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Time-Varying Impacts of Structural Oil Price Shocks on Economic Policy Uncertainty in China: The Role of a Hybrid Monetary Policy Tools Framework

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Abstract: This paper examines the time-varying responses of China's economic policy uncertainty (EPU) to five structural oil-price shocks, with particular attention to the responses of price- and quantity-based monetary policy instruments. Using quarterly data from 2007Q2 to 2025Q1, we estimate a TVP-VAR-SV model that incorporates both the interest rate gap and the money supply gap to capture the coexistence of price- and quantity-based policy tools in China. The results show that only aggregate supply shocks elicit a statistically significant EPU response, while the other oil shocks are mainly associated with output fluctuations. Monetary policy instruments respond primarily to output dynamics, while their median effects on EPU remain limited. Time-varying impulse responses reveal substantial heterogeneity across major events, including the global financial crisis and the COVID-19 pandemic, and indicate shifts in the relative responses of monetary policy instruments during China's transition toward a more price-based policy framework. These findings underscore the importance of distinguishing among oil shock sources and strengthening policy communication during periods of monetary policy transition.

Keywords: Oil prices, Economic policy uncertainty, Hybrid monetary policy tools framework, TVP-VAR-SV model.

JEL Classification: E61, G18, O11, O23, Q41, Q43, Q48.

1. Introduction

Recent major events have led to frequent fluctuations in crude oil prices, making related shocks a key driver of inflationary fluctuations and economic growth pressures (Razmi et al., 2016; Moreira,2025). Rising oil prices create imported inflationary pressure by increasing production costs and commodity prices; on the other hand, it may also suppress investment and consumption demand, lower total output and leading to an economic downturn (Basnet & Upadhyaya, 2015; Kilian, 2008; Wang et al., 2019; Zhang et al., 2022). The coexistence of rising inflation and slowing growth presents opposing demands for monetary policy adjustments. However, for China, which aims to both stabilize growth and control inflation, this conflict complicates policy responses, making it harder for markets to form stable expectations. This leads to a question worth exploring: Does the divergence in expectations alter the dynamic characteristics of economic policy uncertainty (EPU)[1]. EPU can affect trade, employment, and other factors. So, it is important to examine which factors are associated with changes in EPU and to provide a framework that helps policymakers distinguish among different sources of shocks.

Monetary policy rules serve as a crucial framework for central banks to formulate policy decisions and achieve macroeconomic control objectives (Radović & Fabris, 2026). Existing research typically categorizes monetary policy operations into two basic models: quantitative

[1] Economic policy uncertainty (EPU) refers to the unknown and unpredictable events that may occur when a country faces unexpected economic or policy shocks in the future (Baker et al., 2016; Sahinoz & Erdogan, 2018; Tabash, 2025; Zhang et al.,2026).

tool proposed by Friedman (1968) and price-based tool proposed by Taylor (1993)[2]. However, unlike major developed economies, against the backdrop of continuous progress in interest rate liberalization and deepening financial innovation, China uses both quantitative and price-based tools in parallel, resulting in a mixed characteristic in its policy responses (Li et al., 2025; Olorunfemi et al., 2025). In this institutional context, a single Taylor rule or quantitative rule is insufficient to accurately policy responses to oil-price-related shocks and its impact on the EPU. Currently, most existing literature employs the extended Taylor rule, directly incorporating oil price into the Taylor rule to explore how monetary authorities react to shocks to oil prices (Liu et al., 2015; Alekhina & Yoshino, 2019). This approach neglects the role of quantitative tool and is not consistent with China's actual situation. Therefore, it is useful to adopt a monetary policy tools framework that reflects China's institutional background and allows the analysis to examine how oil-related shocks, macroeconomic conditions, and observable monetary policy indicators are dynamically related to EPU.

Furthermore, Aastveit (2013) found that monetary authorities respond differently to different types of oil price-related shocks, underscoring the need to distinguish among them. The current mainstream method for decomposing structural oil price shocks is mainly based on the research of Hamilton (2009) and Kilian (2008), which classify oil price shocks into three types (hereafter three-type shocks): aggregate supply shocks (AS), aggregate demand shocks (AD), and specific demand shocks (P). This method is commonly employed to assess the influence of different types of oil price-related shocks on the macroeconomy and uncertainty (Kang & Ratti, 2013; Lin & Bai, 2021).

However, subsequent studies have pointed out that the above three-type shocks cannot fully explain the mechanism of oil price fluctuations. For example, Kilian and Murphy (2014) argue that crude oil inventory demand shock(*I*) reflects the market's adjustment of expectations for future supply and demand conditions, which is speculative demand shock (SD) that cannot be

[2] Quantitative tool argues that a stable velocity of money and money supply play a crucial role in ensuring price stability; price-based tool emphasizes the importance of inflation and the output gap in policy interest rate decisions, it's widely used to describe policy behavior in developed economies.

reflected by three-type shocks. Juvenal et al. (2011) and Gong et al. (2020) further separated SD and *I* from the three-type shocks. Currently, almost all studies are based on three-type shocks to explore the direct impact of shocks on EPU. For example, Degiannakis et al. (2018) and Kang and Ratti (2013) categorized oil price shocks into AS, AD, and *P* to explore the impact on the US EPU. Existing studies on the relationship between three-type shocks and EPU have neglected *I* and *SD*, which cannot be explained by traditional classifications. Therefore, this study follows the approach by Gong et al. (2020) by distinguishing *I* , SD and three-type shocks and examines the responses of EPU to the five different types of oil price shocks (hereafter five-type shocks) - AD, AS, P, *I* and SD.

Furthermore, current studies exploring the direct impact of oil-price-related shocks on EPU based on a three-type shocks have not yielded unified conclusions. For example, empirical results from Kang and Ratti (2013), Liu and Zhang (2015) and Degiannakis et al. (2018) show that AD reduce EPU, while empirical results from Rehman (2018) found that AD had no impact on EPU in India, Spain, and Japan. This demonstrates that even the same kind of shock could have distinct implications on EPU in different countries. Compared to other countries, China's government plays a central role in resource allocation and industrial policy, shaping a unique political economy (Wang & Lee, 2022). Moreover, oil price-related reforms have strengthened the connection between China's oil pricing system and international oil prices, increasing China economy's exposure to global oil price volatility. Given this unique system and background, will different oil price shocks affect China's EPU? And how will China's EPU respond to different oil price shocks? Hence, it's essential to explore them. Furthermore, while many studies explore how EPU response to three-type shocks, existing literature emphasizes the direct effect of three-type shocks on EPU, neglecting how EPU is influenced by monetary policy adjustments made in response to macroeconomic fluctuations stemming from oil-price-related shocks. Therefore, when examining EPU responses to five-type shocks, we also consider the influence of monetary policy tools adjustments. This may help policymakers better interpret the interaction between five-type shocks, macroeconomic conditions, and monetary policy tools.

Structural Vector Autoregression (SVAR) model is commonly used to explore the impact of oil price shocks on EPU in existing studies (Kang et al., 2017; Degiannakis et al., 2018). However, this model assumes constant shock effects over time, making it difficult to capture the dynamics characteristics of shocks. Moreover, this model overlooks the potential stochastic volatility (SV) inherent in the shocks themselves (Gayaker & Yalcin, 2025). To address these limitations, this study adopts a Time-Varying Parameter Vector Autoregression model with Stochastic Volatility (TVP-VAR-SV) to examine the dynamic effects of five-type shocks on China's EPU. This approach allows for a more detailed characterization of evolving responses, although the time-varying estimates should be interpreted cautiously given the limited sample size. The adoption of this methodology provides empirical evidence for investors, business leaders, and policymakers to better interpret and respond to changes in EPU. Additionally, the study also does robustness checks with different variables to make sure the results are stable and reliable.

The main contributions of this study are reflected in the following three aspects. First, based on the approach by Kilian (2008) and Gong et al. (2020), this study further refines the oil-price-related shocks into five categories: AS, AD, P, SD, and *I*. This classification allows for more refined examination of how China's EPU responds to five-type shocks, thereby addressing the limited differentiation of shock sources in the existing literature. Second, the study contributes to the literature by incorporating monetary policy indicators into the analysis of the oil shock–EPU relationship. While most existing studies focus on the direct response of EPU to oil-price shocks, we examine whether China's price- and quantity-based monetary policy instruments—proxied by the interest rate gap and the M2 gap—respond to oil-shock-induced macroeconomic fluctuations and whether these responses are related to EPU dynamics. This provides a more institutionally grounded interpretation of the oil shock–EPU nexus in China. Third, this study uses the TVP-VAR-SV model to conduct a dynamic analysis of the five-type shocks effect, overcoming the limitations of the static setting of the SVAR model, and revealing the heterogeneous response characteristics of EPU to the five-type shocks amid major events.

The remainder of this study is structured as follows. Section 2 introduces the theoretical framework. Then, Section 3 details the methodology of this study. Furthermore, Section 4 analyzes the findings, and Section 5 summarizes the discoveries of this study.

2.Theoretical framework

2.1. Structural oil price shocks and EPU

This study will adopt the aggregate supply–aggregate framework to explain why EPU may respond differently to five-type shocks. Specifically, oil-price-related shocks from different sources may influence inflation expectations and output levels, thereby triggering policy responses (Kilian, 2014; Wang et al., 2022; Bala & Chin, 2023). Following decomposition method by Kilian (2008), Hamilton (2009), and Gong et al. (2020) oil price shocks can be divided into AD, AS, P, I, and SD.

AS represents the changes of the world oil production, such as OPEC+ production cuts, or political instability in oil-producing countries (Kilian, 2008), which will directly cause an increase in EPU, while adverse supply disruptions may decrease EPU. Furthermore, when crude oil production declines and real oil price rise, it leads to increased inflation and reduced production (Kilian, 2014; Wang & Sun, 2017; Filippidis et al., 2020). Rising inflation expectations may prompt monetary tightening, while declining output calls for expansionary policy. This policy conflict complicates expectation formation and can increase fluctuations in EPU. By contrast, when the central bank’s macroeconomic objectives are clearly defined, policy actions may not affect EPU.

AD is the changes of global economic demand (Kilian, 2008). Global economic expansion drives domestic economic demand growth (Wei, 2019; Koirala and Ma, 2020). Stronger domestic demand may put upward pressure on prices. Furthermore, policy ambiguity—whether to sustain economic activity or curb inflation—prevents the formation of clear expectations, thereby increasing EPU fluctuations. Once the policy objective is clearly defined, monetary policy actions may no longer affect EPU.

I is the changes of the crude oil inventory. It is caused by forward-looking behavior that traders anticipating oil shortages buy and store crude in advance, increasing inventories. (Kilian & Murphy, 2014; Gong et al., 2025). Inventory accumulation by traders tightens supply, raising real oil price, increasing inflation, and reducing output. If the monetary authority lacks a clear macroeconomic objective, the resulting policy ambiguity amplifies EPU fluctuations. Under a clear policy stance, however, EPU may remain unaffected.

SD refers to non-commercial arbitrage activities in the international energy market. Short-term speculative trading driven by these non-commercial arbitrage activities can cause irrational price fluctuations (Juvenal et al., 2011; Kilian, 2014; Yang et al., 2024). For example, rising SD transmits from futures to spot markets, driving up real oil price and amplifying short-term volatility. Higher oil prices increase inflation and suppress output, creating policy trade-offs that heighten EPU fluctuations. With clearly defined macroeconomic objectives, however, EPU may remain unaffected.

P denotes precautionary demand reflecting movements in real oil price, driven by expectations of future supply shortfalls that boost current demand and raise prices (Kilian, 2008). Rising oil prices generate inflationary pressures and reduce output, placing the monetary authority in a policy dilemma; such ambiguity may amplify EPU volatility (Kang and Ratti, 2013; Kilian, 2014). Based on the above framework, we make a conclusion in Table 1:

Table 1: Conclusions for the theoretical framework

	AS (+)	AD (+)	*I* (+)	SD (+)	P (+)
Real oil price	-	+	+	+	+
Inflation	-	+	+	+	+
Output	+	+	-	-	-
Monetary policy tools	Not sure	Not Sure	Not sure	Not sure	Not sure
EPU	-	+	+	+	+

However, when the monetary authority's macroeconomic objectives are clear and policy is well-defined, monetary policy actions may not affect EPU. The status of the EPU is as follows:

Table 2: Conclusions for the theoretical framework when the policy objectives are well-defined

	AS (+)	AD (+)	*I* (+)	SD (+)	P (+)
Real oil price	-	+	+	+	+
Inflation	-	+	+	+	+
Output	+	+	-	-	-
Monetary policy tools	Sure	Sure	Sure	Sure	Sure
EPU	Stable	Stable	Stable	Stable	Stable

2.2. Price- and quantity-based monetary policy tools, structural oil price shocks and EPU

This section first outlines the quantity-based and price-based approaches to monetary policy. Building on Li et al. (2025), we jointly include the interest-rate gap and the money-supply gap to represent the observable operation of China's two main monetary policy instruments. The five structural oil price shocks and EPU are then incorporated into the empirical framework to examine their dynamic interactions within the quantity-based and price-based policy environment.

First, starting with one of the core components of quantity-based approach, the Equation of Exchange, $M_t V_t = P_t Y_t$, we take its logarithm of both sides, and then convert it into a growth rate form. The expression is:

$$\Delta m_t = \pi_t - \Delta v_t + \Delta y_t \tag{1}$$

Where Δm_t represents the growth rate of money supply, π_t represents the price level, Δv_t proxies for the growth rate of the velocity of money, and Δy_t proxies for the output growth rate.

We use $\widehat{m}_t = \Delta m_t - \Delta m_t^*$ to represent the money supply gap, $\hat{\pi}_t = \pi_t - \pi_t^*$ to represent the inflation gap, $x_t = \Delta y_t - \Delta y_t^*$ to represent the output gap, and $\hat{v}_t = \Delta v_t - \Delta v_t^*$ to represent the velocity of money gap. Therefore, the equation (1) can be represented as:

$$\widehat{m_t} + \widehat{v_t} = \hat{\pi}_t + x_t \tag{2}$$

According to the standard money demand theory, we assume that the velocity of money is related to the nominal interest rate, and the two move in the same direction that is:

$$\widehat{m_t} + \gamma(i_t - i_t^*) = \hat{\pi}_t + x_t \tag{3}$$

Here, i_t represents the interest rate, and i_t^* represents the target interest rate. This expression shows that monetary growth adjusts according to the deviation between real nominal income and its target, as well as changes in the policy interest rate.

Next, we present the price-based approach, the Taylor rule. The Taylor rule describes a system in which the policy interest rate is the primary tool for macroeconomic stability. The standard Taylor rule expression is:

$$i_t = r^* + \pi_t + \alpha(\pi_t - \pi_t^*) + \delta x_t \tag{4}$$

Where r^* is the equilibrium real interest rate, and α and δ are the coefficients of inflation gap and the output gap, respectively. Let $\beta = r^* - \alpha\pi_t^*$, Equation (4) can be expressed as:

$$i_t^* = \beta + (1 + \alpha)\pi_t + \delta x_t \tag{5}$$

Equations (3) and (5) above represent quantity-based and price-based approaches, respectively. However, neither of them alone can represent China's current monetary policy framework. Furthermore, due to the lack of a microeconomic basis, we cannot directly combine equation (3) and (5) to represent China's current hybrid policy rule.

