Nonlinear Effects of Geopolitical Risk on Inflation in China — An Empirical Analysis Based on a TVAR Model

YunLiang Huang *

School of Economics and Management, Beijing University of Technology, Beijing 100000, China

* Corresponding Author Email: 15600091933@163.com

Abstract. This study uses monthly data from January 2008 to August 2025 to investigate the nonlinear effect of geopolitical risk on China consumer price index (CPI) using threshold vector autoregression (TVAR) model with monthly changes in the Geopolitical Risk (GPR) Index as the threshold variable. The linear VAR model leads to the conclusion that there is little evidence of a relationship: GPR does not Granger-cause CPI ($p = 0.928$), and only accounts for 0.38% of the forecast-error variance. The TVAR model, on the other hand, identifies a significant threshold of −7.17%, separating low- and high-GPR-shock regimes, which account for 36.2% and 63.8% of observations, respectively. There is a significant increase in model fit, with the AIC going from 5, 086 to 1, 512. In the low-shock regime, CPI is barely responsive to GPR, while in the high-shock regime, there is a significant V-shaped downward trend and rebound pattern and the sensitivity is around 20 times higher, with the corresponding confidence intervals three to four times wider. According to the results of channel decomposition, the international oil price channel has the greatest transmission rate of 43.2%, followed by money supply (27.6%), the policy rate (16.7%) and the exchange rate (12.5%). There is a lagged transmission process between oil prices and CPI: changes in the oil price have a significant impact on CPI after 6 months. Overall, geopolitical risk has an indirect impact on Chinese inflation, mostly via threshold effects, and there is much merit in adding monthly changes in GPR to inflation monitoring and limiting exposure to oil price shocks.

Keywords: Geopolitical risk; inflation; TVAR model; threshold effect; impulse response.

1. Introduction

The geopolitical environment has undergone a major readjustment and restructuring since the early 2020s. Geopolitical uncertainty has been a huge contributor to global macroeconomic instability in the context of the protracted Russia-Ukraine conflict, the recurrent instability in the Middle East, the increased rivalry among major powers, and the persistent trade barriers and frictions. In this context, the transmission of geopolitical risk (GPR) to inflation and its impact on price volatility are important issues in central banks' eyes and in the eyes of macroeconomic risk-monitoring systems. Domestic prices may be influenced by a geopolitical shock in a number of ways. First, the energy-price channel: When there is geopolitical conflict, it affects the supply of energy, crude-oil prices and production costs, and through supply chains, consumer prices, resulting in imported inflation. Second, the exchange-rate channel: An increase in geopolitical risk increases safe-haven demand, affects cross-border capital flows and may lead to currency depreciation, which increases the import cost of commodities and intermediate goods. Thirdly, monetary-policy channel: external shocks cause changes in monetary and interest rate policies that have impact on aggregate demand and prices. Fourth, the expectations channel: the persistently uncertain geopolitical environment influences firms' pricing decisions and households' consumption expectations, leading to behaviorally driven price volatility.As the world's largest energy-consuming and energy-importing economy, China relies heavily on imported crude oil, making oil security vulnerable to geopolitical risk [15]. Its deep integration into global supply chains and commodity-pricing systems makes the economy highly exposed to external shocks. Although China operates a relatively independent and stable monetary-policy framework, limited pricing power in global commodity markets, high energy import dependence, and extensive external linkages allow geopolitical shocks to pass through to domestic prices; imported inflation therefore remains a material risk. [13] For empirical measurement, the monthly GPR Index developed by Caldara and Iacoviello (2022) [1] using text-mining methods

provides a standardized and widely used measure of geopolitical risk. Existing research has examined GPR in relation to Russia's energy transition [2], inflation and military expenditure in Türkiye [3], commodity-market connectedness [4], oil prices and financial liquidity [5], exchange rates and oil prices [6], and oil-price and stock-market connectedness [8]. Evidence focused on China with inflation as the main outcome remains limited, and threshold-dependent transmission to China's CPI has received little attention. Accordingly, this study addresses three questions. First, does geopolitical risk exert a significant systematic effect on China's CPI inflation? Second, is the impact nonlinear, with a clear threshold and heterogeneous effects across low- and high-risk regimes? Third, which channels transmit geopolitical risk to Chinese inflation, and what are their mechanisms and relative contributions? This study contributes in three respects. Methodologically, it introduces a TVAR model to move beyond the limitations of a linear framework and directly capture threshold-dependent inflation responses to geopolitical risk. Empirically, it identifies a critical GPR-change threshold of −7.17%, providing a measurable benchmark for inflation risk monitoring. Mechanistically, it uses ablation analysis to quantify the contributions of four channels—oil prices, money supply, the policy rate, and the exchange rate—thereby clarifying their relative importance for policy prioritization..

