, prior assumptions, and estimation details of the model. Section 4 provides the results of the Bayesian model comparison, and Section 5 discusses the main findings. Section 6 includes three robustness checks and sensitivity analyses, and Section 7 concludes the paper

2. Methodology

The empirical literature on the monetary transmission mechanism largely relies on structural vector autoregression (SVAR) models, which are considered parsimonious and offer a direct approach for identifying monetary policy shocks. However, for comparing multiple regimes and capturing the numerous structural changes that have occurred in India from 1997 to 2024, traditional SVAR models with constant coefficients and homoscedastic innovations are inadequate. In Section 4, we compare various models applied to the data in this study and find that the fit of the standard VAR model is notably poor.

The model must account for potential non-linearities in the simultaneous relationships among the variables and accommodate any changes in the lag structure. To effectively capture significant shocks, such as the COVID-19 pandemic, the model should accommodate variations in the scale of exogenous shocks across different regimes. This can be achieved by constructing a heteroscedastic variance–covariance matrix for the errors. To incorporate these features, we employ a time-varying parameter structural VAR model with stochastic volatility (TVP-VAR-SV), which is estimated using Bayesian methods (Primiceri, 2005; Koop and Korobilis, 2010).[3] The TVP-VAR-SV model offers several advantages for comparing different monetary regimes. It captures shifts in the transmission mechanism of monetary policy over time through time-varying coefficients. Additionally, the heteroscedastic variance–covariance matrix allows the model to account for exogenous shocks, such as the COVID-19 crisis. Crucially, the model enables the data to reveal whether the observed time variations arise from changes in the magnitude of shocks or from alterations in the propagation mechanism.

2.1. Time varying parameter VAR with stochastic volatility

The TVP-BVAR with SV is defined as,

$$y_t = c_t + B_{1,t} y_{t-1} + \cdots . + B_{p,t} y_{t-p} + \delta_{1,t} z_t + \cdots + \delta_{q,t} z_{t-p} + u_t \tag{1}$$

where p and q are the lags of the endogenous and exogenous variables respectively. y_t and c_t are vector of $n \times 1$ endogenous variables and intercepts respectively, whereas z_t is a vector of $k \times 1$ exogenous variables. $B_{i,t}$ is an $n \times n$ time-varying coefficient matrix of the endogenous variables whereas $\delta_{i,t}$ is the time-varying coefficient matrix of the exogenous variables. u_t is the reduced form error term with $n \times n$ variance–covariance matrix of Σ_t. In the paper we use two lags with quarterly data which is based on the bayesian model comparison results shown in the Section 4.

[1] De facto inflation targeting was introduced in 2015 when the government and the RBI signed the monetary policy framework agreement (MPFA) but the bill was enacted only in 2016.

[2] Here, the Lucas critique (1976) about parameter drift is applicable (Sargent, 1999). If the central bank has varied objective functions in the different monetary regimes, then the observed inter-temporal coefficients drift leads to updating of the decision rules of private agents also. This changing weights on price stabilization means that the policy makers and private agents econometric model will have parameters which are drifting across regimes, which cannot be captured in time-invariant models.

[3] TVP-VAR with stochastic volatility can be considered as the reduced form representation of a DSGE model with time-variation (Lubik and Matthes, 2015).

We rewrite (1) in as a state space model. With the measurement equation in the following matrix form,

$$y_t = X_t\theta_t + u_t \tag{2}$$

where $u_t \sim N(0,\Sigma_t)$; $X_t = I_n \otimes (1, y'_{t-1}, \ldots., y'_{t-p}, z'_1, \ldots, z'_{t-p})$ and $\theta_t = vec(c_t, \beta_{1,t}, \ldots., \beta_{p,t}, \delta_{1,t}, \ldots., \delta_{q,t})$. X_t is $n \times b$ matrix and θ_t is $b \times 1$ matrix.

For structural analysis, we will require identification of the elements of the time-varying covariance matrix Σ_t. Following Primiceri (2005) covariance matrix is decomposed as,

$$\Sigma_t = A_t^{-1} D_t (A_t^{-1})' \tag{3}$$

A_t is a lower triangular matrix and D_t is a diagonal matrix. A_t captures the contemporaneous interactions for the endogenous variables whereas D_t includes the variance of the structural errors.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 \end{bmatrix} \qquad D_t = \begin{bmatrix} e^{h_{1,t}} & 0 & 0 & 0 \\ 0 & e^{h_{2,t}} & 0 & 0 \\ 0 & 0 & e^{h_{3,t}} & 0 \\ 0 & 0 & 0 & e^{h_{4,t}} \end{bmatrix}$$

For modeling purposes we will modify the reduced form (2) into structural form based on this relation,

$$y_t = X_t\theta_t + A_t^{-1} D_t^{1/2} \epsilon_t \tag{4}$$

Eq. (4) captures changes in the transmission of structural shocks. We can rewrite the Eq. (4) as,

$$y_t = X_t\theta_t + A_{0,t}\epsilon_t \tag{5}$$

where $A_{0,t}$ is the time-varying structural impact matrix. Thus we have,

$$\Sigma_t = A'_{0,t} A_{0,t} \tag{6}$$

The algorithm for finding $A_{0,t}$ is shown in Appendix.
Now for state equations, we rewrite these matrices into vector form.

Let a_t be the elements of the time-varying contemporaneous interactions matrix which is vectorized as $a_t = (\alpha_{21,t}, \alpha_{31,t}, \alpha_{32,t}, \alpha_{41,t}, \alpha_{42,t}, \alpha_{43,t})'$. And $d_t = (h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t})$ includes the diagonal elements of D_t. These state equations evolve in the following way,

$$\theta_t = \theta_{t-1} + v_t \qquad v_t \sim N(0, R_\theta) \tag{7}$$

$$a_t = a_{t-1} + \zeta_t \qquad \zeta_t \sim N(0, R_a) \tag{8}$$

$$h_t = h_{t-1} + \eta_t \qquad \eta_t \sim N(0, R_h) \tag{9}$$

where $R_a = diag(\omega^2_{\alpha 1}, \omega^2_{\alpha 2}, \omega^2_{\alpha 3}, \omega^2_{\alpha 4}, \omega^2_{\alpha 5}, \omega^2_{\alpha 6},)$. $R_h = diag(\omega^2_{h1}, \omega^2_{h2}, \omega^2_{h3}, \omega^2_{h4})$ and $R_\theta = diag(\omega^2_{\theta_1}, \omega^2_{\theta_2}, \omega^2_{\theta_3}, \ldots., \omega^2_{\theta_m})$ where m is the number of θ parameters. Where θ_t and a_t evolve as driftless random walks whereas $e^{h_{i,t}}$ evolve as geometric random walk processes.

Details about estimation including posterior simulator and algorithm for calculating the structural impact matrix is shown in Appendix.

2.2. Output gap estimation

To estimate the output gap data, we adopt a model-based approach, using a time-varying unobserved components model (Chan et al., 2019). In this approach, we decompose real GDP into trend τ_t and cycle c_t components as follows,

$$y_t = \tau_t + c_t \tag{10}$$

Assuming constant trend growth for India's output from 1997 to 2024 does not appear reasonable. To capture the fluctuations in trend growth over this period, we model the trend component as a random walk process. Meanwhile, the cyclical component c_t is represented as a zero-mean stationary $AR(p)$ process. Additionally, the trend process follows a second-order Markov process, which enables the modeling of time-varying trend growth,

$$\tau_t = 2\tau_{t-1} + \tau_{t-2} + \xi^\tau_t \tag{11}$$

$$c_t = \alpha_1 c_{t-p} + \cdots \ldots + \alpha_p c_{t-p} + \xi^c_t \tag{12}$$

where $\xi^\tau_t \sim N(0, V_\tau)$ and $\xi^c_t \sim N(0, V_c)$ where (11) can also be written as,

$$\Delta\tau_t = \Delta\tau_{t-1} + \xi^\tau_t \tag{13}$$

Output gap is estimated as the gap between actual RGDP (100 times log of RGDP) and the trend component. We also estimated real effective exchange rate gap based on the same procedure. Details about estimation are shown in Appendix.

Table 1
Sign restrictions for the model. The inequality restrictions shows the directional response of the macroeconomic variable to an exogenous shock which are set column wise. ×is for no restrictions showing an agnostic relation between the variables.

	Monetary policy Shock	Cost-push shock
Inflation	≤	≥
Output Gap	≤	≤
REER	≤	×
Interest Rate	≥	×

2.3. Identification

For the structural VAR (SVAR) analysis, we need to recover structural shocks, ϵ_t from the reduced form errors u_t. This is achieved using the standard mapping $u_t = A_{0,t}\epsilon_t$, where $A_{0,t}$ represents the structural impact matrix, and we impose restrictions on it to recover the monetary policy shocks. We focus on two types of shocks: contractionary monetary policy shocks and cost-push inflation shocks. However, as the primary focus of this paper is the monetary transmission mechanism, we will concentrate exclusively on the monetary policy shocks. The identification is based on sign restrictions as shown by Faust (1998) and Uhlig (2005). Sign restrictions are used to construct the necessary orthogonal decomposition. Compared to the more commonly used short and long-run restrictions in the SVAR literature, sign restrictions offer several advantages. First, as all constraints are explicitly stated in the sign restrictions, they provide a clear distinction between identification and inference. In contrast, timing restrictions impose zero constraints, which lead to contemporaneous restrictions among the variables—a practice that can be problematic, as noted by Faust (1998).