Li et al. (2025) proposed and demonstrated a theoretical framework that simultaneously incorporates price-based and quantity-based policy indicators, clarifying the equivalence of quantity and price tools framework, thus resolving the issues. This study will adopt this framework, the expression of which is as follows:

$$\varphi\widehat{m_t} + (1 - \varphi)i_t = (1 - \varphi)i_t^* + \rho_1(\pi_t - \pi_t^*) + \rho_2 x_t \tag{6}$$

where φ represents the coefficients of quantity and price tools. In this study, $0 < \varphi < 1$. When $\varphi = 1$, it indicates that the policy framework is quantity-based; when $\varphi = 0$, it indicates that the policy framework is price-based. ρ_1 and ρ_2 represent the coefficients of the inflation gap and the output gap.

We incorporate five-type shocks into a hybrid monetary policy tools framework:

$$\varphi\widehat{m_t} + (1 - \varphi)i_t = (1 - \varphi)i_t^* + \rho_1(\pi_t - \pi_t^*) + \rho_2 x_t + \omega o_t \tag{7}$$

where o_t represents the five-type shocks. Based on the above theoretical framework, we use the following variables to examine the dynamic relationships among five-type shocks, macroeconomic conditions, the interest-rate gap, the money-supply gap, and EPU:

$$epu_t = ({oil^{AS}}_t, {oil^{AD}}_t, {oil^{I}}_t, {oil^{sd}}_t, {oil^{p}}_t, \widehat{m_t}, i_t - i_t^*, \pi_t - \pi_t^*, x_t). \tag{8}$$

Where oil^{AS} is the AS, oil^{AD} is the AD, oil^{I} is the *I*, oil^{sd} represents the SD, ${oil^{p}}_t$ represents the P, epu_t is China's EPU.

3. Methodology

3.1. Data and variables

Table 3 shows the descriptive statistics of all variables based on quarterly data from the second quarter of 2007 to the first quarter of 2025. Due to the availability of real GDP data, the sample period begins in 2007Q2.

For the three-type shocks, we adopt Kilian (2008)'s method, using the Baltic Dry Index (BDI) to represent AD[3]; world crude oil production to represent AS; and real crude oil price to represent *P*. This study will use West Texas Intermediate (WTI) crude oil price and Brent crude oil price for robustness testing. Furthermore, for *I* and SD that are difficult to capture with

[3] The Baltic Dry Index (BDI), compiled by the Baltic Exchange, is a composite measure of the freight rates in the global dry bulk shipping market and serves as an indicator of global economic activity. A rise in the BDI suggests rising global demand for raw materials and signals global economic expansion, whereas a decline in the BDI indicates a slowdown in global economic activity (Kilian, 2008; Li et al., 2025).

traditional three-type shocks, we will adopt the measurement method of Gong et al. (2025): using OECD crude oil stocks to represent *I*; and the non-commercial arbitrage holdings ratio, measured as the proportion of non-commercial arbitrage holdings to total holdings, to represent SD. Data sources are as follows: world crude oil production and oil inventories are sourced from the U.S. Energy Information Administration(EIA); the BDI index is sourced from Investing.com; WTI and Brent crude oil prices are sourced from the Federal Reserve Economic Data (FRED); and the ratio of non-commercial arbitrage holdings is sourced from the Wind database. Except for SD, we take the logarithmic form of all the above variables.

Under the hybrid tool framework, we select the following variables: output gap (Δy), inflation gap ($\Delta \pi$), money supply gap (Δm), and interest rate gap (Δr). Real Gross Domestic Product (GDP) is used to measure real output, Consumer Price Index (CPI) shows how much prices have changed between two periods, which is how inflation is measured, M2 represents the money supply, and the overnight pledged interbank repo rate represents interest rate. Both real GDP and M2 are transformed into their logarithmic forms. Δy and Δm are calculated as the deviations between logarithmic real GDP and logarithmic potential GDP, and between logarithmic M2 and logarithmic potential M2, respectively. Similarly, $\Delta \pi$ and Δr are measured as the deviations between actual inflation and potential inflation, and between the actual interest rate and potential interest rate. The potential values for GDP, M2, inflation, and interest rate are obtained using the Hodrick-Prescott (HP) filter. All data are sourced from the CEIC database.

In addition, this study adopts the China EPU index developed by Davis et al. (2019) to represent China's EPU. The index is made by counting the number of articles in mainland Chinese newspapers that have a minimum of one of the words "economic," "policy," or "uncertainty" each month and then dividing that by the total number of articles published in those newspapers that month. Within the sample period of this study, the EPU index reaches a maximum value of 499.24950, a minimum of 40.83712, and an average of 193.63130 (Table 4). The EPU index is also used in its logarithmic form in this study.

Table 3: Descriptive statistics

Variables	Definition	Source
Economic policy uncertainty (EPU)	China's economic policy uncertainty index.	https://policyuncertainty.com/
Aggregate supply shock (AS)	World crude oil production.	EIA
Aggregate demand shock (AD)	BDI index.	investing.com
Special demand shock(P)	WTI oil price. Brent oil price.	FRED
Oil inventory(I)	OECD oil stocks.	EIA
Speculative demand shock (SD)	The ratio of non-commercial arbitrage holdings to total positions.	Wind
Output gap (Δy)	The deviation of the logarithmic real GDP and the logarithmic potential GDP. Real GDP is calculated using GDP at constant prices in the current period.	CEInet statistics database
Inflation gap ($\Delta \pi$)	The Deviation of the real inflation and the potential inflation. Inflation is measured by subtracting 100 from the CPI (same month of the previous year = 100).	CEInet statistics database
M2 gap (Δm)	Deviation of logarithmic M2 from the logarithmic potential M2.	CEInet statistics database
Interest rate gap(Δr)	The Deviation of the interest rate and the potential interest rate. Interest rate is overnight interbank pledged repo rate.	CEInet statistics database

Table 4: Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
AS	72	74.20153	2.95721	67.74333	79.57667
AD	72	-3.09264	67.79644	-145.69640	185.68970
P	72	73.18620	21.54161	27.80667	123.95330
I	72	4280.95000	207.40100	3961.82700	4740.97900
SD	72	0.31194	0.04953	0.18667	0.39500
$\Delta\pi$	72	0.02692	1.56449	-4.97993	3.91614
Δy	72	0.00037	0.07833	-0.24601	0.17865
Δm	72	-0.00009	0.01643	-0.06249	0.03138
Δr	72	0.00032	1.54793	-3.54457	3.70987
EPU	72	193.63130	109.95440	40.83712	499.24950

3.2. Empirical Methodology

To empirically evaluate the dynamic effect of five-type shocks on China's EPU, this study will use the TVP-VAR-SV. Compared to conventional VAR or SVAR frameworks, the TVP-VAR-SV model enables both the coefficients and the shock variances to change over time. This characteristic of the model is helpful in capturing the dynamic response of EPU during major events such as COVID-19. The general form of the model is given by:

$$y_t = A_{0,t} + A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + \cdots + A_{p,t}y_{t-p} + \varepsilon_t$$

where A_{jt}denotes the time-varying coefficient matrix at lag j, and $\varepsilon_t \sim N(0, \sum_t)$, with $\sum_t$ being a time-varying covariance matrix that accommodates stochastic volatility. Following Primiceri (2005), the error term ε_t is decomposed as:

$$\varepsilon_t = A_t^{-1} \sum_t^{1/2} \eta_t$$

where Σ_t is a diagonal matrix of time-varying standard deviations, and $\eta_t \sim N(0, I)$ are orthogonal structural shocks. To identify the five-type shocks, we apply recursive (Cholesky) decomposition. The structural matrix A_t^{-1} is assumed to be lower triangular with unit diagonal, consistent with Kilian (2008) and Kilian and Murphy (2014). This method imposes contemporaneous zero restrictions such that each variable is contemporaneously influenced only by variables that appear earlier in the ordering.

To impose identification restrictions on A_t^{-1} in this study, the order of all variables in this study is as follows:

$$y_t = [oil^{AS}{}_t, oil^{AD}{}_t, oil^{I}{}_t\,, oil^{Sd}{}_t, oil^{P}{}_t, \Delta\pi_t, \Delta y_t, \Delta i_t, \Delta m_t, EPU_t]'$$

Where oil^{AS} represents AS, oil^{AD} is AD, oil^{I} represents *I*, oil^{sd} represents the SD, $\Delta\pi$ is the inflation gap, Δy represents the output gap, Δi represents the interest rate gap, Δm represents the money supply gap, EPU is the China's EPU.

First, the five-type shocks are ordered to ensure they are contemporaneously exogenous to the remaining variables. These shocks—denoted $oil^{AS}{}_t, oil^{AD}{}_t, oil^{I}{}_t\,, oil^{Sd}{}_t, oil^{P}{}_t$—represent aggregate supply, aggregate demand, oil inventory, speculative demand, and specific demand shocks, respectively. Within this block, AS is placed first, as high adjustment costs in oil production prevent it from responding contemporaneously to AD fluctuations (Kang and Ratti, 2013). *I*, which reflects expectations about future supply–demand conditions and affects current demand, is ordered after AD (Kilian and Murphy, 2014). SD, proxied by the share of non-commercial positions in total open interest, is placed after inventory shocks, as it is influenced by economic events and resource conditions (Gong et al., 2020). Finally, P is captured by the WTI crude oil price.

Macroeconomic variables follow the five-type shocks, as China, despite being a major oil consumer, does not determine global oil market dynamics. The ordering assumes that oil-price movements first enter China's macroeconomic block through inflation and output, after which monetary policy indicators respond. Under China's hybrid monetary policy tools framework, however, the relative ordering of interest rate and money supply indicators is not uniquely determined; alternative orderings are examined in robustness check. Finally, EPU is placed as the target variable.

In addition, to test the robustness of the model, we also assumed the following variable order:

$$y_t = [oil^{AS}{}_t, oil^{AD}{}_t, oil^{I}{}_t\,, oil^{Sd}{}_t, oil^{P}{}_t, \Delta\pi_t, \Delta y_t, EPU_t]'$$

$$y_t = [oil^{AS}{}_t, oil^{AD}{}_t, oil^{I}{}_t\ , oil^{Sd}{}_t, oil^{P}{}_t, \Delta\pi_t, \Delta y_t, \Delta m_t, \Delta i_t, EPU_t]'$$

We also swap the ordering of *I* and SD to assess whether the relative placement of expectation-driven oil market variables affects the results. The ordering is as follows:

$$y_t = \left[oil^{AS}{}_t, oil^{AD}{}_t, oil^{Sd}{}_t, oil^{I}{}_t\ , oil^{P}{}_t, \Delta\pi_t, \Delta y_t, \Delta i_t, \Delta m_t, EPU_t\right]'$$

The model is estimated under a Bayesian framework via Markov Chain Monte Carlo (MCMC) techniques. Following Nakajima (2011), the posterior distributions are simulated based on 10,000 iterations, with the first 5,000 discarded as burn-in. The estimation is implemented in MATLAB using the BEAR toolbox, which is well suited for large-scale TVP-VAR-SV models with structural identification. Despite the relatively limited sample size, the Bayesian approach remains feasible due to the use of shrinkage priors and random-walk state dynamics, which effectively mitigate parameter proliferation and overfitting, while allowing for gradual structural change (Primiceri, 2005; Nakajima, 2011). Therefore, the time-varying results should be interpreted as suggestive evidence of evolving dynamics rather than precise estimates of structural breaks.

4. Results

4.1. Unit root test

Prior to estimating the TVP-VAR-SV model, we performed the Augmented Dickey-Fuller (ADF) unit root test to test the stationarity of each variable. The results are shown in Table 5. AS, AD, P, I and EPU were logarithmically calculated. They are represented by InAS, InAD, InP, InI, and InEPU. Table 3 shows that InAS, InI, and InEPU are stationary after first differencing, while InAD, InP, $\Delta\pi$, Δy, Δm, and Δr are horizontally stationary.

Table 5: ADF test results of each variable

variables	constant without trend		constant with trend	
	level	first difference	level	first difference
lnAS	-1.971 (3)	-4.274 (3) ***	- -2.495 (3)	-4.236 (3) ***
lnAD	-3.192 (3) **	---------	--2.880 (3)	---------
lnP	-2.683 (2) *	---------	--2.744 (2)	---------
lnI	-1.418 (2)	-3.581 (2) ***	-1.386 (2)	-3.785 (2) **
SD	-2.576 (0) *	---------	-4.105 (0) ***	---------
$\Delta\pi$	-6.013 (3) ***		-5.984 (3) ***	
Δy	-4.236 (4) ***	---------	-4.211 (4) ***	---------
Δm	-3.232 (2) **	---------	-3.199 (2) *	---------
Δr	-3.533 (1) ***	---------	-3.505 (1) **	---------
lnEPU	-2.015 (2)	-6.284 (2) ***	-2.550 (2)	-6.319 (2) ***

Note: Asterisks denote statistical significance at the 1% (***), 5% (**) or 10% (*) level. Values reported in parenthesis are lag length.

4.2. Lag selected

When constructing the TVP-VAR-SV model, it's necessary to select the optimal lag order. As shown in Table 6, the optimal lag order for HQIC, and SBIC is 1, while LR and AIC consider the optimal lag order to be 4. To avoid overfitting, this study ultimately selected a lag of order 1.