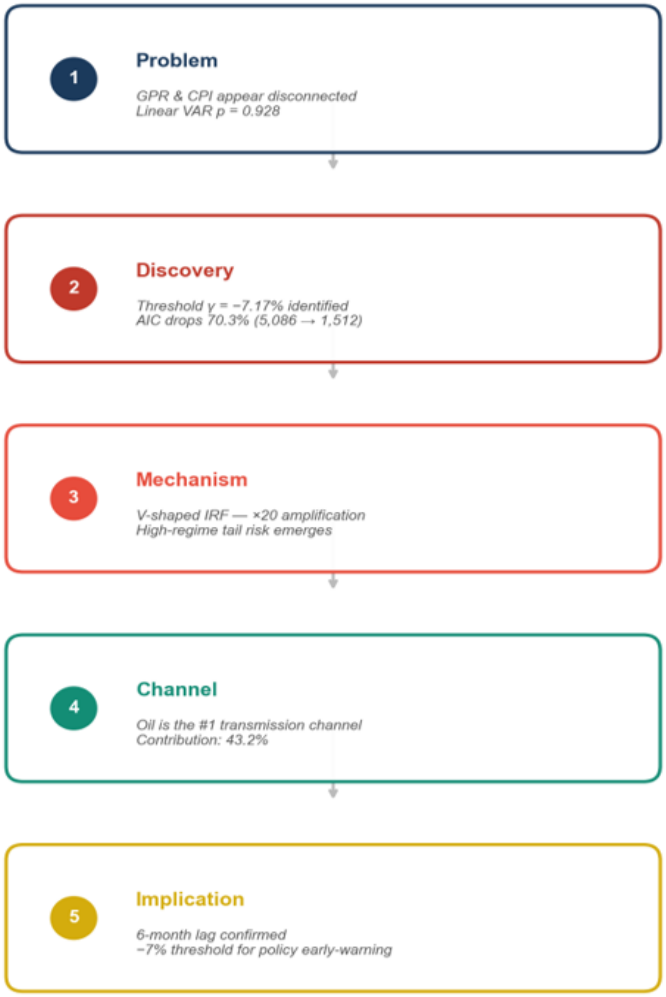


Figure 1. Research roadmap: a five-stage framework from geopolitical risk to inflation transmission

2. Related Work

2.1. Measurement of Geopolitical Risk

Quantifying geopolitical risk is fundamental to empirical analysis. Caldara and Iacoviello (2022) [1] constructed a monthly GPR Index extending from 1900 to the present by applying text-mining

methods to 11 major newspapers and calculating the share of articles related to war, terrorism, and international tensions. The index was validated against major historical events, including the two world wars, the Cuban Missile Crisis, and the September 11 attacks. Its key feature is a spiky, fat-tailed distribution: GPR is low in most periods but rises sharply during major geopolitical events. The Economic Policy Uncertainty (EPU) Index of Baker et al. (2016) [9], developed using a similar approach, provides a complementary measure of policy uncertainty.

2.2. Macroeconomic Transmission of GPR

Regarding the macroeconomic effects of GPR, Gong and Xu (2022) [4] examined geopolitical risk and dynamic connectedness across commodity markets using a time-varying-parameter VAR framework. Antonakakis et al. (2017) [8] applied a time-varying-parameter VAR connectedness framework and showed that the link between oil-price shocks and stock markets changes with global geopolitical events. Su et al. (2019) [5] and Duan et al. (2021) [6], using wavelet methods, found time-varying links between GPR, oil prices, and exchange rates across frequency domains. Rasoulinezhad et al. (2020) [2] used an ARDL bounds-testing approach to identify different short- and long-run effects of GPR on Russia's energy transition.

