Resour Environ Econ, 2026, 8(1): 1-17
DOI: 10.25082/REE.2026.01.001

RESEARCH ARTICLE

Global Oil Price Jumps and China's New Energy Sector: New Evidence from Dynamic Volatility Models

Chuanguo Zhang[1*] **Yujie Du**[1]

[1] School of Economics, Xiamen University, Xiamen 361005, China

Correspondence to: Chuanguo Zhang, School of Economics, Xiamen University, Xiamen 361005, China; Email: cgzhang@xmu.edu.cn

Received: October 19, 2025;
Accepted: January 5, 2026;
Published: January 13, 2026.

Citation: Zhang C, Du Y. Global Oil Price Jumps and China's New Energy Sector: New Evidence from Dynamic Volatility Models. *Resour Environ Econ*, 2026, **8**(1): 1-17. https://doi.org/10.25082/REE.2026.01.001

Abstract: Intensifying geopolitical tensions have recently amplified fluctuations in global crude oil prices, where abrupt price jumps often transmit complex spillovers across energy markets. This paper investigates the asymmetric, heterogeneous, and lagged impacts of oil price jump shocks on China's new energy industry at both aggregate and sub-industry levels spanning the full upstream-midstream-downstream industrial chain. Using an ARMA-EGARCH-ARJI framework, global oil price dynamics are modeled to capture volatility clustering and discrete jumps, while expected/unexpected and lag structures are applied to examine asymmetric and delayed responses. The results reveal a unique asymmetric pattern of dual inhibition/promotion: both expected increases and decreases in oil prices suppress new energy returns, whereas unexpected jumps stimulate the sector. The effects are heterogeneous across sub-industries, with upstream sectors showing weaker sensitivity to anticipated shocks. Moreover, the influence of oil price jumps unfolds with notable time lags. These findings underscore the evolving interplay between market-oriented energy transformation and policy stability, offering implications to enhance the resilience and efficiency of China's new energy transition.

Keywords: oil price, new energy industry chain, dynamic jumps, asymmetric effect

1 Introduction

The sharp fluctuations in international oil prices have a profound impact on the development of China's new energy industry, especially in the context of the global energy landscape shifting to low-carbon solutions. China is the world's largest energy consumer and crude oil importer. Due to its high dependence on foreign oil, which has reached 71.9% in 2024, it is particularly sensitive to oil price fluctuations. At the same time, China is actively fulfilling its commitment to carbon peak and carbon neutrality, promoting the rapid development of new energy fields. Under the dual pressure of energy security concerns and carbon emission reduction targets, the relationship between oil price trends and new energy development has become the core of China's energy strategy. Oil price fluctuations affect the competitiveness of new energy through channels such as cost transmission and market substitution, and then affect the investment decisions and policy responses of the entire industry.

Existing studies, even those emphasizing oil price jumps [1–7], mostly focus on conventional gradual volatility rather than discrete shocks' dynamics. By contrast, this research centers on "time-varying jumps"–abrupt, substantial oil price shifts driven by geopolitical conflicts, extreme weather-induced supply disruptions or financial market speculation. Unlike static oil price jumps in prior research, these time-varying jumps capture dynamic shock evolution and exert strong instantaneous spillover effects, rapidly reshaping new energy projects' cost-benefit structures and investment risks. A key innovation lies in decomposing time-varying fluctuations into expected and unexpected components. Expected jumps include pre-announced OPEC+ production cuts while unexpected jumps encompass sudden geopolitical outbreaks, marking a departure from prior studies that treat jumps as homogeneous. By systematically exploring their heterogeneous transmission paths and lagged effects, this research clarifies nonlinear, asymmetric shock mechanisms.

In addition, this study also differs from prior research by analyzing the full new energy industrial chain spanning production, storage, and consumption, covering six sub-sectors with distinct operational characteristics. Each link shows unique technical, market and policy characteristics: upstream production includes solar photovoltaic (SP), wind power (WP), nuclear power (NP) and hydropower (HP) is heavily dependent on technological innovation and cost reduction. Midstream storage is represented by lithium batteries (LB), tied to the prices of key materials such as lithium and cobalt. Downstream consumption focuses on new energy vehicles, responsive to oil-electricity price ratios and charging infrastructure coverage. This comprehensive scope addresses a key limitation of existing studies such as Deng and Xu (2024) [8] and Su and He (2025) [9], which often focus on partial sub-sectors or omit critical links like hydropower and lithium batteries. By capturing heterogeneous responses across the entire chain, this research clarifies how oil price jumps transmit through China's new energy system.

This paper focus on the time-varying fluctuations of international oil prices and the heterogeneous impact of China's new energy industry chain. In addition, this paper conducts a comparative analysis of the different components of the oil price jump shock, and considers not only the lag effect but also the asymmetric effect in the investigation of the oil price shock on the new energy industry. This comprehensive approach expands new perspectives on oil price shocks and the new energy industry, providing strategic insights for the sustainable and high-quality development of China's new energy industry under the current context of international market uncertainty.

2 Literature review

The volatility of oil markets, particularly the phenomenon of price jump behavior, has attracted widespread interest due to its critical implications for global economic stability and energy policy design. In this research field, there are two main streams of research: the first focuses on the intrinsic characteristics and driving factors of oil price increases, while the second examines their asymmetric and time-varying spillover effects in macroeconomic systems, industrial sectors, and energy transition paths. This dual focus highlights the multifaceted nature of oil price shocks, where sudden price fluctuations not only reflect the dynamics of specific markets, but also propagate systemic risks that will reshape economic outcomes and decarbonization trajectories differently.

In recent years, the sharp fluctuations in international oil prices have had a significant impact on the global economy. Especially in the context of frequent oil crises, the high-intensity jump characteristics of oil prices have attracted widespread attention [10]. Unlike conventional fluctuations, oil prices are driven by factors such as geopolitical conflicts, market supply and demand imbalances, and financial speculation, showing sudden and extreme fluctuations, which significantly affect market volatility [3, 6]. Empirical studies have confirmed the existence of these jumps and emphasized their significant contribution to price fluctuations [1, 2, 4, 5, 7]. To better capture these dynamic changes, scholars have developed various analytical methods, providing fundamental tools for identifying jumps in price series. These include the Stochastic Volatility with Jumps (SVCJ) model [11, 12], the volatility matrix method, and the GMM estimator [11, 12], among others. At the same time, heteroskedasticity [13], conditional jumps and time-varying volatility in time series have also been paid attention to [14, 15]. These studies together emphasize the necessity of considering time-varying jumps in the dynamic modeling of oil prices in order to better understand market risks and economic impacts.

Early studies focused on the impact of oil price fluctuations on macroeconomic performance, and the results showed significant multifaceted and time-varying effects. The negative impact of oil price shocks on China's economic growth and inflation is more significant [16]. Advanced economies that benefit from energy substitution, strategic reserves, and efficiency policies are more resilient to oil price fluctuations, while emerging economies such as China are more vulnerable [17]. The nature of oil price shocks is also crucial; political events driving supply shocks have direct effects on China's output and inflation, while specific demand shocks contribute more to long-term effects [18]. Global financial uncertainty amplifies these effects, leading to divergence in monetary policy between BRICS oil importers and oil exporters [19]. In China, the impact of oil price fluctuations on inflation and output varies over time, reflecting the changing focus of monetary policy [20]. Moreover, regional and resource endowments further exacerbate the impact of oil prices, with European and Central Asian economies highly dependent on oil exports, while East Asian economies face exchange rate pressures from non-oil exports [21].