The restrictions are imposed on the structural impact matrix $A_{0,t}$. We estimate $A_{0,t}$ using the algorithm developed by Rubio-Ramirez et al. (2010), as detailed in Appendix. In this paper we define the monetary policy shock as a one percent increase in interest rates. Theoretically, a contractionary monetary policy shock is expected to result in a reduction in both prices and the output gap. Accordingly, non-positive restrictions are imposed on both inflation and the output gap, as shown in Table 1. A contractionary monetary shock, in the context of developing economies, typically leads to a depreciation of the real effective exchange rate. This depreciation occurs because the output and fiscal cost effects tend to dominate the liquidity demand effects (Hnatkovska et al., 2016). The monetary policy shock is normalized to represent a one percent increase in interest rates on impact at each point in time.

For the cost-push shock, we impose restrictions solely on inflation and the output gap. Specifically, we apply non-negative restrictions to both inflation and the output gap in response to a one percent increase in the cost-push shock. The inclusion of cost-push (inflation) shocks is essential for identifying supply-side inflation, a common phenomenon in India. Factors such as supply delays, weather-related disruptions, infrastructure bottlenecks, and weak supply chains often lead to reduced output. These constraints, in turn, drive up costs and contribute to price increases.

The identification of cost-push shocks in this study follows a similar approach to that in other monetary policy SVAR literature (e.g., (Cross, 2019)). For the cost-push shock, we leave the real effective exchange rate and interest rate unrestricted. No additional restrictions are applied.

3. Priors, estimation and data

3.1. Priors and estimation

This paper follows the approach of Koop and Korobilis (2010) to establish the priors for the TVP-BVAR model with stochastic volatility. The priors for the initial conditions of the state equations are assumed to follow a Gaussian distribution,

$$\theta_1 \sim N(0, 4 \times \mathbf{I_{b\times b}})$$

$$a_1 \sim N(0, 4 \times \mathbf{I_{n\times n}})$$

$$h_1 \sim N(0, 4 \times \mathbf{I_{m\times m}})$$

Priors of the diagonal of the error covariances are independently distributed as,

$$\omega^2_{\theta_i} \sim IG(\nu_{\theta_i}, S_{\theta_i}) \quad \text{for} \quad i = 1, \dots, b$$

$$\omega^2_{a_i} \sim IG(\nu_{a_i}, S_{a_i}) \quad \text{for} \quad i = 1, \dots, n$$

$$\omega^2_{h_i} \sim IG(\nu_{h_i}, S_{h_i}) \quad \text{for} \quad i = 1, \dots, m$$

The degrees of freedom parameters are set as, $\nu_{\theta_i} = 10; \nu_{a_i} = 2; \nu_{h_i} = 2$. Whereas the scale parameters are set as $S_{\theta_i} = S_{\theta_i} = S_{\theta_i} = 0.1^2$ (Chan and Eisenstat, 2018) and Cross (2019).

The estimation of the TVP-BVAR-SV model is carried out using Markov Chain Monte Carlo (MCMC) methods. We run 105,000 iterations to obtain the posterior draws, discarding the first 35,000 iterations to allow the Markov chain to converge to its ergodic distribution. For Gibbs sampling, we use the precision sampler of Chan and Jeliazkov (2009), as it is more efficient than Kalman filter-based algorithms. Further estimation details are provided in Appendices A.1 and A.2 of Appendix.

Appendix includes Fig. A1, which shows the inefficiency factors of the retained draws to assess whether the Markov chain has converged to the ergodic distribution. The inefficiency factor is calculated following Geweke (1991).

To construct the time-varying impulse response functions, we use the non-linear generalized impulse response function (GIRF) proposed by Koop et al. (1996). The GIRF is computed as the difference between the conditional expectations of the endogenous variables with and without the shock. More details are provided in Appendix A.3 of Appendix.

3.2. Data

The primary objective of an inflation-targeting central bank is to stabilize inflation, while also considering the output gap. To capture shifts in the Reserve Bank of India's monetary policy stance, we specify a generalized Taylor (1993) rule with fewer constraints which is shown by the model's interest rate equation. This rule includes headline CPI inflation as the target variable, along with the output gap, exchange rate gap, and the short-term interest rate. In emerging economies, headline inflation is widely regarded as a more relevant measure for guiding monetary policy compared to core inflation, which is more commonly used in the analysis of developed economies. Anand et al. (2015) demonstrate that headline inflation is pivotal in shaping effective monetary interventions and significantly improving overall welfare in developing economies, surpassing the utility of core inflation in this regard.

The paper utilizes quarterly data spanning from 1997Q4 to 2023Q4. The starting point of 1997Q4 is due to the unavailability of real GDP data prior to 1996. Quarterly GDP data is generally considered the least noisy measure of real output. Real GDP is preferred over industrial production to construct the output gap, as the latter captures only a subset of total output, and its share fluctuates over time, making it an unstable proxy (Kilian and Lutkepohl, 2017). Moreover, unlike real GDP, industrial production does not measure value-added, reducing its reliability as an indicator of overall economic activity. The 91-day Treasury bill is used as a measure of the short-term interest rate because the transmission from the repo rate (the policy instrument) to the 91-day Treasury bill is considered both complete and instantaneous (Kapur, John, and Mitra, 2019). Unlike the call money rate, which is more volatile and primarily reflects short-term liquidity, the 91-day Treasury bill better captures market expectations and broader macroeconomic trends. As an exogenous variable, we employ Dubai crude oil prices as a proxy for global oil prices, as they constitute approximately 70 percent of the Indian oil basket. To ensure consistency and obtain a relatively long data series, we sourced the CPI, GDP, real effective exchange rate, and global oil prices from the FRED Economic Database (St. Louis Federal Reserve), while the 91-day treasury bill rate was obtained from the Reserve Bank of India database. The data were seasonally adjusted using the ARIMA X-12 technique. CPI inflation is calculated as the annualized growth rate of the CPI index.

The output gap is not estimated using filter-based methods, such as the Hodrick–Prescott filter, which can produce spurious dynamics (Hamilton, 2018). Instead, we estimate the output gap using a time-varying unobserved components model, with estimation details provided in Appendix. For the exchange rate, we use the real effective exchange rate (REER), which reflects the competitiveness of a currency against the currencies of its major trading partners. Following Mishra et al. (2016), we use the real exchange rate gap, but estimate it using the unobserved components approach. The 91-day treasury bill rates are used without any transformation.

4. Model selection

In this section, we present the bayesian model comparison (BMC) to identify the model that best captures the Indian data analyzed in this paper. We do the BMC among different VAR models. Bayesian model comparison is proceeded by computation of the Bayes factor of model M_i against M_j.

For comparing the models, Bayes factor computes the ratio of the marginal likelihood.

$$BF_{ij} = \frac{P(y|M_i)}{P(y|M_j)}$$

Where marginal likelihood of a model can be written as,

$$P(y|M_i) = \int p(y|\psi_k, M_k)p(\psi_k|M_k)d\psi_k$$

The model which is preferred by the data has the higher marginal likelihood values. For example, Bayes factor BF_{12} with a value greater than one, shows that the observed data is more likely under first model compared to the second model.

Computing marginal likelihood for high-dimensional TVP-VAR models presents a significant challenge. Conventional methods for estimating marginal likelihoods using conditional likelihood have been found to be imprecise (Chan and Grant, 2016). Following Chan and Eisenstat (2018), we first compute the integrated likelihood by integrating out the time-varying coefficients and error variances using importance sampling techniques. We then calculate the marginal likelihood using an outer importance sampling routine.

Table 2 presents the results of the log marginal likelihood for various VAR models, based on 8000 simulations of the integrated