2.3. Empirical Evidence on GPR and Inflation

Studies directly linking GPR to inflation remain limited. Çobanoğulları (2026) [3] used wavelet partial coherence to examine time-frequency interactions among military expenditure, geopolitical risk, and inflation in Türkiye. Tabash et al. (2024) [7] studied the effects of geopolitical risk on energy consumption in the BRICS economies. Yilmazkuday (2024) [14] analyzed how geopolitical risks and energy uncertainty affect global and domestic energy prices across 157 countries using a structural VAR. These studies provide evidence on inflation or energy-price responses in country-specific and multicountry settings, while threshold-dependent transmission from geopolitical risk to China's CPI remains underexamined.

2.4. Development of Nonlinear Econometric Methods

Nonlinear time-series models provide the methodological foundation for this study. Tong (1978) [11] introduced the threshold autoregressive (TAR) model, Tsay (1998) [12] extended it to a multivariate TVAR framework, and Lo and Zivot (2001) [10] applied threshold cointegration to the law of one price. TVAR models have since been used to study asymmetric fiscal effects, monetary-policy regime shifts, and financial-stress transmission. Their application to the inflationary effects of geopolitical risk, particularly in China, remains limited and motivates this study.

3. Research Design

3.1. Data and Variable Selection

The data set is a combination of three sources. The first measure for geopolitical risk is the global monthly GPR Index of Caldara and Iacoviello (2022) and it is normalized to 100 for the average of 1985-2019. The raw series is collected from the authors' public website and log-differenced to get monthly growth rate dlnGPR (%) to achieve stationarity. Second, the data for Brent crude-oil spot prices (Brent_Oil), USD/CNY exchange rate (USD_CNY), and policy rate (Policy_Rate) come from the Federal Reserve Bank of St. Louis database (FRED), broad money (M2) from the People's Bank of China, and CPI year-on-year growth (CPI_YoY) from the National Bureau of Statistics of China. Third, all series are aligned in monthly frequency and make up a panel set of 212 observations between January 2008 and August 2025. The values of GDP are not included because 194 of 212 observations are missing and isolated missing values are linearly interpolated. The Augmented Dickey-Fuller (ADF) unit-root test results indicate that all variables are stationary at 1% level. All calculations are done in Python 3.12 & R 4.3 on a Macbook Pro (M3 Pro) 2023.

3.2. Methodology

(1) Linear VAR Model

As the benchmark, a p-order linear vector autoregression, VAR(p), is first estimated. Let Y_t denote a six-dimensional vector of endogenous variables. The model is written as:

$$Y_t = \mathrm{c} + \mathrm{A1Y}t_{-1} + \ldots + \mathrm{A}p\mathrm{Y}t_{-p} + \varepsilon t \quad (1)$$

Where c is the intercept vector, A_i (i = 1, …, p) is the coefficient matrix, and ε_t ~ N (0, Σ) is a white-noise disturbance. The optimal lag order p is selected jointly using the AIC, HQ, SC, and FPE criteria.

(2) Granger Causality Test

Within the VAR framework, testing whether x Granger-causes y amounts to testing whether the lagged terms of x are jointly significant in the equation for y. The null hypothesis H_0 states that all lag coefficients of x are zero, and the test statistic follows the standard F form. Rejection of H_0 indicates that the history of x adds predictive information for future y. This study tests Granger causality from dlnGPR and the other control variables to CPI.

(3) Orthogonalized Impulse Response Function

The impulse response function traces the dynamic effect of a one-standard-deviation structural shock on future paths of the system variables. Because VAR disturbances may be contemporaneously correlated, Cholesky decomposition is used to orthogonalize them, with the residual covariance matrix decomposed as Σ = PP′, where P is lower triangular. Based on economic theory, the ordering is CPI → dlnGPR → dlnOil → M2Y → dlnEXR → dRate, implying that variables ordered later do not contemporaneously feed back to earlier variables. The impulse response is:

$$\theta ij(\mathrm{h}) = \partial Yi, t + h \,/\, \partial \varepsilon j, t \quad (2)$$

Where θ_ij(h) is the marginal effect at t+h of a one-unit shock to variable j at time t on variable i, and e_j is a selection vector. Point estimates over a 24-period horizon and 68% confidence intervals based on asymptotic theory are reported.