At the industry level, in addition to directly affecting cost fluctuations, rising oil prices can disrupt production and demand in oil-intensive industries such as petrochemicals and metal manufacturing [22] and trigger a chain reaction of price increases across industries. Oil effects on stock market are minimal for most sectors, except manufacturing and specific oil companies, whose prices may be depressed [23]. Agricultural commodity impacts are asymmetric, with only natural rubber significantly affected by oil price jumps [24]. Quantile analysis shows transportation negatively impacted at lower quantile due to costs , while agriculture faces effects at more quantiles but negative impacts are more easily offset [25]. In nonferrous metals, shocks have positive short-term effects on output, inflation, and employment [26]. Oil/gas extraction, refining, and nuclear fuel sectors experience the largest output/consumption effects, and public utilities investment is highly sensitive to price changes [27]. Vehicle markets react diversely, where fuel sales decline with oil prices, while electric vehicle sales generally benefit [28].

Research on the relationship between international oil prices and the new energy industry focuses on causality, dependence, and volatility spillover effects, extending to asymmetry, short- and long-term impacts, market structures, and supply-demand shocks. Some studies find linear Granger causality between oil and new energy [29, 30]. Long-term impacts remain debated, with Managi and Okimoto (2013) [31] noting structural changes post-2007, Bondia et al. (2016) [32] highlighting short-term effects, and Reboredo et al. (2017) [33] observing strengthened long-term connections. Dependence studies reveal both positive correlations [34, 35] and tail dependencies [36, 37], especially after global crises [38]. Volatility spillover research shows significant positive spillovers from oil to renewable energy, with asymmetric effects and greater impacts during oil price declines [34, 36, 39].

Although the existing literature has made significant progress in understanding the relationship between international oil prices and the new energy industry, there are still some significant deficiencies that deserve further exploration. First, there are few studies focusing on the segmented characteristics of international oil price jumps. Although the existence of oil price jumps has been widely recognized, few studies have systematically analyzed their size, direction, expectations, and lags, and further explored how the characteristics of these jump behaviors affect the spillover mechanism. Second, there is a lack of research on the impact of oil price fluctuations on China's segmented new energy industries. Most studies focus on the overall new energy industry, ignoring the rapidly developing segments. In addition, existing methods focus on correlation and volatility spillover effects, while the exploration of lag effects and asymmetric effects is insufficient.

3 Methodology

This study takes the GARCH model as the basic framework and ARJI model is introduced for the price jump characteristics, forming the composite model ARMA-EGARCH-ARJI model for oil price measurement. Further, the oil price shock factor captured by the composite model is introduced as an external factor into the EGARCH model to construct the ARMA-EGARCH-expected/unexpected and ARMA-EGARCH-lagged effect model.

3.1 The ARMA-EGARCH-ARJI model

Chan and Maheu (2002) [40] first introduced the jump component into the GARCH model and established a new conditional jump model (ARJI model) to capture the jump behavior of the market, which is used to study the jump dynamics in stock market returns. First, the jump characteristics are extracted from the crude oil yield series as follows:

$$r_t = \mu + \sum_{i=1}^{p} \emptyset_i r_{t-i} + \sum_{j=1}^{q} \varphi_j \epsilon_{t-j} + \epsilon_t \tag{1}$$

$$\epsilon_t = e_{1,t} + e_{2,t} \tag{2}$$

Here, r_t denotes the logarithmic return on oil price and ϕ_i and φ_j are coefficients of the ARMA model. The residual, ε_t, is decomposed into smooth fluctuation $e_{1,t}$ and jump fluctuation $e_{2,t}$.

The processing of the smooth fluctuation part $e_{1,t}$ is shown in equation (3). Since a large number of empirical results show that the volatility of financial asset yield series often has asymmetric effects [41], the conditional variance follows the EGARCH process:

$$e_{1,t} = \sqrt{x_t}\varepsilon_t, \text{ where } \varepsilon_t \sim \text{NID}(0,1) \tag{3}$$

$$\ln(x_t) = \alpha_0 + \alpha_1 \left(|\varepsilon_{t-1}| - E[\varepsilon_{t-1}]\right) + \alpha_2 \varepsilon_{t-1} + \beta \ln(x_{t-1}) \tag{4}$$

Where $\alpha_1 \left(|\varepsilon_{t-1}| - E[\varepsilon_{t-1}]\right)$ measures the intensity of the unexpected effect shock. tests the leverage effect. When $\alpha_2 > 0$, the impact of positive shocks (good news) on volatility is greater than that of negative shocks (bad news). On the contrary, $\alpha_2 < 0$ means that the impact of negative shocks (bad news) on volatility is greater than that of positive shocks (good news), and the leverage effect exists. In addition, the condition $\beta < 1$ needs to be satisfied.

The treatment of the jump volatility part follows the setting of Maheu and McCurdy (2004) [42]:

$$e_{2,t} = J_t - E\left[U_t \mid K_{t-1}\right] \tag{5}$$

$$I_t = \sum_{i=1}^{N_t} J_{t,i} \tag{6}$$

Here, the jump amplitude $J_{t,i}$ is normally and independently distributed with mean θ_t and variance δ^2. And the number of jumps in period t, N_t, is assumed to follow a Poisson process with non-negative intensity λ_t under the K_{t-1} information set, where λ_t follows an AR(1) process.

After extracting the volatility of crude oil yields, the ARJI model can be modified as follows:

$$N_t \mid K_{t-1} \sim P(\lambda_t) \tag{7}$$

$$\lambda_t = \max\left(0, \lambda_0 + \rho\lambda_{t-1} + \gamma v_{t-1}\right) \tag{8}$$

For the unknown parameter jump intensity residual γ_t, we use the setting of Maheu and McCurdy (2004) [42].

$$\begin{aligned} v_{t-1} &= E\left[N_{t-1} \mid K_{t-1}\right] - \lambda_t \\ &= \sum_{j=0}^{\infty} jP\left(N_{t-1} = j \mid K_{t-1}\right) - \lambda_{t-1}, \quad j = 0, 1, 2, \ldots \end{aligned} \tag{9}$$

According to Bayes' rule:

$$P\left(N_t = n \mid K_t\right) = \frac{f\left(r_t \mid N_t = n, K_{t-1}\right) P\left(N_t = n \mid K_{t-1}\right)}{P\left(r_t \mid K_{t-1}\right)}, \quad j = 0, 1, 2, \ldots \tag{10}$$

$$f\left(r_t \mid N_t = n, K_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(x_t + n\sigma^2\right)}} \exp\left[\frac{\left(r_t - \mu - \sum_{i=1}^{p} \phi_i r_{t-1} - \sum_{j=1}^{q} \psi_j \varepsilon_{t-1} + \theta_t \lambda_t - n\mu\right)^2}{2\left(x_t + n\sigma^2\right)}\right] \tag{11}$$

Finally, model parameters are estimated by maximizing the log-likelihood over the sample period T:

$$L(\Psi) = \sum_{t=1}^{T} \ln\left[P\left(r_t \mid K_{t-1}, \Psi\right)\right] \tag{12}$$

Where, the model parameter values to be estimated are $\Psi = (\mu, \phi_i, \psi_i, \alpha_0, \alpha_1, \alpha_2, \beta, \lambda_0, \rho, \gamma, \theta_0, \eta_1, \delta^2)$.