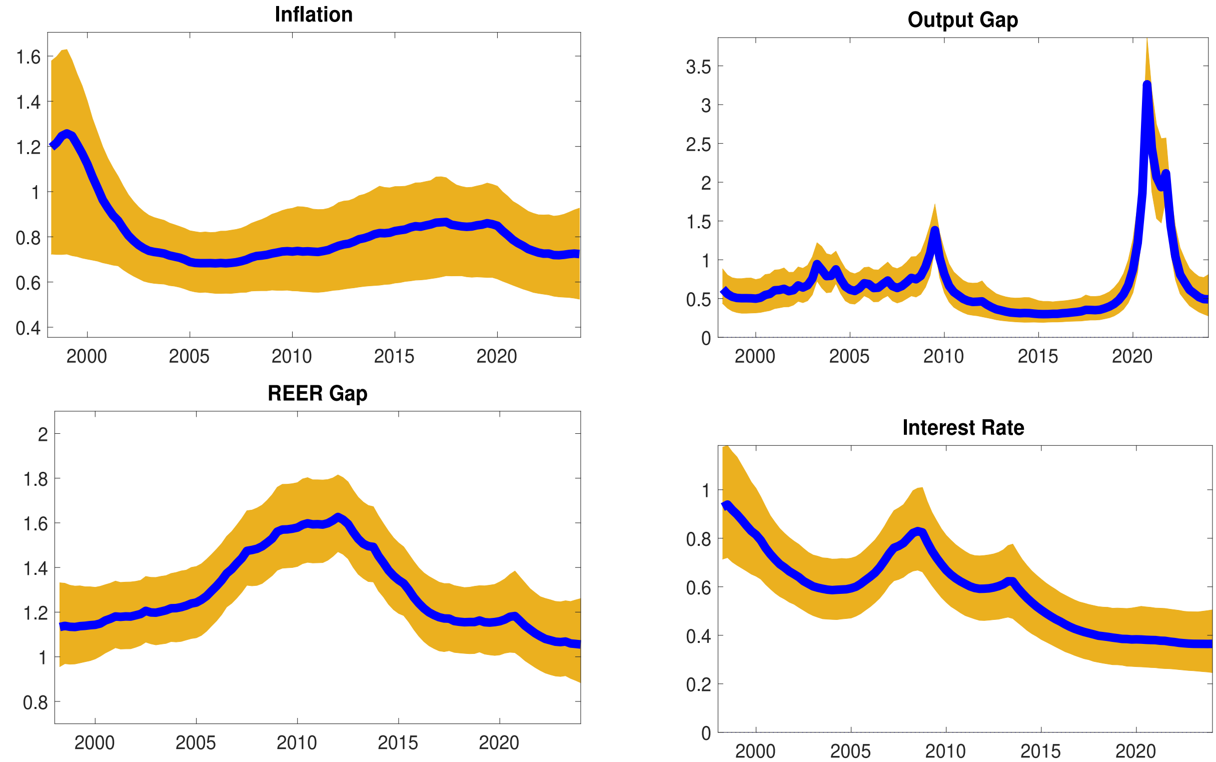

Fig. 1. Estimated posterior median of the standard deviation of the residuals for each equation. Blue solid line is the posterior median and orange spread is the 68 percent credible interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Log marginal likelihood estimates for different vector autoregression models.

Lags	VAR	TVP-VAR-SV	TVP-VAR
2	−915.1	**−823.2**	−920
3	−952.6	−873.9	−965.8
4	−996.8	−926.5	−1016

likelihood. The model with the highest log marginal likelihood value is considered the best fit for the data. The results indicate that the time-varying parameter VAR with stochastic volatility (TVP-VAR-SV) is clearly the preferred model for the data, achieving the highest log marginal likelihood of −823.2. Additionally, the data suggests that a lag of two is optimal for capturing the underlying dynamics. In comparison, both the constant coefficient VAR and the time-varying parameter VAR model without stochastic volatility (TVP) perform less effectively at capturing the data's dynamics, particularly due to their assumption of homoscedastic innovations.

5. Results

5.1. Volatility of monetary policy shocks

To assess whether the volatility of monetary policy shocks has shifted during the inflation targeting (IT) years relative to the pre-IT period, we plot the time-varying volatilities of residuals for the four structural equations used in the main model in Fig. 1. We construct 68% credible intervals of the posterior distribution to evaluate the accuracy of the estimates.[4]

[4] Credible intervals, the Bayesian counterpart of frequentist confidence intervals, provide the probability of the estimate falling within a positive or negative region.

The stochastic volatility estimates for all equations are precisely measured, with narrow credible intervals. In Fig. 1, the standard deviation of the residuals from the interest rate equation (bottom right) captures the volatility of monetary policy shocks. During the pre-IT era, we observe relatively higher volatility in these shocks. However, following the informal announcement of inflation targeting in 2014, there is a consistent decline in their volatility. We find that the variance of monetary policy shocks is nearly halved during the inflation-targeting period. Notably, this decline persists even through major economic disruptions, such as the 2016 demonetization, when 86 percent of the currency in circulation was invalidated overnight and during the COVID-19 pandemic years.

The reduction in monetary policy volatility appears to be largely driven by inflation targeting, as we do not observe a similar decline in the volatility of supply-side factors, as indicated by the inflation equation (top left). While there is a reduction in exchange rate volatility(bottom left) starting in 2011, we do not see a significant change between 2015 and 2020 during the inflation targeting years.

Non-systematic policy, measured by exogenous monetary policy shocks, dominated the pre-inflation targeting years, with sharp spikes in volatility around 1998 (following the East Asian Crisis) and during 2008–09 (the Great Recession). The stochastic volatility of the output gap is consistently low during the inflation targeting years, except for a significant spike during the COVID-19 period. Thus, the inflation targeting years show a much more systematic approach to monetary policy compared to the earlier regime.

5.2. Time-variation in the monetary transmission

5.2.1. Intertemporal comparison between pre-inflation targeting, inflation targeting years and COVID-19 years

To assess whether the transmission of monetary policy shocks has changed in India from 1997 to 2024, and whether inflation targeting has altered the transmission mechanism, we present the intertemporal

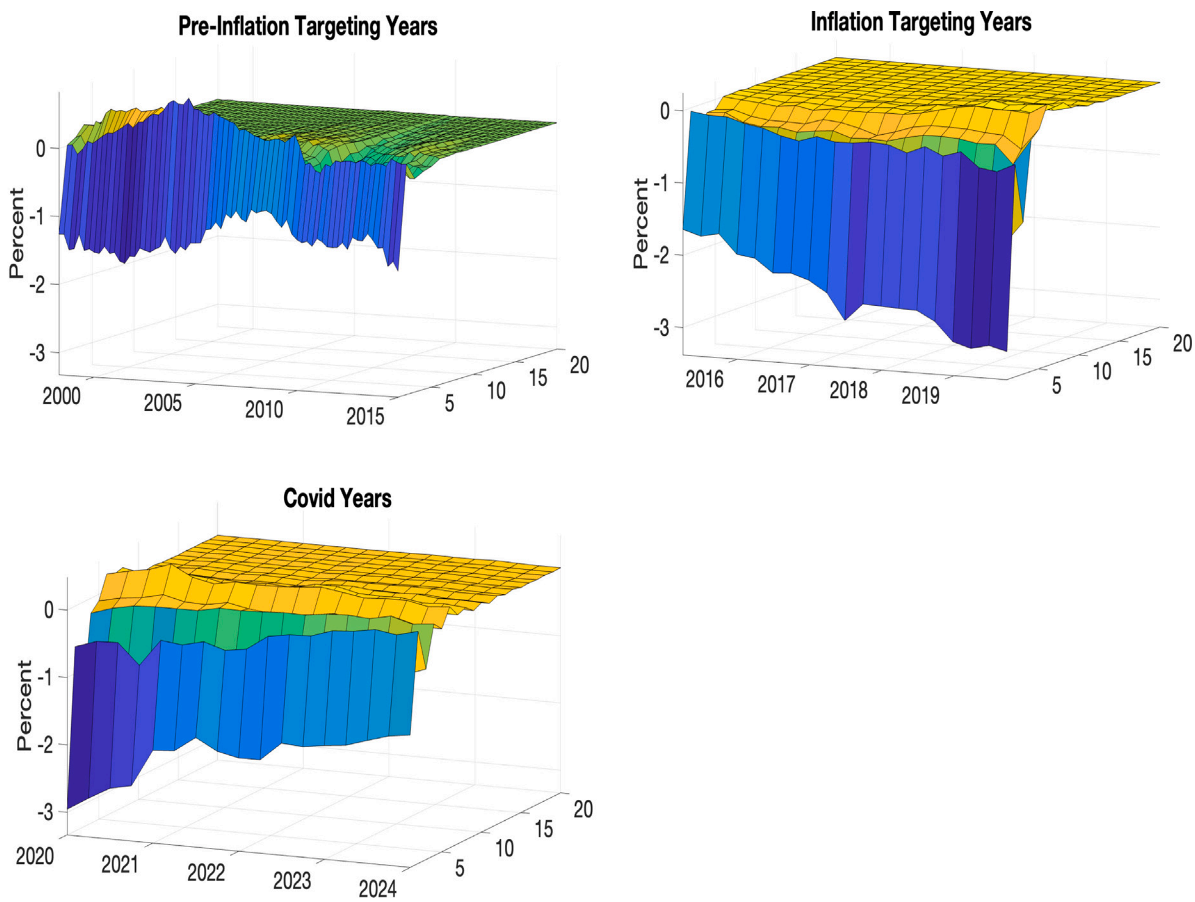

Fig. 2. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on CPI inflation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

generalized impulse response functions (GIRFs) for a one percent contractionary monetary policy shock on CPI inflation, output gap, real effective exchange rate gap, and interest rates (91-day Treasury bill rate).

We construct three sets of GIRFs to compare the pre-inflation targeting period, the inflation targeting years, and the COVID-19 period. The pre-inflation targeting period spans from 1997Q3 to 2014Q4, the inflation targeting period from 2015Q1 to 2019Q4, and the COVID-19 period from 2020Q1 to 2023Q4. Although the COVID-19 years technically fall within the inflation targeting regime, they are considered separately due to the unprecedented nature of the shock.

In time-varying SVAR models, conventional impulse response functions from constant coefficient VAR models are not directly applicable because the scale of identified shocks varies over time, making cross-regime comparisons challenging. To address this, we assess time-varying responses against a benchmark scenario using non-linear impulse response functions. Specifically, we use the generalized impulse response functions (GIRF) method proposed by Koop et al. (1996).