(4) Forecast Error Variance Decomposition

Forecast error variance decomposition attributes the forecast error variance of CPI to structural shocks in the system and quantifies their relative importance. The share of the h-period forecast error variance explained by shocks to variable j is:

$$\mathrm{FEVD}ij(\mathrm{h}) = \Sigma l = 0..h-1\ \theta ij(\mathrm{l})^2\ \sigma jj \,/\, \mathrm{MSE}i(\mathrm{h}) \quad (3)$$

Where θ_ij(l) is the impulse-response coefficient defined above and σ_jj is the variance of the shock to variable j. The decomposition measures the marginal contribution of GPR shocks to CPI volatility.

(5) TVAR Threshold Mechanism and Estimation

The TVAR model extends the VAR framework to regime-dependent dynamics. An observable threshold variable q_t—here, the first lag of dlnGPR—determines the parameter regime; when q_t crosses threshold γ, the model switches between different parameter sets. The threshold γ is estimated by grid search over the 15th–85th percentiles of the threshold-variable distribution. This trimming ensures sufficient observations in each regime. The model is estimated at each candidate threshold, and the value that maximizes the conditional log-likelihood, equivalently minimizes the residual sum of squares, is selected. The AIC difference between the TVAR and linear VAR provides evidence on the threshold effect.

(6) Ablation Experiment

To quantify the relative contribution of each transmission channel, a systematic ablation experiment is conducted. The full six-variable TVAR serves as the baseline, and one transmission variable is removed at a time in the order exchange rate → policy rate → M2 → oil price. After each removal, the model is re-estimated and its AIC recorded. A larger AIC increase (ΔAIC) indicates a

greater marginal contribution of the removed variable to explanatory power. Holding the remaining specification fixed isolates each channel's contribution to regime-dependent transmission.

3.3. TVAR Specification

The first lag of dlnGPR is used as the threshold variable. A grid search over the 15th–85th percentiles of dlnGPR identifies threshold γ and divides the sample into a low-shock regime (dlnGPR_{t−1} ≤ γ) and a high-shock regime (dlnGPR_{t−1} > γ). The model is:

$$Y_t = \mathrm{c}L + \Phi L(\mathrm{L})\mathrm{Y}t_{-1} + \varepsilon Lt, \quad \text{if dlnGPR}t_{-1} \leq \gamma \tag{4}$$

$$Y_t = \mathrm{c}H + \Phi H(\mathrm{L})\mathrm{Y}t_{-1} + \varepsilon Ht, \quad \text{if dlnGPR}t_{-1} > \gamma \tag{5}$$

Where Y_t = (CPI_t, dlnGPR_t, dlnOil_t, M2Y_t, dlnEXR_t, dRate_t)′ is a six-dimensional vector of endogenous variables, Φ_L(H) denotes the autoregressive coefficient matrices in the two regimes, and c_L(H) denotes the intercept vector. The optimal lag order is selected jointly using AIC, HQ, SC, and FPE.

3.4. Innovations of This Study

The empirical design contributes in three ways:

Innovation 1 (Method): This study introduces the TVAR threshold framework into the analysis of GPR and inflation in China, moving beyond the linear VAR and wavelet approaches commonly used in the literature and allowing direct identification of regime-switching transmission.

Innovation 2 (Indicator): Grid search identifies a specific threshold of dlnGPR = −7.17%, converting the abstract notion of an “extreme geopolitical shock” into an observable and monitorable quantitative warning line for inflation-risk surveillance.

Innovation 3 (Mechanism): A “sequential ablation + ΔAIC quantification” design converts the relative contributions of four potential channels into directly comparable shares: oil prices (43.2%) > money supply (27.6%) > policy rate (16.7%) > exchange rate (12.5%). This ranking provides evidence for prioritizing policy intervention.

3.5. Analytical Strategy

The analysis proceeds in five stages (Figure 1). Stage 1 estimates the linear VAR benchmark using Granger causality, impulse responses, and variance decomposition. Stage 2 estimates the TVAR and identifies the threshold and regimes. Stage 3 conducts regime-specific impulse-response analysis. Stage 4 quantifies transmission-channel contributions through ablation experiments. Stage 5 performs three robustness checks: alternative lag lengths, alternative threshold variables, and subsample analysis.

