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Asset Prices, Regime Switches, and Monetary Policy: Evidence from China

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Abstract

This paper develops a regime-switching DSGE model that can capture time-varying volatilities in economic activity and monetary policy. The model is then used to study regime switches in macroeconomic dynamics and monetary policy in China. The results suggest a better fitness of the regime-switching model than conventional constant-parameter models. We also find notable differences in macroeconomic dynamics and monetary policy reactions between high and low volatility regimes. Further counterfactual analysis suggests that, at least in an environment with regime-switching volatilities, the optimal reaction of monetary policy involves responses to asset price variations. The findings of the paper shed new light on the regime-switching properties of the economy and the optimal choice of monetary policy within this context.

JEL Classification: E32, E52, E61
Keywords: regime switch; asset price; monetary policy

1. Introduction

It has been widely acknowledged that the volatilities of many macroeconomic and financial variables are nonlinear and time-varying. Such characteristics are also proved to be crucial for understanding the dynamics and mechanisms of the real economy as well as the real-financial interactions (Benchimol and Ivashchenko 2021; Fernández-Villaverde and Rubio-Ramírez 2010; Justiniano and Primiceri 2008; Reyes-Heroles and Tenorio 2019).

In response to the time-varying volatility of the real economy and the financial system, one question of particular interest is whether monetary policy is subject to regime changes. The conventional Taylor rule has prescribed a linear reaction of monetary policy to inflation and the output gap. However, many doubts revolve around such a rule, especially in the sense that the reaction of monetary policy is not always linear. For example, Bianchi (2013, 2016) finds that the Fed shifted between a Hawk and a Dove regime during 1954Q3-2009Q2. Liu et al. (2011) document that the postwar U.S. economy could be better described by a regime-switching model with synchronized shifts in shock variances.

Similar phenomena are also found in other countries. To illustrate this, let's take China as an example. In the past decades, China has experienced several significant shocks, including:

- Economic shocks: the 1997-1998 Asian financial crisis, the 2007-2008 global financial crisis, and the COVID-19 crisis.
- Asset price shocks: the 2007 Chinese stock bubble and the 2015 Chinese stock market crash.

The periods of these shocks are presented in Table 1. To summarize, the shock periods, also regarded as high-volatility periods, are 1997Q3-1998Q4, 2007Q2-2009Q1, 2015Q2-2015Q3, and 2019Q4-2022Q4. Table 2 reports the statistical moments of four main macroeconomic variables in China over the period of 1996Q2-2020Q2. It is apparent to see the differences between periods of shocks and other periods. Specifically, from the bottom panel of Table 2 we can see that, as compared with periods of shocks, the standard deviation of output growth falls by 78% during other periods, the standard deviation of inflation falls by 46%, and that of stock return falls by 35%. The top panel shows that, compared with periods of shocks, the mean of output growth increases by 9%, the mean of inflation increases by 12%, and the mean of stock return increases by 176%. These results indicate that a low-volatility environment is beneficial for achieving high economic growth and high asset prices.

Table 1. Classification of shock periods

Type of shock	Event	Period
Economic shock	The Asian financial crisis	1997Q3-1998Q4
	The global financial crisis	2007Q2-2009Q1
	The COVID-19 crisis	2019Q4-2022Q4
Asset price shock	The 2007 Chinese stock bubble	2007Q2-2007Q2
	The 2015 Chinese stock market crash	2015Q2-2015Q3

Notes: (1) This table *summarizes* the significant shocks to China's economy over the period of 1996Q2-2020Q2; (2) Source: Authors' compilation.

Table 2. Performance of main macroeconomic variables

Mean (%)	Output growth	Inflation rate	Interest rate	Stock return
All sample	2.08	0.52	3.49	1.27
Shock periods	1.94	0.48	3.81	-2.94
Other periods	2.12	0.53	3.41	2.22
Other /Shock	109.21	112.41	89.42	-75.67
Relative change	9.21	12.41	-10.58	-175.67
Std (%)	**Output growth**	**Inflation rate**	**Interest rate**	**Stock return**
All sample	1.59	0.70	2.36	12.02
Shock periods	13.65	4.32	2.20	65.94
Other periods	3.05	2.35	2.40	42.72
Other /Shock	22.35	54.53	109.17	64.79
Relative change	-77.65	-45.47	9.17	-35.21

Notes: (1) This table reports the mean and standard deviation of four main macroeconomic variables in China over the period of 1996Q2-2020Q2, based on annual terms; (2) The classification of shock periods is presented in Table 1; (3) Output growth and inflation are reported on a quarterly basis; (4) Interest rate refers to the 7-day interbank rate, which is the most frequently and widely used monetary policy rate in China; (5) Stock return is calculated using the Shanghai Composite Stock Market Index.

Besides regime switches in the economy, monetary policy in China also exhibits regime-switching properties. Table 3 summarizes the statements of the People's Bank of China (PBOC, China's central bank) regarding its monetary policy stance for each period, according to the Monetary Policy Report released quarterly by the PBOC since 1996. Again we can see that monetary policy in China typically shifts between tight and loose regimes depending on the macroeconomic and financial conditions in each period.

Table 3. Monetary policy stance and macroeconomic conditions

Period	1996-1997	1998-2007	2008-2010	2011-2020
Monetary policy stance	Moderately tight	Prudent	Moderately loose	Prudent
Policy rate (%)	11.37	2.85	2.16	3.33
GDP target (%)	8.00	7.40	8.00	7.06
GDP growth (%)	9.58	10.00	9.90	6.85
CPI target (%)	10.00	2.78	3.93	3.35

CPI inflation (%)	5.55	1.13	2.83	2.51
Stock return (%)	9.03	5.11	-12.68	-0.52

Notes: (1) This table summarizes the monetary policy stances and the associated macroeconomic and financial conditions in China over the period of 1996Q2-2020Q2; (2) The classification of monetary policy stance is based on the corresponding statements in the *Monetary Policy Report* released quarterly by the People's Bank of China since 1996; (3) Policy rate refers to the 7-day interbank rate, which is the most frequently and widely used monetary policy rate in China; (4) GDP and CPI targets are obtained from the *Government Work Report* delivered annually by the Premier at the National People's Congress of the People's Republic of China; (5) Stock return is calculated using the Shanghai Composite Stock Market Index; (6) The numbers reported are annual averages.

Recent studies also document that China's monetary policy is subject to regime changes. For example, Zheng et al. (2012) analyze China's monetary policy using a two-regime Taylor rule. Ma (2014) identifies a policy regime shift over the period of 1999Q1-2013Q3. Klingelhöfer and Sun (2018) find nonlinearities in China's monetary policy in that it fights against economic slowdown and high inflation but becomes tolerant when faced with low inflation or economic overheating. Chen et al. (2018) characterize China's monetary policy with a quantity-based rule and claim that the PBOC is inclined to take an unusually aggressive monetary policy when output growth falls below the government's target.

In recent years, the importance of using time-varying parameters to capture the nonlinearities in macroeconomic dynamics has been recognized by many researchers, as rational agents adjust their expectations over different regimes in a changing environment. However, except for the few studies mentioned above, most of the existing studies still assume a linear model when studying the Chinese economy and its monetary policy. In the current paper, we attempt to partially fill this gap by developing a regime-switching dynamic general equilibrium (RS-DSGE) model featuring regime switches in both volatility changes and the monetary policy rule. Such a model can capture nonlinear changes in the economy and thus can generate richer dynamics of main variables of interest by allowing for regime-switching parameters. It can also be applied or tailored to study a variety of topics that are related to regime-switching properties or time-dependent structures.

Besides the general contribution in modeling regime-switching dynamics within a DSGE framework, other contributions of the current paper can be summarized into three main aspects. The first contribution is to analyze the evolution of China's economy over the past two decades using the RS-DSGE model, with a particular focus on the potential regime switches that have been largely ignored in the previous literature. In particular, our model takes into account not only the regime switches that occur in various shocks to the economy, but also the corresponding changes in the monetary policy responses to these shocks. In our model, changes in the volatility of structural shocks are considered stochastic, and regime switches in the monetary policy rule are assumed to be reversible and synchronized with the shifts in volatility. This is essential for understanding the law of motion that governs macroeconomic dynamics in China.

The second contribution of our study is to analyze whether China's monetary policy takes account into regime switches. Although there are a few studies discussing possible regime switches in the U.S. monetary policy (e.g., Aastveit et al. 2021; Finocchiaro and von Heideken 2013; Hur 2017), similar studies for the Chinese monetary policy are largely absent. To address this issue, we allow for regime changes in the reaction coefficients of monetary policy rule within the RS-DSGE model and find that China's monetary policy follows a two-regime switching behavior in which monetary policy reacts more aggressively to inflation and output under the high and low volatility regime respectively. We also discuss whether the regime-switching monetary policy outperforms the conventional linear monetary policy by comparing the stabilization effects of the switching monetary policy with that of the standard Taylor rule. We find that the regime-switching monetary policy has a better stabilizing effect under both demand and supply shocks, which accounts for a major portion of the output and inflation variations in the Chinese economy.

The third contribution of our study is to analyze whether and how monetary policy should react to asset prices. Although the traditional view insists that inflation targeting is sufficient to achieve macroeconomic stability (e.g., Bernanke and Gertler 2001; Gilchrist and Leahy 2002), increasing empirical evidence suggests that monetary policy should also be concerned about excessive fluctuations in asset prices, especially the ones that may lead to dangerous financial instabilities (e.g., Caballero and Simsek 2019; Dong et al. 2020; Mishkin 2017). According to our results, the reaction coefficient on asset prices is found to be moderate and stable across high and low volatility regimes, indicating that asset price changes are one of the concerns of the PBOC. We then analyze whether and how monetary policy should react to asset prices by conducting a counterfactual analysis using the RS-DSGE model. We find that the welfare loss of an unresponsive stance is seven times larger than that of a responsive one under a switching regime, indicating that monetary policy indeed should respond to asset prices in a regime-switching environment.

The remainder of the paper is structured as follows. Section 2 develops the RS-DSGE model. Section 3 describes the data and estimation strategy. Section 4 presents the estimation results and evaluates the variants of the model. Section 5 discusses the time-varying dynamics of the Chinese economy based on the preferred model. Section 6 conducts monetary policy analysis. Section 7 concludes the paper.

2. The model

Our model is largely based on the standard New Keynesian DSGE models with price rigidities (e.g., Smets and Wouters 2003; Gali and Monacelli 2005) but extends these models in two major aspects. First, we introduce asset (stock) price dynamics into the model by assuming that households buy shares issued by firms. Second, we allow for regime switches in both volatility changes and monetary policy. Specifically, we assume that: (i) the variance of each shock switches between a finite number of regimes denoted by $s_t^* \in S^*$ with the Markov transition matrix $Q=\left[q_{ij}\right]$, where $q_{ij}=Prob\left[s_{t+1}^*=i \middle| s_t^*=j\right]$; and (ii) the reaction coefficients of monetary policy switch between a finite number of regimes denoted by $s_t \in S$ with the Markov transition matrix $P=\left[p_{ij}\right]$, where $p_{ij}=Prob\left[s_{t+1}=i \middle| s_t=j\right]$. These extensions allow us to analyse the real-financial dynamics as well as policy reactions in a regime-switching environment.

2.1 The demand side of the economy

The demand side of the economy is populated by a continuum of infinitely lived identical households. They decide on consumption, asset holdings (bonds and shares) and labor supply to maximize their period-by-period utility, which is given by a standard constant relative risk aversion utility function:

$$U(C_t, N_t) = \left(\frac{(C_t - hC_{t-1})^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) \quad (1)$$

where C_t denotes consumption, and N_t is hours worked. σ is the inverse of the intertemporal elasticity of substitution, φ is the Frisch labour supply elasticity, and h is the habit formation parameter.

The portfolios of households consist of bonds and shares. They use wage income, interest payments, and asset returns to consume and rebalance their portfolios according to the following budget constraint:

$$C_t + b_t + \zeta_t q_t A_t = w_t N_t + \frac{1}{1+\pi_t}(1+r_{t-1})b_{t-1} + \zeta_t q_t A_{t-1} \quad (2)$$

where $b_t = B_t / P_t$ denotes real bond holdings; $q_t = Q_t / P_t$ denotes the real price of each share (asset price or stock price for short hereafter); ζ_t is an exogenous shock to the financial (stock) market which affects the share price (financial shock for short hereafter); $w_t = W_t / P_t$ is real wage; and $\pi_t = \frac{P_t}{P_{t-1}} - 1$ denotes CPI inflation.

In each period, the optimization problem of the representative household is given by:

$$E_t \sum_{s=0}^{\infty} \beta^s \left[\frac{(C_{t+s} - hC_{t+s-1})^{1-\sigma}}{1-\sigma} - \frac{N_{t+s}^{1+\varphi}}{1+\varphi} \right]$$
$$s.t. \;\; C_t + b_t + \zeta_t q_t A_t = w_t N_t + \frac{1}{1+\pi_t}(1+r_{t-1})b_{t-1} + \zeta_t q_t A_{t-1} \quad (3)$$

where β is the discount factor. Other variables are the same as defined above.

The first-order conditions for the above problem are given by:

$$\frac{1}{1+r_t} = \beta E_t \left[\left(\frac{C_{t+1} - hC_t}{C_t - hC_{t-1}} \right)^{-\sigma} \frac{P_t}{P_{t+1}} \right] \quad (4)$$

$$(C_t - hC_{t-1})^{\sigma} N_t^{\varphi} = w_t \quad (5)$$

$$q_t \zeta_t = \frac{E_t q_{t+1} \zeta_{t+1}}{1+r_t}(1 + E_t \pi_{t+1}) \quad (6)$$

where Eqs. (4)-(6) stand for the consumption Euler equation, the labour supply equation and the asset (stock) demand equation, respectively.

As mentioned earlier, to allow for potential regime switches in shock volatilities, the financial shock ζ_t is assumed to follow the following AR (1) process with regime-switching innovations:

$$\frac{\zeta_t}{\zeta} = \left(\frac{\zeta_{t-1}}{\zeta} \right)^{\rho_\zeta} \exp\left[\varepsilon_t^q (s_t^*) \right] \quad (7)$$

where ζ is the steady-state values of ζ_t, and s_t^* is an unobservable state variable that governs the volatility regime at time t.