3.2 The ARMA-EGARCH-expected/unexpected Model

In order to reflect the expected and unexpected shocks of international oil prices, we take the direct oil price shock and oil price fluctuation as external factors, and introduce the mean equation and variance equation to construct the shock response model. According to the ARMA part of the oil price fluctuation model in Section 3.1, the oil price changes are decomposed into the expected international oil price changes $\hat{r}_t$ and the unexpected international oil price changes $\tilde{r}_t$ with positive and negative directions, respectively.

$$\hat{r}_t = \hat{\mu} + \sum_{i=1}^{p} \hat{\phi}_i r_{t-i} + \sum_{i=1}^{q} \hat{\varphi}_i \varepsilon_{t-i} \tag{13}$$

$$\tilde{r}_t = r_t - \hat{r}_t \tag{14}$$

Then, we take these four items $\{\hat{l}_t, \tilde{r}_t, \hat{p}_t, \tilde{p}_t\}$ as external factors of the mean equation, and then introduces smooth fluctuations and transition fluctuations into the variance equation to measure the impact of oil price fluctuations on the yield of the new energy industry.

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \tag{15}$$

$$R_t = \eta_1 \widehat{r}_t^p + \eta_2 \widetilde{r}_t^n + \eta_3 \widehat{r}_t^p + \eta_4 \widetilde{r}_t^n + r_t \tag{16}$$

$$\varepsilon_t = \sqrt{x_t} D_t, \quad D_t \sim \mathrm{NID}(0,1) \tag{17}$$

$$\begin{aligned} \ln(x_t) = \omega + \sum_{i=1}^{\tau} d_i X_{t-i+1} + \sum_{i=1}^{\tau} d_i \lambda_{t-i+1} + \sum_{i=1}^{T} \left(\gamma_i \left(|\varepsilon_{t-i}| - E[\varepsilon_{t-i}]\right) + \alpha_i \varepsilon_{t-i}\right) \\ + \sum_{i=1}^{T} \beta_i \ln(x_{t-i}) \end{aligned} \tag{18}$$

3.3 The ARMA-EGARCH- lag Model

In order to examine the stability of the model and conclusions, the current term and hysteresis term of the yield are introduced. In order to ensure the comparability of the model, this paper also introduces the jump intensity λ_{t-i+1} of the current and hysteresis period into the model:

$$\begin{aligned} R_t &= \sum_{i=1}^{v} \chi_i r_{t-i+1} + r_t \\ &= \sum_{i=1}^{v} \chi_i r_{t-i+1} + \kappa + \sum_{i=1}^{p} \Phi_i r_{t-i} + \sum_{j=1}^{q} \phi_j \varepsilon_{t-j} + \varepsilon_t \end{aligned} \tag{19}$$

$$\varepsilon_t = \sqrt{x_t} D_t, \quad D_t \sim \mathrm{NID}(0,1) \tag{20}$$

$$\begin{aligned} \ln(x_t) = \omega + \sum_{i=1}^{\tau} d_i \lambda_{t-i+1} + \sum_{i=1}^{s} \left(\gamma_i \left(|\varepsilon_{t-i}| - E[\varepsilon_{t-i}]\right) + \alpha_i \varepsilon_{t-i}\right) \\ + \sum_{i=1}^{v} \beta_i \ln(x_{t-i}) \end{aligned} \tag{21}$$

When exploring the impact of introducing lagged terms on economic models, a common challenge is the aggravation of multicollinearity, which is usually accompanied by the problem of excessive model variance and reduced statistical significance. In particular, as the number of lagged terms increases, the multicollinearity problem will deteriorate sharply, significantly affecting the stability and explanatory power of the model.

To effectively address this challenge, this paper uses high-frequency data as the basis for analysis. By expanding the observation sample, high-frequency data can disperse the covariation trend between variables to a certain extent, thereby reducing the impact of multicollinearity and making the model estimation more robust and reliable. In addition, on the basis of pursuing the significance of the results, this paper focuses on the exploration of short-term lag effects to avoid the information redundancy and multicollinearity problems caused by too long lag terms. Focusing on the dynamic relationship between variables in the short term enables this paper to more accurately capture the immediate feedback mechanism in economic phenomena.

4 Data and empirical results

4.1 Data sources

Considering the representativeness of oil prices and its correlation with Asian oil prices, we use Brent crude oil futures prices to represent international oil prices. For China's new energy sector, we construct a comprehensive industrial chain dataset from the WIND database, covering both the aggregate new energy industry index (NE) and six sub-sector indices that explicitly map to the upstream-midstream-downstream structure. Specifically, the indices for upstream solar power (SP), wind power (WP), and nuclear power (NP), midstream lithium battery (LB), and downstream new energy vehicles (NEV) are proprietary indices compiled by WIND (Shanghai Wind Information Co., Ltd). For the upstream hydropower (HP) sector, we employ the Hydropower Index compiled by CITIC (CITIC Securities Co., Ltd) rather than the WIND Hydropower Construction Index. This choice ensures the data reflects the actual situation of the entire hydropower industry rather than merely infrastructure construction activities. Overall, this dataset enables a more complete representation of production, storage, and consumption linkages within the new energy industrial chain, thereby addressing the partial sub-sector coverage common in existing studies. The sample period spans from January 2011 to February 2025, with daily frequency data. And all data are sourced from the WIND financial database. Asset returns are calculated using the logarithmic difference formula:

$$r_t = [\ln(P_t) - \ln(P_{t-1})] \times 100 \tag{22}$$

where P_t is the price at time t. To handle non-synchronous trading days across international oil futures and Chinese new energy markets, we align the dataset based on return availability rather than raw prices, resulting in a final sample of 3,380 valid daily observations (prices and corresponding returns) with no artificial data interpolation.

4.2 Descriptive statistics

Prior to model estimation, we conduct a rigorous suite of pre-testing procedures to validate data suitability and justify methodological choices.

To avoid spurious regression, we employ three complementary unit root/stationarity tests (ADF, PP, KPSS) with cross-validation. As shown in Table 1, the ADF and PP tests uniformly reject the null hypothesis of a unit root at the 1% significance level for all new energy sub-sector return series, while the KPSS test fails to reject the null of stationarity. This triangulation confirms the strong stationarity of all return series, laying a robust foundation for subsequent time-series modeling.

Table 1 Unit root and stationary test (2011-2025)

Variable	ADF	PP	KPSS	Variable	ADF	PP	KPSS
Oil	-13.89***	-3439.23***	0.04	NP	-14.40***	-3241.01***	0.09
NE	-14.21***	-3235.22***	0.07	HP	-15.78***	-3164.85***	0.04
WP	-14.12***	-3265.29***	0.06	LB	-13.73***	-3151.55***	0.10
SP	-14.68***	-3215.83***	0.09	NEV	-14.39***	-3064.39***	0.06

Notes: The sample size was 3380. The ADF test is the augmented Dickey-Fuller test. The PP test is Phillips-Perron test and the KPSS test is Kwiatkowski-Phillips-Schmidt-Shin test. ***, **, * indicates statistical significance at 1%, 5% and 10%, respectively.