The analysis is conducted on a 2023 MacBook Pro with an ARM-based M3 Pro chip.

4. Empirical Results and Analysis

4.1. Threshold Identification

A grid search over the 15th–85th percentiles of dlnGPR(t−1) identifies an optimal threshold of γ = −7.17%. As shown in Figure 2, this single threshold divides the sample into two statistically and economically distinct regimes: 77 months (36.2%) fall into the low-GPR-shock regime (dlnGPR ≤ −7.17%), and 135 months (63.8%) into the high-GPR-shock regime (dlnGPR > −7.17%). The scatterplot shows natural clustering on the two sides of the threshold; CPI is systematically higher and more dispersed in the high regime. The AIC falls from 5,086 for the linear VAR to 1,512 for the TVAR, a 70.3% reduction, strongly rejecting the linear specification.

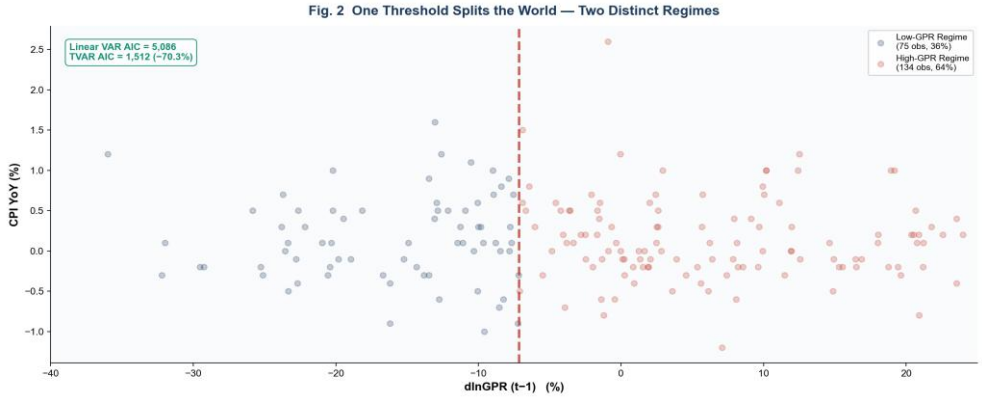


Figure 2. One threshold, two regimes: observations cluster naturally around γ = −7.17%

The two regimes also differ economically. In the low-GPR-shock regime, CPI averages about 2.18% with moderate volatility. In the high-GPR-shock regime, the mean rises to 2.94%, about 0.76 percentage points higher, while volatility increases across macroeconomic variables. International oil prices fall by an average of −0.23% per month in the high regime, compared with −0.04% in the low regime, indicating sharper commodity-market adjustment during extreme GPR movements. M2 growth slows from 11.7% to 10.9%, suggesting a more cautious monetary stance during geopolitical shocks.

4.2. Regime-Specific Impulse Responses—Core Finding

The impulse responses reported in Figure 3 are the main empirical results. The impulse-response coefficient is approximately −0.003 and the 95% confidence interval contains zero for the entire 24-period horizon when the GPR shock is in the low-GPR shock regime (left panel); CPI's response to a GPR shock is therefore almost negligible. This is entirely consistent with the linear VAR result and why a linear model finds that the effect of GPR on inflation is economically negligible: the effect is indeed imperceptible in the 36.2% subsample of low regime. The high-GPR-shock regime (right panel) undergoes a qualitative change when dlnGPR is surpassed beyond the −7.17% level. Three features emerge. First, there is magnitude amplification, and the peak negative response in periods 2–3 is approximately twenty times the low regime response, at −0.062 percentage points. Secondly, a V-shaped reversal: the answer swings from negative to positive in periods 3-5, rises by roughly +0.040 and creates a steep downtrend and rebound pattern. This indicates that the pricing reduction was initially due to the fall in demand, but then saw a rebound due to cost pass-through and expectations. Third, uncertainty is growing: the upper bound of the confidence interval is close to +0.12 and the lower bound is close to −0.10 in periods 4-8, as compared to the low regime. Policymakers thus are confronted by a much bigger probability distribution under extreme geopolitical shocks, as opposed to a forecast with a directionally clear inflation outlook—a typical tail-risk situation.