Table 6: Optimal lag order selection

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	431.93				1.90E-18	-12.41	-12.28	-12.08
1	827.73	791.60	100	0	3.30E-22	-21.11	**-19.69***	**-17.52***
2	920.68	185.89	100	0	4.90E-22	-20.90	-18.19	-14.05
3	1059.74	278.13	100	0	**2.6e-22***	-22.05	-18.04	-11.93
4	1186.92	**254.36***	100	0	3.80E-22	**-22.85***	-17.55	-9.468

*Note: *marks lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz Bayesian Information Criterion; HQIC: Hannan-Quinn information criterion.*

4.3. Impulse Response Analysis

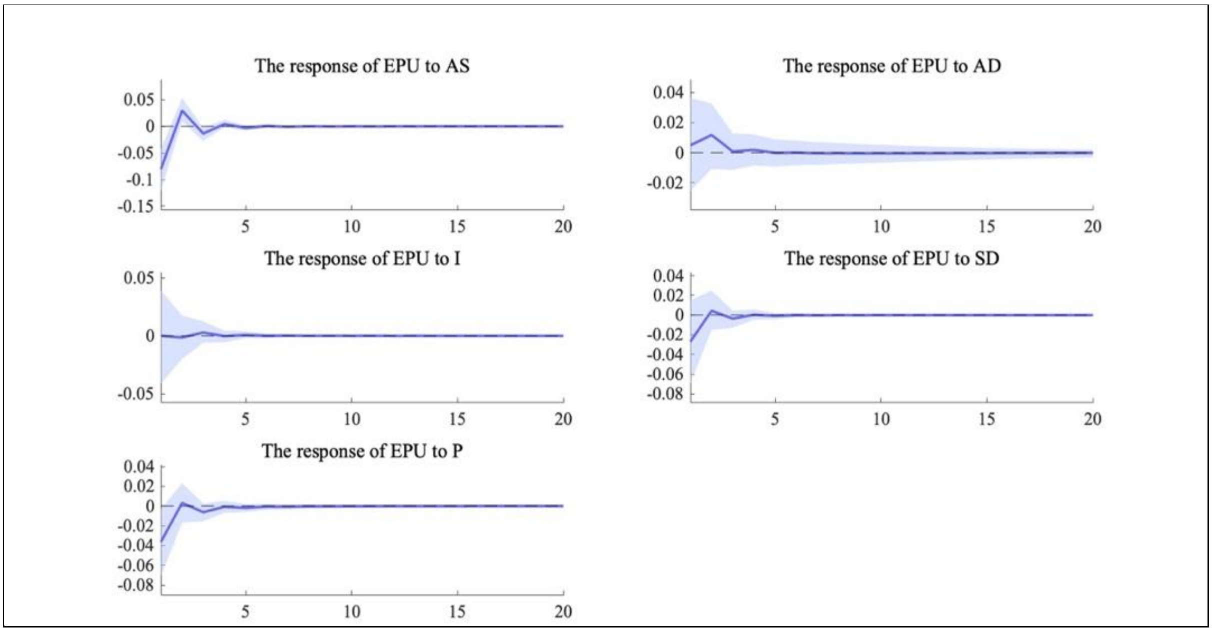
This section has two parts: the analysis of the median impulse response (IRF) (Figure 1- 6) and the analysis of the time-varying IRF (Figure 7- 12). The former focuses on the response of variables in the short and long term, while the latter analyzes the time-varying nature of the variable response.

4.3.1. The impact of structural oil price shocks on EPU based on the Hybrid monetary policy tools framework

In this part, we will analyze the results of the median IRF (Figure 1- 6). The shaded areas represent the 68 percent posterior credible intervals. Here we will explain in detail those statistically significant responses.

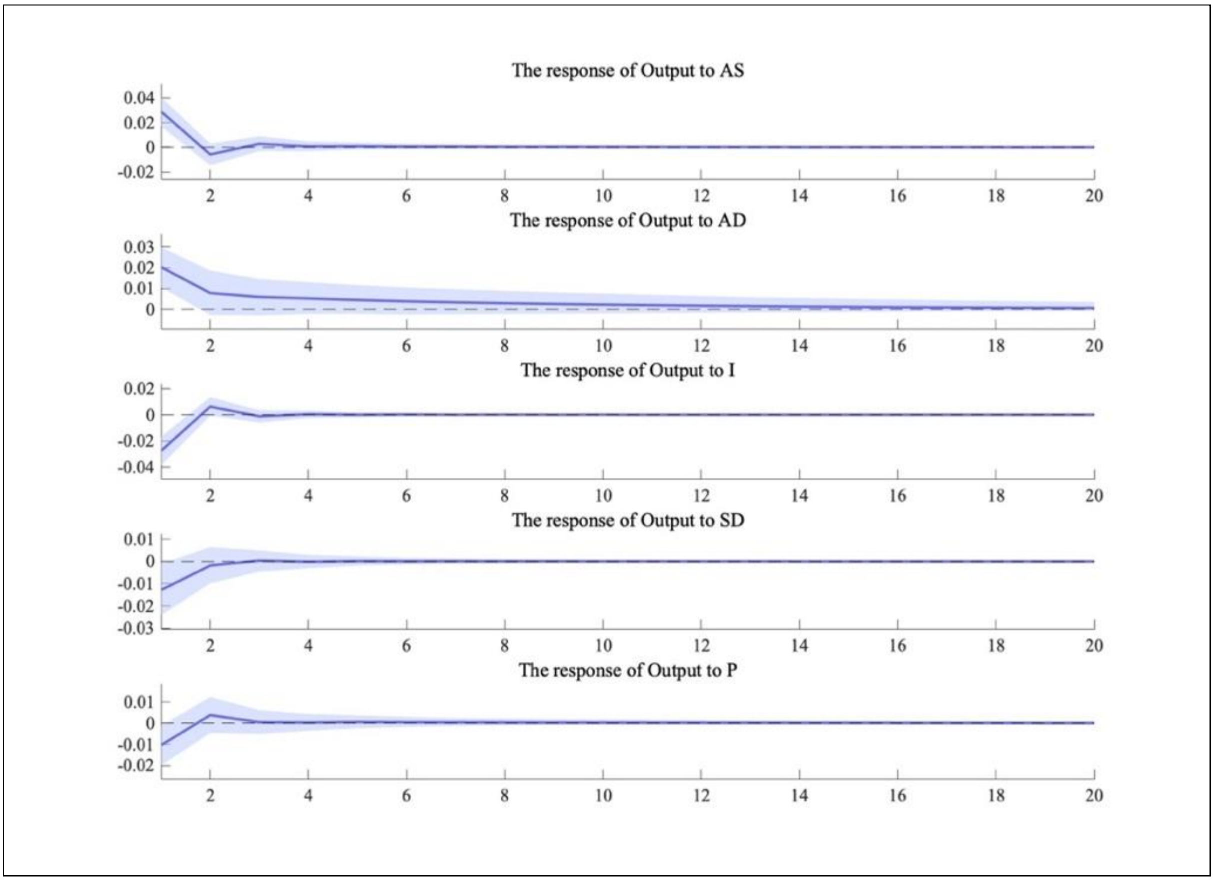
As shown in Figure 1, among the five structural oil price shocks, only AS significantly reduces China's EPU in the short run under the median IRF. This finding is consistent with theoretical expectations and aligns with Kang et al. (2017) who show that increases in oil production significantly lower U.S. EPU.

Figure 1: The median response of EPU to five-type shocks



As illustrated in Figure 2, output responds positively to an AS shock in the short run, indicating a rapid expansion of actual output beyond its potential level. This is consistent with theoretical expectations and with the findings of Basnet & Upadhyaya (2015), Gong et al. (2020) and Zhang et al. (2022), who show that increased oil supply boosts global economic expectations, supports demand recovery, and thereby raises output.

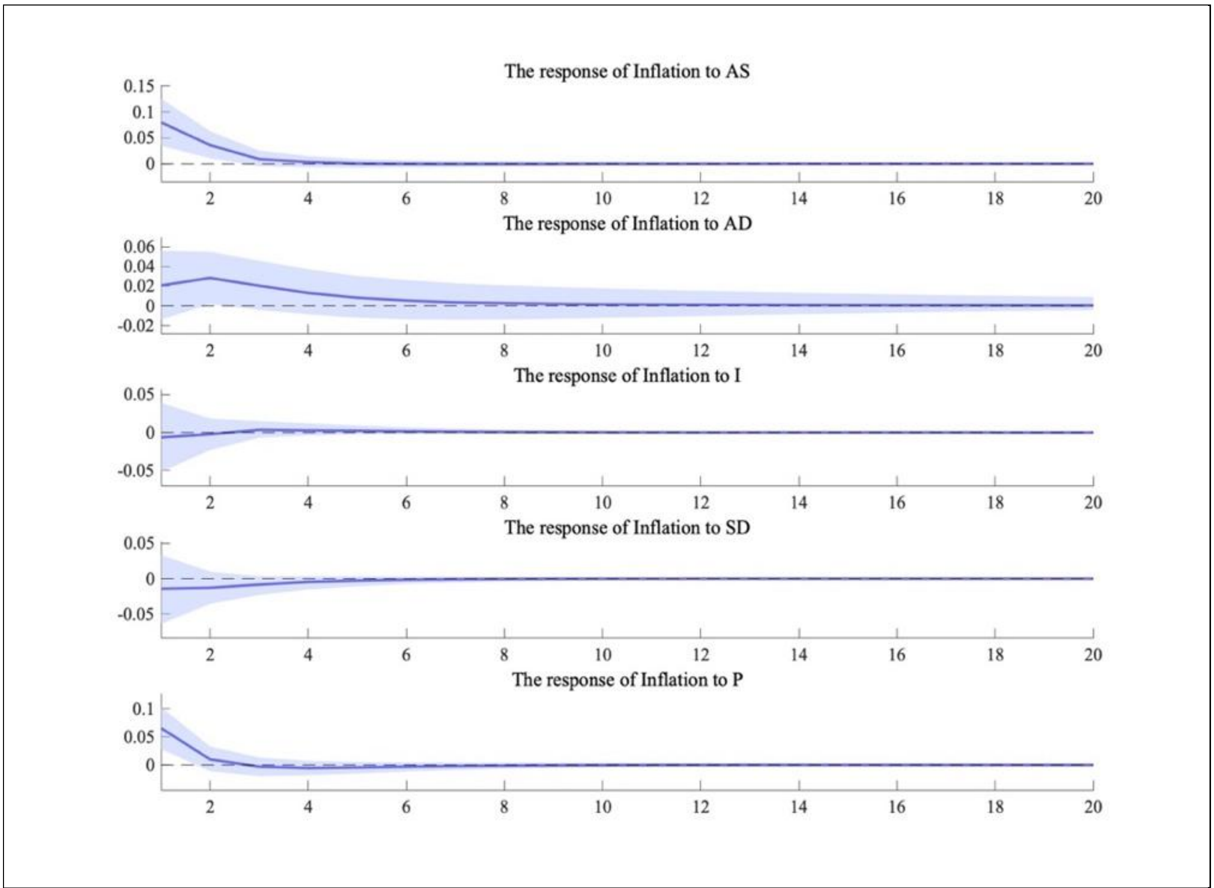
Figure 2: The median response of output to five-type shocks



Output shows a sharp positive response to an AD shock in the short run, likely reflecting China’s export-oriented structure, whereby stronger global demand stimulates exports and boosts output. This is consistent with theoretical expectations and with Duong (2024), who finds that AD significantly raises output in Vietnam. By contrast, *I* exerts a significantly negative short-run effect on output, in line with theory and with Juvenal et al. (2011) who report a negative impact of inventory-driven shocks on industrial production.

As shown in Figure 3, the AS shock significantly raises inflation in the short run, which accords with Aastveit et al. (2026), who document a similar short-run increase in U.S. inflation. However, this finding runs counter to our theoretical expectation. Although higher oil production lowers oil price, the resulting stimulus to domestic economic activity in China generates upward pressure on prices (Embergenov et al.,2022; Zhang et al.,2022). In addition, a one-unit positive shock to P significantly increases inflation, consistent with Arsalane and Kim (2024), who show that rising real oil price increase production costs in oil-intensive manufacturing, which are ultimately passed on to consumers.

Figure 3: The median response of inflation to five-type shocks



As the results shown in Figure 4, EPU shows a significant short-run response to an output shock: a positive output shock is followed by a marked increase in EPU. This is consistent with Jiang et al. (2018) who show that EPU tends to rise with economic growth.

Figure 4: The median response of EPU to inflation & output

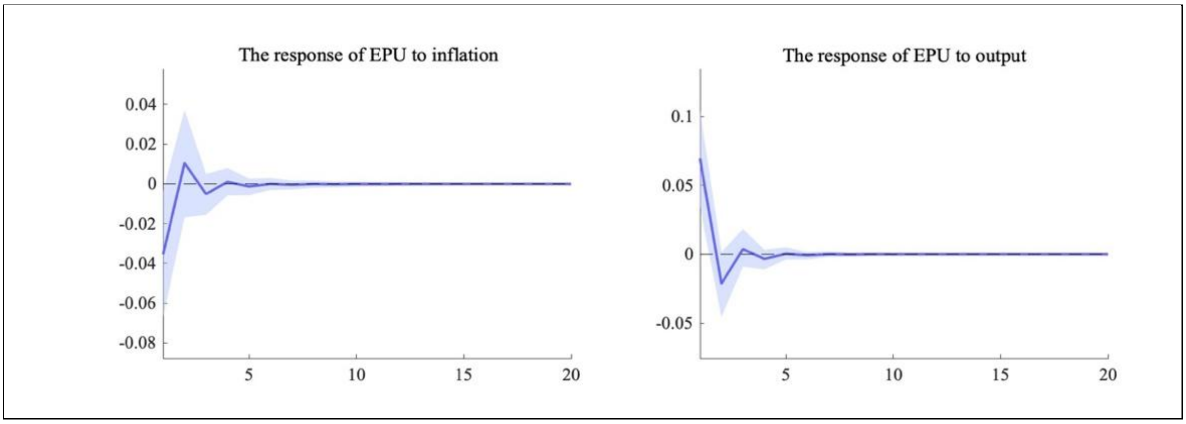
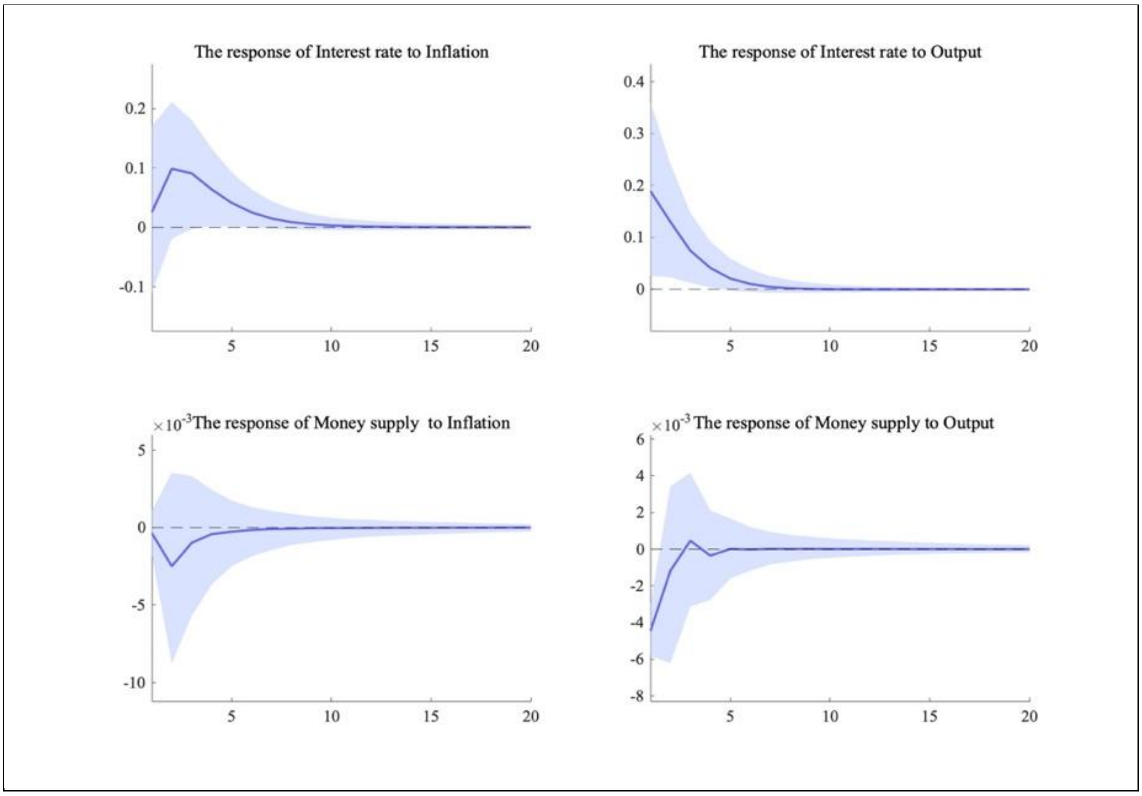