The dynamic effects of the monetary policy shock are normalized to reflect a one percent increase in interest rates on impact at each point in time. This approach allows us to track whether a consistent one percent increase each quarter leads to differing effects across various years. In the absence of changes in the transmission mechanism, we would expect minimal variation in the impulse response functions over time.

Inflation response to one percent contractionary monetary policy shock

Fig. 2 presents the intertemporal generalized impulse response functions (GIRFs) across the three time periods, illustrating the effects of a contractionary monetary policy shock on inflation. In Fig. 2's color gradient, the dark blue shade represents the strongest impact of monetary policy shocks. In contrast, the light green shade signifies a weaker impact, while the yellow shade indicates minimal or no effect. Overall, darker shades correspond to a stronger impact of monetary policy shocks on the variable in question, whereas lighter shades represent a lesser or negligible impact.

We observe considerable variation in the response over the years, despite the same size of monetary policy shock each quarter. The peak response typically occurs in the second or third quarter following the shock.

In the pre-inflation targeting (pre-IT) years, particularly during the 2000s, we see the classic price puzzle (Barth and Ramey, 2001; Romer and Romer, 2004) where inflation increases following a contractionary monetary policy shock. As shown in Section 6.2, even after incorporating an information variable, the price puzzle persists in the pre-IT years, suggesting it is not simply a misspecification issue. However, after the defacto adoption of the inflation targeting regime in 2015, this price puzzle disappeared. This finding aligns with Florio (2018), who attributes disappearance of the price puzzle in the European Union to more active monetary policy and better-anchored expectations. It also echoes the fiscal theory of the price level, which suggests that passive monetary and active fiscal stances can generate upward pressure on prices (Leeper and Leith, 2016). During the IT years, the dark blue bands in 2017Q2 and from 2019Q2 to Q4 indicate that a one percent monetary policy shock had the most significant effect on inflation, with impacts ranging from −2.5 to −3 percent.

During the COVID-19 period, the RBI's accommodative posture weakened the transmission of monetary policy shocks to inflation, allowing CPI to temporarily breach the target band. Two key insights emerge from Fig. 2. First, inflation targeting significantly amplifies the

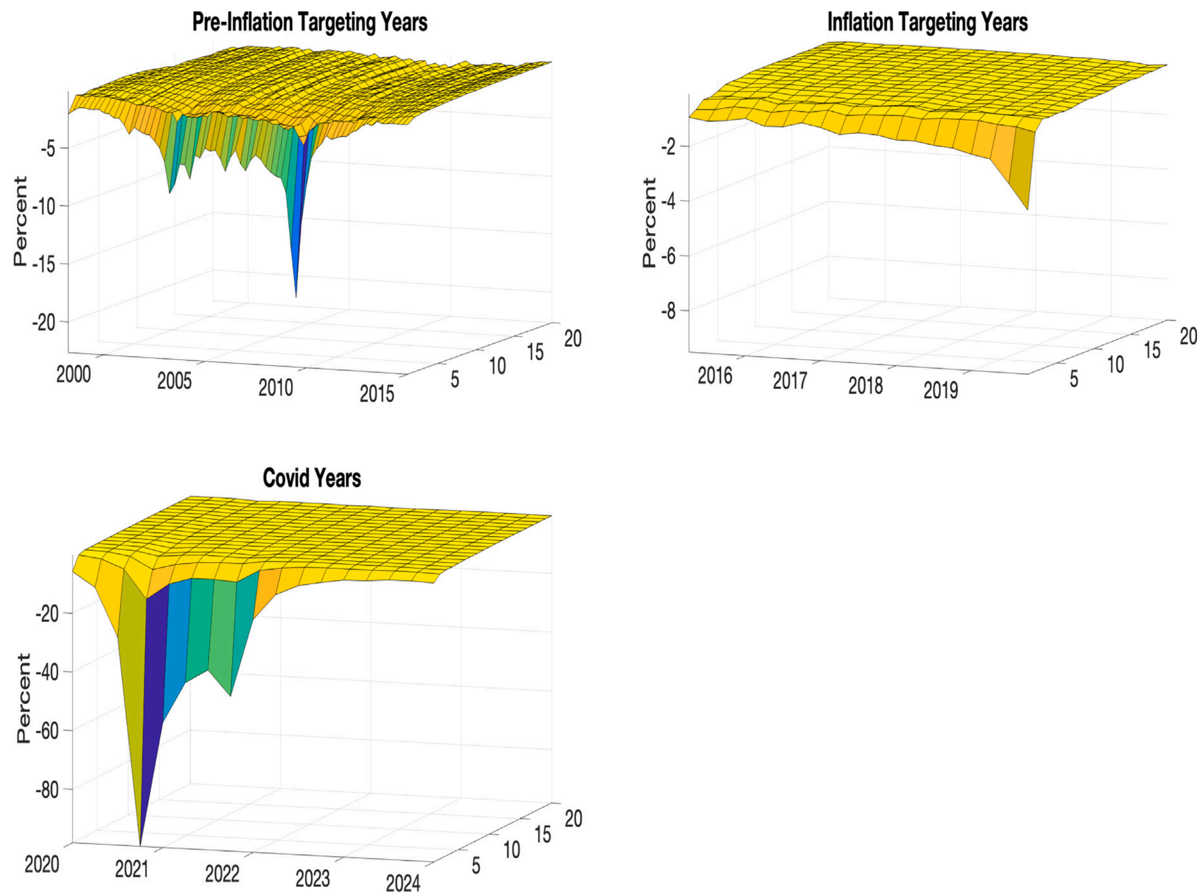

Fig. 3. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on the output gap.

impact of monetary policy shocks on CPI, nearly doubling their magnitude between 2017 and 2020. Second, this amplification reflects a deliberate recalibration of the RBI's monetary reaction function toward stronger price stabilization, thereby validating the effectiveness of the inflation-targeting regime.

Output gap response to one percent contractionary monetary policy shock

Fig. 3 illustrates the intertemporal response of the output gap to a contractionary monetary policy shock. In the pre-inflation targeting (pre-IT) period, the impact of monetary policy on the output gap was significantly higher compared to the inflation-targeting years. A one percent monetary policy shock in the pre-IT period led to an average output gap response exceeding three percent, whereas this impact dropped below two percent during the IT years. This suggests that, during the pre-IT period, the Reserve Bank of India placed greater emphasis on output stabilization within its monetary policy framework.

This shift reflects the RBI's increased focus on inflation stability during IT period, with reduced emphasis on output fluctuations. It indicates a deliberate adjustment in the monetary reaction function during the IT years, prioritizing price stability over dual objectives. Woodford (2004) argues that clearer expectations among consumers and firms regarding central bank objectives foster greater output gap stability, an effect that appears evident during the IT period for India.

In the COVID-19 years, particularly around 2020Q4, we observe a sharp drop in the output gap, following a contractionary monetary policy shock. This effect persists through the second quarter of 2022, highlighting the significant impact of the pandemic on the economy and the challenges faced by the Reserve Bank of India in managing monetary policy during this unprecedented period.

Real effective exchange rate gap response to one percent contractionary monetary policy shock

Fig. 4 depicts the intertemporal response of the real effective exchange rate (REER) to a contractionary monetary policy shock. Hnatkovska et al. (2016) argue that in developing economies, a contractionary monetary policy shock results in a depreciation of the exchange rate. This effect is attributed to the dominance of output and fiscal costs, which outweigh the liquidity demand effects in these economies.

In Fig. 4, we observe a consistent depreciation in the REER gap across most years. During the pre-inflation targeting (pre-IT) years, the Reserve Bank of India followed a monetary policy framework with a multiple indicator approach, where exchange rate stability was a key objective. As a result, monetary policy shocks had a more pronounced effect on the REER gap during this period. A particularly sharp depreciation of the REER gap is observed during the taper tantrum years (2013–2014), underscoring the Reserve Bank of India's active role in stabilizing the exchange rate.

However, in the inflation targeting (IT) years, we notice a diminished influence of monetary policy on the exchange rate. This suggests that the Reserve Bank of India has shifted its focus away from direct exchange rate management, prioritizing inflation stability instead. Interestingly, during the COVID-19 period, monetary policy appears to exert relatively greater influence on the exchange rate, likely reflecting some degree of exchange rate management by the Reserve Bank of India amid the economic uncertainty triggered by the pandemic.

Overall, the findings suggest that during the inflation targeting years, the Reserve Bank of India has taken a less interventionist stance on exchange rate management compared to the pre-IT years. This shift has led to a reduced monetary policy impact on the exchange rate, contributing to greater stabilization of the REER during the IT period.