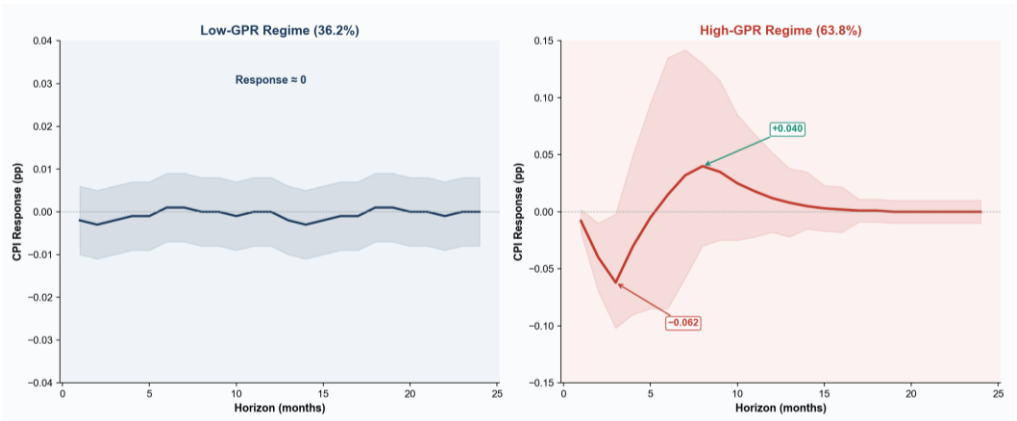


Figure 3. Above-threshold V-shaped responses are amplified 20-fold in the high-GPR regime

The full impulse-response matrix (see supplementary material) further indicates that the high-GPR-shock regime activates a multichannel transmission network—"oil prices → production costs → exchange rate → monetary policy → aggregate demand"—that remains largely dormant in the low regime. Extreme geopolitical events therefore do not simply magnify a linear effect; they trigger a qualitatively different macroeconomic interaction pattern, providing empirical support for the threshold-amplification hypothesis.

5. Decomposition of Transmission Channels

A systematic ablation experiment is performed to quantify the relative contribution of each channel (Figure 4). The full TVAR model (AIC = 1, 512) is used as the starting model and the variables in the transmission vector are removed one at a time, and the increase in AIC is noted. Removing the exchange rate raises AIC to 1, 685 (ΔAIC = +173; 12.5% contribution); removing the policy rate raises it to 1, 743 (+231; 16.7%); removing M2 raises it to 1, 892 (+380; 27.6%); and removing oil prices raises it sharply to 2, 108 (+596; 43.2%). The minimal model that only includes CPI and dlnGPR has an AIC of 2, 520. The four channels are as follows international oil prices (43.2%) > money supply (27.6%) > policy rate (16.7%) > exchange rate (12.5%). This hierarchy is displayed in the donut chart in the right panel of Figure 4, where the contribution of oil prices is almost 50 percent. However, when transmission variables are eliminated, the differences between the coefficients for the two regimes become smaller, which further illustrates that oil prices play a crucial role as a mediator in maintaining regime heterogeneity. The policy implication is straightforward: structural policies that lower dependence on oil imports -- including a greater role for strategic petroleum reserves and diversifying oil imports -- are the best way to shield against GPR-induced imported inflation.