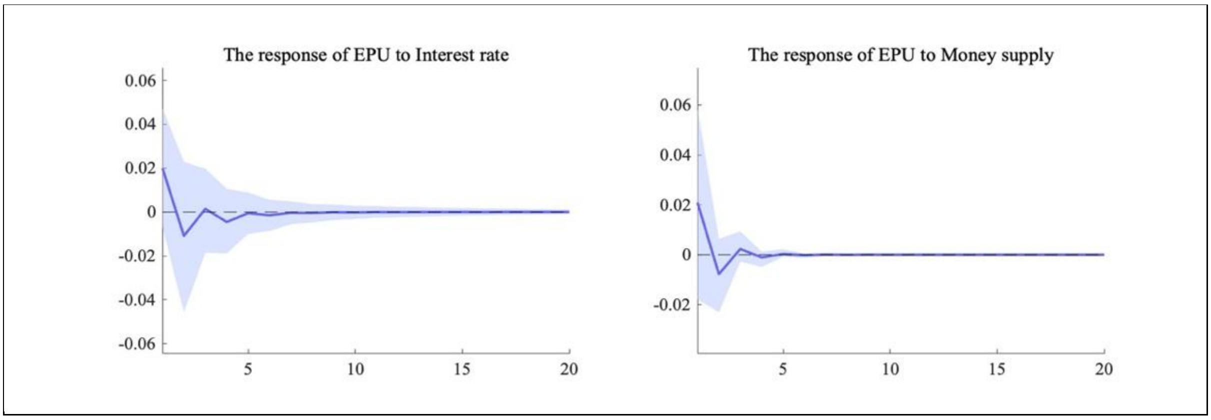
Figure 5 shows that interest-rate gap and the money-supply gap do not show statistically significant responses to inflation. In contrast, both indicators respond significantly to output in the short run: a positive output shock raises interest rates and reduces money supply. López-Villavicencio (2013) supports this finding, indicating that tightening through higher interest rates and lower money supply is used to curb excess demand during periods of overheating.

Figure 5: The median response of monetary policy indicators to inflation & output



Under the median IRF (Figure 6), a one-unit increase in the interest rate is not associated with a statistically significant response of EPU, consistent with Funashima (2022), which finds that contractionary monetary policy does not significantly affect uncertainty. Likewise, EPU does not show a statistically significant response to a positive money-supply-gap shock. One possible interpretation is that EPU reflects policy uncertainty or informational opacity (Baker et al., 2016), and Dotsey and King (1983) argue that predictable, rule-based monetary expansion does not increase policy uncertainty. Taken together, Figures 5 and 6 indicate that output expansions are associated with higher interest rates and lower money supply, while the benchmark median responses provide little evidence that these policy indicators independently amplify EPU fluctuations.

Figure 6: The median response of EPU to monetary policy indicators



In sum, the median IRFs indicate heterogeneous responses of EPU to different structural oil price shocks. Among the five shocks, AS displays the clearest statistically significant association with EPU, whereas the direct responses of EPU to the other shocks are not statistically significant. In addition, AS, AD, and I are associated with output fluctuations, which are followed by changes in EPU. Regarding monetary policy indicators, the results suggest that output expansions are accompanied by higher interest rates and lower money supply.

4.3.2. The time-varying impact of structural oil price shocks on EPU based on the Hybrid monetary tools framework

The impact of oil price shocks on China's economy varies over time (Cross & Nguyen,2017), implying that time variation should be accounted for when assessing their effects on EPU. While median impulse responses provide a useful benchmark, they mask substantial temporal heterogeneity. Time-varying impulse responses complement this analysis by identifying periods when specific shocks exert significant effects. We then discuss the evolution of these responses over time. In Figures 7-12, the X-axis proxies for the time of occurrence of five-type shocks, the Y-axis represents the duration of the target variable's response to five-type shocks, and the Z-axis represents the median value of the target variable's response to five-type shocks. As shown in Figure 7, EPU exhibits time-varying responses to AD and *I*. In particular, the top-right panel indicates that EPU's response to AD declines after the 2008 financial crisis.

Figure 7: The time-varying response of EPU to five-type shocks

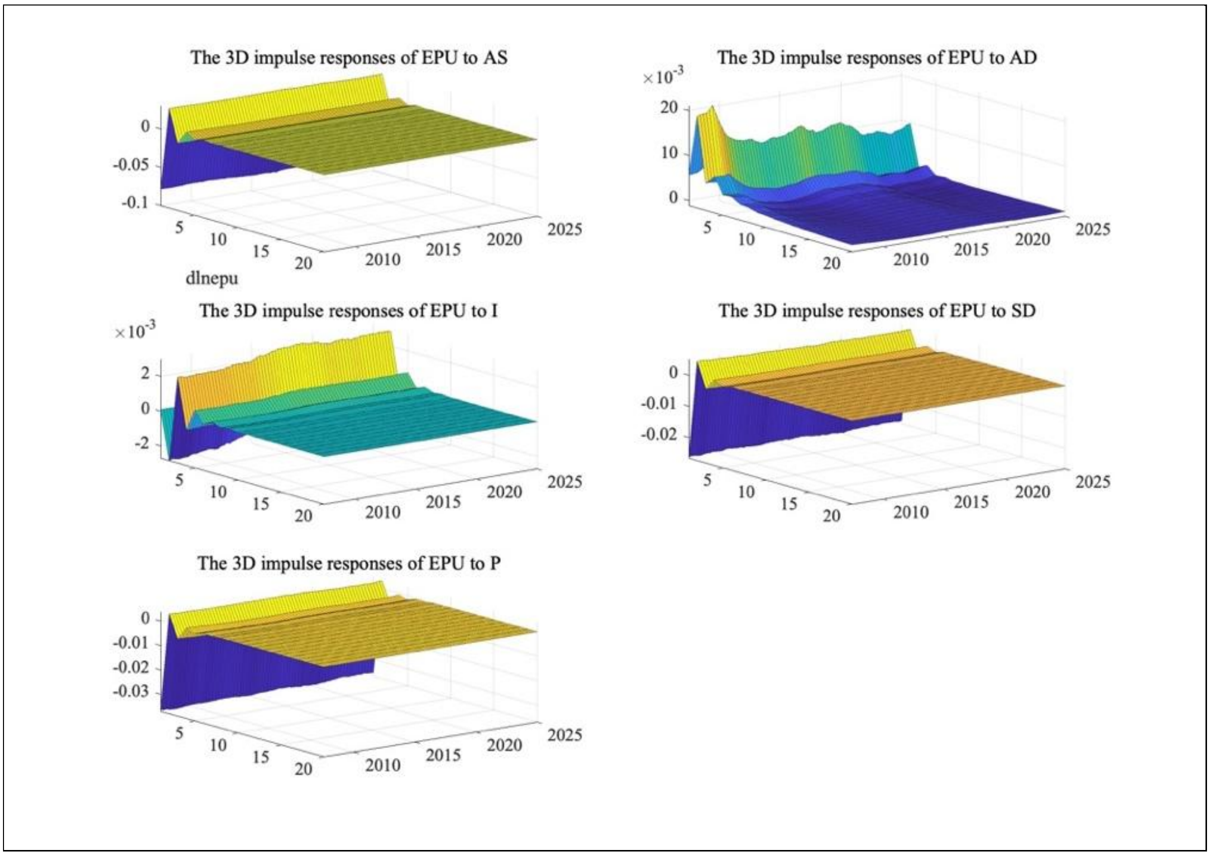


Figure 8 shows that inflation exhibits time-varying responses to AD and *I*. The upper-right panel indicates that inflation's response to AD declines sharply after the 2008 financial crisis, and following the 2020 COVID-19 shock, it first increases and then decreases. The second-row, first-column panel further shows a steady decline in inflation's response to *I* over the sample period.

Figure 8: The time-varying response of inflation to five-type shocks

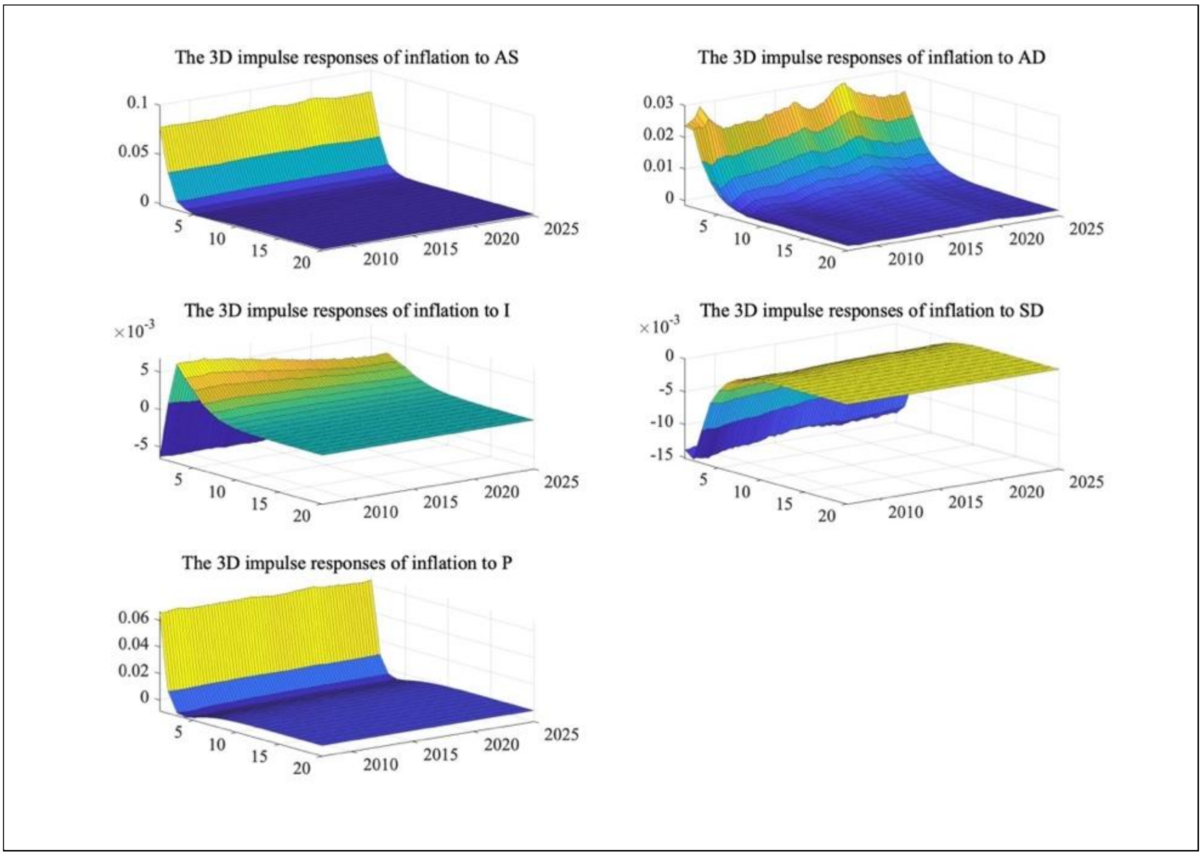


Figure 9 shows that output exhibits pronounced time variation in its response to AD. The upper-right panel indicates a sharp decline in this response after the 2008 financial crisis, followed by an increase and subsequent decrease after the 2020 COVID-19 shock. Figure 10 shows no significant time variation in EPU's responses to inflation and output.