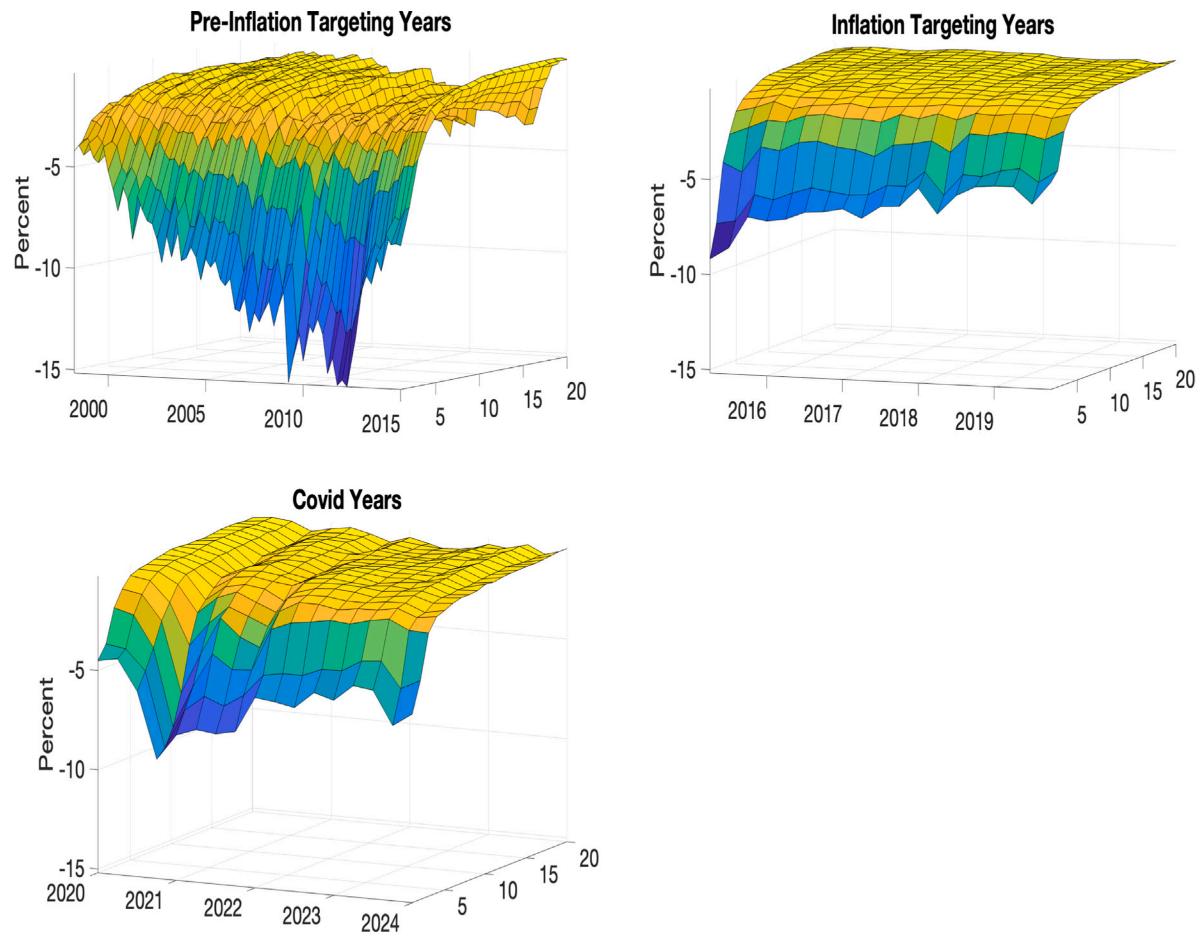

Fig. 4. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on the REER gap.

91-day treasury bill response to one percent contractionary monetary policy shock

Fig. 5 illustrates the construction of the monetary policy shock. The dynamic effects of a monetary policy shock have been normalized to get a one percent increase in interest rates on impact at each point in time.

5.3. Importance of monetary policy shocks

In this section, we evaluate the contribution of monetary policy shocks to forecast error variance of inflation during the pre-inflation targeting period (1997Q3 - 2014Q4) and the inflation targeting period (2015Q1 - 2023Q4). Table 3 presents the time-varying forecast error variance decomposition (FEVD), illustrating the median contribution of monetary policy shocks to forecast error variance of inflation across four different forecast horizons. The values are expressed as percentages.

In the pre-inflation targeting years, the contribution of monetary policy shocks to the forecast error variance of inflation after 10 quarters is approximately 12.2%. In contrast, this contribution increases to 14.5% during the inflation targeting years. Across all four forecast horizons, the median contribution of monetary policy shocks to forecast error variance of inflation in the pre-IT period ranges from 11.7% to 12.6%. However, in the inflation targeting years, we observe a consistent increase of around two percentage points, with the median contribution ranging from 13.9% to 14.5%.

Table 3
Forecast error variance decomposition: Median of the contribution of the monetary policy shocks to the forecast error variance of inflation.

Forecast horizon	2	5	10	20
Pre-Inflation Targeting years	12.6	12.3	12.2	11.7
Inflation Targeting years	14.5	14.3	14.2	13.9

An effective inflation targeting regime, with a stronger emphasis on inflation control, is expected to result in a greater contribution of monetary policy shocks to inflation (Canova and Gambetti, 2009). The results in Table 3 clearly demonstrate this, as we observe a noticeable increase in the influence of monetary policy shocks on inflation during the inflation targeting years compared to the pre-inflation targeting regime.

6. Robustness and sensitivity analysis

6.1. Measuring estimation uncertainty: 16th and 84th percentiles of the posterior distribution

Response to monetary policy shocks

Data from developing economies are often inherently noisy and constrained by relatively short time series. Ramey (2016) has highlighted in her literature review that due to central banks' systematic responses to output and inflation, obtaining a truly exogenous monetary policy shock is controversial. In this section, we assess the robustness of the impulse response functions presented earlier. We plot the generalized impulse response functions for a contractionary monetary policy shock, using the 16th and 84th percentiles of the posterior distribution. This range captures 68% of the highest posterior probability, offering a more informative alternative to frequentist confidence intervals, which

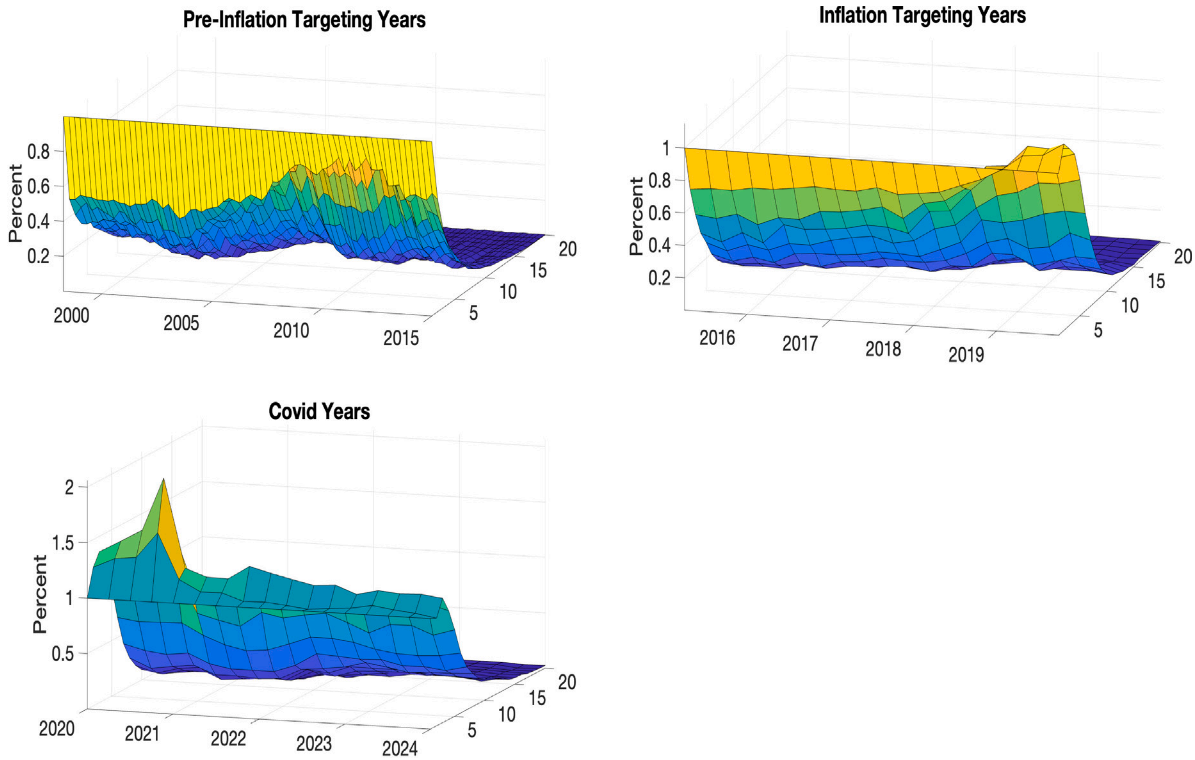

Fig. 5. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on the 91-day treasure bill.