2.2 The supply side of the economy

The supply side of the economy consists of a retail sector producing final consumption goods and a wholesale sector producing a continuum of differentiated intermediate goods. The retail sector produces the final consumption goods Y_t by using constant returns to scale technology in a perfectly competitive market: $Y_t = \left[\int_0^1 Y_t(i)^{\frac{\varepsilon-1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}}$, where $\varepsilon > 1$ measures the elasticity of substitution. Equilibrium in the final sector leads to the typical input demand function $Y_t(i) = \left[\frac{P_t(i)}{P_t} \right]^{-\varepsilon} Y_t$ and the aggregate price index $P_t = \left[\int_0^1 P_t(i)^{1-\varepsilon} di \right]^{\frac{1}{1-\varepsilon}}$.

The firms in the wholesale sector produce differentiated goods in monopolistic competition with a linear technology: $Y_{jt} = Z_t N_{jt}$. To focus on the impact of asset prices on the economy and for the sake of simplicity, we assume that there is no internal finance and firms have only one source of external funds to pay their wage bills: the stock market.[1] Under these assumptions, the firm j raises funds by issuing shares with an amount that is equal to the payment of the wage bill[2]:

$$w_t N_{jt} = q_t A_{jt} \quad (8)$$

Then the firm's total cost is given by $TC_{jt} = E_t q_{t+1} A_{jt}$. Plugging Eq. (8) into TC_{jt} we have: $TC_j = \frac{E_t q_{t+1}}{q_t} w_t N_{jt}$. Then the real marginal cost can be written as:

$$\psi_t = \frac{E_t q_{t+1}}{q_t} \frac{w_t}{Z_t} \quad (9)$$

Note that, in contrast to the conventional approach which delivers a real marginal cost of $\psi_t = \frac{w_t}{Z_t}$, the real marginal cost given by Eq. (9) includes a term denoting the cost of external finance, which is equal to the capital gain $\frac{E_t q_{t+1}}{q_t}$.

As in Gali and Monacelli (2005), we assume that firms reset their prices according to the Calvo-Yun rule and receive a price signal at a constant rate θ_H for simplicity.

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[1] This simplification helps us to concentrate on the main purpose of the paper while avoiding the complications arising from the modelling of the credit market as well as the accumulation of net worth.

[2] By integrating the share price over the continuum of firms, $q_t = \int_0^1 q_t(j) dj$, it is easy to think of q_t as an aggregate real stock-price index.

Define θ_H^k as the probability that the price set at time t still holds at time $t+k$. This pricing technology leads to the following equation for newly set prices:

$$p_t^{new} = (1-\beta\theta_H) E_t \left\{ \sum_{k=0}^{\infty} (\beta\theta_H)^k (\psi_{t+k} + p_{t+k}) \right\} \quad (10)$$

The aggregate price index is then given by:

$$P_t = \left[\theta_H (P_{t-1})^{1-\varepsilon} + (1-\theta_H)(P_t^{new})^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} \quad (11)$$

2.3 Monetary policy with regime switches

As a main focus of the paper, we assume that the central bank sets interest rates according to the following regime-switching monetary policy rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r(s_t)} \left[\left(\frac{\pi_t}{\pi}\right)^{\phi_\pi(s_t)} \left(\frac{y_t}{y}\right)^{\phi_y(s_t)} \left(\frac{\Delta q_t}{\Delta q}\right)^{\phi_q(s_t)} \right]^{1-\rho_r(s_t)} \exp\left[\varepsilon_t^r (s_t^*)\right] \quad (12)$$

where s_t is an unobservable state variable that governs the policy regime at time t and $\varepsilon_t^r (s_t^*) \sim i.i.d.(0, \sigma_r^2(s_t^*))$ is a regime-switching monetary policy shock.

It is worth emphasizing that the setting of policy regimes is not based purely on the stance of monetary policy. This is due to the vague tone of the PBOC's statements, making it difficult to fully reflect policy implementation through monetary policy stance alone. For instance, although the PBOC claimed to have implemented a prudent monetary policy stance in both 2011 and 2016, the deposit reserve ratio was raised several times in 2011 and the interbank interest rate reached 4%, indicating a contractionary monetary policy. In contrast, the deposit reserve ratio was lowered in 2016, and the interbank interest rate fell to 2.5%, indicating an expansionary monetary policy.

As for the number of regimes, the two-regime specification is widely used in the modelling of switching monetary policies (e.g., Alstadheim et al. 2021; Chen et al. 2018; Liu et al. 2011; Zheng et al. 2012). In particular, Zheng et al. (2012) estimated a regime-switching Taylor rule, revealing that China's monetary policy switches between two states rather than three states. Hence, we assume that the monetary policy parameters follow a two-state Markov process that differs primarily in its responses to the policy targets (inflation, output, and asset prices). Specifically, all the coefficients in the monetary policy rule are assumed to be dependent on the policy state variable, s_t, which follows a two-state Markov switching process with the following transition probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \quad (13)$$

where the transition probabilities are given by $p_{ij} = Prob\left[s_t = j \middle| s_{t-1} = i\right]$ for $\forall i, j \in \{1,2\}$.

2.4 Equilibrium and log-linearization

The optimal conditions that characterize the demand side of the economy are given by Eqs. (4)-(6). Log-linearizing Eqs. (4)-(6) around the steady state we have:

$$\hat{c}_t = \frac{h}{1+h}\hat{c}_{t-1} + \frac{1}{1+h}E_t\hat{c}_{t+1} - \frac{1-h}{(1+h)\sigma}\left(\hat{r}_t - E_t\hat{\pi}_{t+1}\right) \qquad (14)$$

$$\hat{w}_t = \varphi\hat{n}_t + \frac{\sigma}{1-h}\hat{c}_t - \frac{\sigma h}{1-h}\hat{c}_{t-1} \qquad (15)$$

$$\hat{q}_t = E_t\hat{q}_{t+1} - \left(\hat{r}_t - E_t\hat{\pi}_{t+1}\right) + E_t\hat{\zeta}_{t+1} - \hat{\zeta}_t \qquad (16)$$

where lowercase letters with a "hat" denote the log deviations of the respective variable from its steady state value.

In equilibrium, the goods market clearing condition requires that total output equals consumption: $\hat{y}_t = \hat{c}_t$. Plugging this condition into Eq. (14), we obtain the following dynamic IS curve:

$$\hat{y}_t = \frac{h}{1+h}\hat{y}_{t-1} + \frac{1}{1+h}E_t\hat{y}_{t+1} - \frac{1-h}{(1+h)\sigma}\left(\hat{r}_t - E_t\hat{\pi}_{t+1}\right) + u_t \qquad (17)$$

where u_t is an exogenous demand shock that follows the AR (1) process:

$u_t = \rho_y u_{t-1} + \varepsilon_t^y(s_t^*)$.

With respect to the supply side of the economy, log-linearizing (11) and combining with (10) we get the following forward-looking Phillips curve:

$$\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa\hat{\psi}_t + \upsilon_t \qquad (18)$$

where $\kappa \equiv \left(\frac{\left(1-\theta_H\right)\left(1-\beta\theta_H\right)}{\theta_H}\right)$, and υ_t is an exogenous cost-push shock that follows the AR (1) process: $\upsilon_t = \rho_\pi \upsilon_{t-1} + \varepsilon_t^\pi(s_t^*)$, $\varepsilon_t^\pi(s_t^*) \sim i.i.d.(0, \sigma_\pi^2(s_t^*))$.

Meanwhile, the log-linearization of the production function yields:

$$\hat{y}_t = \hat{z}_t + \hat{n}_t \qquad (19)$$

where the productivity shock is assumed to follow the AR (1) process: $\hat{z}_t = \rho_z\hat{z}_{t-1} + \varepsilon_t^z(s_t^*)$, $\varepsilon_t^z(s_t^*) \sim i.i.d.(0, \sigma_z^2(s_t^*))$.

To derive the real marginal cost dynamics, log-linearizing Eq. (9) yields:

$$\hat{\psi}_t = \hat{w}_t - \hat{z}_t + E_t\hat{q}_{t+1} - \hat{q}_t \qquad (20)$$

Using Eqs. (15) and (19) together with the goods market equilibrium condition, Eq. (20) can be rewritten as:

$$\hat{\psi}_t = (\varphi + \frac{\sigma}{1-h})\hat{y}_t - \frac{\sigma h}{1-h}\hat{y}_{t-1} - (1+\varphi)\hat{z}_t + \Delta\hat{q}_t \qquad (21)$$

Plugging Eq. (21) into (18) we get:

$$\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa\left[(\varphi + \frac{\sigma}{1-h})\hat{y}_t - \frac{\sigma h}{1-h}\hat{y}_{t-1} - (1+\varphi)\hat{z}_t + \Delta\hat{q}_t\right] + \upsilon_t \qquad (22)$$

Meanwhile, log-linearizing the Markov-switching monetary policy rule (12) yields:

$$\hat{r}_t = \rho_r(s_t)\hat{r}_{t-1} + (1-\rho_r(s_t))\left[\phi_\pi(s_t)\hat{\pi}_t + \phi_y(s_t)\hat{y}_t + \phi_q(s_t)\Delta\hat{q}_{t\text{-}1}\right] + \varepsilon_t^r(s_t^*)$$

(23)

where $\varepsilon_t^r(s_t^*) \sim i.i.d.(0, \sigma_r^2(s_t^*))$ is a regime-switching monetary policy shock as specified in the previous section.

Finally, apart from the monetary policy shock, all exogenous shocks are assumed to follow AR (1) processes with regime-switching innovations:

$$u_t = \rho_y u_{t-1} + \varepsilon_t^y(s_t^*) \quad (24)$$

$$\upsilon_t = \rho_\pi \upsilon_{t-1} + \varepsilon_t^\pi(s_t^*) \quad (25)$$

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_t^z(s_t^*) \quad (26)$$

$$\hat{\zeta}_t = \rho_\zeta \hat{\zeta}_{t-1} + \varepsilon_t^q(s_t^*) \quad (27)$$

where the innovations $\varepsilon_t^y(s_t^*) \sim i.i.d.(0, \sigma_y^2(s_t^*))$, $\varepsilon_t^\pi(s_t^*) \sim i.i.d.(0, \sigma_\pi^2(s_t^*))$, $\varepsilon_t^z(s_t^*) \sim i.i.d.(0, \sigma_z^2(s_t^*))$, $\varepsilon_t^q(s_t^*) \sim i.i.d.(0, \sigma_q^2(s_t^*))$ are all assumed to be regime-switching to capture the potential volatility changes of the economy. Specifically, we assume that the associated state variable follows a two-state Markov switching process with the following transition probability matrix:

$$Q = \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \quad (28)$$

where the transition probabilities are given by $q_{ij} = Prob\left[s_t^* = j \middle| s_{t-1}^* = i\right]$ for $\forall i, j \in \{1,2\}$.

In summary, the model consists of the following equations:

$$\hat{y}_t = \frac{h}{1+h}\hat{y}_{t-1} + \frac{1}{1+h}E_t\hat{y}_{t+1} - \frac{1-h}{(1+h)\sigma}(\hat{r}_t - E_t\hat{\pi}_{t+1}) + u_t \quad (29)$$

$$\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa\left[(\varphi + \frac{\sigma}{1-h})\hat{y}_t - \frac{\sigma h}{1-h}\hat{y}_{t-1} - (1+\varphi)\hat{z}_t + \Delta\hat{q}_t\right] + \upsilon_t \quad (30)$$

$$\hat{q}_t = E_t\hat{q}_{t+1} - (\hat{r}_t - E_t\hat{\pi}_{t+1}) + E_t\hat{\zeta}_{t+1} - \hat{\zeta}_t \quad (31)$$

$$\hat{r}_t = \rho_r(s_t)\hat{r}_{t-1} + (1-\rho_r(s_t))\left[\phi_\pi(s_t)\hat{\pi}_t + \phi_y(s_t)\hat{y}_t + \phi_q(s_t)\Delta\hat{q}_t\right] + \varepsilon_t^r(s_t^*) \quad (32)$$

$$u_t = \rho_y u_{t-1} + \varepsilon_t^y(s_t^*) \quad (33)$$

$$\upsilon_t = \rho_\pi \upsilon_{t-1} + \varepsilon_t^\pi(s_t^*) \quad (34)$$

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \varepsilon_t^z(s_t^*) \quad (35)$$

$$\hat{\zeta}_t = \rho_\zeta \hat{\zeta}_{t-1} + \varepsilon_t^q(s_t^*) \quad (36)$$

2.5 Alternative model specifications

Still, there remains a crucial question about the model specification: Can the underlying assumption of independent Markov chains accurately characterize the actual situation? A recent stream of literature studies the relationships between monetary policy and financial market volatility (e.g., Apergis et al. 2020; Gallo et al. 2021; Georgiadis and Gräb 2016; Lacava et al. 2022) and the empirical evidence suggests that the hypothesis of unconditional independence between the policy state and the volatility state is overly strong in practice.

To address this issue, one can adopt the Multi-Chain Markov Switching (MCMS) model proposed by Otranto (2005), where the Markov chains of the two variables are mutually dependent, with the possibility of verifying their interdependence and direction of causality, as in Gallo and Otranto (2008). However, the interdependence of the Markov chains might increase the complexity of estimating the model as well as explaining the dynamics and interactions of economic variables. An alternative method, the one we follow, is to estimate a single-chain model, where the policy state and the volatility state are controlled by a common Markov chain (i.e., $s_t = s_t^*$). By comparing the single-chain model to the independent double-chain model, we can obtain informative results in testing the hypothesis of independent Markov chains. Moreover, the single-chain model also has the advantage of easier to understand than the MCMS model, as it implies that the states of monetary policy are entirely dependent on the contemporaneous states of the volatilities of shocks. In addition, the single-chain model is also the specification that are most frequently used in the RS-DSGE literature (e.g., Liu et al. 2011; Liu and Mumtaz 2011; Alstadheim et al. 2021).

Meanwhile, to compare whether the regime-switching model fits the data well, it is instructive to estimate a time-invariant specification for reference. To sum up, we estimate three versions of the proposed model: (Ⅰ) the conventional time-invariant model with no regime switches; (Ⅱ) the *single-chain* model allowing for *synchronized* regime switches in both monetary policy parameters (ϕ_π, ϕ_y, ϕ_q) and the volatilities of shocks ($\varepsilon_t^r, \varepsilon_t^y, \varepsilon_t^\pi, \varepsilon_t^z, \varepsilon_t^q$) and (Ⅲ) the *double-chain* model assuming *independent* regime switches in monetary policy and the volatilities of structural shocks.