Figure 9: The time-varying response of output to five-type shocks

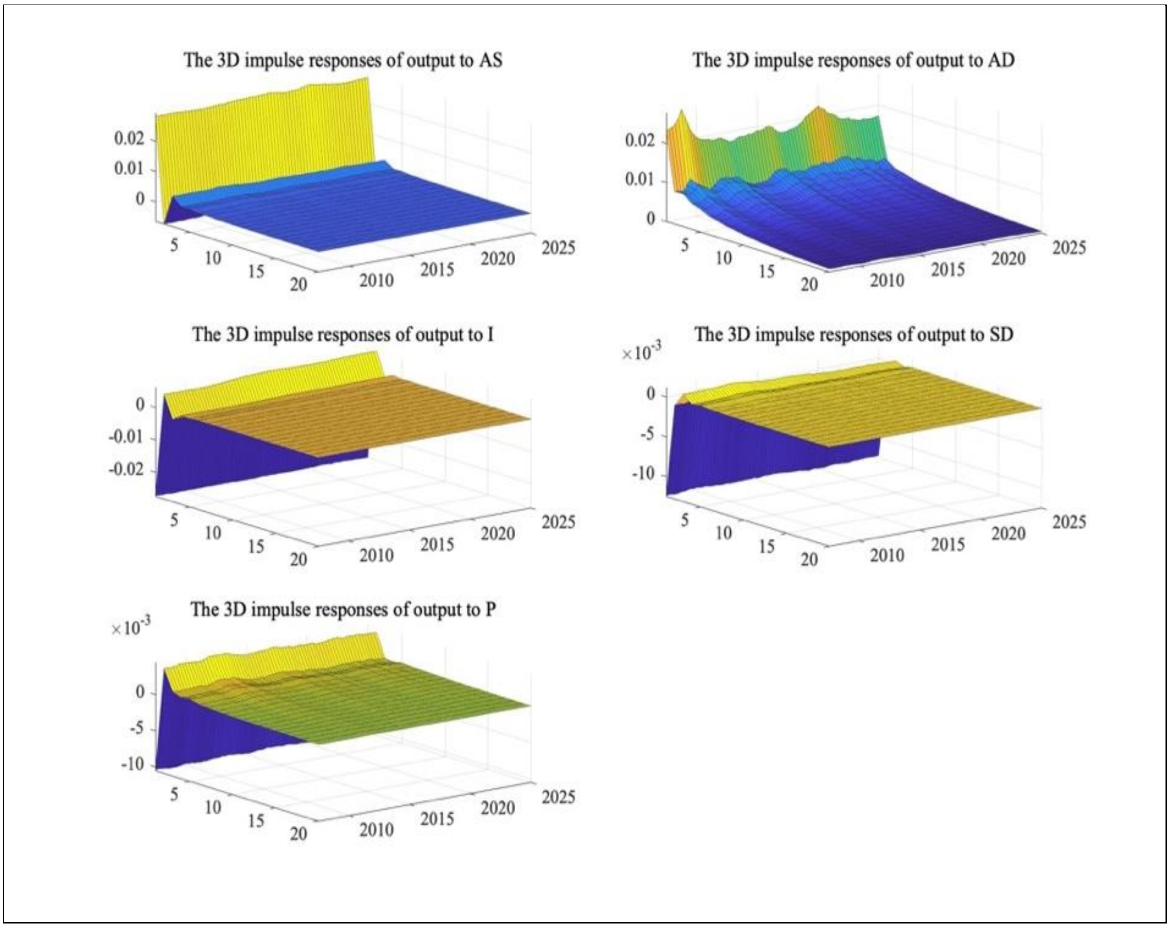


Figure 10: The time-varying response of EPU to inflation & output

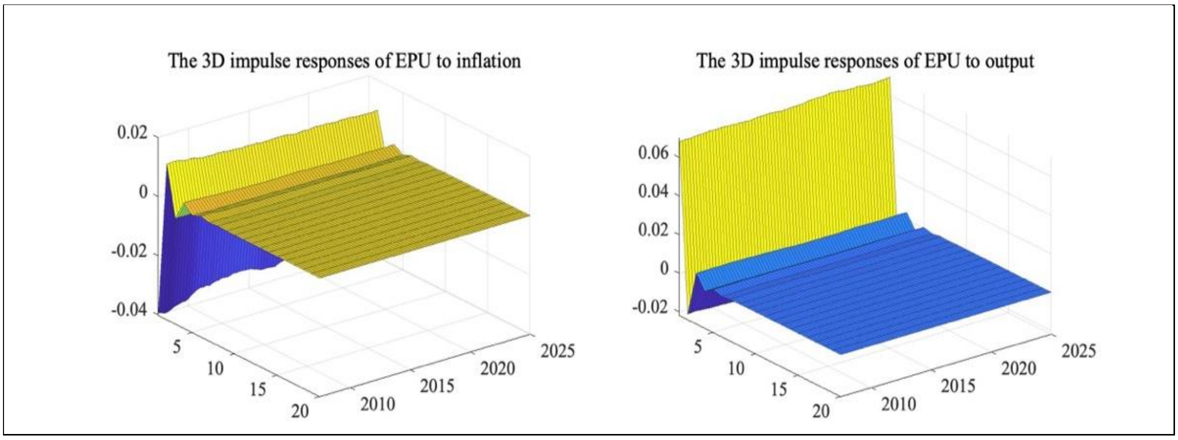
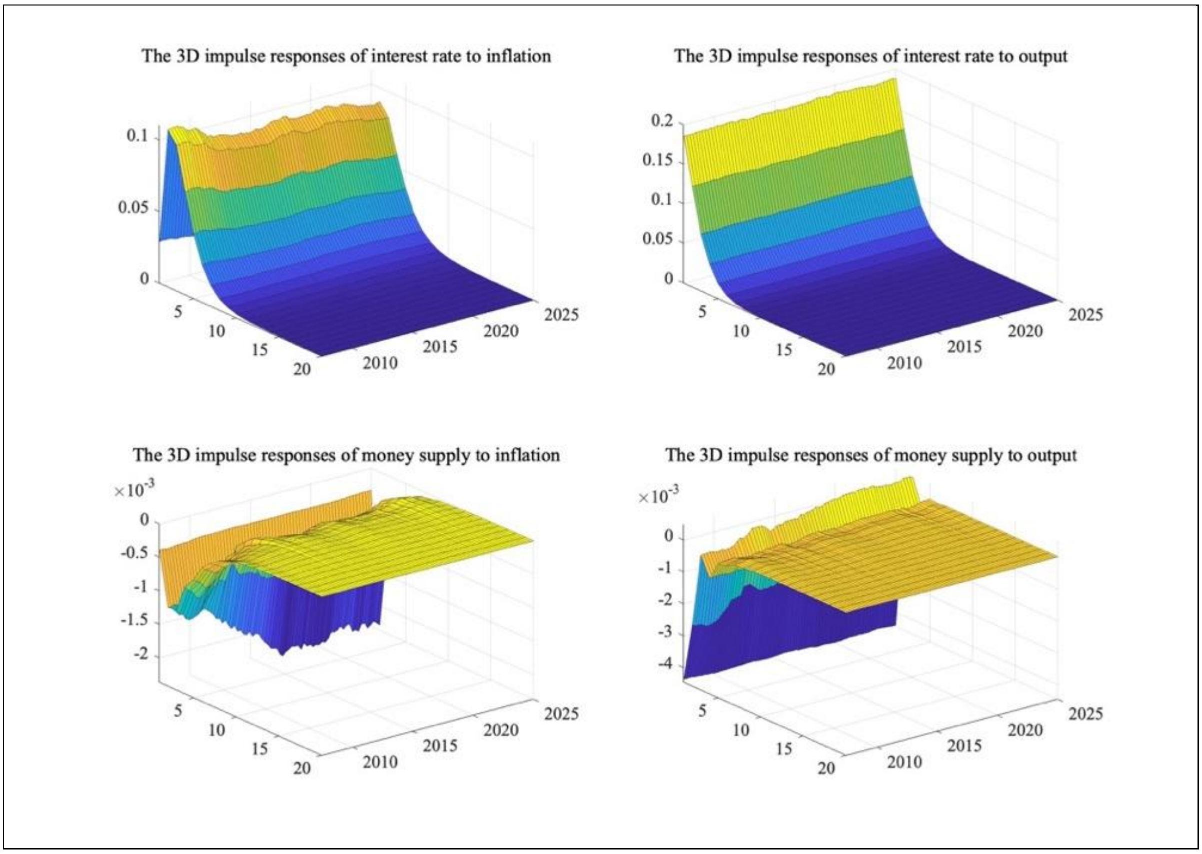


Figure 11 (upper-left panel) indicates that, prior to 2017, the response of the interest-rate gap to inflation gradually weakens, while the lower-left panel indicates that the negative response of the money-supply gap to inflation intensifies over the same period. This result suggests that, in the earlier part of the sample, quantity-related policy indicators played a relatively more visible role in responses to inflationary pressures. After 2017, the responses become more consistent with China's broader transition toward a more price-oriented monetary policy framework, particularly following the discontinuation of explicit M2 growth targets after 2018.

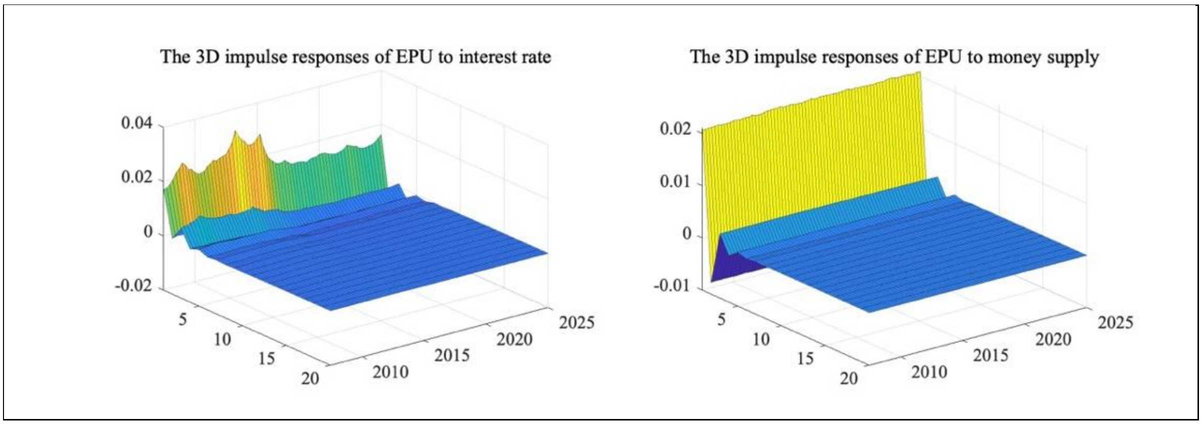
Figure 11: The time-varying response of monetary policy indicators to inflation & output



In response to output fluctuations, as shown in the upper-right panel of Figure 11, only money supply exhibits time variation: after 2013, the negative response of the money-supply gap to output fluctuations gradually weakens. This pattern broadly coincides with China's transition toward a more price-oriented monetary policy framework, particularly following the full liberalization of the lending-rate floor.

The right panel of Figure 12 shows that the response of EPU to the interest rate gap is time-varying. The positive response intensifies notably during the 2008 Global Financial Crisis, following the full liberalization of the lower bound on lending rates in 2013, and after the removal of the ceiling on deposit rate floating in 2015. It suggests that the monetary-policy transition period was associated with stronger sensitivity of EPU to interest-rate-related policy indicators.

Figure 12: The time-varying response of EPU to monetary policy indicators

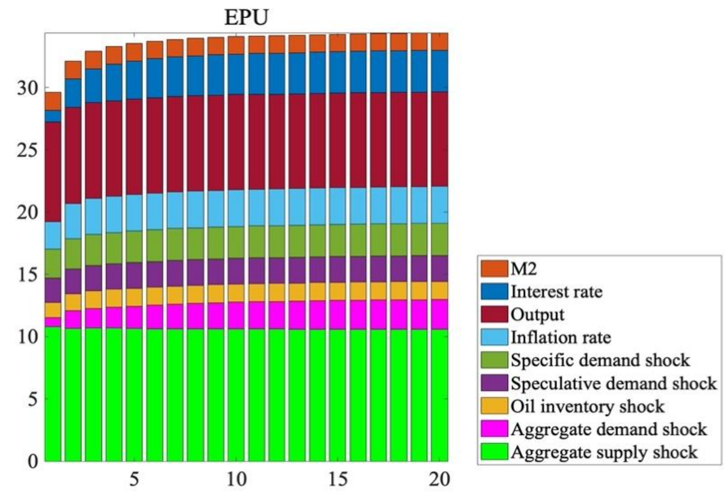


Overall, the time-varying IRFs reveal pronounced temporal heterogeneity. Shocks that are insignificant under the median response—such as AD—exhibit markedly stronger or weaker effects on EPU, output, and inflation during specific periods, notably the 2008 Global Financial Crisis. In addition, the responses of monetary policy indicators evolve over time. In the early sample, inflation is associated with a stronger response of the money supply, although this relationship gradually weakens. It is consistent with China's broader transition toward a more price-oriented monetary policy framework. Meanwhile, the response of EPU to the interest rate appears more pronounced around key reform periods during this transition.

4.4. Variance decomposition

The variance decomposition results (Figure 13) further supplement the impulse response analysis. Overall, the fluctuations of China's EPU are primarily explained by its own internal factors. From Figure 13, we found that, among different oil price shocks, AS consistently have the strongest explanatory power for EPU volatility, while AD, SD, *P*, and *I* contribute relatively little. Furthermore, the direct contributions of the interest-rate gap and the money-supply gap to EPU are less than those of output and inflation, with output accounting for a much larger share than inflation. These results suggest that, within the benchmark specification, monetary policy indicators have limited direct explanatory power for EPU fluctuations, while macroeconomic conditions—particularly output—play a more visible role.

Figure 13: Variance decomposition for EPU



4.5. Robustness check

This section shows the results of the robustness checks, aiming to further verify the results discussed above. We conduct robustness tests by replacing variables, removing monetary policy variables, and alternative ordering.

(1) Replacing variables

We use Brent oil price instead of WTI oil price. Figures 14 to 18 illustrate the median IRFs. This robustness check results are consistent with the previously proposed conclusions.