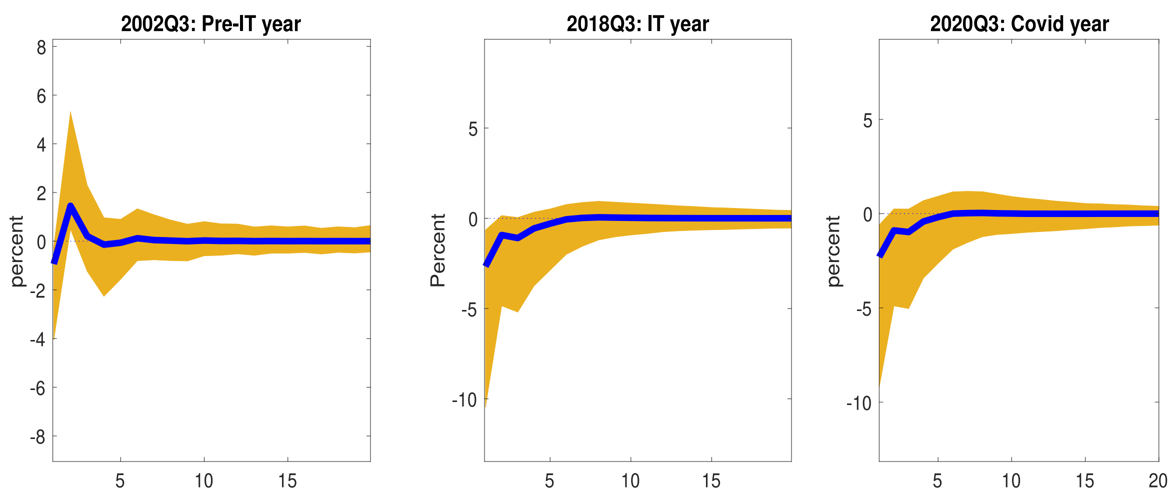

Fig. 6. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on CPI inflation. Blue solid line is the posterior median and orange spread is the 16th and 84th percentiles of the posterior distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

primarily capture sampling uncertainty and are insignificant when intervals contain zero. Bayesian credible sets, on the other hand, are regarded as more reliable as they account for parameter uncertainty and indicate the region where the highest probability mass of the posterior distribution is located.

To check the robustness of the estimates, we randomly select three distinct quarters: one from the pre-inflation targeting period, one from the inflation targeting years, and one from the COVID-19 period.

Fig. 6 displays the response of CPI inflation to a contractionary monetary policy shock. The dynamic effects of the monetary policy shocks are normalized to reflect a one percent increase in interest rates on impact. For the pre-inflation targeting quarter (2002Q3), we observe the persistence of the price puzzle after a contractionary monetary policy shock. The majority of the posterior mass lies in the positive region during the first four quarters, indicating the presence of the price puzzle. While our estimated effects of monetary policy shocks on inflation exhibit some uncertainty, indicating that although a relationship exists, it is measured imprecisely. These results are broadly consistent with earlier studies that report weak or statistically insignificant effects of monetary policy on inflation during the MIA period (e.g., (Mallick and Sousa, 2012; Mishra et al., 2016)). However, our findings do not imply insignificance.

In contrast, for the inflation targeting quarter (2018Q3), we do not observe the price puzzle. Instead, most of the posterior mass falls in the

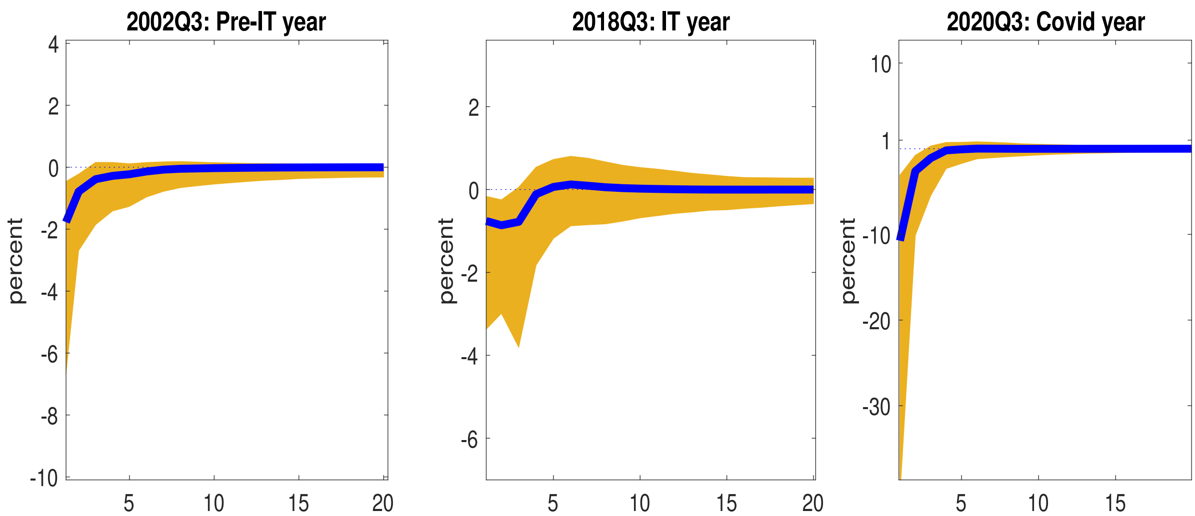

Fig. 7. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on output gap. Blue solid line is the posterior median and orange spread is the 16th and 84th percentiles of the posterior distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

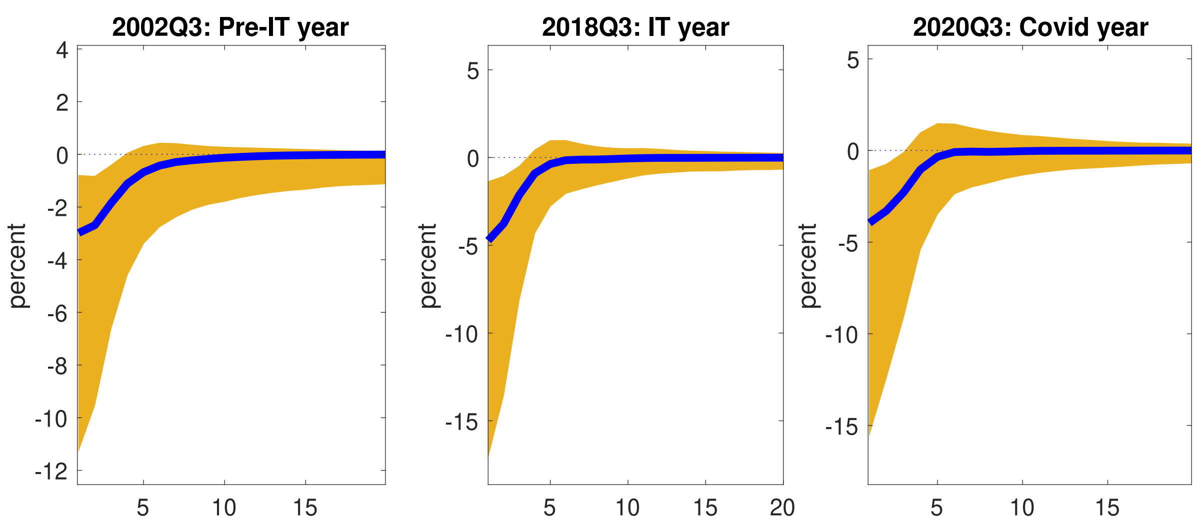

Fig. 8. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on real effective exchange rate gap. Blue solid line is the posterior median and orange spread is the 16th and 84th percentiles of the posterior distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

negative region during the first four quarters, suggesting that monetary policy shocks are more effectively identified during this period. A similar pattern emerges for the COVID-19 quarter, albeit with greater uncertainty in the estimates.

In summary, we find that monetary policy shocks on inflation are properly identified in the inflation targeting years. However, during the pre-inflation targeting years, non-systematic policy approach of Reserve Bank of India to inflation led to the persistence of the price puzzle.

Fig. 7 illustrates the impact of a contractionary monetary policy shock on the output gap. The impulse response functions are estimated with greater precision, as the majority of the posterior mass falls in the negative region. However, some estimation uncertainty emerges after five quarters. We observe that the 2018Q3 quarter, which falls within the inflation targeting (IT) period, exhibits less uncertainty compared to the other two quarters. In contrast, the COVID-19 quarter displays the widest credible bands, indicating the highest degree of uncertainty.

Fig. 8 presents the impulse response functions (IRFs) of a contractionary monetary policy shock on the real effective exchange rate (REER). The majority of the posterior mass lies in the negative region, indicating a depreciation of the exchange rate following the shock. The IRF for 2018Q3, during the inflation targeting (IT) period, exhibits less uncertainty and suggests proper identification of the monetary policy shock. In contrast, the COVID-19 quarter is characterized by greater uncertainty, as reflected in the wider spread of the posterior distribution.

Fig. 9 illustrates the construction of the monetary policy shock. The estimate for the inflation targeting quarter is the most precisely identified, indicating clearer recognition of monetary policy shocks during the IT period. In contrast, the pre-inflation targeting quarter and, to some extent, the COVID-19 period exhibit greater uncertainty, reflecting the more non-systematic conduct of monetary policy during these times.