3. Data and methodology

3.1 Data

The models are estimated using quarterly data of the Chinese economy over the period of 1996Q2-2020Q2, due to data availability. The observable variables used for estimation include output (real GDP), inflation (CPI), nominal interest rate (7-day interbank rate), and asset price index (Shanghai Composite Stock Market Index). The first three time series are constructed and updated to 2020Q2 based on the method of Chang et al. (2016), who have constructed a standard set of Chinese macroeconomic data in line with the definitions of the U.S. time series. The Shanghai Composite Stock Market Index is obtained from the Wind database. To ensure the stationarity of the variables, all the data are seasonally adjusted, detrended with the Hodrick-Prescott (HP) filter, and expressed as the percentage deviation from the HP trend.

3.2 Estimation methodology

To estimate the RS-DSGE model developed in Section 2, we use the RISE (Rationality in Switching Environment) toolbox proposed by Maih (2015). This toolbox is efficient in finding minimum state variable (MSV) solutions for RS-DSGE models by using the higher-order perturbation method based on functional iteration and Newton techniques. Specifically, the generic Markov-switching model is given by:

$$E_t \sum_{s_{t+1}=1}^{h} p_{s_t,s_{t+1}}\left(\mathrm{I}_t\right)\tilde{d}_{s_t}(v)=0$$

where the regime indicator $s_t = 1,2,\ldots,h$ is assumed to follow an h-regime Markov chain. The information set I_t contains all the information that can be obtained in period t, including switching parameters, unobservable and observable variables. The transition probability $p_{s_t,s_{t+1}}$ is a function of the information set I_t. $\tilde{d}_{s_t}$ is a vector including both linear and nonlinear functions of the argument v. The argument v is an $n_v \times 1$ vector, which is defined as:

$$v \equiv \left[b_{t+1}\left(s_{t+1}\right)' \quad f_{t+1}\left(s_{t+1}\right)' \quad a_t\left(s_t\right)' \quad m_t\left(s_t\right)' \quad b_t\left(s_t\right)' \quad f_t\left(s_t\right)' \quad m_{t-1}' \quad b_{t-1}' \quad \varepsilon_t' \quad \theta_{s_{t+1}}' \right]'$$

where b_t is the vector of predetermined and forward-looking variables, f_t is the vector of forward-looking variables, a_t is the vector of static variables, m_t is the vector of predetermined variables, ε_t is the vector of shocks, and θ_{s_t} is the vector of switching parameters. In our model, $b_t = [y_t]'$, $f_t = [\pi_t]'$, $a_t = [\Delta q_t]'$, $m_t = [r_t, u_t, v_t, \zeta_t]'$, $\varepsilon_t = [\varepsilon_t^r, \varepsilon_t^y, \varepsilon_t^\pi, \varepsilon_t^z, \varepsilon_t^q]'$.

Denoting the perturbation parameter as σ_P, the solution of the model is given by:

$$x_t(s_t) \equiv \begin{bmatrix} a_t(s_t) \\ m_t(s_t) \\ b_t(s_t) \\ f_t(s_t) \end{bmatrix} = \mathrm{T}^{s_t}(z_t) \equiv \begin{bmatrix} \mathrm{A}^{s_t}(z_t) \\ \mathrm{M}^{s_t}(z_t) \\ \mathrm{B}^{s_t}(z_t) \\ \mathrm{F}^{s_t}(z_t) \end{bmatrix}$$

where x_t is the vector of endogenous variables, and z_t is the vector of the state variables defined as $z_t \equiv \begin{bmatrix} m_{t-1}' & b_{t-1}' & \sigma_P & \varepsilon_t' & \varepsilon_{t+1}' & \cdots & \varepsilon_{t+k}' \end{bmatrix}'$.

Regarding the estimation approach, Bayesian methods are adopted in the majority of the regime-switching DSGE literature (Best and Hur 2019; Bianchi 2013; Liu and Mumtaz 2011; Liu et al. 2011). By combining actual data with the subjective belief of researchers, Bayesian estimation can better deal with the identification problems and get more accurate posterior distributions of parameters. It also outperforms alternative estimation approaches in small samples. Therefore, we employ Bayesian techniques to obtain the posterior estimates of the parameters. The equations of the model, coded in RISE language, are processed by the software to compute the perturbation solution and the state-space form for likelihood evaluation.

4. Results

4.1 Prior specification

In the estimation, the only calibrated parameter is the discount factor β, which is set to 0.9916 to produce an annual interest rate of 3.4% (equal to the historical average over the sample period) in the steady state. All other parameters are estimated by Bayesian approach using actual data. The prior distributions and posterior estimates are reported in Table 4. Most of the priors that we use are standard in the literature (e.g., Smets and Wouters 2003; Ireland 2004; Lubik and Schorfiede 2005, 2007). Meanwhile, for all regime-switching parameters, the prior distributions for the two regimes are assumed to be the same so as to let the data speak if there exist differences between the two regimes.

Table 4. Prior distributions and posterior estimates of the parameters

Parameter	Prior Distribution*	Single-chain Model		Double-chain Model	
		Posterior Mode	Posterior Std.	Posterior Mode	Posterior Std.

		Structural parameters			
σ	Gamma [2, 0.75]	2.0714	0.5543	2.0139	0.2819
φ	Gamma [2, 0.5]	1.7421	0.3239	1.7403	0.2048
h	Beta [0.7, 0.1]	0.7778	0.0671	0.7662	0.0919
θ_H	Beta [0.75, 0.05]	0.9242	0.0149	0.9240	0.0162
		Persistence parameters			
ρ_y	Beta [0.6, 0.2]	0.2776	0.1212	0.3110	0.1046
ρ_π	Beta [0.6, 0.2]	0.6480	0.0733	0.6354	0.0579
ρ_q	Beta [0.6, 0.2]	0.9373	0.0266	0.9374	0.0270
ρ_z	Beta [0.6, 0.2]	0.6667	0.1952	0.6667	0.0859
		Regime-switching monetary policy parameters			
$\rho_r(s_t = 1)$	Beta [0.75, 0.2]	0.9466	0.0162	0.9339	0.0150
$\rho_r(s_t = 2)$	Beta [0.75, 0.2]	0.9644	0.0081	0.9764	0.0076
$\phi_\pi(s_t = 1)$	Gamma [2, 0.5]	1.6114	0.2477	1.6553	0.3083
$\phi_\pi(s_t = 2)$	Gamma [2, 0.5]	1.9841	0.3412	1.6553	0.3694
$\phi_y(s_t = 1)$	Gamma [1, 0.25]	1.0563	0.2084	1.0434	0.1211
$\phi_y(s_t = 2)$	Gamma [1, 0.25]	0.8595	0.1674	0.9130	0.1196
$\phi_q(s_t = 1)$	Gamma [0.5, 0.2]	0.2139	0.0793	0.1525	0.0552
$\phi_q(s_t = 2)$	Gamma [0.5, 0.2]	0.2888	0.1021	0.4218	0.1429
		Regime-switching shocks			
$\sigma_r\left(s_t^* = 1\right)$	Inv gamma [0.5, ∞]	0.4803	0.1013	0.4798	0.0455
$\sigma_r\left(s_t^* = 2\right)$	Inv gamma [0.5, ∞]	0.5265	0.0721	0.4561	0.0625
$\sigma_y\left(s_t^* = 1\right)$	Inv gamma [3, ∞]	0.5176	0.1172	0.4902	0.0841

$\sigma_y\left(s_t^*=2\right)$	Inv gamma [3, ∞]	4.2768	0.6391	4.1174	0.4102
$\sigma_\pi\left(s_t^*=1\right)$	Inv gamma [3, ∞]	0.5742	0.1180	0.5847	0.0978
$\sigma_\pi\left(s_t^*=2\right)$	Inv gamma [3, ∞]	1.2722	0.2681	1.2853	0.1690
$\sigma_q\left(s_t^*=1\right)$	Inv gamma [0.5, ∞]	0.8915	0.0856	0.8915	0.0860
$\sigma_q\left(s_t^*=2\right)$	Inv gamma [0.5, ∞]	1.3476	0.1217	1.3439	0.1041
$\sigma_z\left(s_t^*=1\right)$	Inv gamma [0.5, ∞]	0.1683	0.1065	0.1683	0.0915
$\sigma_z\left(s_t^*=2\right)$	Inv gamma [0.5, ∞]	0.1683	0.0895	0.1683	0.1011
Regime-switching probabilities					
q_{12}	Beta [0.1, 0.05]	0.0875	0.0274	0.0916	0.0340
q_{21}	Beta [0.1, 0.05]	0.0517	0.0228	0.0499	0.0232
p_{12}	Beta [0.1, 0.05]			0.0437	0.0278
p_{21}	Beta [0.1, 0.05]			0.0980	0.0477

Notes: (1) This table reports the prior distributions and posterior estimates of the parameters in the single-chain model and the double-chain model; (2) The results are obtained by Bayesian estimation using quarterly data of the Chinese economy over the period of 1996Q2-2020Q2; (3) Numbers in the square brackets are prior means and standard deviations; (4)The state of monetary policy parameters is synchronized with the volatility state (i.e., $s_t = s_t^*$) in the single-chain model.

4.2 Posterior estimates of the single-chain model

The posterior estimates of the single-chain model are presented in the third and fourth columns of Table 4. From the results in Table 4, we can see that the inverse of the intertemporal elasticity of substitution (σ) is estimated to be 2.07, consistent with the RBC literature documenting an elasticity of substitution ($1/\sigma$) less than one (Smets and Wouters 2003). The posterior estimate of the elasticity of labour supply φ is 1.74, which is slightly higher than that in advanced economies (e.g., Smets and Wouters 2003; Lubik and Schorfeide 2005), implying a relatively lower elasticity of labour supply in China. The posterior estimate of the habit formation parameter (h) is 0.78, implying a considerable degree of habit persistence in the consumption of Chinese households. The Calvo price stickiness parameter θ_H is estimated to be 0.92, which is close to that reported in the previous studies (e.g., Smets and Wouters 2003; Justiniano and Primiceri 2008) and suggests that the average duration of firms' price change is about three years.

Turning to the regime-switching parameters, which are the main focus of the paper, we find that there indeed exist substantial differences between the two regimes. In particular, all the shocks exhibit greater volatility in the second regime ($s_t = 2$) than in the first regime ($s_t = 1$). Meanwhile, we find a higher degree of interest rate smoothing in the second regime. The reaction coefficient of monetary policy to inflation (ϕ_π) is estimated to be 1.61 and 1.98 in the first and second regime respectively, indicating a more aggressive reaction of monetary policy to inflation variations during times of high volatility. By comparison, the reaction of monetary policy to the output gap (ϕ_y) is less aggressive during times of high volatility. As for the reaction of monetary policy to asset price changes, the coefficient (ϕ_q) is slightly different between the two regimes, which are estimated to be 0.21 and 0.29 in the first and second regimes respectively. This implies a moderate reaction of monetary policy to asset prices in both regimes. Overall, two main conclusions can be obtained from the above results: (i) there indeed exist regime-switching features in both the volatility of shocks and the reaction coefficients of monetary policy; (ii) during periods of high volatility, China's monetary policy is more smoothing and reacts more aggressively to inflation variations, and the reverse is true during periods of low volatility.

Finally, the estimates of the transition matrices can be summarized as

$$\hat{Q} = \begin{bmatrix} 0.9483 & 0.0875 \\ 0.0517 & 0.9125 \end{bmatrix},$$

which means that the estimated probabilities of the current policy regime taking place in the next period are around 0.95 and 0.91 for Regimes 1 and 2, respectively. This suggests that while both regimes exhibit a considerable degree of persistence, the first regime characterized by high volatility shocks and a stronger reaction of monetary policy to the inflation target is more persistent than the second regime. To give an intuitive illustration, we plot the smoothed probabilities of both regimes in Fig. 1. It is interesting to find that during the three major crisis periods, i.e., the 1997-1998 Asian financial crisis, the 2007-2008 U.S. subprime crisis, and the 2020 COVID-19 crisis, the dominant regime is the second regime. This is quite reasonable since the second regime is characterized by economic and financial instability (high volatility shocks) and a more aggressive monetary policy to stabilize the economy.

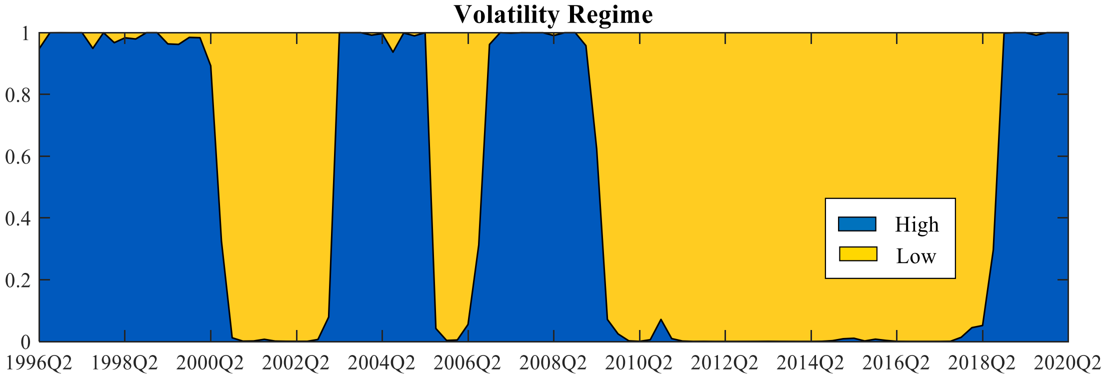

Figure 1. Smoothed probabilities of the single-chain model

Notes: The figure reports the smoothed regime probabilities of the single-chain model evaluated at the posterior mode. The yellow shaded areas indicate the probability of the low volatility regime (i.e., $s_t = s_t^* = 1$), while the blue ones indicate that of the high volatility regime (i.e., $s_t = s_t^* = 2$).

To verify the rationality of the regime classification, we present the historical data of macroeconomic variables and smoothed probabilities in Fig. 2. As one can see, for the four main periods of high volatility over the entire sample period, i.e., 1996Q2-2000Q2, 2003Q2-2005Q2, 2006Q4-2009Q2, and 2018Q4-2020Q2, the variances of the actual data are higher than those in the rest time. For example, output, inflation, asset prices, and interest rates have all increased since the fourth quarter of 2006, peaked at the end of 2007, and then declined in 2008. The most recent data for 2020 show that output and inflation have dropped very sharply due to the outbreak of COVID-19, thus it is quite reasonable to identify this period as a high-volatility regime.