Figure 14: The median response of EPU to five-type shocks

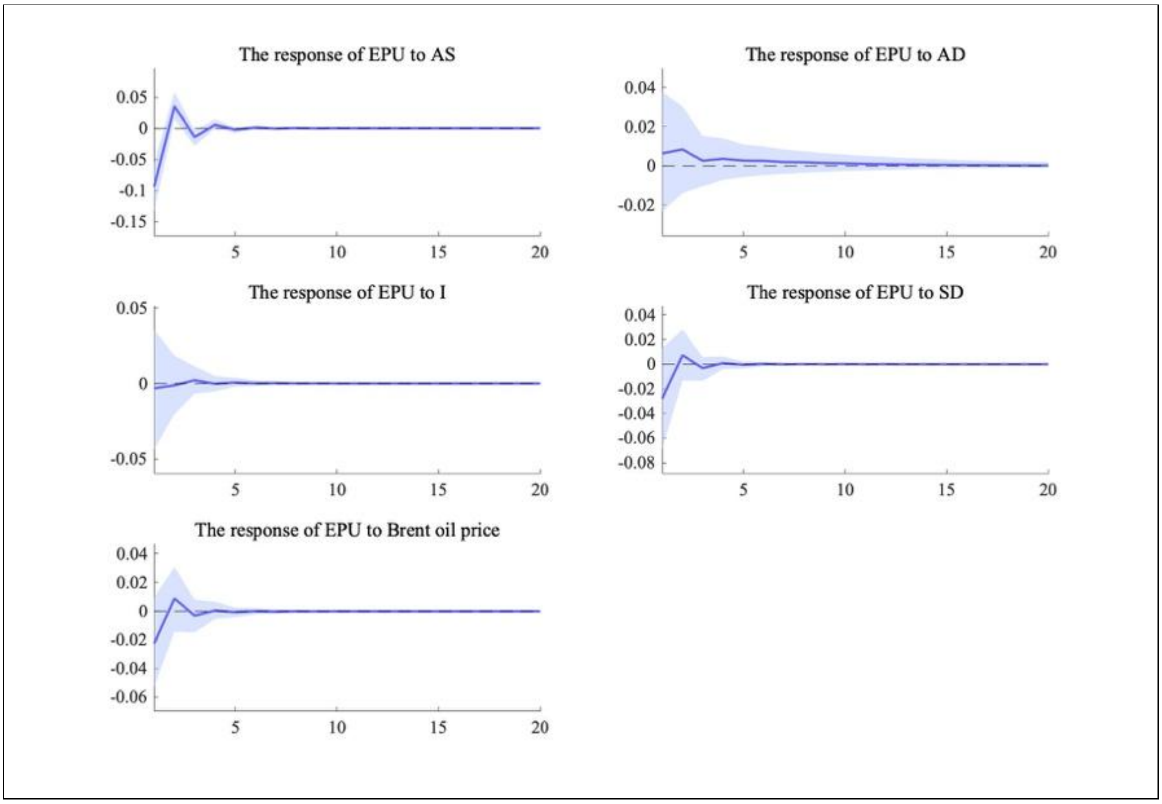


Figure 15: The median response of output & inflation to five-type shocks

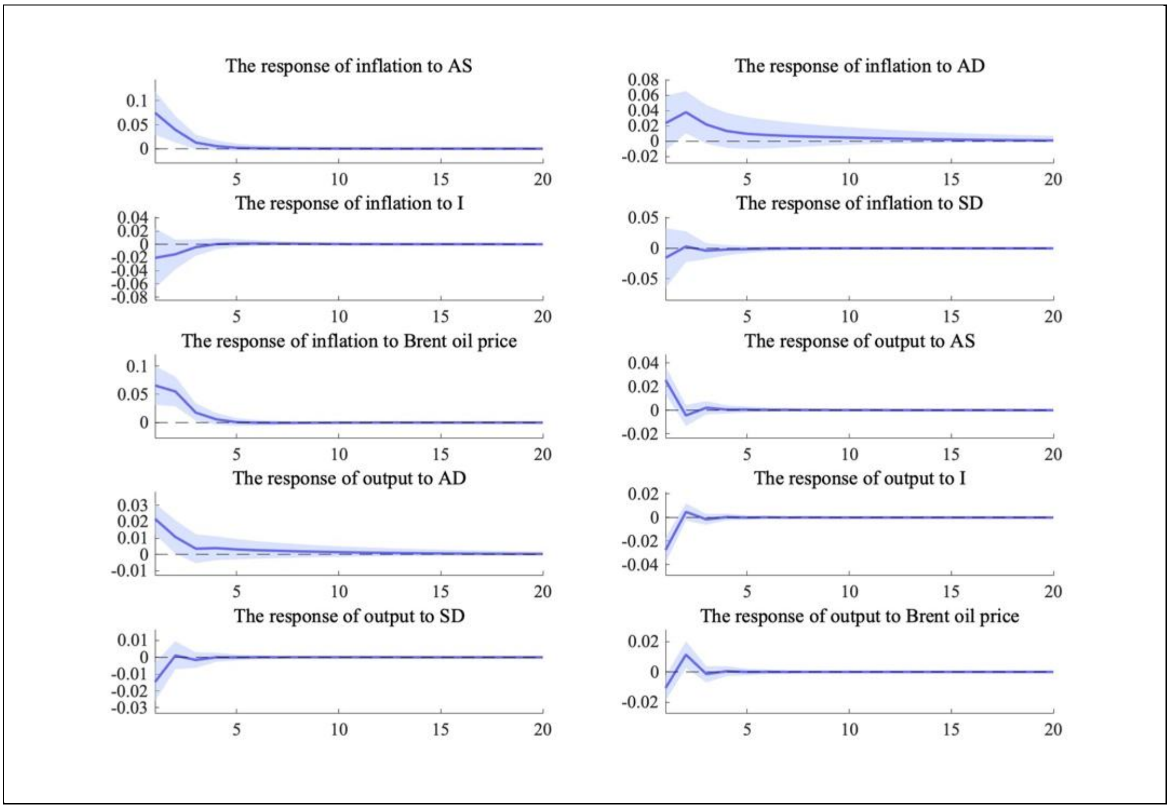


Figure 16: The median response of EPU to inflation & output

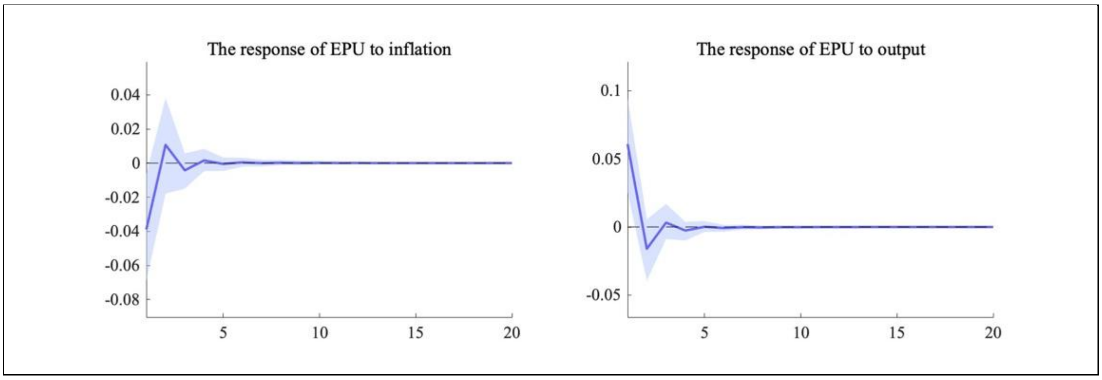


Figure 17: The response of hybrid monetary tools to inflation & output

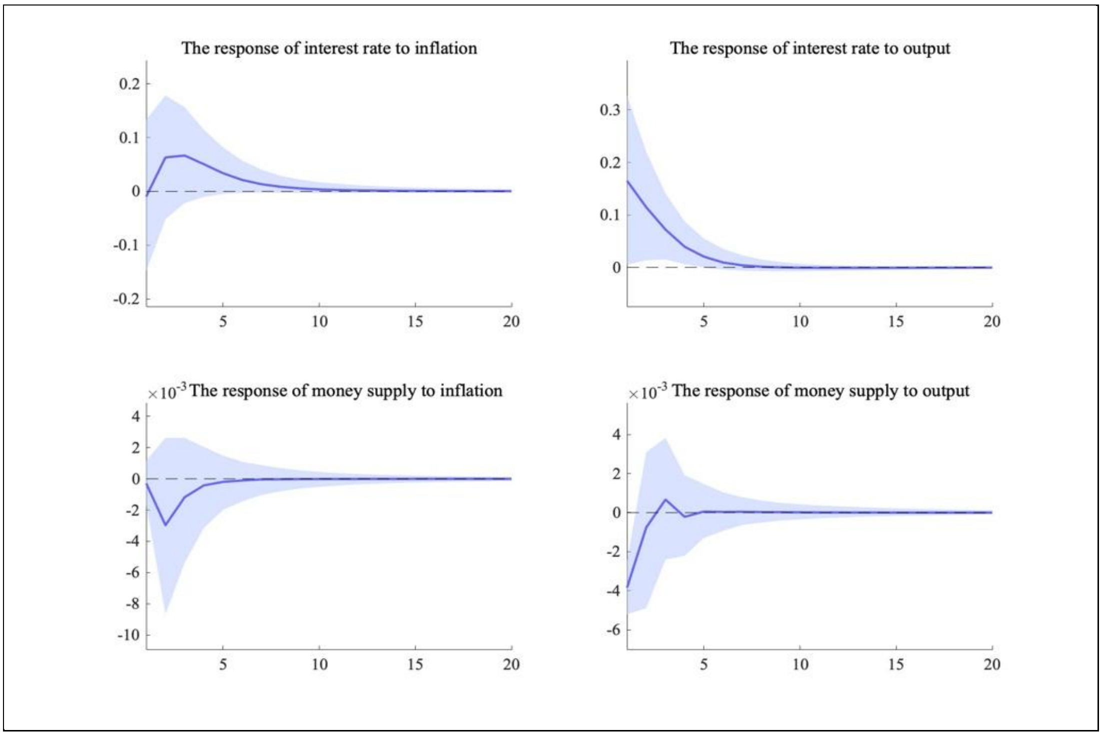
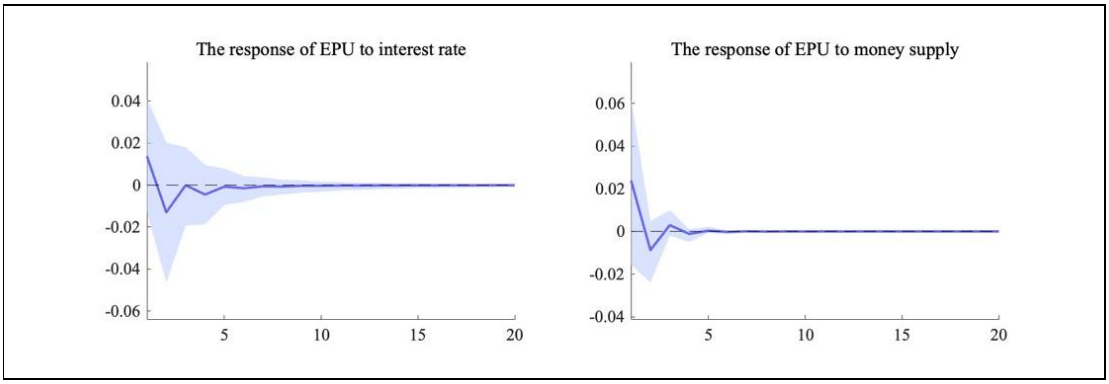


Figure 18: The response of EPU to hybrid monetary tools



(2) Removing monetary policy variables

As an additional robustness check, we re-estimate the model after excluding the monetary policy variables. Figures 19 to 21 illustrate the median IRFs. The results are broadly consistent with the benchmark specification: AS remains the only oil-related shock associated with a statistically significant EPU response, while the responses of inflation and output to the five-type shocks remain qualitatively similar. Moreover, the results continue to suggest that output plays a more visible role in linking oil-related shocks to EPU than the direct monetary policy indicators considered in the benchmark mode.

Figure 19: The median response of EPU to five-type shocks (without monetary variables)

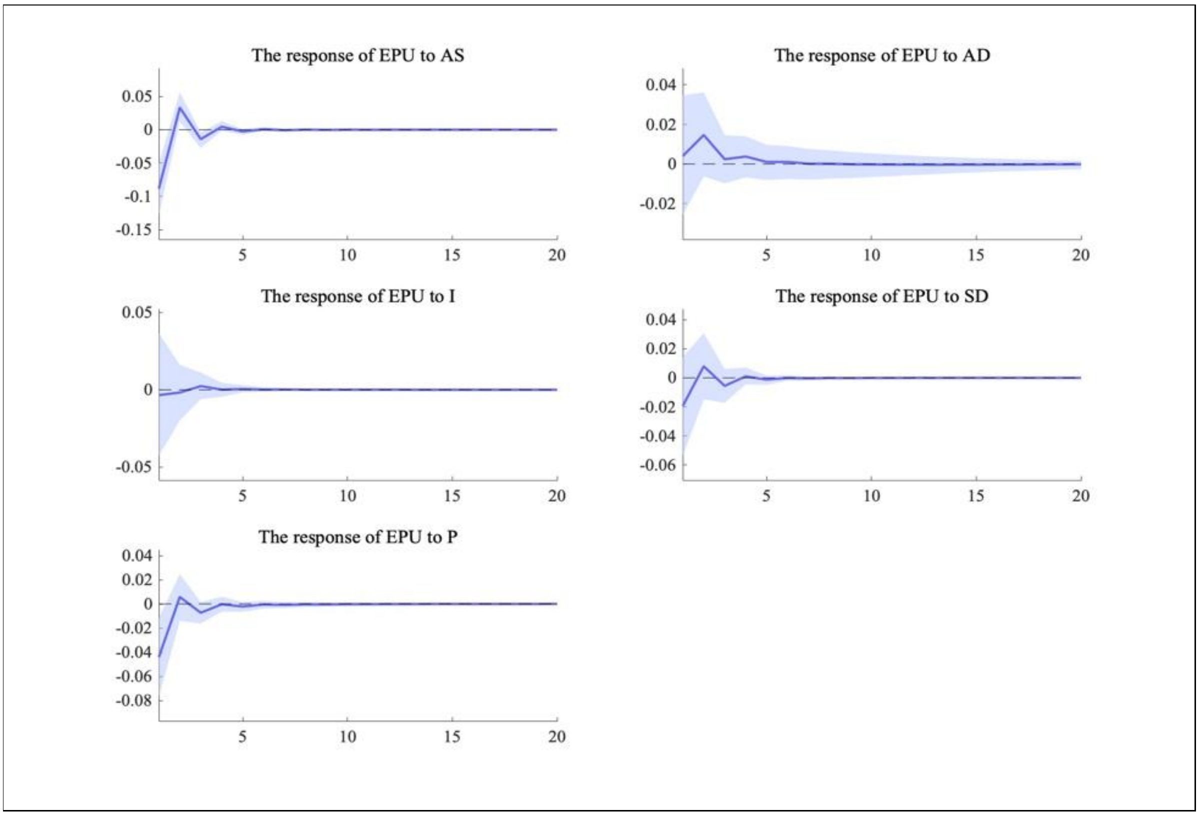


Figure 20: The median response of inflation/output to five-type shocks (without monetary variables)

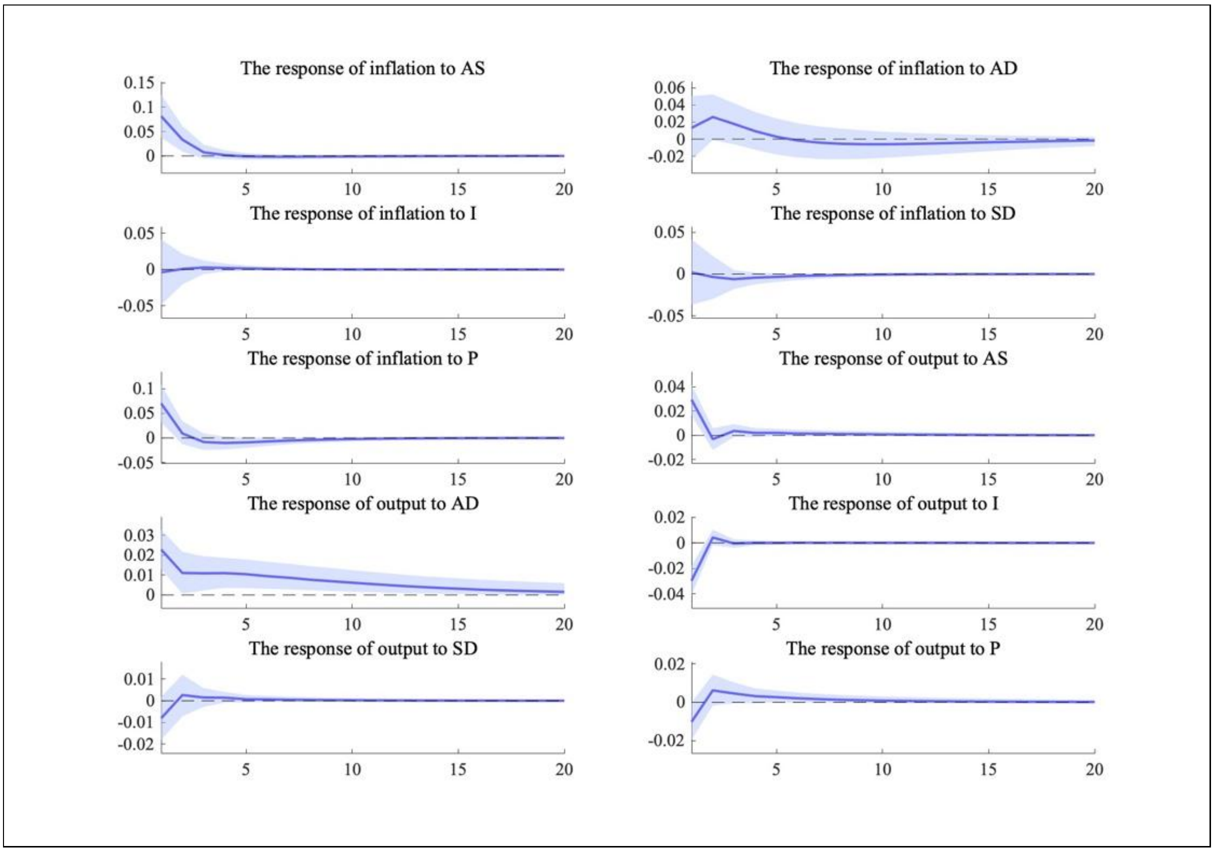
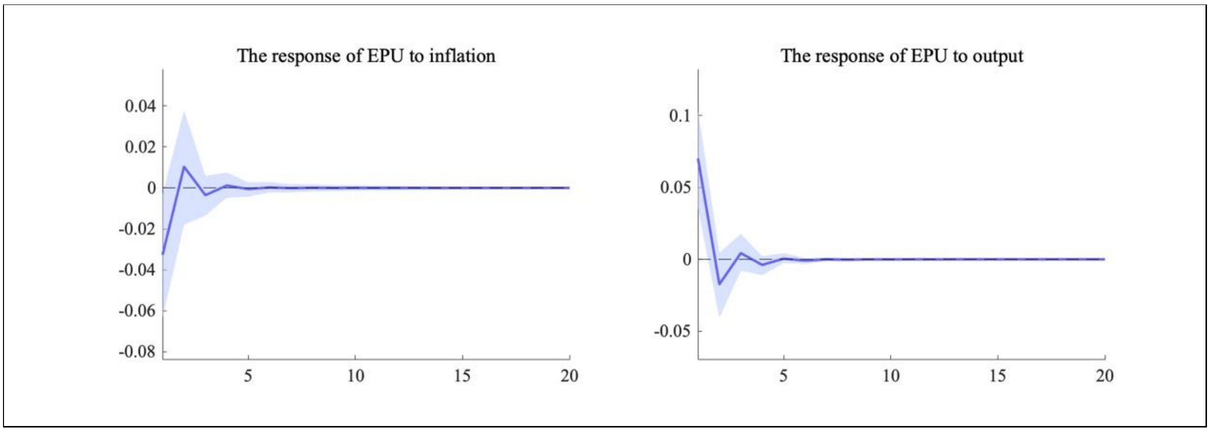