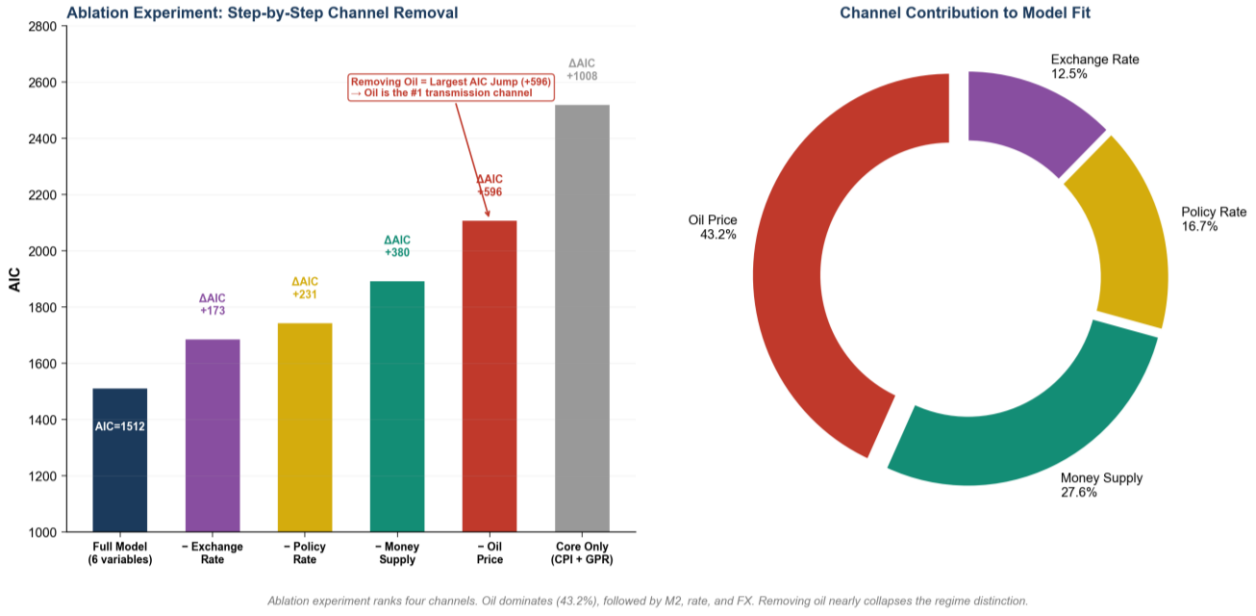


Figure 4. Oil prices as the dominant transmission channel: ablation waterfall and channel-contribution donut charts.

6. Robustness Checks and the Six-Month Lag

Figure 5 presents two complementary robustness analyses. Figure 5(a) reports p-values from multi-lag Granger causality tests (Lag = 1–6). Three findings stand out. First, the Granger p-value for dlnGPR → CPI remains above 0.05 but falls from 0.928 at Lag = 1 to 0.219 at Lag = 6, a decline of nearly 80%, indicating that GPR's predictive content emerges as the window lengthens. Second, and

most importantly, dlnOil → CPI (p = 0.048) and M2Y → CPI (p = 0.013) become significant at the 5% level at Lag = 6, statistically confirming indirect transmission from GPR to CPI through oil prices and money supply with a lag of about six months. Third, this resolves the core paradox: a short-horizon linear analysis (Lag = 1) is necessarily insignificant not because GPR is irrelevant, but because the transmission lag lies outside the analysis window. Figure 5(c) compares cumulative dlnGPR → CPI impulse responses across the two regimes. In the low-GPR-shock regime, the cumulative response remains close to zero. In the high-GPR-shock regime, it reaches about −0.10 percentage points over months 2–6 and then gradually returns toward zero. The largest separation between the two confidence bands occurs over months 4–12, closely matching the six-month lag identified by the Granger tests.