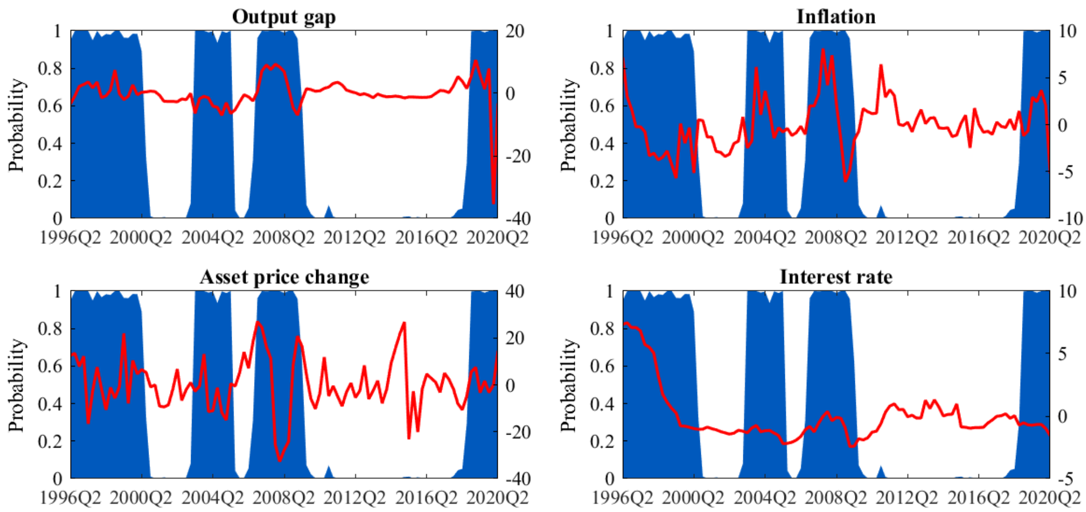

Figure 2. Historical data and smoothed probabilities of the single-chain model

Notes: The blue shaded area corresponds to the smoothed probability of the high volatility regime of the single-chain model (left axis), and the solid red line refers to the actual data (right axis).

4.3 Posterior estimates of the double-chain model

The last two columns of Table 4 present the posterior estimates of our double-chain switching specification, that is, the model that allows the policy parameters and the volatility of shocks to switch independently. As shown in Table 4, the time-invariant estimates of the structural parameters and the persistence parameters are quite close to those estimates obtained in the above single-chain specification. Also, the estimated volatility parameters of shocks are roughly in line with the previous specification, except that the monetary policy shock (σ_r) has greater volatility in the first regime.

Noticeable differences between these two specifications are mainly attributed to the estimates of the monetary policy parameters. In particular, the reaction coefficients to inflation are almost the same in the two regimes of the double-chain model, whilst the discrepancies between regimes have enlarged in terms of the smoothing coefficients and the reactions to asset price. The coefficient on asset price is 0.42 in the high smoothing regime, in contrast to 0.15 in the low persistence regime. Hence, the second policy regime can be interpreted as an extended Taylor rule that emphasizes policy smoothing and a strong response to asset price, while the first regime is characterized by low persistence and a weak response to asset price.

Regarding the transition probability, the estimates of the transition matrices can be summarized as

$$\hat{P} = \begin{bmatrix} 0.9020 & 0.0437 \\ 0.0980 & 0.9563 \end{bmatrix} \text{ and } \hat{Q} = \begin{bmatrix} 0.9501 & 0.0916 \\ 0.0499 & 0.9084 \end{bmatrix}.$$

Again, the transition probabilities of volatility are similar to the results in the single-chain specification. Note that in the transition matrix of policy parameters, $p_{21} > p_{12}$, implying that the probability of moving from the high smoothing regime with a strong response to asset price to the weak response regime is greater than moving from a weak to a strong response regime. Consequently, the policy remains in the low smoothing and weak response state for a longer time.

Fig. 3 displays the smoothed probabilities of the double-chain model. The yellow shaded areas in the top panel show the smoothed probabilities of being in a state with low response to asset prices, which was dominant during the 1990s and the early 2000s. The period of financial crisis (2006-2008) saw a brief switch to regime 2, but the probability of the low-response state increased again until 2017Q2. The blue areas in the bottom panel present the probability of being in a high-volatility regime. It is interesting to find that the volatility regime is clearly in line with the single-chain specification. We also find that the high policy response regime is largely associated with the high-volatility state, suggesting a potential violation of the independent Markov chains assumption.

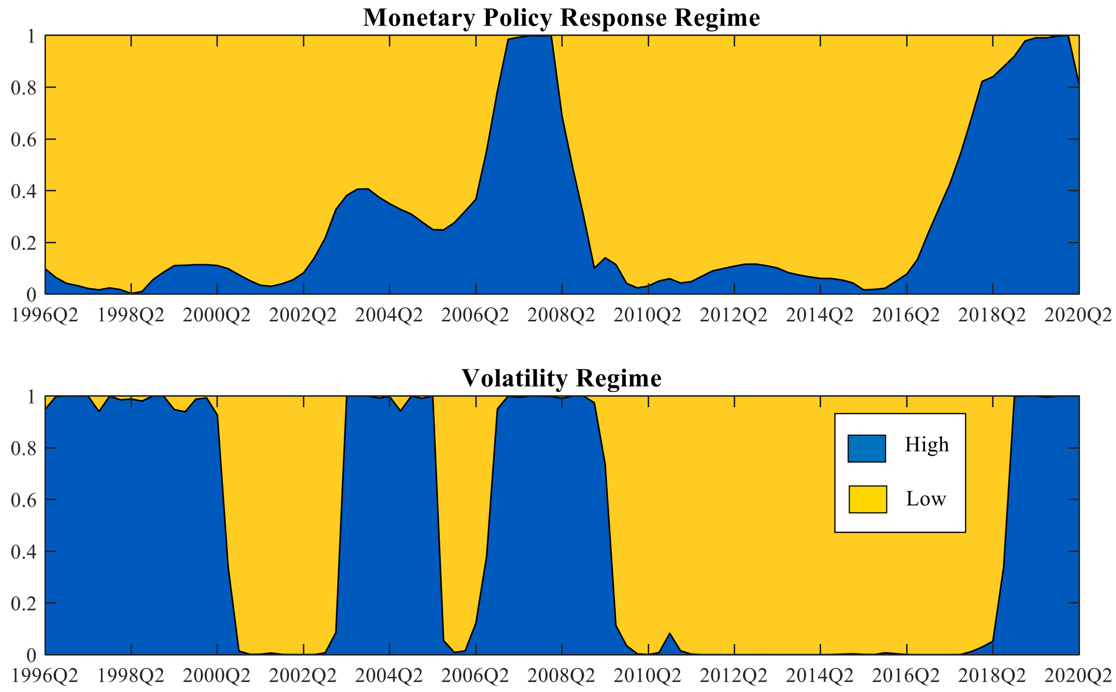

Figure 3. Smoothed probabilities of the double-chain model

Notes: The figure reports the smoothed regime probabilities of the double-chain model evaluated at the posterior mode. In the upper panel, the yellow shaded areas represent the probability of the monetary policy regime with a low response to asset price ($s_t = 1$), while the blue ones indicate that with a high response ($s_t = 2$). In the lower panel, the yellow shaded areas stand for the probability of the low-volatility regime ($s_t^* = 1$), while the blue areas represent that of the high-volatility regime ($s_t^* = 2$).

4.4. Model evaluation

To assess the goodness of fit, Table 5 presents several representative in-sample statistics for the above specifications. The first four indicators are the log-posterior, log-likelihood, log-prior, and log-marginal data density (MDD), with larger statistics indicating better performances. Although the marginal data density has incorporated a penalty for the number of estimated parameters, we report as a robustness check the Akaike information criteria (AIC) and the Bayesian information criteria (BIC) in the last two columns of Table 5.

Clearly, the switching models have better performances than the time-invariant model, no matter what criterion is used. This suggests that regime switches in both monetary policy and macroeconomic volatility are important features of the Chinese economy and using a regime-switching model is essential for capturing these features and thus improving the goodness of fit of the model to the actual data.

However, we find the measures of fit are quite close in the switching models. In particular, the single-chain model slightly underperforms the double-chain model in terms of AIC, but outperforms the double-chain model in terms of MDD and BIC. Since MDD and BIC are the most commonly used indicators in the RS-DSGE literature (e.g., Best and Hur 2019; Bianchi 2013; Liu and Mumtaz 2011; Liu et al. 2011), the results indicate that allowing the monetary policy to follow a Markov process independent of the volatility state does not improve the goodness of fit relative to the single-chain model. This finding is consistent with Liu et al. (2011), in which the researchers show that data prefer the parsimoniously parameterized model. Hence, we take the single-chain model assuming synchronized regime switching in the policy state and volatility state as our benchmark specification in the subsequent analysis.

Table 5. Model fit

Model specification	Log-post	Log-likelihood	Log-prior	Log-MDD	AIC	BIC
No switching (Ⅰ)	-992.85	-980.25	-12.61	-1019.92	1994.49	2038.26
Single-chain (Ⅱ, benchmark model)	-923.39	-913.70	-9.69	**-973.31**	1865.40	**1914.32**
Double-chain (Ⅲ)	-917.25	-911.31	-5.93	-977.38	1864.62	1918.69

Notes: (1) This table reports six representative indicators measuring the goodness of fit for the following models: (Ⅰ) the conventional time-invariant model with no regime switches; (Ⅱ) the *single-chain* model allowing for *synchronized* regime switches in both monetary policy parameters (ϕ_π, ϕ_y, ϕ_q) and the volatilities of shocks ($\varepsilon_t^r, \varepsilon_t^y, \varepsilon_t^\pi, \varepsilon_t^z, \varepsilon_t^q$) and (Ⅲ) the *double-chain* model assuming *independent* regime switches in monetary policy and the volatilities of structural shocks; (2) For the first four indicators (i.e., the log-posterior, log-likelihood, log-prior, and log-marginal data density), a larger statistic indicates a better model fit. For the last two indicators (i.e., AIC and BIC), a smaller statistic indicates a better model fit.

5. Time-varying dynamics of the Chinese economy

5.1. Impulse responses

To investigate the differences between the two regimes of the benchmark model, we compare the impulse responses of the main variables under each regime. Fig. 4 plots the impulse responses of output, inflation, interest rate and asset prices to the five exogenous shocks (i.e., demand shock u_t, supply shock υ_t, productivity shock z_t, financial shock ζ_t, and monetary policy shock ε_t^r). In each subgraph, the solid line represents the impulse responses under the low-volatility regime (Regime 1), while the dashed line represents the impulse responses under the high-volatility regime (Regime 2). Recalling that the estimated persistent probabilities for Regime 1 and Regime 2 are 0.95 and 0.91 respectively (see Table 4), such a high degree of persistence implies that there is little chance of regime-switching leading to dramatic changes in impulse responses. Therefore, impulse responses are calculated with no regime changes in the structural parameters over the entire horizon, as in Bianchi (2013). However, the results still differ from constant-coefficient models due to the agents' expectations of possible regime changes.

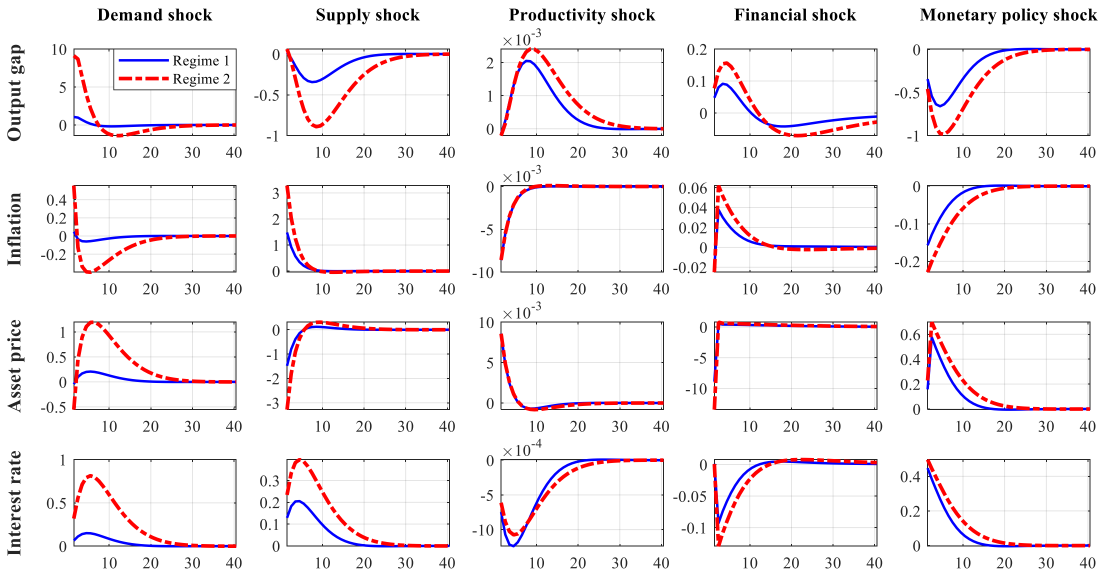

Figure 4. Impulse responses to structural shocks

Notes: The solid blue line and the red dashed line assume that a specific regime dominates the entire horizon. The horizontal axis refers to quarters. The initial shock is a positive unit standard deviation under the corresponding regime.

As shown in the first column of Fig. 4, a demand shock moves output and inflation upward, which leads to an increase in interest rate under the Taylor rule. In the model, as interest rate smoothing prevails in the decision of monetary policy, the variation in expectation of inflation exceeds the variation in interest rate, resulting in an initial fall in asset prices. The dynamics of interest rate and expected inflation then turn over due to deflation following the decay of the shock, which raises asset prices. Compared with the high-volatility regime, the increase in interest rate is less pronounced under the low-volatility regime with the benefit of a better stabilization effect on the economy.

Supply shock moves inflation upward significantly. To control inflation, the central bank raises the interest rate as a response. As indicated by the monetary policy reaction coefficients, the increase in interest rate under Regime 2 is larger than that under Regime 1. However, the high-persistent policy reacts inadequately to the shock (the increase in nominal interest rate is smaller than the increase in inflation), which lowers the real interest rate and asset prices. In a model without investment, external financing from outstanding securities dominates the scale of output. As such, output declines until asset prices recover to the steady state. However, if monetary policy is more flexible (as in Regime 1), the declines in output and asset prices would be less persistent. Besides, the initial shock is smaller in size under the low volatility regime, which makes the shock less contractionary on inflation and output.