Figure 21: The median response of EPU to inflation/output (without monetary variables)



(3) Alternative ordering

This section comprises two parts: one is the alternation of I and SD, and the other is the alternation of interest rate gap and money supply gap. After the replacement orders, the median IRFs results are basically consistent with the main model.

a) Alternative the order of SD and I

Figure 22: The median response of EPU to five-type shocks

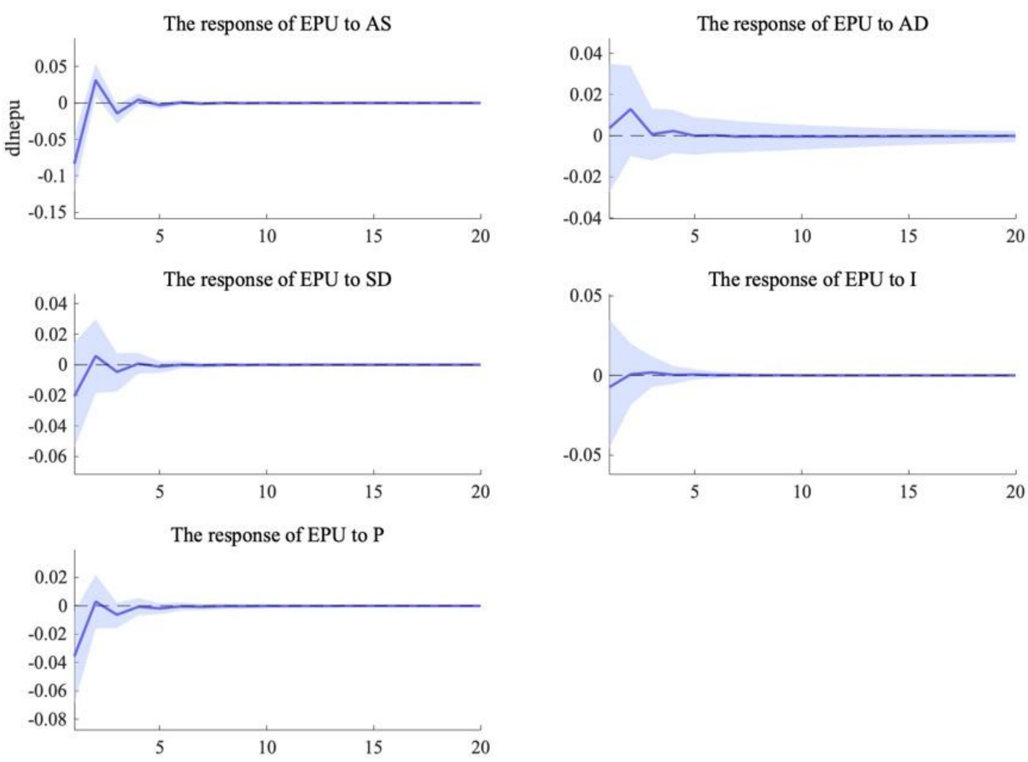


Figure 23: The median response of output & inflation to five-type shocks

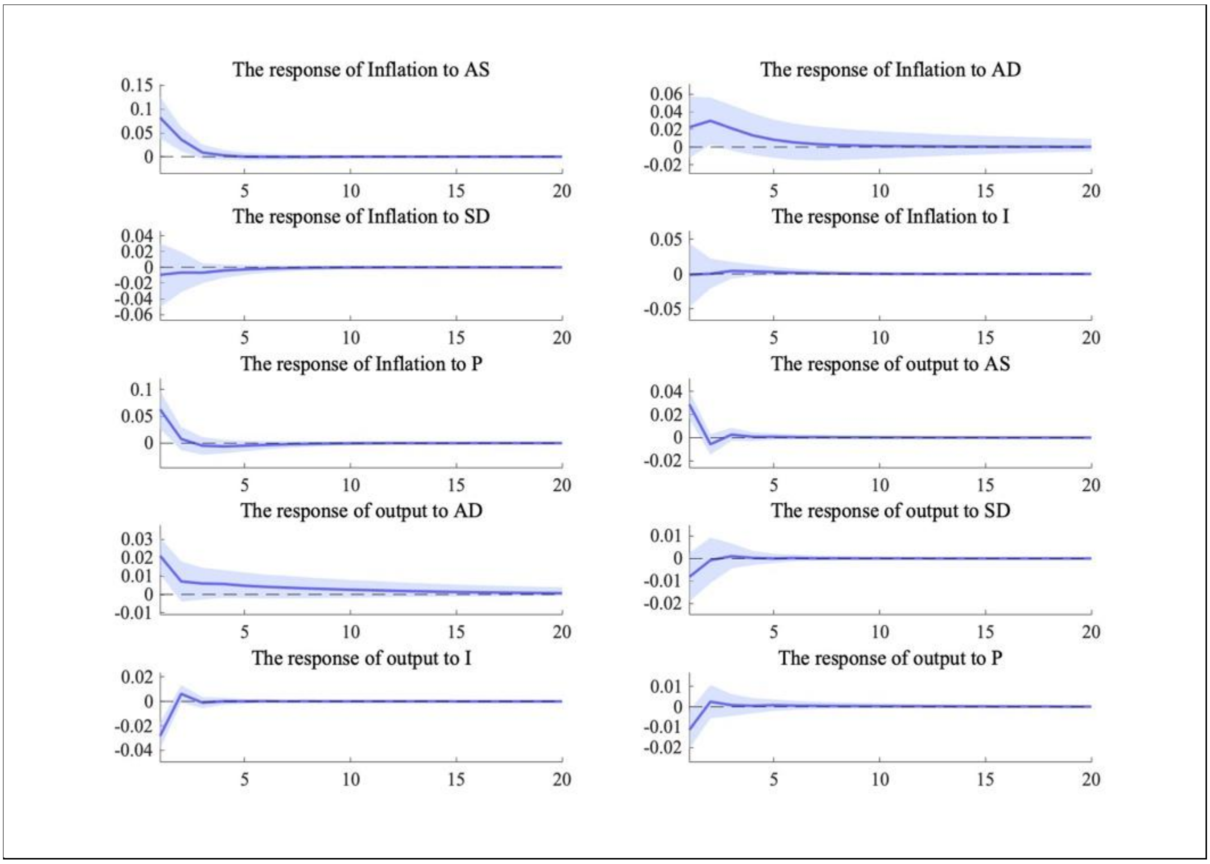


Figure 24: The median response of EPU to inflation & output

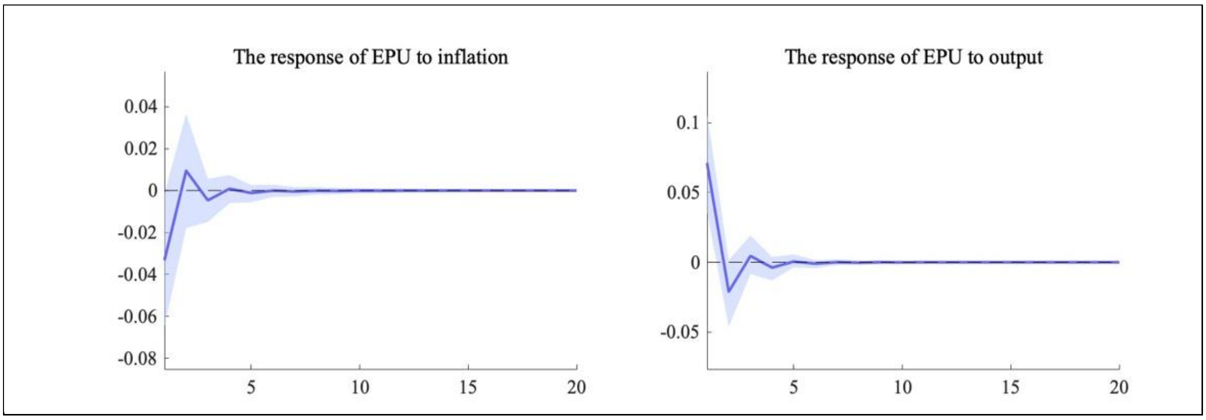


Figure 25: The response of hybrid monetary tools to inflation & output

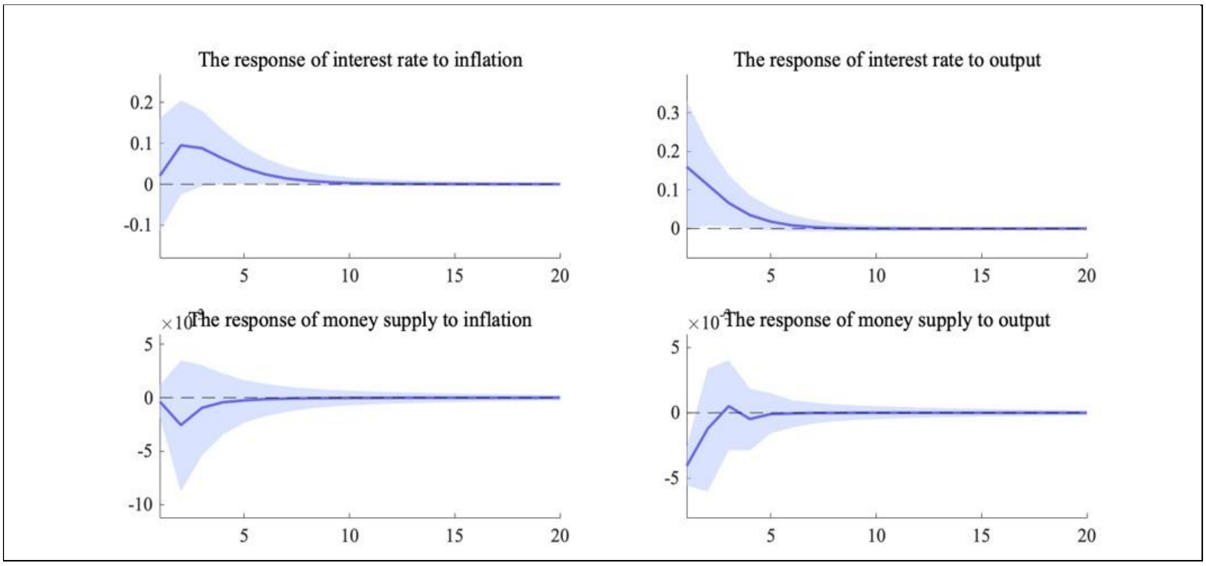
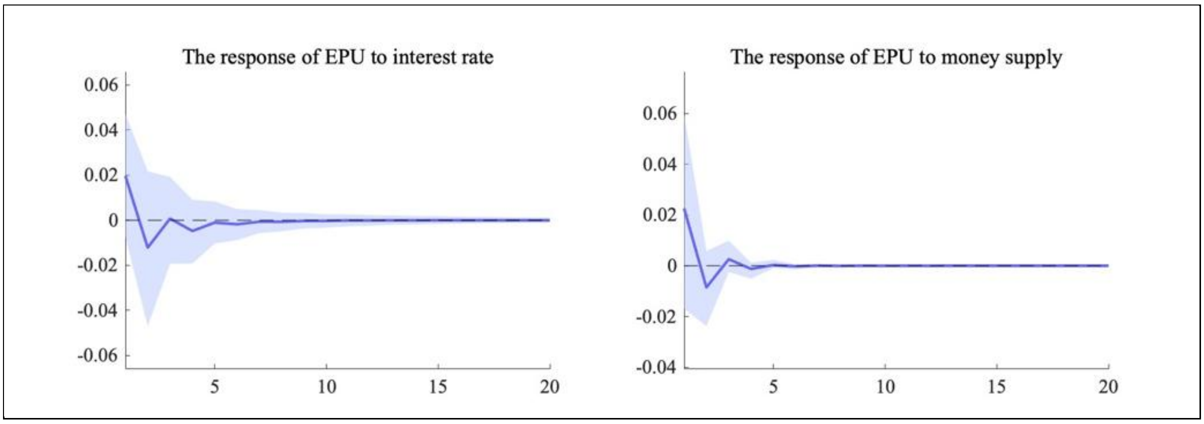