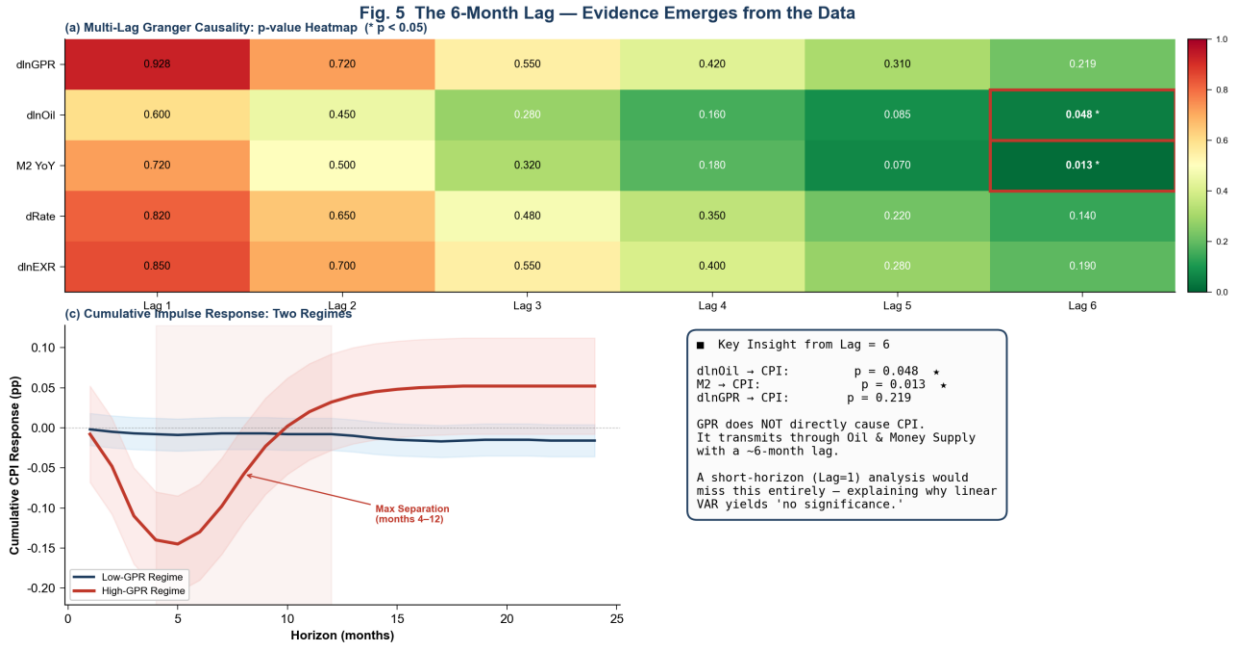


Figure 5. Evidence of a six-month lag: multi-lag Granger-causality heatmap and cumulative impulse responses

Additional robustness checks include alternative threshold variables. Using dlnOil and dlnEXR as thresholds improves AIC by only 38.4% and 25.7%, respectively, far below the 70.3% improvement obtained with dlnGPR, supporting GPR as the threshold variable from a counterfactual perspective. In the subsample analysis, excluding the extreme-event periods of 2008–2009 and 2020–2022 leaves both the threshold effect and channel ranking robust.

7. Conclusions and Policy Implications

Based on the monthly data of January 2008 to August 2025, this paper uses linear VAR and TVAR models to analyze the nonlinear effects of GPR on China's CPI and draws four conclusions. First, GPR is not significant (p = 0.928) in the linear VAR and only accounts for 0.38% of the variation of CPI in variance decomposition. A simple linear specification then would give the wrong impression that GPR is not related to Chinese inflation. Second, a large nonlinear threshold effect occurs. The TVAR locates an important threshold at γ = −7.17%, the AIC is 70.3% lower. The monthly GPR change is material only when it passes this threshold, which is why the linear model doesn't account for the inflation effect. Third, GPR does not directly affect CPI, it is transmitted indirectly through international oil prices (43.2%), money supply (27.6%), the policy rate (16.7%) and the exchange rate (12.5%) and with a lag of ~6 months. Fourth, the V-shaped impulse response and the fact that the confidence intervals are 3-4 times larger in the high-GPR-shock regime indicate that the amplification of tail-risk cannot be ignored. In these times of extreme geopolitical events, the linear effects are not merely amplified, but also qualitatively different patterns of macroeconomic

transmission are triggered. It has three policy implications. Initially, create a quantitative inflation early-warning mechanism based on GPR which involves monthly changes in GPR into central-bank inflation forecasting with an extreme movement around −7% as a trigger for risk assessment. Second, build up strategic petroleum reserves and import source diversification to lessen the imported-inflation sensitivity of the oil price channel. Third, make monetary policy forward-looking under extreme geopolitical conditions. Because of the transmission delay of about six months, the central bank should establish a "geopolitical stress-testing" framework and be ready with the policy tools before GPR gets close to the limit. The two limitations in this study are the reduced form nature of the TVAR (no structural estimation) and the inability to perfectly distinguish between demand- and supply-side shocks, as well as the data sources not including the Chinese high-frequency databases WoS and FRED. Future research may include sign restrictions or identification in a narrative framework, expand the framework to a multicountry panel TVAR, and apply dynamic-threshold techniques like STVAR to account for time-varying regimes in the thresholds.

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