As for the technology shock, following an advancement in technology, inflation moves downward due to the decline in marginal cost. Thus, even a positive productivity shock would initially suppress output due to deflation. The subsequent movements of output and asset prices depend to a large extent on the reaction of monetary policy. Specifically, a decrease in the nominal interest rate pushes down the real interest rate, which boosts asset prices and output. In addition, the differences between Regime 1 and Regime 2 are trivial under the technology shock.

Turning to the financial shock, asset prices absorb a large fraction of the adverse effect. Financial shock in the model is a disturbance on the demand side of the assets market. A positive financial shock reduces the demand for assets, which lowers the equilibrium price of assets. As shown in the fourth column of Fig. 4, a positive financial shock is associated with a decrease in asset prices. As a response of the central bank, interest rates were cut in both regimes. The decreases in the price of capital and real interest rate lead to an increase in output and inflation. These two variables decrease later as asset prices and interest rate converge to the steady-state level. Note that monetary policy under Regime 2 exhibits more remarkable adjustments due to larger reaction coefficient to asset prices. As a result, it takes a longer time for output to return to the steady state.

The monetary policy shock captures discretionary changes in the interest rate. Suppose the central bank makes an extra interest rate increase to cool down the economy. This leads to an immediate increase in the real interest rate, followed by the decline in output and inflation, as implied by the model. Compared with Regime 1, the standard deviation of monetary policy shock is slightly larger in Regime 2, resulting in greater fluctuations in macroeconomic variables. Moreover, due to a larger persistent coefficient of monetary policy, the impulse response curvature under Regime 2 is slightly lower than that under Regime 1, which delays the time for the economy to return to the steady-state level.

Overall, it appears that variables under Regime 2 are more vulnerable to exogenous shocks than under Regime 1. This is partly because the standard deviations under Regime 2 are greater, which means that the impact of a one-unit standard deviation shock would correspondingly be more pronounced. However, it is clear that both regimes have their pros and cons. In particular, the interest rate operation under Regime 2 has higher persistence and reacts more aggressively to inflation, which is conducive to restoring confidence when the economy is suffering from instability (volatile shocks). By comparison, monetary policy under Regime 1 has lower persistence and reacts more aggressively to output, indicating that the PBOC has greater flexibility to promote economic growth during times of low volatility.

5.2. Variance decompositions

To detect the main driving forces of economic fluctuations in the model, we compute variance decompositions attributed to the five shocks. As in the previous section, variance decompositions are calculated by conditioning on a specific regime. Fig. 5 displays the results, in which the first and second rows report the variance decompositions under the low-volatility regime (Regime 1) and the high-volatility regime (Regime 2), respectively.

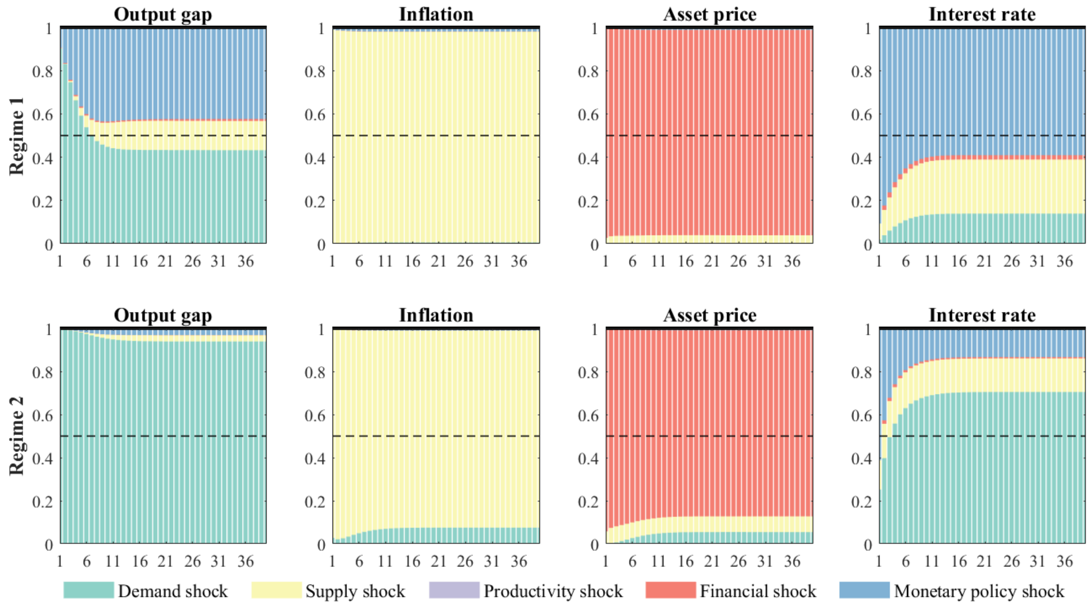

Figure 5. Variance decomposition

Notes: Variance decomposition is calculated under the assumption that a specific regime prevails over the entire horizon. The vertical axis indicates shares of variance, and the black dashed line reports the position of the 50% share for reference. The horizontal axis refers to quarters.

From Fig. 5 we can see that demand shocks are the primary driver of output dynamics under both regimes, which in the long run explain about 50% and over 90% of output fluctuations under Regime 1 and 2, respectively. Meanwhile, monetary policy shocks account for almost the other half of the variations in output under Regime 1. In contrast, the contribution of monetary policy shocks is less than 5% under Regime 2. The reason lies in the fact that monetary policy under the low volatility regime is less persistent and weighs more on output, which amplifies the impact of monetary policy shocks on output. In the medium and long run, however, the significance of supply and monetary policy shock increases, dampening the impacts of demand shocks. By comparison, the impacts of productivity shocks and financial shocks on output variations seem to be trivial. This is understandable since these two shocks do not have a direct impact on output and can only affect output through their impacts on inflation, as predicted by the aggregate demand curve and the New-Keynesian Phillips Curve (NKPC) respectively.

Turning to inflation, the most significant source of inflation fluctuations comes from the supply shocks for both regimes, accounting for more than 95 percent of variations in the short run, and more than 90 percent over long horizons. Comparing the two diagrams in the second column of Fig. 5, one can see that the high volatility regime intensifies the role of demand shocks in inflation variation, while it suppresses those of supply shocks and monetary policy shocks.

The variances of asset prices are explained primarily by financial shocks, which contribute more than 80% of the asset price variations over the entire horizon. This result is not surprising since financial shocks directly affect asset prices through the asset pricing equation (32). Note that the demand shocks and supply shocks jointly explain over 10% of the variations in asset prices in the second regime. This has an interesting implication that shocks to the real economy do matter for asset price changes during times of high volatility.

Interest rate dynamics are mainly driven by the demand shocks under the high volatility regime. However, under the low volatility regime, the contribution of demand shocks is largely restricted and monetary policy shocks become the dominant source of variations in interest rate. Also, the contribution of supply shocks is amplified by about 10%. As for financial shocks and productivity shocks, the former keeps a steady share of 1% over the entire horizon, whereas the latter is almost trivial.

On the whole, a distinctive regime-specific feature that can be drawn from decomposition analysis is that the contribution of demand shocks with the high-volatility regime being in place is more substantial. On the contrary, monetary policy shocks occurring under the low volatility regime account for a larger fraction of the overall variances. Put differently, the contribution of demand shocks under Regime 2 is replaced by the contribution of monetary policy shocks, as well as supply shocks, financial shocks and productivity shocks under Regime 1. This means that the monetary policy rule under Regime 2 is more conducive to mitigating fluctuations triggered by supply shocks, financial shocks and monetary policy shocks, while the policy rule under Regime 1 is more effective in alleviating the fluctuations caused by demand shocks.

5.3. Historical decompositions

To see how the historical contribution of each shock to macroeconomic fluctuations evolves across time, we conduct historical variance decompositions in this sub-section. Fig. 6 reports the estimates for the historical decompositions of exogenous shocks to variations in output, inflation, asset price, and interest rate. For the sake of comparison, we also display the historical data with solid black lines in each panel.

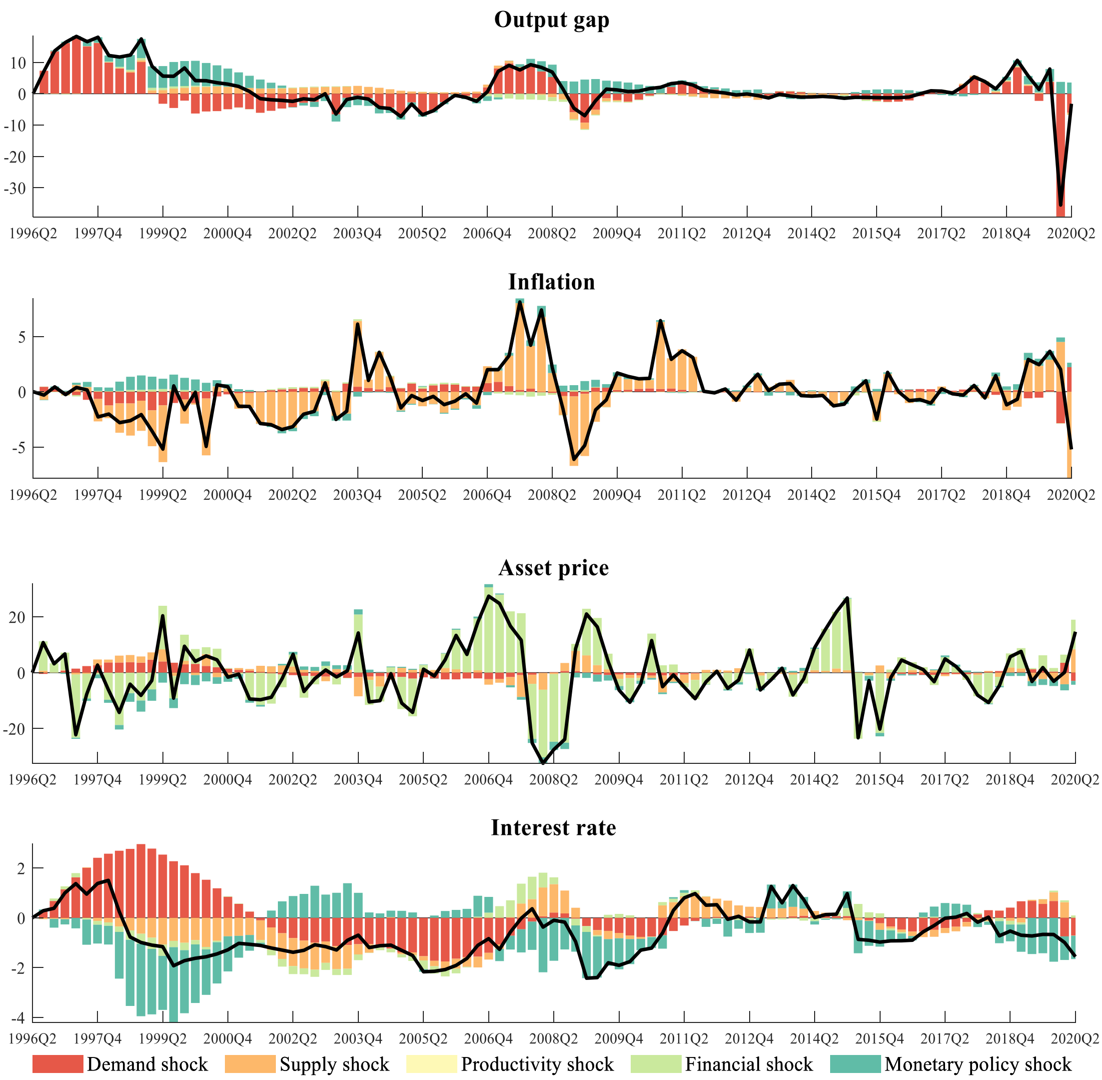

Figure 6. Historical decompositions

Notes: The result of historical decomposition is a weighted average of the two regimes, with the smoothed probabilities as the weights. The solid black line represents actual data.

From the first panel, we can see that demand shocks play a dominant role in output fluctuations over the entire horizon. Note that even in times of financial crisis, demand shocks, rather than financial shocks, are the primary determinant of economic trends. Indeed, financial shocks negatively contributed to output variations in 2006-2008, but demand shocks offset this impact. In times of crises where demand shocks drag down the economy (e.g., the Asian financial crisis in 1998-2000, the global financial crisis in 2008-2010, the COVID-19 in 2019Q4-2020Q2), monetary policy shocks have a particular significance in accounting for economic recovery. Supply shocks are another source of output variations, especially during the period of 1999-2005. Productivity shocks are in general inconsequential in accounting for output variations.

Supply shocks explain a significant portion of the inflation movements. In particular, there are four main periods of adverse supply shocks: (i) 1997Q4-1999Q2. During this period, state-owned enterprises in China suffered from low productivity and negative profits, and the reform in 1998 accelerated the mergers and bankruptcies of these enterprises, leading to a considerable decline in supply. (ii) 2001Q1-2002Q4. China's accession to the WTO in 2001 resulted in a sharp drop in the production costs of enterprises, triggering a decline in the overall price level. (iii) 2008Q3-2009Q3. Affected by the U.S. financial crisis, a large amount of small and medium-sized enterprises in China went bankrupt. (iv) 2020Q2. Due to the outbreak of COVID-19, almost all economic activities were suspended, resulting in a decline in aggregate supply. Turning to other shocks, the overall impact of demand shocks on inflation is much more limited than that on output. Monetary shocks account for a relatively stable portion of inflation dynamics, especially before the 2000s. In contrast, the share of inflation dynamics attributed to financial shocks surged during 2007-2008, due to the impact of the global financial crisis.

According to the third panel of Fig. 6, changes in asset prices are mainly driven by financial shocks. As expected, the contribution of financial shocks to variations in asset prices is highly consistent with the major periods of booms and busts in the Chinese stock market, e.g., the bull in 2006Q1-2007Q3 and 2014Q2-2015Q2, and the bear in 2007Q3-2008Q4 and 2015Q2-2016Q1.

Unlike the previous variables, none of the five shocks dominate the interest rate fluctuations exclusively. As expected, monetary policy shocks play a substantial role in influencing interest rate dynamics. Besides, demand shocks, supply shocks and financial shocks also enter the interest rate decision of the central bank, as predicted by the Taylor rule. In addition, the variations of interest rates largely hinge on the comparative importance of the demand shocks and the monetary policy shocks.