Figure 26: The response of EPU to hybrid monetary tools



b) Alternative the order of interest rate and money supply

Figure 27: The median response of EPU to five-type shocks

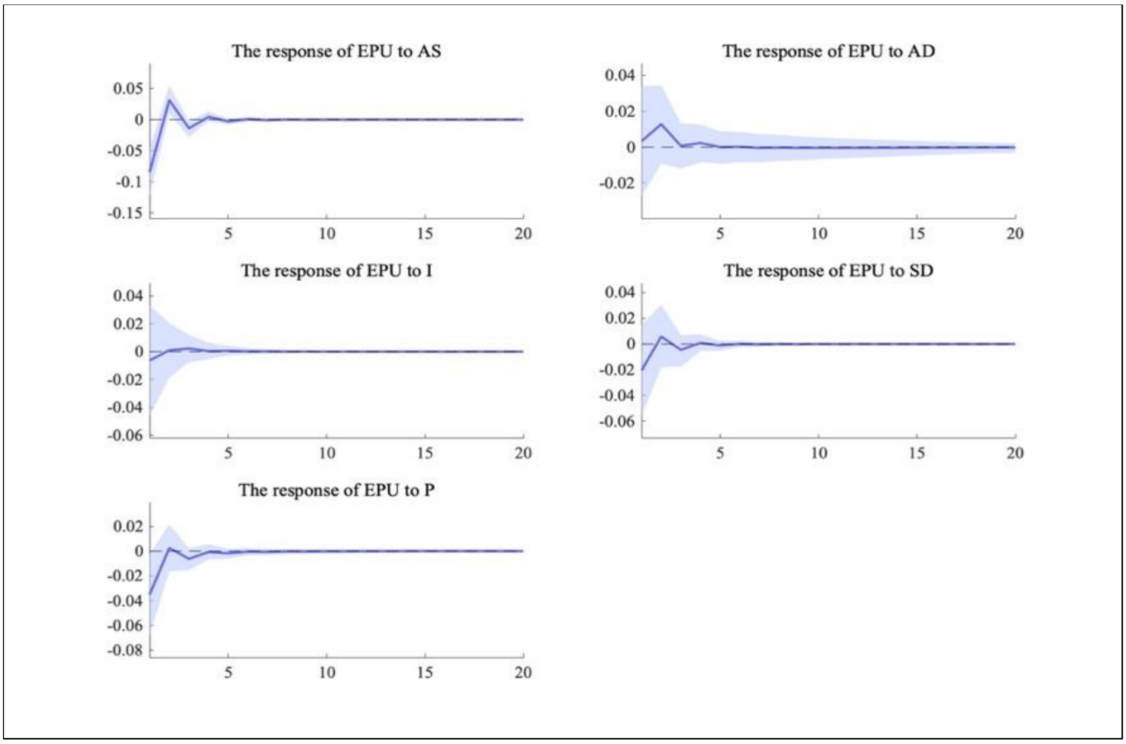


Figure 28: The median response of output & inflation to five-type shocks

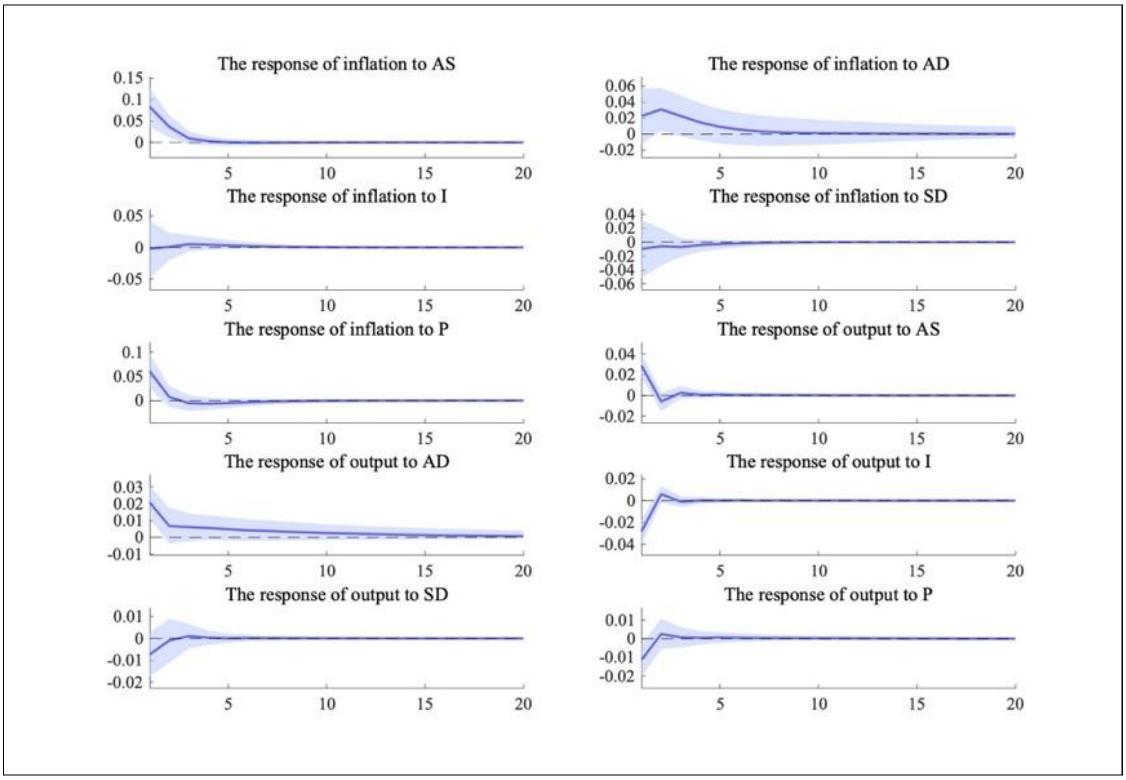


Figure 29: The median response of EPU to inflation & output

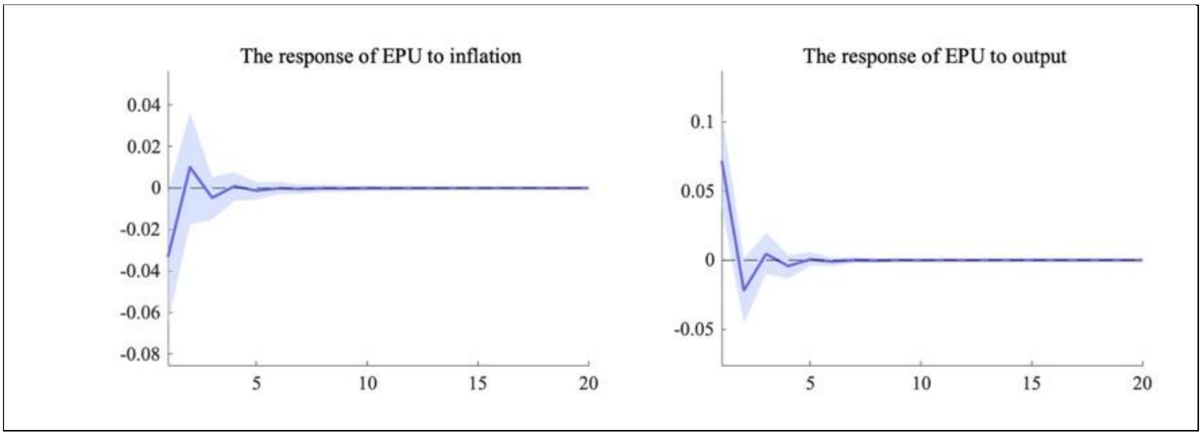


Figure 30: The median response of hybrid monetary tools to inflation & output

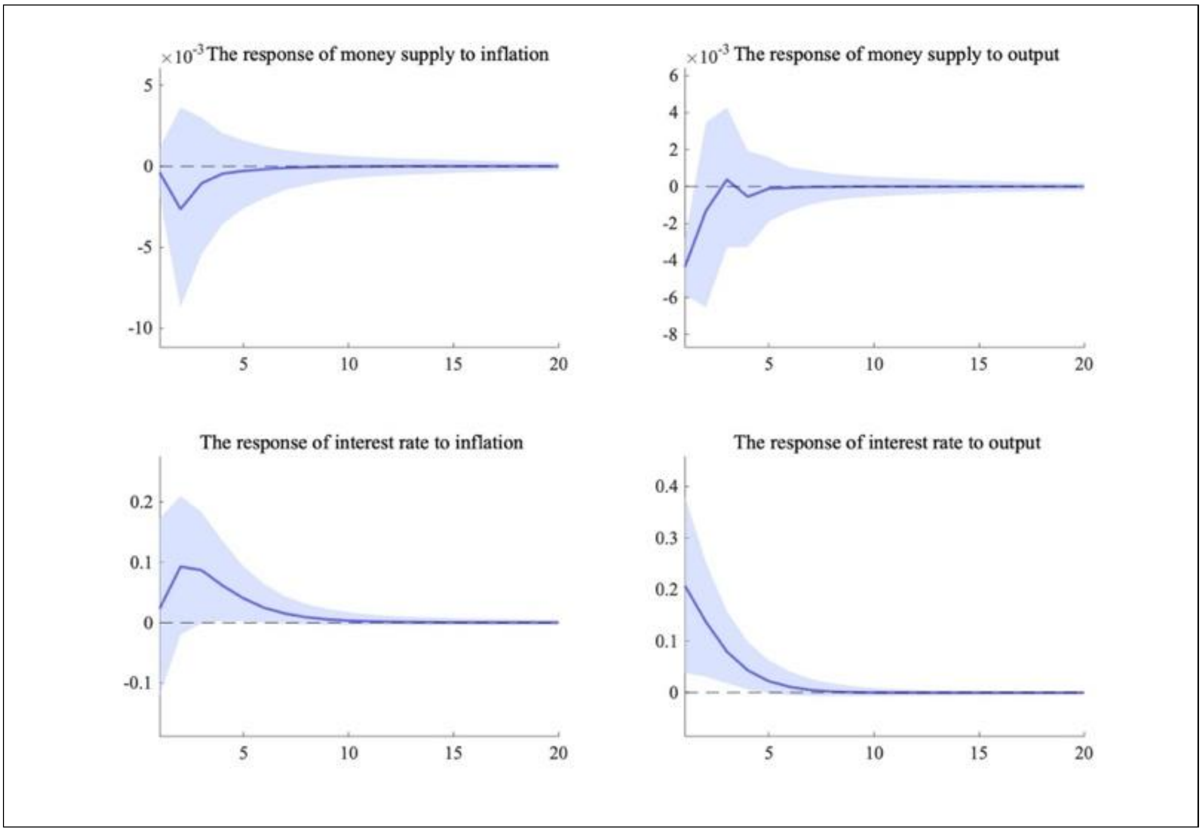
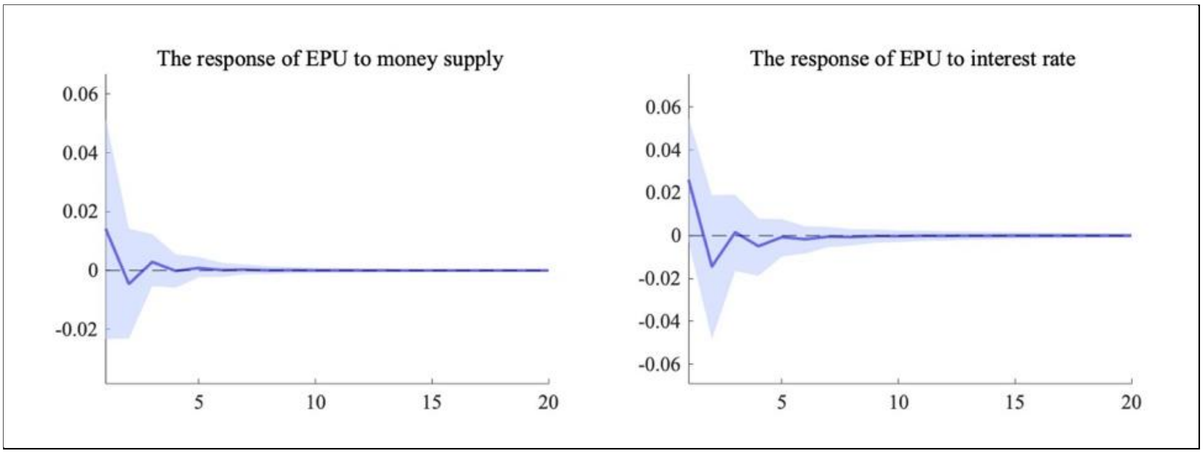


Figure 31: The median response of EPU to hybrid monetary tools



5. Conclusion

This study examines the time-varying impact of five-type shocks from the second quarter of 2007 to the first quarter of 2025 on EPU by constructing a TVP-VAR-SV model, and examines how China's price- and quantity-based monetary policy instruments respond within the dynamic relationship between five-type shocks and EPU. The key results are summarized below:

The median IRFs show that EPU responds differently to the five-type shocks. Among them, AS displays the clearest statistically significant association with EPU, while other shocks do not. Instead, AS, AD, and I are also linked to fluctuations in output, and output is more closely associated with subsequent changes in EPU. In contrast, shocks to the interest-rate gap and the money-supply gap do not generate statistically significant responses of EPU, suggesting that monetary policy indicators are more strongly associated with macroeconomic conditions than with direct changes in EPU.

The time-varying IRFs highlight pronounced temporal heterogeneity that is not captured by the median IRFs. Shocks that are insignificant under median IRFs—such as AD—display more pronounced responses during specific periods, particularly around the 2008 Global Financial Crisis and the COVID-19. Meanwhile, the responses of monetary policy indicators evolve over time: inflation is associated with a stronger response of the money-supply gap, whereas this relationship gradually weakens later. It is consistent with China's transition toward a price-based monetary policy framework. In addition, the response of EPU to the interest-rate gap becomes more visible around certain reform periods, suggesting that changes in the policy environment may coincide with greater sensitivity of measured policy-related uncertainty to interest-rate-related developments.

The variance decomposition results show that, among five-type shocks, AS consistently have the strongest explanatory power for EPU volatility, while AD, SD, *P*, and *I* contribute relatively little. The direct contributions of the interest-rate gap and the money-supply gap are also limited compared with those of output and inflation, with output playing a more prominent role. These results suggest that monetary policy indicators have limited direct explanatory power for EPU fluctuations, while macroeconomic conditions, especially output, account for a larger share of EPU volatility.

Several limitations should be noted. First, the analysis does not structurally estimate a complete monetary policy reaction function. The joint inclusion of the interest-rate gap and the money-supply gap is intended to reflect China's price- and quantity-based monetary policy environment. Future research could adopt alternative identification strategies or structural frameworks to characterize monetary policy behavior more directly. Second, the sample contains only 72 quarterly observations, which is relatively limited for a high-dimensional TVP-VAR-SV model. Future research could use longer time series data, provided that such data is available, to provide stronger evidence for dynamic evolution. Third, the newspaper-based EPU index may capture not only policy-related uncertainty but also broader political and media sentiment. Future research could examine alternative uncertainty measures or compare different indicators to assess the robustness of the findings and better distinguish policy uncertainty from other sources of uncertainty.

Drawing on the foregoing results, we outline the following policy implications. First, the findings point to the potential value of a state-dependent monetary policy framework should adopt a state-dependent framework, allowing flexible adjustments based on changes in macroeconomic conditions, especially during crises where the impact of shocks can be significantly amplified. Second, greater policy transparency and forward-looking guidance may help anchor market expectations, particularly during monetary policy transitions. Third, monetary policy reforms should be gradual and phased to reduce the uncertainty brought about by institutional changes. Finally, more differentiated monitoring of oil-market shocks may help reduce the risk of uncertainty amplification.

Acknowledgements

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