Table 2 summarizes the descriptive statistics of the sample. The crude oil market displays markedly higher volatility than China's new energy industries, as reflected by its larger standard deviation, higher kurtosis, and more pronounced skewness, indicating sharper price fluctuations and fat-tailed distributions in the oil market. The Jarque-Bera (JB) statistics further reject the null of normality for all return series, consistent with the stylized fact of non-Gaussianity in financial and energy time series. To confirm the necessity of GARCH-family models, we conduct Ljung-Box tests for autocorrelation ($Q(12)$), and conditional heteroskedasticity ($Q^2(12)$ for squared returns). The results show that the return series of crude oil and all energy sources have significant autocorrelation and ARCH effects, indicating that their volatility has volatility clustering characteristics. These findings confirm the presence of volatility clustering and provide a basis for the subsequent establishment of a time series model to capture the volatility behavior of these returns.

Table 2 Descriptive statistical characteristics (2011-2025)

Variable	Mean	Std	Skewness	Kurtosis	JB statistics	$Q(12)$	$Q^2(12)$
Oil	-0.0067	0.9567	-1.0627	18.7447	50188.61***	26.44***	550.38***
NE	0.0018	0.8352	-0.5052	3.5255	1898.17***	29.12***	1540.84***
WP	0.0082	0.8307	-0.4979	3.5683	1936.90***	25.59**	1449.46***
SP	0.0098	0.8927	0.1093	9.5366	12835.04***	34.46***	488.48***
NP	0.0082	0.7965	-0.7438	4.2509	2861.92***	26.48***	2105.80***
HP	0.0160	0.6145	-0.7421	11.3639	18524.66***	93.14***	7548.88***
LB	0.0190	0.9231	-0.3272	2.6260	1033.98***	33.44***	1208.75***
NEVs	0.0132	0.8312	-0.4616	3.0212	1408.64***	36.03***	1438.92***

Notes: The sample size was 3380. The JB statistic is a statistic of the Jarque-Bera Test. $Q(12)$ and $Q^2(12)$ are the statistics of the Ljung-Box Test. ***, **, * indicates statistical significance at 1%, 5% and 10%, respectively.

The Brent price trend and its return changes are shown in Figure 1. And the indices and returns of China's new energy industries as well as its six subsectors are shown in Figure 2. In the past 14 years, the changes in international oil prices and the price changes in the new energy industry are roughly inversely related. In addition, the volatility of the return of the new energy industry is much lower than that of crude oil, with fewer extreme values, more obvious volatility clustering. Moreover, similar fluctuation patterns are observed across the six new energy subsectors, reflecting their strong co-movement under macro-level shocks.

4.3 Fitting results of crude oil price volatility

Table 3 reports the estimation results of the ARMA-EGARCH-ARJI model for global oil returns. This paper uses ARMA-MSEGARCH-ARJI to analyze the volatility of international oil

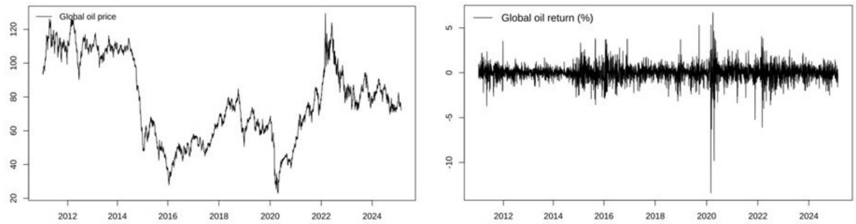

Figure 1 Brent oil price and its return (2011-2025)

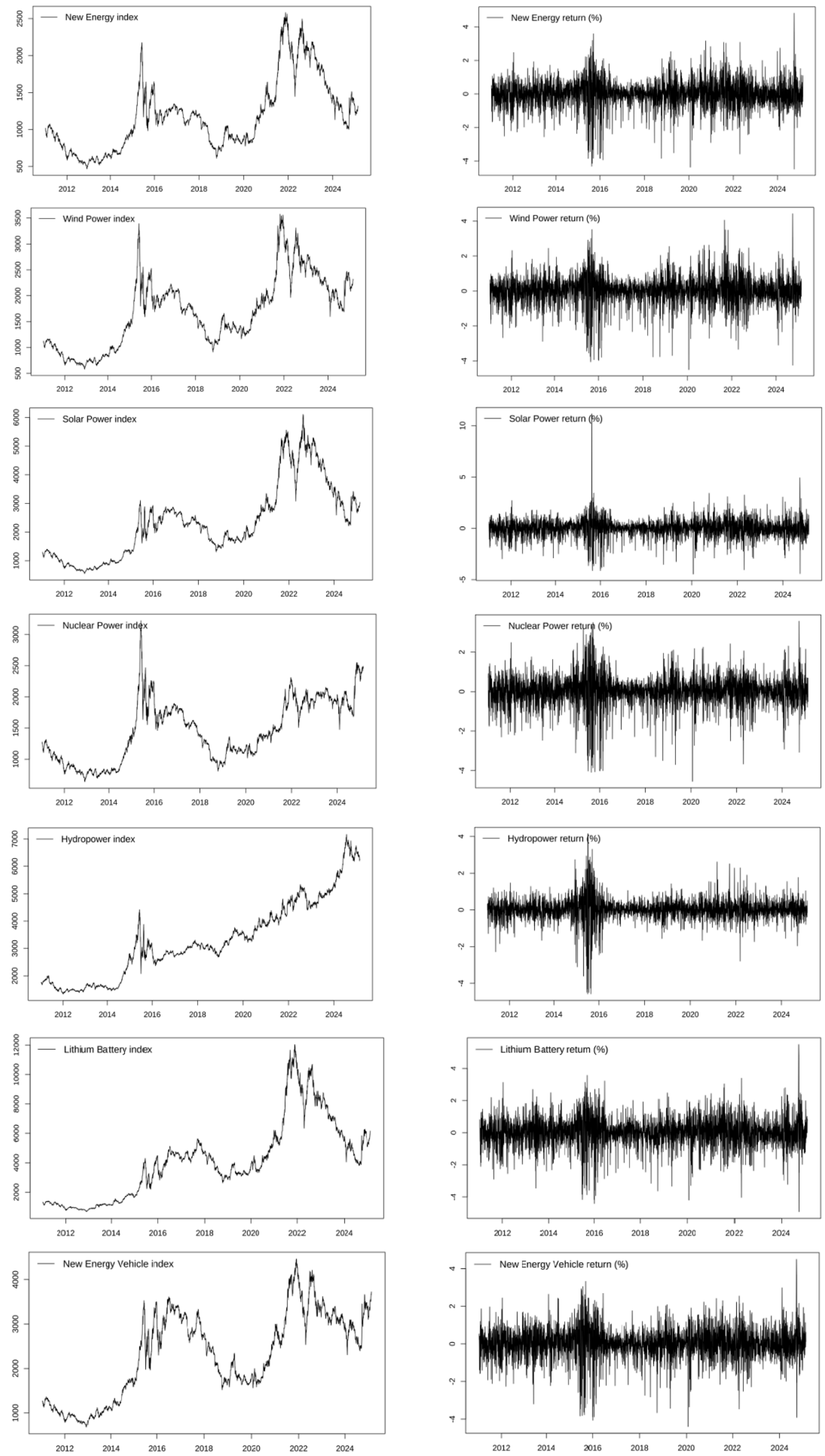

Figure 2 China's new energy price indices and their returns (2011-2025)

yields. The model fitting results of oil price fluctuations are shown in Table 4, where (μ, ϕ_1, φ_1) are the parameters of the ARMA model, $(\alpha_{0,1}, \alpha_{1,1}, \alpha_{2,1}, \beta_1)$ are the parameters of the EGARCH model under low volatility, and $(\alpha_{0,2}, \alpha_{1,2}, \alpha_{2,2}, \beta_2)$ are the parameters of the EGARCH model under high volatility. The model parameters are significantly different from 0 at the 1% significance level, indicating that the crude oil series have smooth fluctuations and a volatility clustering effect. Among them, $(\alpha_{2,1}, \alpha_{2,2})$ are all less than 0 at the 1% significance level, which shows that the international crude oil yield has a significant leverage effect, that is, it is more sensitive to negative information.