6. Monetary policy analysis

6.1 Constant-parameter versus switching-parameter policy in a regime-switching environment

The results in Section 4.2 indicate that the regime-switching model fits the data well. It follows that the switching feature of shock volatilities is at the heart of the narrative of data in our model. Still, we cannot conclude whether the stability effects of monetary policy could have been better if it had not switched synchronized with the volatilities of shocks. To address this question, we estimate an alternative model with constant policy parameters under a switching volatility environment. Again, we employ impulse responses to compare the stabilizing effects of the two policy rules.

Fig. 7 plots the mean impulse responses of the main variables under the actual (regime-switching) monetary policy and the counterfactual (constant-parameter) monetary policy. From the results we can see that the differences between the two policies stand out mainly in the impulse responses of output and interest rate. The first three columns make it clear that macroeconomic fluctuations are larger under the demand, supply and monetary policy shocks. Nevertheless, the responses to financial and productivity shocks under the switching policy regime are slightly more volatile than those under the constant-parameter policy, but in most cases the differences are quite small.

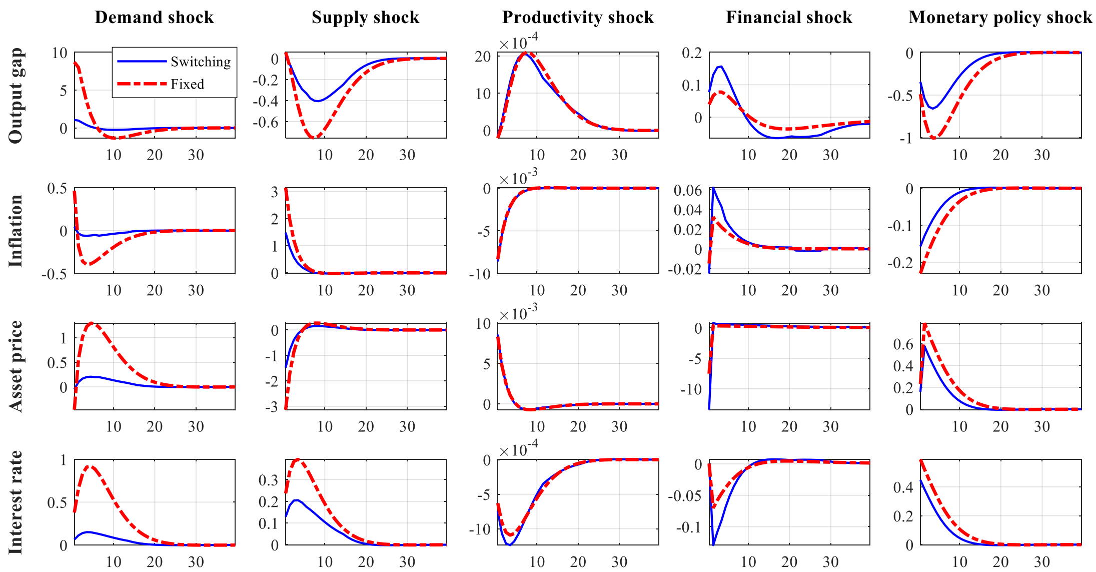

Figure 7. Impulse responses under regime-switching and constant-parameter monetary policy rules

Notes: (1) The solid blue line refers to the impulse response of the switching policy regime, and the red dashed line represents the impulse response of the constant policy regime; (2) Calculations of impulse responses have considered the probability of regime-changing; (3) The horizontal axis indicates quarters.

6.2 Responsive versus unresponsive policy toward asset prices

The standard Taylor rule assumes that monetary policy decision only aims to stabilize inflation and output. Whether monetary policy should also respond to asset prices is a remaining issue in macroeconomics literature. In light of this, this sub-section employs counterfactual analysis to explore the stabilization effects of different policy responsiveness toward asset prices. Specifically, we consider the following scenarios in the switching volatility environment: (i) a responsive switching-parameter policy (i.e., the benchmark model); (ii) an unresponsive switching-parameter policy; (iii) a responsive constant-parameter policy; and (iv) an unresponsive constant-parameter policy. For the latter three scenarios, we re-estimate the parameters of the corresponding models, with the estimation results presented in Table 6.

Table 6. Posterior estimates of parameters under three alternative monetary policy rules

Parameter	Unresponsive switching-parameter (I)		Responsive constant-parameter (II)		Unresponsive constant-parameter (III)	
	Mode	Std.	Mode	Std.	Mode	Std.
σ	2.3442	0.5200	2.1209	0.2380	2.0408	0.3501
φ	1.8559	0.3236	1.7470	0.1586	1.7433	0.2794
h	0.3927	0.0769	0.7780	0.0495	0.7844	0.0612
θ_H	0.8592	0.0261	0.9256	0.0162	0.9267	0.0151
ρ_y	0.8122	0.0531	0.2540	0.0647	0.2435	0.2797
ρ_π	0.5388	0.0814	0.6450	0.0376	0.6559	0.1743
ρ_q	0.9742	0.0271	0.9402	0.0250	0.9477	0.0415
ρ_z	0.6666	0.2622	0.6667	0.2230	0.6667	0.3715
$\rho_r(s_t=1)$	0.9849	0.0061	0.9557	0.0077	0.9495	0.0184
$\rho_r(s_t=2)$	0.9429	0.0099				
$\phi_\pi(s_t=1)$	2.0978	0.4602	1.6850	0.2052	1.5962	0.7529
$\phi_\pi(s_t=2)$	1.8082	0.3539				
$\phi_y(s_t=1)$	0.8630	0.1767	0.8915	0.0880	0.8139	0.2784
$\phi_y(s_t=2)$	0.8040	0.3079				
$\phi_q(s_t=1)$			0.2273	0.0587		
$\sigma_r(s_t=1)$	0.2190	0.0616	0.3667	0.0663	0.3678	0.1117
$\sigma_r(s_t=2)$	0.5110	0.0646	0.6272	0.0748	0.6092	0.0815
$\sigma_y(s_t=1)$	4.5721	1.5451	0.5358	0.0773	0.5370	0.2819
$\sigma_y(s_t=2)$	0.5896	0.0920	4.2430	0.4836	4.2066	0.8318

$\sigma_\pi(s_t=1)$	6.1873	1.7030	0.6072	0.0759	0.6052	0.0984
$\sigma_\pi(s_t=2)$	1.1499	0.1702	1.2184	0.1480	1.1791	0.1614
$\sigma_q(s_t=1)$	0.4887	0.2136	0.7546	0.1266	0.7384	0.1508
$\sigma_q(s_t=2)$	1.1616	0.0928	1.4171	0.1096	1.4199	0.1971
$\sigma_z(s_t=1)$	0.1684	0.0988	0.1683	0.1142	0.1683	0.1728
$\sigma_z(s_t=2)$	0.1683	0.0896	0.1684	0.0722	0.1684	0.1892
q_{12}	0.0474	0.0262	0.1090	0.0300	0.1068	0.0375
q_{21}	0.0332	0.0142	0.0590	0.0223	0.0605	0.0266

Notes: (1) This table reports the parameter estimates under three scenarios with time-varying volatilities of shocks: (I) an unresponsive switching-parameter policy, (II) a responsive constant-parameter policy, and (III) an unresponsive constant-parameter policy; (2) The unresponsive switching-parameter policy refers to the scenario that monetary policy parameters are time-varying, but monetary policy does not react to asset price changes; (3) The *responsive* constant-parameter policy refers to the scenario that monetary policy responds to asset price changes given time-invariant policy parameters; (4) The unresponsive constant-parameter policy refers to the scenario that monetary policy does not respond to asset price changes given time-invariant policy parameters.

To obtain the unconditional volatilities of the counterfactual series, we simulate the model with stochastic shocks over 1000 periods under each scenario. The third and fourth columns of Table 7 summarize the results. For switching-parameter policies, the responsive policy reduces the volatility of output and inflation simultaneously, as the percentage differences between the two series are far from zero. For constant-parameter policies, the responsive policy reduces inflation volatility while increasing output volatility. However, no matter whether the policy parameters are switching or time-invariant, the responsive policy outperforms the unresponsive policy in stabilizing inflation.

Table 7. Unconditional volatilities

Scenario	Policy stance	Output SD (%)	Inflation SD (%)	Quadratic loss $(\times 10^{-4})$		
				ϖ=0.003	ϖ=0.016	ϖ=0.034

Switching parameters	Responsive	12.97	3.77	14.73	16.92	19.95
	Unresponsive	27.22	10.39	110.15	119.79	133.12
	Relative change	109.81	175.47	647.84	608.10	567.37
Constant parameters	Responsive	12.69	3.63	13.65	15.74	18.64
	Unresponsive	11.68	3.77	14.62	16.39	18.85
	Relative change	-7.92	3.87	7.06	4.10	1.10

Notes: (1) This table reports the quadratic losses under different monetary policy scenarios; (2) quadratic loss is calculated as linear combinations of the variances of output and *inflation*: $QL(\varpi) = \varpi \, \mathrm{var}(y) + \mathrm{var}(\pi)$, where the weight on output (ϖ) takes three reference values of 0.003, 0.016 and 0.034, as in Hur (2017); (3) for each regime, the third row and the last row report the percentage differences between the responsive and unresponsive policy stance estimates.

Based on the counterfactual series, quadratic losses under each scenario can be directly calculated as linear combinations of the variances of output and inflation, i.e., $QL(\varpi) = \varpi \, \mathrm{var}(y) + \mathrm{var}(\pi)$. Following Hur (2017), we use three reference values for the weight on output, as indicated in the last three columns of Table 7.

For both regimes, the responsive policy stance is associated with significantly lower quadratic losses, implying the responsive stance has better macroeconomic stabilization effects than the unresponsive stance. As the weights increase, however, the percentage differences between the two stances shrink. Still, a policy that responds to asset prices consistently outperforms its unresponsive counterparts, regardless of the weights. In particular, the welfare losses of an unresponsive stance are six times larger than those of a responsive one given a switching policy. This result provides strong support for the model of this paper, in which the reaction coefficient of monetary policy to asset prices ϕ_q is greater than 0.2 in both regimes (see Table 4).

In summary, the results in Table 7 suggest that whether monetary policy should respond to asset prices is largely independent of the regimes and the relative weights of the loss function. Under both regimes and all the given forms of loss functions, the optimal monetary policy rule involves responses to asset prices.

7. Conclusions

How to capture the nonlinear dynamics in real-financial interactions is an emerging and unresolved question in the post-crisis era. In this paper, we develop a simple regime-switching DSGE model that can capture time-varying volatilities in economic activity, asset prices and monetary policy. As an application, the model is then estimated using quarterly data of the Chinese economy over the period of 1996Q2-2020Q2. Besides theoretical contributions in modelling regime switches within a DSGE framework, the empirical contributions of this paper lie in answering the following three questions: (i) Does the Chinese economy exhibit regime-switching properties? (ii) Is China's monetary policy subject to regime-switching? and (iii) Whether and how should monetary policy respond to asset price?

To answer the first question, we compare the fitness of the regime-switching model and the constant-parameter models. The results shed light on the existence of synchronized regime changes in both the volatilities of structural shocks and the monetary policy parameters. The estimation results show that the high volatility regime mainly lasts from 1996Q2-2000Q2, 2003Q2-2005Q2, 2006Q4-2009Q2, and 2018Q4-2020Q2, while the low volatility regime takes up the rest of the observation period. To distinguish the differences between the two regimes, we further investigate the characteristics of each regime. The variance decomposition shows that demand shocks have more remarkable contributions to the economy under the high volatility regime, whereas monetary policy shocks have more significant contributions to the economy under the low volatility regime. Historical decompositions further show that during periods of crises, demand shocks are the dominant force dragging down output, and monetary policy shock has a particular significance in accounting for the recovery of the economy.

As for the second question, our estimation results show that regime-switching responsiveness is a distinctive feature of China's monetary policy. In particular, China's monetary policy exhibits a higher persistence and places more weight on the inflation target during periods of high volatility. However, when economic conditions improve and become stable, monetary policy becomes more flexible in coordinating the target of maintaining output growth with other policy targets. Further counterfactual analysis suggests that under a volatility-switching environment, monetary policy rule with switching parameters outperforms the conventional constant-parameter rules.

Finally, regarding whether monetary policy should respond to asset prices, our estimation results indicate that China's monetary policy indeed involves responses to asset price changes over the observation period of 1996Q2-2020Q2, with a reaction coefficient between 0.2 and 0.3. In addition, historical variance decompositions show that a notable fraction of the historical variance of interest rate can be attributed to financial shocks, implying that China's monetary policy reacts to asset price variations in practice. To investigate whether monetary policy should respond to asset prices, we compare welfare losses under alternative monetary policy rules. The results show that given a switching policy, the welfare loss of the unresponsive stance is six times larger than that of the responsive stance. Therefore, at least in an environment with regime-switching volatilities, the optimal conduct of monetary policy involves responses to asset price variations.

Declaration of interest statement

No potential conflict of interest was reported by the authors.

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Figures

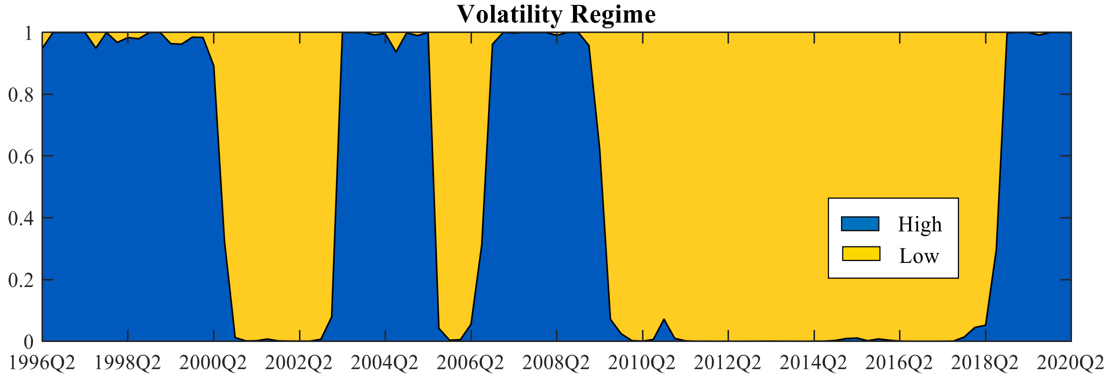

Figure 1. Smoothed probabilities of the single-chain model
Notes: The figure reports the smoothed regime probabilities of the single-chain model evaluated at the posterior mode. The yellow shaded areas indicate the probability of the low volatility regime (i.e., $s_t = s_t^* = 1$), while the blue ones indicate that of the high volatility regime (i.e., $s_t = s_t^* = 2$).