6.2. Checking the robustness of the price puzzle in the pre-IT years

To investigate the credibility hypothesis, we introduce an exogenous information variable into our model. In this case, we use global oil prices, specifically Dubai crude oil prices, as a proxy. Oil prices are a key external factor for India, given its status as a major oil importer, and they can provide valuable information for the monetary policy

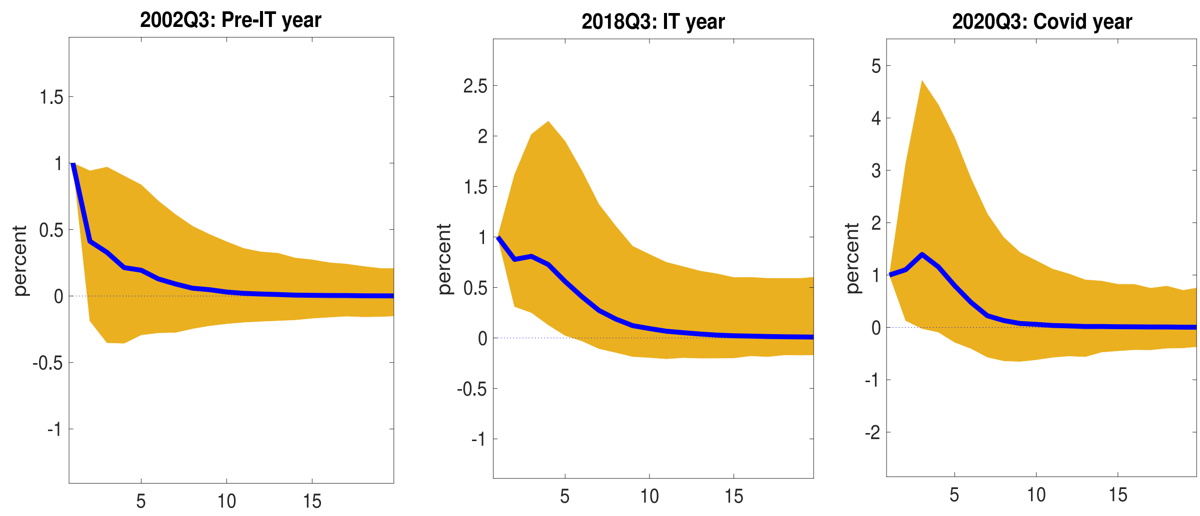

Fig. 9. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on 91-day treasury bill. Blue solid line is the posterior median and orange spread is the 16th and 84th percentiles of the posterior distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

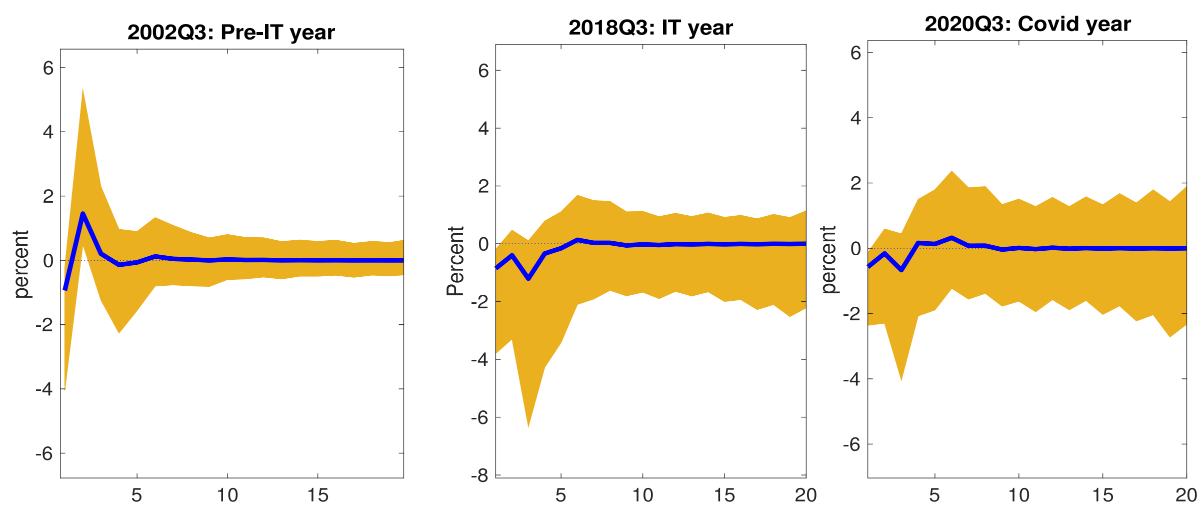

Fig. 10. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates (91-day treasure bill) on CPI inflation. Blue solid line is the posterior median and orange spread is the 68 percent credible interval. We have used global oil prices as the exogenous variable. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

framework. Dubai crude oil prices constitute 70 percent of India's oil basket and are therefore a relevant information variable for our analysis.

Fig. 10 presents the generalized impulse response functions of a contractionary monetary policy shock on inflation across the three quarters. Even after incorporating the information variable (global oil prices), the price puzzle remains evident during the pre-inflation targeting period. This suggests that the price puzzle is not attributable to model misspecification. In contrast, no price puzzle is observed during the inflation targeting period, including the COVID-19 period. These findings support the credibility hypothesis, highlighting that the adoption of a credible inflation targeting framework has played a significant role in eliminating the price puzzle in India.

6.3. *Prior sensitivity*

For checking whether the results are sensitive to the priors we conduct prior sensitivity checks. We will be changing the variance of the initial conditions.

$\theta_1 \sim N(a_\theta, V_\theta)$

$a_1 \sim N(a_a, V_a)$

$h_1 \sim N(a_h, V_h)$

In the main estimation earlier, we had kept the prior variance values at $V_\theta = V_a = V_h = 4$. For the prior sensitivity analysis we increase these values to $V_\theta = V_a = V_h = 10$. In Fig. 11, we present the impact of a contractionary monetary policy shock on CPI inflation in all the three time segments with the increased values of the prior variance.

When comparing Fig. 11 with Fig. 2, where the prior variance values were smaller, there is minimal difference between the two figures. The price puzzle persists, and the influence of monetary policy on inflation remains higher during the inflation targeting (IT) years. However, the impact of monetary policy shocks on inflation has slightly diminished in the IT years. Specifically, the peak median response of monetary policy shocks on inflation has decreased to −1.2 percent in Fig. 11, compared to −1.6 percent in Fig. 2.

7. Conclusion

This paper provides new evidence on shifts in the monetary policy stance of a large emerging economy, India, across two distinct

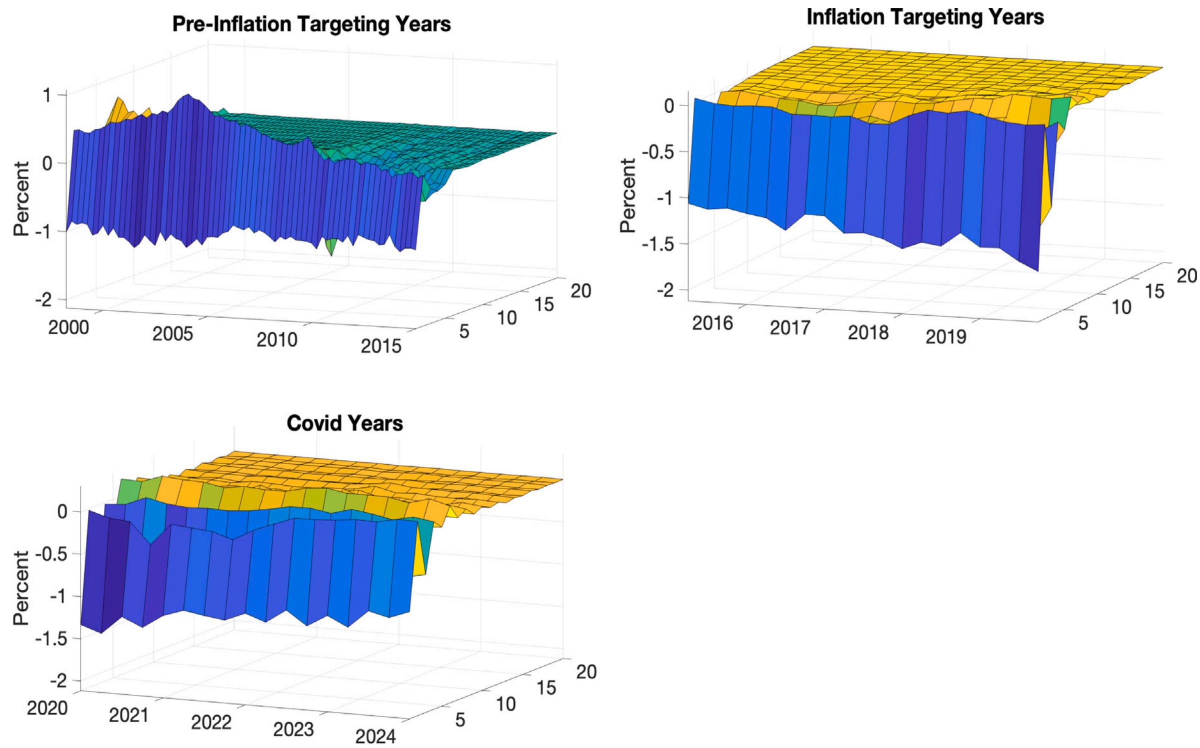

Fig. 11. Posterior median of the generalized impulse response functions following an exogenous one percent increase in the interest rates on CPI inflation.

monetary regimes, while also accounting for the impact of the COVID-19 shock. Using a time-varying Bayesian VAR model with stochastic volatility, we find that during the pre-inflation targeting period, the Reserve Bank of India followed a non-systematic and less credible monetary policy. During this time, greater emphasis was placed on output and exchange rate stabilization, with weak transmission of monetary shocks to inflation. The presence of a pronounced price puzzle—one that we demonstrate is not attributable to model misspecification, further underscores the limited credibility of the monetary policy regime. Moreover, this period was marked by high volatility in monetary policy shocks, the exchange rate, and the output gap.