Table 3 ARMA (1,1)-EGARCH (1,1)-ARJI model on Brent futures (2011-2025)

Parameter	Coefficient	Std	t-Value	Pr(> |t|)
μ	-0.0042	0.0135	-0.3082	0.7580
ϕ_1	-0.5627***	0.0076	-74.2501	0.0000
φ_1	0.5456***	0.0083	65.3637	0.0000
$\alpha_{0,1}$	-0.0235***	0.0048	-4.9415	0.0000
$\alpha_{1,1}$	0.1212***	0.0200	6.0562	0.0000
$\alpha_{2,1}$	-0.0561***	0.0100	-5.5928	0.0000
β_1	0.9862***	0.0031	316.1573	0.0000
$\alpha_{0,2}$	0.3267***	0.1217	2.6840	0.0036
$\alpha_{1,2}$	0.6790***	0.2166	3.1340	0.0009
$\alpha_{2,2}$	-0.2415***	0.1025	-2.3547	0.0093
β_2	0.9028***	0.0559	16.1487	0.0000
λ_0	0.0039	0.0028	1.3866	0.1656
ρ	0.8022***	0.1873	4.2829	0.0000
γ	0.2219	0.1811	1.2252	0.2206
θ_0	-0.4786	0.4748	-1.0079	0.3136
η_1	0.6211*	0.3179	1.9537	0.0508
δ^2	2.1199***	0.4360	4.8619	0.0000
$SP1$	0.8895	-	-	-
$SP2$	0.1105	-	-	-
Q(12)	3.4176	-	-	0.9918
Q^2*(12)*	4.4600	-	-	0.8786

Notes: (1) The sample size was 3380. (2) μ, ϕ_1, φ_1 is the coefficient of ARMA model defined in equation (1). $\alpha_{0,1}$, $\alpha_{1,1}$, $\alpha_{2,1}$, β_1, $\alpha_{0,2}$, $\alpha_{1,2}$, $\alpha_{2,2}$, β_2 is model MSEGARCH coefficient. is the probability of state 1 in MSEGARCH. is the probability of state 2 in MSEGARCH. λ_0, ρ, γ are the coefficients of the ARJI model defined in equation (6), θ_0 and η_1 are the influence coefficients of the mean jump amplitude and the unexpected return of the previous period, respectively. δ^2 is the variance of the jump amplitude. *Q(12)* and Q^2*(12)* are the statistics of the Ljung-Box Test. (3) ***, **, * indicates statistical significance at 1%, 5% and 10%, respectively.

Table 4 ARMA-EGARCH-expected/unexpected model on China's new energy industries: Expected and unexpected oil price shocks (2011-2025)

Variable	NE	WP	SP	NP	HP	LB	NEV
μ	-0.040* (0.022)	-0.017 (0.022)	-0.006 (0.007)	-0.024*** (0.009)	0.017** (0.009)	-0.010 (0.010)	-0.015* (0.009)
ϕ_1	0.193*** (0.003)	-0.832*** (0.008)	-1.410*** (0.007)	-0.816*** (0.010)	-0.274*** (0.000)	-0.762*** (0.007)	0.360*** (0.008)
ϕ_2	0.803*** (0.004)	-	-0.574*** (0.015)	-0.013** (0.006)	-0.999*** (0.000)	-	-
φ_1	-0.156*** (0.002)	0.856*** (0.007)	1.434*** (0.008)	0.823*** (0.007)	0.274*** (0.000)	0.804*** (0.006)	-0.325*** (0.008)
φ_2	-0.831*** (0.000)	-	0.583*** (0.012)	-	1.000*** (0.000)	-	-0.058*** (0.012)
η_1	-2.152*** (0.617)	-2.241* (1.206)	-1.698*** (0.584)	-1.785** (0.836)	1.731*** (0.023)	-2.979*** (0.546)	-2.032** (0.886)
η_2	-1.407*** (0.471)	-1.485* (0.758)	-1.387 (1.111)	-1.817*** (0.397)	0.093 (0.189)	-1.679*** (0.587)	-2.240*** (0.857)
η_3	0.028* (0.016)	0.037 (0.024)	0.031* (0.019)	0.050*** (0.016)	0.016*** (0.002)	0.042*** (0.010)	0.027 (0.017)
η_4	0.058*** (0.011)	0.032* (0.016)	0.059*** (0.023)	0.043*** (0.013)	0.037*** (0.006)	0.048** (0.021)	0.057** (0.024)
ω	-0.007* (0.004)	-0.015* (0.008)	-0.006 (0.004)	-0.013 (0.009)	-0.017*** (0.004)	-0.008 (0.005)	-0.007 (0.005)
α_1	-0.111*** (0.038)	-0.025 (0.016)	-0.008 (0.010)	-0.023 (0.017)	0.018 (0.033)	-0.087** (0.038)	-0.094*** (0.036)
α_2	0.095*** (0.035)	-	-	-	-0.003 (0.033)	0.066* (0.036)	0.081** (0.033)
β_1	0.983*** (0.000)	0.577*** (0.005)	0.985*** (0.000)	0.548*** (0.004)	0.993*** (0.000)	0.975*** (0.008)	1.000*** (0.001)
β_2	-	0.394*** (0.005)	-	0.428*** (0.004)	-	-	-0.015** (0.006)
κ_1	0.172*** (0.066)	0.244*** (0.035)	0.164*** (0.021)	0.254*** (0.036)	0.212*** (0.049)	0.168*** (0.060)	0.132** (0.057)
κ_2	-0.001 (0.056)	-	-	-	-0.075* (0.045)	0.015 (0.053)	0.014 (0.049)
d_1	0.045*** (0.007)	0.055*** (0.011)	0.021*** (0.008)	0.003 (0.004)	-0.278*** (0.067)	0.001 (0.023)	0.009* (0.005)
d_2	-0.044*** (0.007)	-0.057*** (0.012)	-0.021** (0.008)	-0.003 (0.005)	0.269*** (0.065)	-0.001 (0.023)	-0.010** (0.005)
d_3	0.080 (1.555)	1.154*** (0.303)	0.546** (0.267)	2.162*** (0.363)	2.440 (1.805)	1.594** (0.701)	1.152** (0.485)
d_4	-0.220 (1.536)	-1.185*** (0.294)	-0.597** (0.279)	-2.350*** (0.335)	-1.691 (1.712)	-1.607** (0.688)	-1.172** (0.483)
$L(\Psi)$	-3698.25	-3667.80	-3909.87	-3418.32	-2224.23	-4151.31	-3764.37
AIC	2.2007	2.1809	2.3248	2.0339	1.3285	2.4676	2.2399
BIC	2.2388	2.2136	2.3592	2.0683	1.3666	2.5021	2.2779
LM Test	Lag[6] 0.3294 [0.9378]	Lag[6] 2.4850 [0.3930]	Lag[5] 0.9637 [0.7437]	Lag[6] 1.8934 [0.5147]	Lag[6] 1.7879 [0.5393]	Lag[6] 1.7264 [0.5540]	Lag[5] 0.5199 [0.4709]