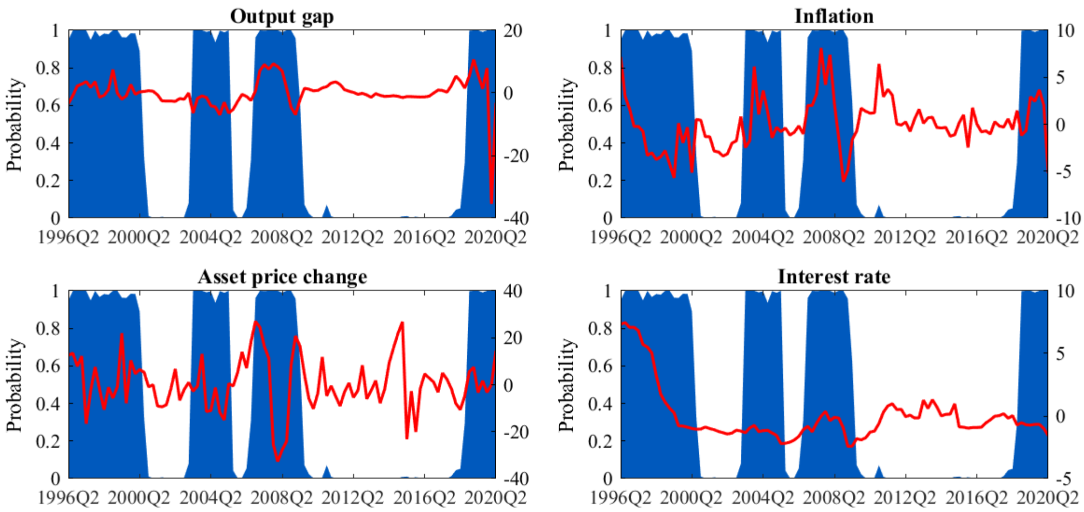

Figure 2. Historical data and smoothed probabilities of the single-chain model
Notes: The blue shaded area corresponds to the smoothed probability of the high volatility regime of the single-chain model (left axis), and the solid red line refers to the actual data (right axis).

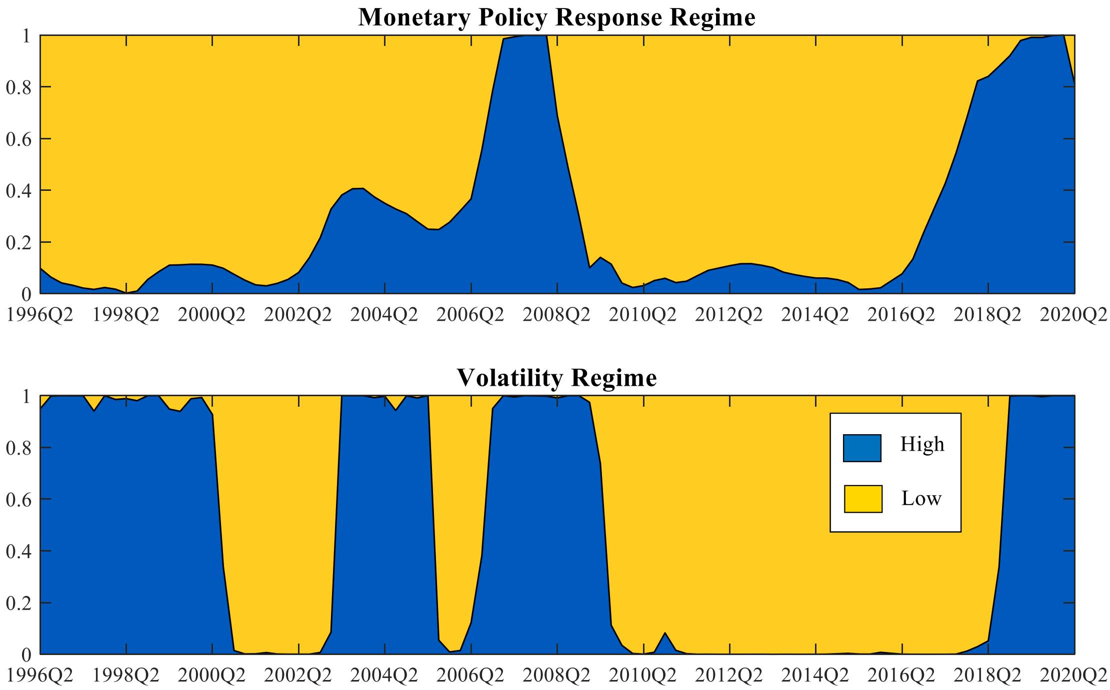

Figure 3. Smoothed probabilities of the double-chain model

Notes: The figure reports the smoothed regime probabilities of the double-chain model evaluated at the posterior mode. In the upper panel, the yellow shaded areas represent the probability of the monetary policy regime with a low response to asset price ($s_t = 1$), while the blue ones indicate that with a high response ($s_t = 2$). In the lower panel, the yellow shaded areas stand for the probability of the low-volatility regime ($s_t^* = 1$), while the blue areas represent that of the high-volatility regime ($s_t^* = 2$).

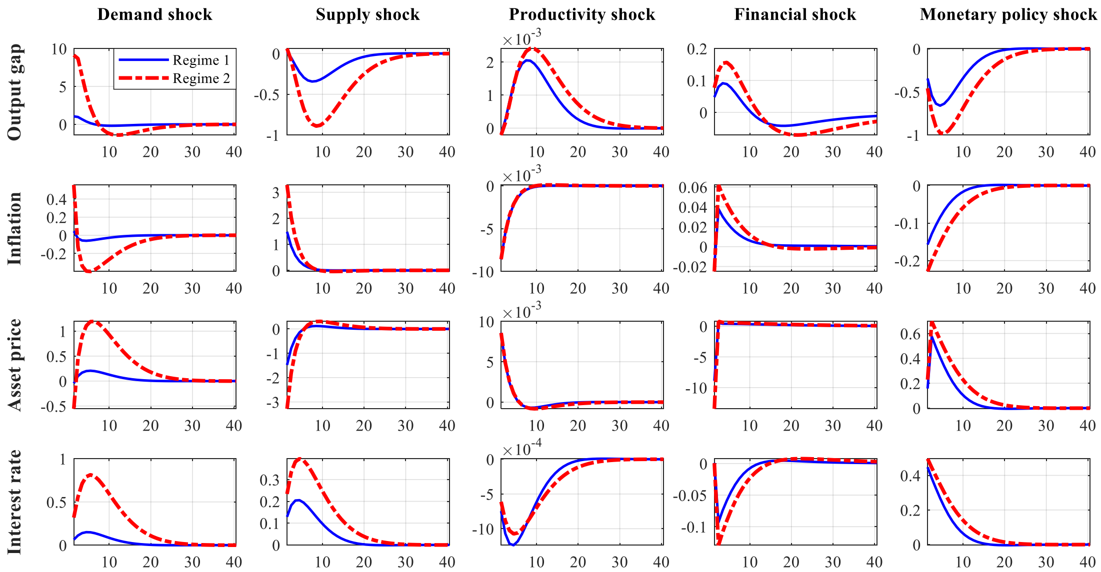

Figure 4. Impulse responses to structural shocks

Notes: The solid blue line and the red dashed line assume that a specific regime dominates the entire horizon. The horizontal axis refers to quarters. The initial shock is a positive unit standard deviation under the corresponding regime.

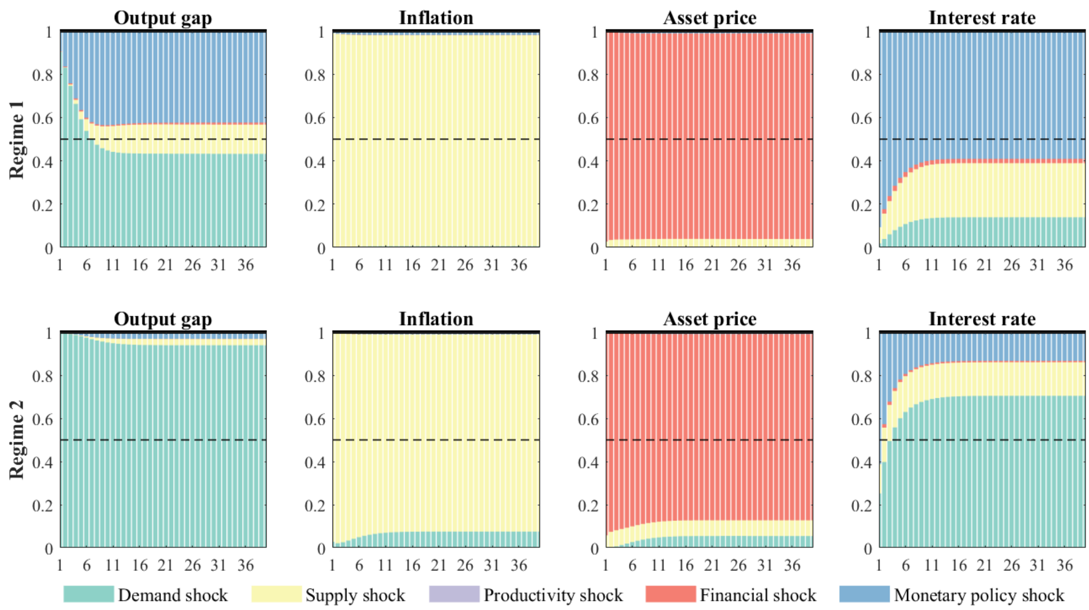

Figure 5. Variance decomposition

Notes: Variance decomposition is calculated under the assumption that a specific regime prevails over the entire horizon. The vertical axis indicates shares of variance, and the black dashed line reports the position of the 50% share for reference. The horizontal axis refers to quarters.

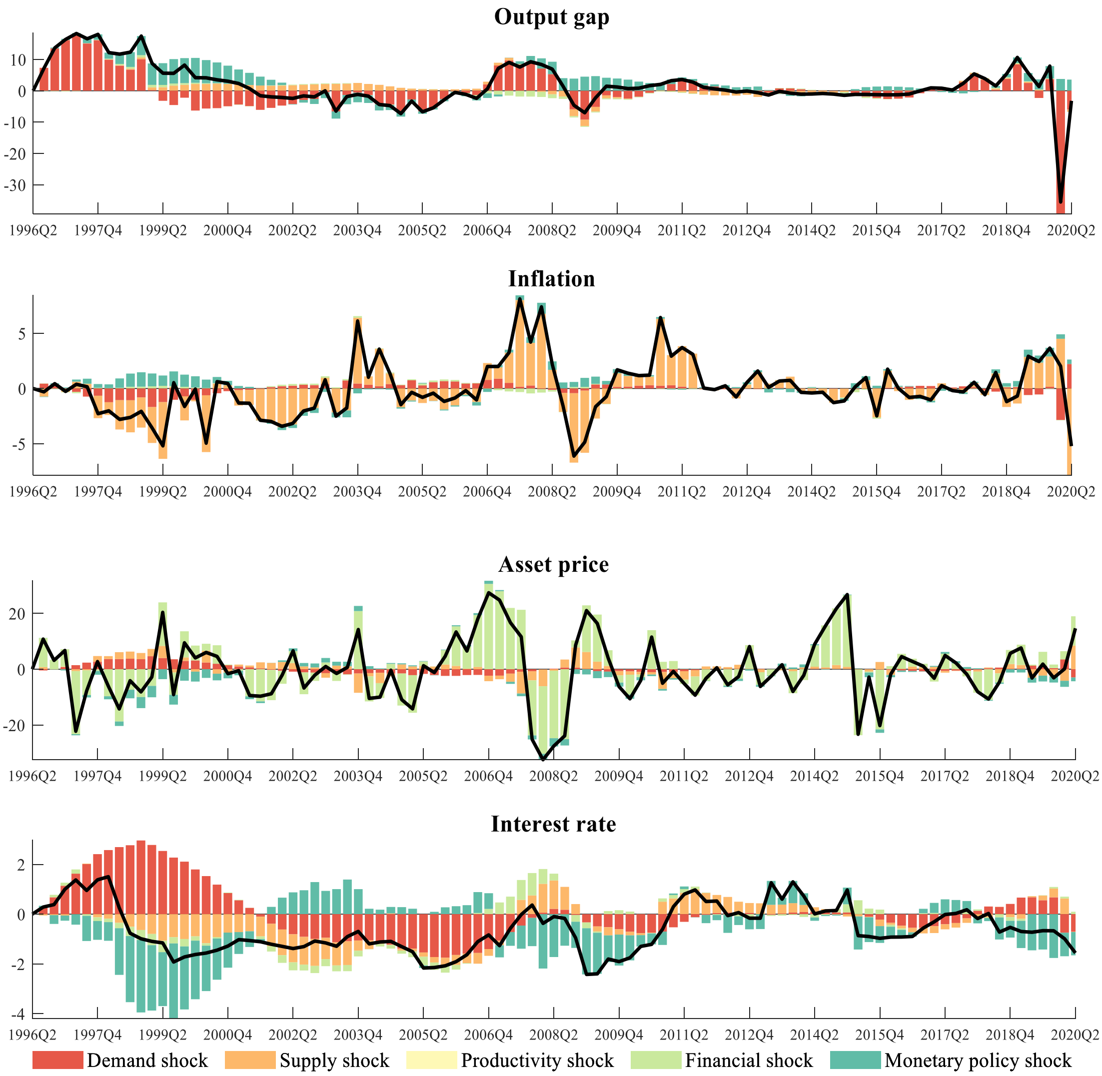

Figure 6. Historical decompositions

Notes: The result of historical decomposition is a weighted average of the two regimes, with the smoothed probabilities as the weights. The solid black line represents actual data.