In contrast, following the adoption of the inflation targeting framework, monetary policy shocks began to exert a stronger and more systematic influence on CPI inflation, reflecting improved monetary transmission and the Reserve Bank of India's enhanced credibility and commitment to price stability. The disappearance of the price puzzle under the IT regime underscores improvements in policy signaling and a decline in ad hoc interventions.

Variance decompositions further reveal that the proportion of inflation fluctuations explained by monetary policy shocks rose significantly during the IT period, even as the impact of these shocks on the output gap and the real effective exchange rate declined. This indicates a deliberate reorientation of policy toward fulfilling the inflation mandate.

However, we observe a deviation from systematic monetary policy during the COVID-19 episode, as the Reserve Bank of India adopted a distinctly accommodative stance, allowing inflation to remain above the target band for extended periods while intensifying exchange rate interventions.

Overall, these findings demonstrate that India's inflation-targeting framework has significantly enhanced the systematic conduct and effectiveness of monetary policy, despite temporary departures during crisis periods.

Future research could build on this foundation by extending the analysis to high-dimensional time-varying BVAR or FAVAR frameworks that incorporate broader macroeconomic linkages, by applying alternative identification strategies such as proxy-SVARs to isolate policy shocks more robustly, and by embedding trend inflation dynamics into the Indian economy to better distinguish persistent inflationary pressures from transitory shocks. Such advances would further illuminate the complexity of monetary transmission in emerging economies and refine our understanding of policy effectiveness under evolving institutional regimes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1. Posterior simulation: Markov chain Monte Carlo (MCMC) algorithm

For estimation of the posterior distributions, we use MCMC methods. Simulating the joint posterior is computationally intensive, so conditional posteriors such as Gibbs Samplers are used. We use Gibbs Sampler to sequentially draw from a six block conditional posterior,

1. $p(\theta|y, h, a, R_\theta, R_h, R_a)$
2. $p(h|y, \theta, a, R_\theta, R_h, R_a)$
3. $p(a|y, \theta, h, R_\theta, R_h, R_a)$
4. $p(R_\theta|y, \theta, h, a, R_h, R_a)$
5. $p(R_h|y, \theta, h, a, R_\theta, R_a)$
6. $p(R_a|y, \theta, h, a, R_\theta, R_h)$

Rather than employing the traditional Kalman filter, which is commonly used for state-space models, we will employ Precision Sampler techniques, which are regarded as more efficient than Kalman filter (Chan and Jeliazkov, 2009). These Precision Sampler methods will be

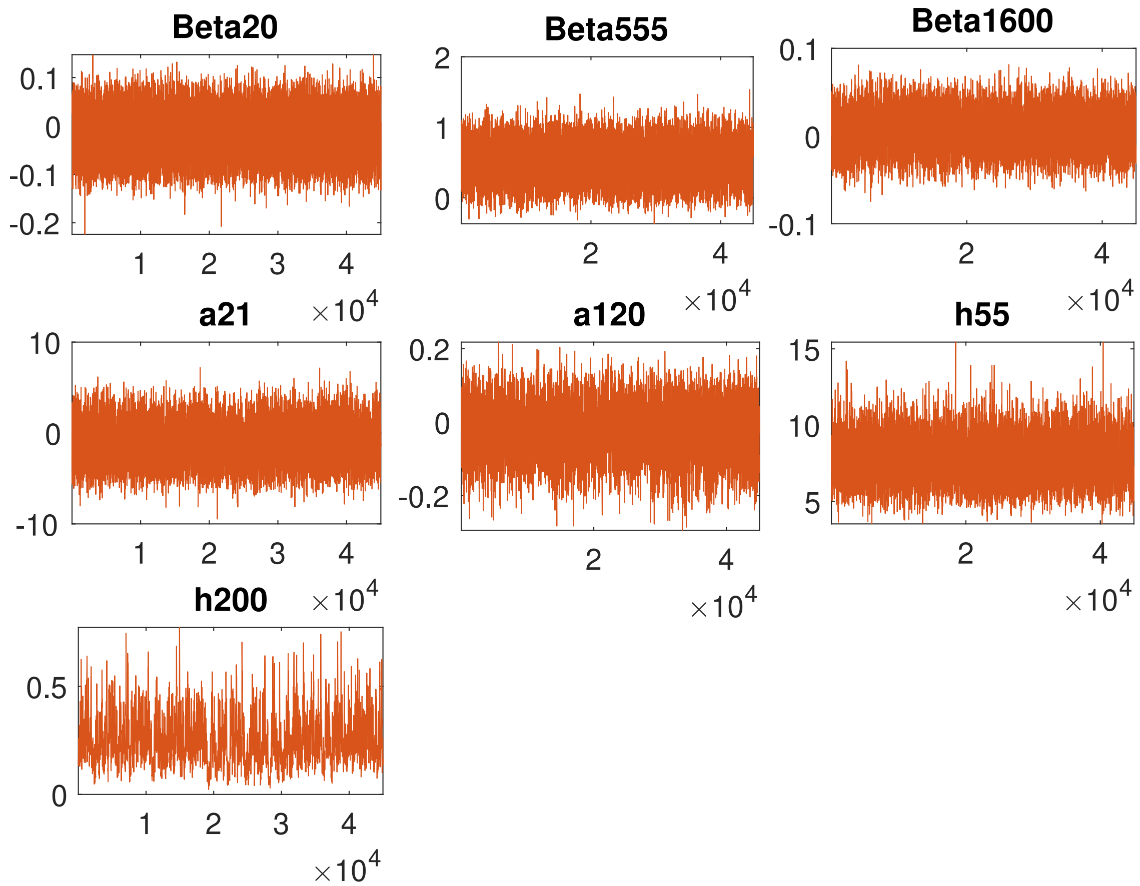

Fig. A1. Trace plot of selected parameters.

applied to all model blocks, with the exception of the second block, which is responsible for estimating the stochastic volatilities. For this second block, we will utilize the auxiliary mixture sampler as proposed by Kim et al. (1998).

A.2. Algorithm for identification by sign restrictions

For obtaining the structural impact matrix ($A_{0,t}$) for identification of the structural shocks, we will be using the algorithm of Rubio-Ramirez et al. (2010).

1. Eigenvalue–eigenvector decomposition of the reduced form time-varying variance–covariance matrix is done, $A_{0,t} = G_t D_t G_t'$. D_t being a diagonal matrix of eigenvalues and G_t with the eigenvectors.
2. Then we draw a $n \times n$ matrix P from standard normal distribution with each draw being independent.
3. QR decomposition of P is implemented where $P = QR$, with Q being the rotation matrix and R is the upper triangular matrix whose elements are normalized to be positive.
4. Q being an orthogonal matrix, we show in Eq. (9) that $\Sigma_t = A_{0,t}' A_{0,t}$. The candidate structural model will be based on selected draws of Q. With the above, we calculate the time-varying structural impact matrix as $A_{0,t} = G_t D_t^{1/2} Q'$ based on draws where the restrictions are satisfied, otherwise the draws are discarded.

A.3. Generalized impulse response functions

Once we obtain the contemporaneous impact matrix from section 8.2, we calculate the generalized impulse response functions (GIRFs) using the Monte Carlo integration procedure outlined by Koop et al. (1996). The GIRFs are computed as:

$$IRF_{t+h} = E(Y_{t+h}|\epsilon_t, \Omega_t) - E(Y_{t+h}|\Omega_t)$$

Here, $Y_{t+h}|\epsilon_t, \Omega_t$ represents the forecast of the endogenous variables up to horizon h, conditioned on the entire information set Ω_t and the structural shock ϵ_t. This calculation involves using a Gibbs sampler to draw from the current state of the economy, incorporating time-varying coefficients and elements of the variance–covariance matrix. Structural shocks are recovered via the identity $u_t = A_{0,t}\epsilon_t$. The benchmark case is simulated without the shock, denoted as $E(Y_{t+h}|\Omega_t)$. The GIRF is then the difference between the conditional expectations with and without the shock. For estimation, we follow the procedure outlined by Baumeister and Peersman (2013).

A.4. Output gap estimation

Eqs. (10), (12) and (13) can be written in state space form. With measurement equation as,

$$y = \tau + c$$

And the two state equations as,

$$H_\alpha c = \xi^c$$

$$H_\phi \tau = \Psi_\tau + \xi^\tau$$

where $\Psi_\tau = (\tau_0 + \Delta\tau_0, \tau_0, 0, \dots, 0)$ and $K = (\tau_0, \tau_{-1})$. H_α and H_ϕ are band matrices. Assuming priors to be independent, we use the five block Gibbs Sampler as shown in Chan et al. (2019) to simulate the posterior.

1 $p(\tau|y, \alpha, V_\tau, V_c, K)$
2 $p(\alpha|y, \tau, V_\tau, V_c, K)$
3 $p(V_\tau|y, \tau, \alpha, V_c, K)$
4 $p(V_c|y, \tau, \alpha, V_\tau, K)$
5 $p(K|y, \tau, \alpha, V_\tau, V_c)$

A.5. Convergence of the Markov chain

In Fig. A1, we show the trace plots of the inefficiency factors. For knowing whether the Markov chain has converged to an ergodic distribution we calculate the inefficiency factor based on Geweke (1991). Primiceri (2005) has shown that inefficiency factor values less than 20 are regarded satisfactory for convergence. We notice that all the values are within 20 showing that the Markov chain has converged to a stationary distribution.

Data availability

Data will be made available on request.

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