Notes: (1) The sample size was 3380. (2) μ, ϕ_i, φ_j is the coefficient of ARMA model defined in equation. ω, α_i, β_j, κ_k is the coefficient of EGARCH model. are shock coefficients of expected positive oil price, expected negative oil price, unexpected positive oil price and unexpected negative oil price, respectively. d_1, d_2, d_3, d_4 are the current and lagged one-period coefficients of smooth and jump fluctuations, respectively. The standard error of each parameter is shown on the bracket. (3) $L(\Psi)$ represents the logarithmic maximum likelihood value of the model. (4) AIC and BIC are the information criteria to measure the goodness of model fitting. (5) The LM Test is used to test whether the residual term still has an ARCH effect. The null hypothesis of the test is that the sequence does not have an ARCH effect, and the square brackets are the corresponding p-values. (6) ***, **, * indicates statistical significance at 1%, 5% and 10%, respectively.

More importantly, the model effectively captures the sudden jump risk and heterogeneity characteristics in oil price fluctuations. $(\lambda_0, \rho, \gamma, \theta_0, \eta_1, \delta^2)$ are the parameters of the ARJI model. Among them, ρ represents the first-order autoregressive coefficient of jump intensity, which is significantly positive at the significance level of 1%, indicating that the jump intensity has strong persistence, and the jump intensity of the previous period has a significant positive impact on the current period, forming a volatility clustering effect. η_1 is the coefficient of the impact of the previous period's unexpected return on the jump amplitude, which is significantly positive at the significance level of 10%, indicating that unexpected market shocks will directly affect the jump amplitude of crude oil prices. The variance δ^2 of the jump amplitude is highly significant, indicating that the jump amplitude is not a fixed value, but there is heterogeneous risk. The jump intensity constant term λ_0 is not significant, indicating that the jump is mainly driven by dynamic processes rather than fixed background risks. The impact of unexpected returns γ is not significant, indicating that the impact of unexpected oil price changes on jump intensity is weak, and jumps are more likely to be directly triggered by exogenous shocks rather than market information transmission. The jump amplitude mean θ_0 is not significant and the long-term average amplitude is close to zero, indicating that the mean effects of positive and negative jumps may offset each other.

In order to ensure the robustness of the results, this paper conducts Ljung-Box Test on the residuals after fitting the composite model. *Q(12)* and Q^2*(12)* are the statistics of tests of the residuals and the squared residuals respectively. The results cannot reject the null hypothesis that the sequence does not have significant autoregression and conditional heteroskedasticity. Therefore, our model can effectively capture the ARCH effect of the sequence, and our model is sufficient to fit the international yield.

The jump intensity sequence of crude oil yields is further extracted as shown in Figure 3. The jump intensity has obvious changes in different periods. Figure 4 describes the overall volatility of international crude oil yields and the smooth fluctuations and jump parts that can be fitted by the model, and the gray area at the bottom is the actual volatility. In the absence of unexpected shocks, low volatility is the norm for oil price yields. In 2015 and 2019, the dual effects of incentive policies and the sudden drop in international oil prices pushed oil prices from a low volatility state to a high volatility state, which lasted for quite a while. In early 2020, oil prices fluctuated violently due to the epidemic, which is reflected in the figure that the jump intensity of oil prices also increased with unexpected abnormal information. The results show that the model in this paper can better characterize oil prices, and on the other hand, it also shows that the time-varying jumps in crude oil prices are closely related to emergencies.

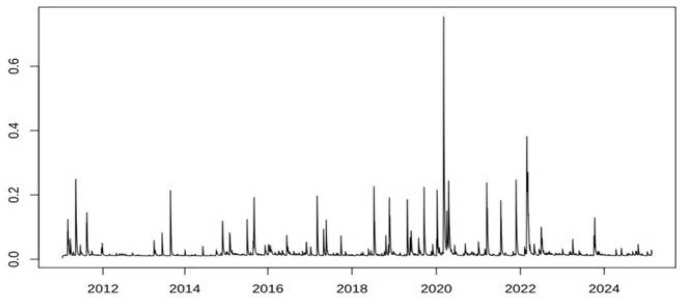

Figure 3 Jump intensity of global crude oil prices (2011-2025)

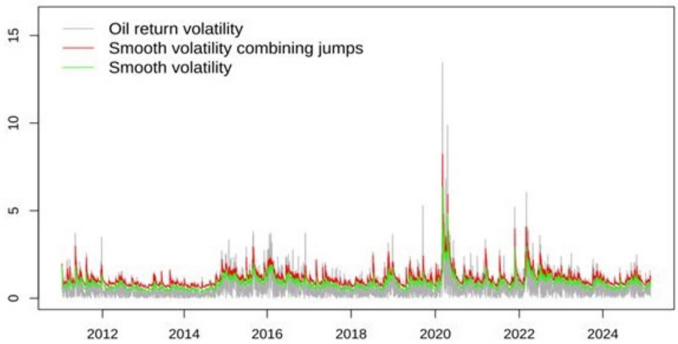

Figure 4 Volatility decomposition of global crude oil prices (2011-2025)

4.4 Empirical results of oil price shocks on China's new energy industries: considering expected and unexpected effects

Table 4 shows the results of the ARMA-EGARCH-expected/unexpected model analysis of the impact of expected/unexpected international oil price changes on the new energy industry and its sub-industries.

From the perspective of the ARMA-EGARCH model coefficients, only the α_1 coefficients of the new energy industry, lithium batteries and new energy vehicles are significantly negative, indicating the presence of a leverage effect. In addition, the α_2 coefficients of these industries are also significantly positive, indicating that the new energy industry, lithium batteries and new energy vehicle sub-industries will react violently to major yield changes in both positive and negative directions. There is an obvious volatility clustering phenomenon in the new energy industry and all sub-industries, among which the volatility of wind power, nuclear power and new energy vehicles is affected by fluctuations in a longer time span. The κ_1 coefficients of all industries are significantly positive, indicating that the two external shocks of smooth fluctuations and jumps in oil prices generally increase the volatility of various new energy industries. Only the κ_2 coefficient of hydropower is significantly negative, indicating that the previous oil price fluctuation jump has a suppressive effect on the volatility of hydropower.

From the perspective of the coefficients of oil price expectations and unexpected shocks (η_1, η_2, η_3, η_4), except for hydropower, the expected oil price increase (η_1) has a significant negative impact on the new energy industry as a whole, wind power, solar energy, nuclear energy, lithium batteries and new energy vehicle sub-industries, and the downstream industries of lithium batteries and new energy vehicles are more sensitive. The expected oil price increase has a significant positive impact only on hydropower, reflecting its risk-averse properties. The expected oil price drop (η_2) has a significant negative impact on the new energy industry as a whole, wind power, nuclear energy, lithium batteries and new energy vehicles. Except for wind power and new energy vehicles, the new energy industry as a whole and the remaining sub-industries have a weak positive response to the unexpected oil price increase (η_3), reflecting the market's speculative trading on short-term fluctuations. The unexpected oil price drop (η_4) has a positive and significant impact on the new energy industry as a whole and all sub-industries, especially solar energy, lithium batteries and new energy vehicles. Judging from the coefficients of the four types of oil price shocks, all sub-industries are more sensitive to expected oil price shocks, but less responsive to unexpected shocks; and the downstream industries of lithium batteries and new energy vehicles react more strongly to expected oil price shocks than most upstream sub-industries, showing the market's direct response to the logic of oil price substitution. Hydropower is the only industry that responds significantly and positively to both expected oil price increases and unexpected oil price decreases, highlighting its low volatility and risk aversion properties.