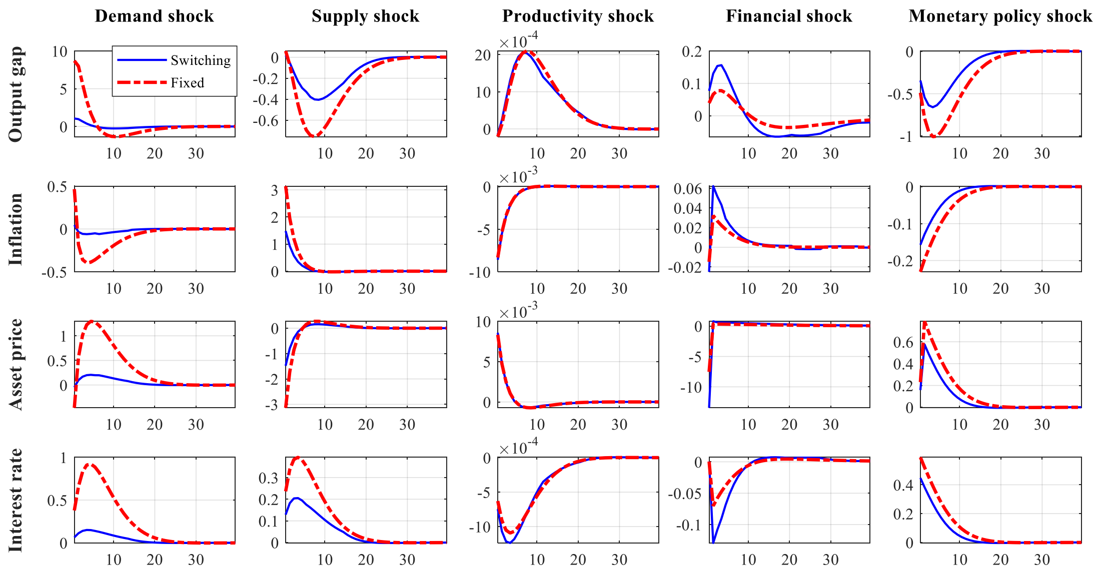

Figure 7. Impulse responses under regime-switching and constant-parameter monetary policy rules

Notes: (1) The solid blue line refers to the impulse response of the switching policy regime, and the red dashed line represents the impulse response of the constant policy regime; (2) Calculations of impulse responses have considered the probability of regime-changing; (3) The horizontal axis indicates quarters.

Table

Table 1. Classification of shock periods

Type of shock	Event	Period
Economic shock	The Asian financial crisis	1997Q3-1998Q4
	The global financial crisis	2007Q2-2009Q1
	The COVID-19 crisis	2019Q4-2022Q4
Asset price shock	The 2007 Chinese stock bubble	2007Q2-2007Q2
	The 2015 Chinese stock market crash	2015Q2-2015Q3

Notes: (1) This table *summarizes* the significant shocks to China's economy over the period of 1996Q2-2020Q2; (2) Source: Authors' compilation.

Table 2. Performance of main macroeconomic variables

Mean (%)	Output growth	Inflation rate	Interest rate	Stock return
All sample	2.08	0.52	3.49	1.27
Shock periods	1.94	0.48	3.81	-2.94
Other periods	2.12	0.53	3.41	2.22
Other /Shock	109.21	112.41	89.42	-75.67
Relative change	9.21	12.41	-10.58	-175.67
Std (%)	Output growth	Inflation rate	Interest rate	Stock return
All sample	1.59	0.70	2.36	12.02
Shock periods	13.65	4.32	2.20	65.94
Other periods	3.05	2.35	2.40	42.72
Other /Shock	22.35	54.53	109.17	64.79
Relative change	-77.65	-45.47	9.17	-35.21

Notes: (1) This table reports the mean and standard deviation of four main macroeconomic variables in China over the period of 1996Q2-2020Q2, based on annual terms; (2) The classification of shock periods is presented in Table 1; (3) Output growth and inflation are reported on a quarterly basis; (4) Interest rate refers to the 7-day interbank rate, which is the most frequently and widely used monetary policy rate in China; (5) Stock return is calculated using the Shanghai Composite Stock Market Index.

Table 3. Monetary policy stance and macroeconomic conditions

Period	1996-1997	1998-2007	2008-2010	2011-2020
Monetary policy stance	Moderately tight	Prudent	Moderately loose	Prudent
Policy rate (%)	11.37	2.85	2.16	3.33
GDP target (%)	8.00	7.40	8.00	7.06
GDP growth (%)	9.58	10.00	9.90	6.85
CPI target (%)	10.00	2.78	3.93	3.35
CPI inflation (%)	5.55	1.13	2.83	2.51
Stock return (%)	9.03	5.11	-12.68	-0.52

Notes: (1) This table summarizes the monetary policy stances and the associated macroeconomic and financial conditions in China over the period of 1996Q2-2020Q2; (2) The classification of monetary policy stance is based on the corresponding statements in the *Monetary Policy Report* released quarterly by the People's Bank of China since 1996; (3) Policy rate refers to the 7-day interbank rate, which is the most frequently and widely used monetary policy rate in China; (4) GDP and CPI targets are obtained from the *Government Work Report* delivered annually by the Premier at the National People's Congress of the People's Republic of China; (5) Stock return is calculated using the Shanghai Composite Stock Market Index; (6) The numbers reported are annual averages.

Table 4. Prior distributions and posterior estimates of the parameters

Parameter	Prior Distribution*	Single-chain Model		Double-chain Model	
		Posterior Mode	Posterior Std.	Posterior Mode	Posterior Std.
Structural parameters					
σ	Gamma [2, 0.75]	2.0714	0.5543	2.0139	0.2819
φ	Gamma [2, 0.5]	1.7421	0.3239	1.7403	0.2048
h	Beta [0.7, 0.1]	0.7778	0.0671	0.7662	0.0919
θ_H	Beta [0.75, 0.05]	0.9242	0.0149	0.9240	0.0162
Persistence parameters					
ρ_y	Beta [0.6, 0.2]	0.2776	0.1212	0.3110	0.1046
ρ_π	Beta [0.6, 0.2]	0.6480	0.0733	0.6354	0.0579
ρ_q	Beta [0.6, 0.2]	0.9373	0.0266	0.9374	0.0270
ρ_z	Beta [0.6, 0.2]	0.6667	0.1952	0.6667	0.0859
Regime-switching monetary policy parameters					
$\rho_r(s_t = 1)$	Beta [0.75, 0.2]	0.9466	0.0162	0.9339	0.0150
$\rho_r(s_t = 2)$	Beta [0.75, 0.2]	0.9644	0.0081	0.9764	0.0076
$\phi_\pi(s_t = 1)$	Gamma [2, 0.5]	1.6114	0.2477	1.6553	0.3083
$\phi_\pi(s_t = 2)$	Gamma [2, 0.5]	1.9841	0.3412	1.6553	0.3694
$\phi_y(s_t = 1)$	Gamma [1, 0.25]	1.0563	0.2084	1.0434	0.1211
$\phi_y(s_t = 2)$	Gamma [1, 0.25]	0.8595	0.1674	0.9130	0.1196
$\phi_q(s_t = 1)$	Gamma [0.5, 0.2]	0.2139	0.0793	0.1525	0.0552
$\phi_q(s_t = 2)$	Gamma [0.5, 0.2]	0.2888	0.1021	0.4218	0.1429
Regime-switching shocks					
$\sigma_r\left(s_t^* = 1\right)$	Inv gamma [0.5, ∞]	0.4803	0.1013	0.4798	0.0455
$\sigma_r\left(s_t^* = 2\right)$	Inv gamma [0.5, ∞]	0.5265	0.0721	0.4561	0.0625
$\sigma_y\left(s_t^* = 1\right)$	Inv gamma [3, ∞]	0.5176	0.1172	0.4902	0.0841
$\sigma_y\left(s_t^* = 2\right)$	Inv gamma [3, ∞]	4.2768	0.6391	4.1174	0.4102

$\sigma_\pi\left(s_t^*=1\right)$	Inv gamma [3, ∞]	0.5742	0.1180	0.5847	0.0978
$\sigma_\pi\left(s_t^*=2\right)$	Inv gamma [3, ∞]	1.2722	0.2681	1.2853	0.1690
$\sigma_q\left(s_t^*=1\right)$	Inv gamma [0.5, ∞]	0.8915	0.0856	0.8915	0.0860
$\sigma_q\left(s_t^*=2\right)$	Inv gamma [0.5, ∞]	1.3476	0.1217	1.3439	0.1041
$\sigma_z\left(s_t^*=1\right)$	Inv gamma [0.5, ∞]	0.1683	0.1065	0.1683	0.0915
$\sigma_z\left(s_t^*=2\right)$	Inv gamma [0.5, ∞]	0.1683	0.0895	0.1683	0.1011
Regime-switching probabilities					
q_{12}	Beta [0.1, 0.05]	0.0875	0.0274	0.0916	0.0340
q_{21}	Beta [0.1, 0.05]	0.0517	0.0228	0.0499	0.0232
p_{12}	Beta [0.1, 0.05]			0.0437	0.0278
p_{21}	Beta [0.1, 0.05]			0.0980	0.0477

Notes: (1) This table reports the prior distributions and posterior estimates of the parameters in the single-chain model and the double-chain model; (2) The results are obtained by Bayesian estimation using quarterly data of the Chinese economy over the period of 1996Q2-2020Q2; (3) Numbers in the square brackets are prior means and standard deviations; (4)The state of monetary policy parameters is synchronized with the volatility state (i.e., $s_t = s_t^*$) in the single-chain model.

Table 5. Model fit

Model specification	Log-post	Log-likelihood	Log-prior	Log-MDD	AIC	BIC
No switching (Ⅰ)	-992.85	-980.25	-12.61	-1019.92	1994.49	2038.26
Single-chain (Ⅱ, benchmark model)	-923.39	-913.70	-9.69	**-973.31**	1865.40	**1914.32**
Double-chain (Ⅲ)	-917.25	-911.31	-5.93	-977.38	1864.62	1918.69

Notes: (1) This table reports six representative indicators measuring the goodness of fit for the following models: (Ⅰ) the conventional time-invariant model with no regime switches; (Ⅱ) the *single-chain* model allowing for *synchronized* regime switches in both monetary policy parameters (ϕ_π, ϕ_y, ϕ_q) and the volatilities of shocks ($\varepsilon_t^r, \varepsilon_t^y, \varepsilon_t^\pi, \varepsilon_t^z, \varepsilon_t^q$) and (Ⅲ) the *double-chain* model assuming *independent* regime switches in monetary policy and the volatilities of structural shocks; (2) For the first four indicators (i.e., the log-posterior, log-likelihood, log-prior, and log-marginal data density), a larger statistic indicates a better model fit. For the last two indicators (i.e., AIC and BIC), a smaller statistic indicates a better model fit.

Table 6. Posterior estimates of parameters under three alternative monetary policy rules

Parameter	Unresponsive switching-parameter (I)		Responsive constant-parameter (II)		Unresponsive constant-parameter (III)	
	Mode	Std.	Mode	Std.	Mode	Std.

σ	2.3442	0.5200	2.1209	0.2380	2.0408	0.3501
φ	1.8559	0.3236	1.7470	0.1586	1.7433	0.2794
h	0.3927	0.0769	0.7780	0.0495	0.7844	0.0612
θ_H	0.8592	0.0261	0.9256	0.0162	0.9267	0.0151
ρ_y	0.8122	0.0531	0.2540	0.0647	0.2435	0.2797
ρ_π	0.5388	0.0814	0.6450	0.0376	0.6559	0.1743
ρ_q	0.9742	0.0271	0.9402	0.0250	0.9477	0.0415
ρ_z	0.6666	0.2622	0.6667	0.2230	0.6667	0.3715
$\rho_r(s_t=1)$	0.9849	0.0061	0.9557	0.0077	0.9495	0.0184
$\rho_r(s_t=2)$	0.9429	0.0099				
$\phi_\pi(s_t=1)$	2.0978	0.4602	1.6850	0.2052	1.5962	0.7529
$\phi_\pi(s_t=2)$	1.8082	0.3539				
$\phi_y(s_t=1)$	0.8630	0.1767	0.8915	0.0880	0.8139	0.2784
$\phi_y(s_t=2)$	0.8040	0.3079				
$\phi_q(s_t=1)$			0.2273	0.0587		
$\sigma_r(s_t=1)$	0.2190	0.0616	0.3667	0.0663	0.3678	0.1117
$\sigma_r(s_t=2)$	0.5110	0.0646	0.6272	0.0748	0.6092	0.0815
$\sigma_y(s_t=1)$	4.5721	1.5451	0.5358	0.0773	0.5370	0.2819
$\sigma_y(s_t=2)$	0.5896	0.0920	4.2430	0.4836	4.2066	0.8318
$\sigma_\pi(s_t=1)$	6.1873	1.7030	0.6072	0.0759	0.6052	0.0984
$\sigma_\pi(s_t=2)$	1.1499	0.1702	1.2184	0.1480	1.1791	0.1614
$\sigma_q(s_t=1)$	0.4887	0.2136	0.7546	0.1266	0.7384	0.1508
$\sigma_q(s_t=2)$	1.1616	0.0928	1.4171	0.1096	1.4199	0.1971
$\sigma_z(s_t=1)$	0.1684	0.0988	0.1683	0.1142	0.1683	0.1728
$\sigma_z(s_t=2)$	0.1683	0.0896	0.1684	0.0722	0.1684	0.1892
q_{12}	0.0474	0.0262	0.1090	0.0300	0.1068	0.0375
q_{21}	0.0332	0.0142	0.0590	0.0223	0.0605	0.0266

Notes: (1) This table reports the parameter estimates under three scenarios with time-varying volatilities of shocks: (I) an unresponsive switching-parameter policy, (II) a responsive constant-parameter policy, and (III) an unresponsive constant-parameter policy; (2) The unresponsive switching-parameter policy refers to the scenario that monetary policy parameters are time-varying, but monetary policy does not react to asset price changes; (3) The *responsive* constant-parameter policy refers to the scenario that monetary policy responds to asset price changes given time-invariant policy parameters; (4) The unresponsive constant-parameter policy refers to the scenario that monetary policy does not respond to asset price changes given time-invariant policy parameters.

Table 7. Unconditional volatilities

Scenario	Policy stance	Output SD (%)	Inflation SD (%)	Quadratic loss $(\times 10^{-4})$		
				ϖ=0.003	ϖ=0.016	ϖ=0.034

Switching parameters	Responsive	12.97	3.77	14.73	16.92	19.95
	Unresponsive	27.22	10.39	110.15	119.79	133.12
	Relative change	109.81	175.47	647.84	608.10	567.37
Constant parameters	Responsive	12.69	3.63	13.65	15.74	18.64
	Unresponsive	11.68	3.77	14.62	16.39	18.85
	Relative change	-7.92	3.87	7.06	4.10	1.10

Notes: (1) This table reports the quadratic losses under different monetary policy scenarios; (2) quadratic loss is calculated as linear combinations of the variances of output and *inflation*: $QL(\varpi) = \varpi \operatorname{var}(y) + \operatorname{var}(\pi)$, where the weight on output (ϖ) takes three reference values of 0.003, 0.016 and 0.034, as in Hur (2017); (3) for each regime, the third row and the last row report the percentage differences between the responsive and unresponsive policy stance estimates.