From the coefficients of smoothed volatility (d_1, d_2) and jump volatility (d_3, d_4), the current smoothed volatility coefficient d_1 of the new energy industry, wind power, solar power and new energy vehicle sub-industries is significantly positive, and the lagged coefficient d_2 is significantly negative, indicating that the smoothed volatility of oil prices has led to increased volatility in most new energy industries, while the lagged oil price volatility will suppress current volatility. The coefficient direction of hydropower is exactly opposite to that of other industries. The smoothed volatility coefficients of nuclear power and lithium batteries are not significant. The current jump volatility coefficient d_3 of wind power, solar energy, nuclear energy, lithium batteries and new energy vehicles is significantly positive, and the lagged one-period jump volatility coefficient d_4 is significantly negative. The current and one-period jump volatility coefficients of the new energy industry and hydropower are not significant, indicating that the decentralization of the overall new energy industry or the stability of hydropower can offset the impact of international oil price jump fluctuations to a certain extent. The absolute values of the smooth volatility coefficients of wind power, solar energy and new energy vehicle sub-industries are much smaller than the absolute value of the jump volatility coefficient.

These results show that the volatility of the yield of new energy industries is dominated by the jump fluctuations of international oil prices. New energy has a certain resistance to the smooth fluctuations of international oil prices and has limited sensitivity to unexpected shocks to short-term oil prices. In addition, there is also great heterogeneity in upstream and downstream industries. The current analysis has shown that the current impact of oil price fluctuations on the new energy industry is significantly asymmetric and heterogeneous. However, due to the existence of factors such as delayed corporate decision-making, consumer behavior inertia and policy response lags, the dynamic adjustment process of the energy market has a natural lag. In addition, only analyzing the current oil price shock may underestimate its long-term effect. Introducing the lag term can more completely characterize the dynamic relationship between oil prices and the new energy industry. Therefore, we introduce the lag term of international oil prices into the model and construct the ARMA-EGARCH-lag model to test the lag of international oil price shocks.

4.5 Empirical results of oil price jump impact on China's new energy industries: considering the hysteresis

Table 5 reports the estimation results of the ARMA-EGARCH-lag model, which introduces the current and lagged effects of oil prices as external regression factors into the mean equation, confirming that oil price fluctuations have a lagged effect on the new energy industry, and also reveals the differentiated performance of this effect among different sub-industries. Specifically, the optimal lag orders for oil returns were determined by minimizing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The results show that for the new energy industry, the current and lagged changes in international oil prices have a positive impact on the rate of return, indicating that the new energy industry has a lagged effect on the response of international oil prices. From the perspective of coefficient size, the lagged one-period impact coefficient η_2 is 21.7% lower than the current coefficient η_1, and it remains significant, indicating that the shock effect decays rapidly over time, but still retains some influence in the future.

Table 5 ARMA-EGARCH-lag model on China's new energy industries: Hysteresis of oil jumps (2011-2025)

Variable	NE	WP	SP	NP	HP	LB	NEV
μ	-0.046 (0.032)	-0.012 (0.015)	-0.027 (0.059)	-0.014*** (0.005)	0.017** (0.007)	-0.011 (0.015)	-0.018*** (0.007)
ϕ_1	0.200*** (0.005)	-0.830*** (0.014)	0.259*** (0.011)	-0.817*** (0.007)	0.034*** (0.008)	-0.749*** (0.030)	0.360*** (0.018)
ϕ_2	0.797*** (0.005)	-	0.736*** (0.011)	-0.012** (0.006)	-0.998*** (0.002)	-	-
φ_1	-0.163*** (0.002)	0.854*** (0.011)	-0.227*** (0.004)	0.825*** (0.006)	-0.034*** (0.009)	0.792*** (0.026)	-0.338*** (0.017)
φ_2	-0.824*** (0.000)	-	-0.759*** (0.000)	-	0.998*** (0.000)	-	-0.056*** (0.009)
η_1	0.046*** (0.013)	0.034*** (0.012)	0.048*** (0.013)	0.046*** (0.011)	0.021** (0.009)	0.045*** (0.013)	0.047*** (0.014)
η_2	0.036*** (0.013)	0.037** (0.018)	0.036** (0.016)	0.036*** (0.006)	0.011 (0.010)	0.055*** (0.014)	0.035*** (0.012)
η_3	-	-	-	-0.010* (0.006)	-	-	-
ω	-0.008 (0.005)	-0.015 (0.009)	-0.006 (0.004)	-0.013* (0.008)	-0.010*** (0.004)	-0.008 (0.005)	-0.013** (0.006)
α_1	-0.111*** (0.040)	-0.026 (0.017)	-0.014 (0.014)	-0.023 (0.017)	0.029 (0.032)	-0.088** (0.038)	-0.011 (0.010)
α_2	0.096*** (0.037)	-	-	-	-0.014 (0.031)	0.066* (0.036)	-0.018* (0.010)
β_1	0.982*** (0.005)	0.559*** (0.005)	0.984*** (0.001)	0.546*** (0.004)	0.995*** (0.001)	0.975*** (0.008)	-0.011*** (0.000)
β_2	-	0.411*** (0.005)	-	0.429*** (0.004)	-	-	0.983*** (0.000)
κ_1	0.167** (0.066)	0.247*** (0.035)	0.165*** (0.021)	0.256*** (0.035)	0.193*** (0.049)	0.167*** (0.060)	0.154*** (0.001)
κ_2	0.007 (0.057)	-	-	-	-0.080 (0.050)	0.017 (0.053)	0.136*** (0.000)
d_1	0.046*** (0.005)	0.063*** (0.011)	0.022*** (0.002)	0.016*** (0.003)	0.001 (0.037)	0.006** (0.002)	-0.035*** (0.011)
d_2	-0.045*** (0.005)	-0.065*** (0.009)	-0.022*** (0.002)	-0.016*** (0.003)	-0.005 (0.038)	-0.006** (0.003)	0.029*** (0.011)
d_3	0.119 (0.969)	1.125 (1.475)	0.835*** (0.152)	2.113*** (0.349)	0.996 (1.417)	1.676*** (0.238)	0.821*** (0.312)
d_4	-0.266 (0.960)	-1.160 (1.461)	-0.891*** (0.146)	-2.307*** (0.319)	-0.710 (1.430)	-1.690*** (0.239)	-0.648** (0.311)
$L(\Psi)$	-3699.88	-3668.82	-3909.87	-3418.80	-2210.26	-4150.89	-3767.32
AIC	2.2005	2.1804	2.3248	2.0336	1.3191	2.4662	2.2404
BIC	2.2350	2.2094	2.3592	2.0662	1.3535	2.4970	2.2749
LM Test	Lag[6] 0.2689 [0.9528]	Lag[6] 2.2520 [0.4377]	Lag[5] 0.9637 [0.7437]	Lag[6] 1.8254 [0.5304]	Lag[6] 1.6653 [0.5689]	Lag[6] 1.5889 [0.5879]	Lag[5] 0.8148 [0.3667]

Notes: (1) The sample size was 3380. (2) μ, ϕ_i, φ_j is the coefficient of ARMA model defined in equation. ω, α_i, β_j, κ_k is the coefficient of EGARCH model. are shock coefficients of expected positive oil price, expected negative oil price, unexpected positive oil price and unexpected negative oil price, respectively. d_1, d_2, d_3, d_4 are the current and lagged one-period coefficients of smooth and jump fluctuations, respectively. The standard error of each parameter is shown on the bracket. (3) $L(\Psi)$ represents the logarithmic maximum likelihood value of the model. (4) AIC and BIC are the information criteria to measure the goodness of model fitting. (5) The LM Test is used to test whether the residual term still has an ARCH effect. The null hypothesis of the test is that the sequence does not have an ARCH effect, and the square brackets are the corresponding p-values. (6) ***, **, * indicates statistical significance at 1%, 5% and 10%, respectively.

The response of new energy sub-industries to the lagged shock of oil prices shows significant heterogeneity. The performance of solar energy and new energy vehicles is similar to that of the new energy industry. In contrast, the response patterns of wind energy and lithium battery industries are more complex. The lagged one-period impact coefficients η_2 of wind energy and lithium batteries are slightly higher than the current coefficient η_1, and are significant at a significance level of 1%. The impact of crude oil price shock on hydropower is positive in the current period, and the impact of the first period of lag quickly fades, highlighting its low volatility. The nuclear energy industry shows that the coefficient of the first period of lag η_2 decreases, and the coefficient of the second period of lag η_3 turns negative.

Although the positive impact of the current and first-order changes in oil prices on the yield of the new energy industry is contrary to the basic law of traditional supply and demand, it is in line with the actual situation in China's specific economic environment, that is, the rise in oil prices can have a positive impact on the new energy industry through inflationary pressure and economic growth stimulus mechanisms in the short term.

5 Discussion

5.1 Oil price jumps have an asymmetric effect on China's new energy industry

Contrary to the symmetric "positive shocks are beneficial and negative shocks are harmful" assumption in asset pricing theory, both expected oil price increases and decreases have a significant negative impact on new energy returns. On the contrary, whether it is rising or falling, unexpected oil price fluctuations will stimulate the performance of the new energy industry, forming an asymmetric effect of dual inhibition and promotion.

Existing literature has laid the foundation for understanding the differential transmission of oil price shocks, with Engle and Ng (1993) [41] emphasizing that investors react more strongly to negative news, Kilian (2009) [43] distinguishing between supply and demand shock sources as key transmission regulators. Recent studies also confirm divergent spillovers: Zhang et al. (2020) [44] find quantile-dependent oil and clean energy linkages. Zhang et al. (2025) [45] studied China's new energy sector, carbon market and international oil market in the context of the COVID-19 pandemic and the Russia-Ukraine conflict, revealing that the spillover effects between the three markets exhibit significant time-varying and asymmetric characteristics.

This study innovatively uncovers that the asymmetric responses of China's renewable energy sector to oil price shocks originate from structural tensions inherent in its policy-driven transition—an understudied mechanism in existing literature. Unlike prior research that simplifies policy-market interactions as one-dimensional, we identify two novel, counterintuitive patterns: First, the "double dampening" effect under anticipated shocks arises from the sector's regulatory design over the past several years: expected price hikes compress profit margins due to regulated electricity pricing like fixed feed-in tariffs, while anticipated declines create uncertainty regarding the continuity of policy support. Hydropower uniquely escapes this suppression, as its stable tariff regime attracts defensive capital during oil-driven uncertainty. Second, the "double boost" phenomenon under unanticipated shocks stems from dynamic policy-market interactions—sudden price drops immediately lower input costs while sparking expectations of compensatory measures like carbon tax adjustments, whereas unexpected surges temporarily reinforce energy transition incentives, drawing speculative inflows despite underlying cost risks. These dual patterns underscore the sector's transitional challenges: retaining a dependence on state support to offset early-stage cost disadvantages yet exposed to volatile oil market competition during marketization. The misalignment between predetermined policy instruments and rapid market adjustments exposes the industry to cyclical risks, including impediments to cost transmission, regulatory time-lags, and divergent expectations.

5.2 Oil price jumps has a heterogeneous impact on China's new energy sub-industries

Heterogeneous responses across new energy sub-sectors to oil price shocks exist, driven by divergent technological, institutional, and market structures. Notably, anticipated and unanticipated shocks exert polarized directional impacts: anticipated oil price increases impose the strongest negative effects on downstream industries, with new energy vehicles (NEVs) and lithium batteries exhibiting 2–3 times higher sensitivity than upstream wind and nuclear sectors, while hydropower uniquely demonstrates positive returns as a safe-haven asset. Conversely, unanticipated oil price declines uniformly stimulate new sub-sectors, particularly solar, lithium batteries, and NEVs.

To date, research on the heterogeneity of the new energy sub-sectors has been relatively scattered, lacking a systematic analysis of the upstream and downstream industrial chains in China's industry. An early study by Reboredo and Ugolini (2018) [46] explored the overall impact of traditional energy prices on the western renewable energy market, but only classified traditional energy sources. The coverage of recent studies remains partial: Deng and Xu (2024) [8] examined the correlation between oil prices and China's new energy sub-sectors, but did not distinguish between different links in the industrial chain; while Su and He (2025) [9] focused solely on new energy vehicles, ignoring other core components of China's complete new energy industrial chain.

This study innovatively identifies that the observed heterogeneity originates from the interplay between sector-specific techno-economic features and institutional constraints–an underexplored dynamic in existing literature. Unlike prior research that overlooks chain-level transmission differences, we reveal that downstream industries' demand elasticity governs price transmission efficiency: NEVs markets, as direct substitutes for oil consumption, react instantly to fuel cost margins, yet lithium battery firms buffer unanticipated shocks through long-term raw material contracts, delaying cost realization. Upstream sectors, conversely, face policy inertia, 18-month grid integration approvals for wind projects and national security protocols for nuclear plants insulate them from short-term volatility but amplify sensitivity to anticipated shocks via new quota systems. Hydropower's unique safe-haven status arises from fixed tariff mechanisms and state-backed low-risk profiles, attracting defensive capital during oil-driven macroeconomic uncertainty.

A key innovative insight lies in linking technological cycles and supply chain complexity to heterogeneous shock responses. Lithium batteries' multi-stage production, like mining, cathode synthesis, cell assembly, creates staggered cost transmission, explaining their lagged shock absorption. Nuclear energy's delayed negative coefficients reflect policy balancing, where governments accelerate project approvals to counter short-term shocks, but protracted infrastructure cycles delay market signal internalization. Solar's heightened responsiveness to unanticipated declines stems from immediate input cost relief and speculative positioning in modular, rapidly scalable technologies. Crucially, this heterogeneity underscores structural tensions between market-driven substitution dynamics and institutionally adjustment processes.

5.3 Oil price jumps have lag impacts on China's new energy industry

Our results show that while new energy returns are significantly positively correlated with contemporaneous and lagged first-order oil price fluctuations at the aggregate level, there are significant differences in the responses of different sub-sectors: the lag effect gradually decays in the solar, nuclear, and new energy vehicle sectors, while the lag coefficients gradually increase in the wind and lithium battery sectors, a counterintuitive pattern that has not been fully explored in the traditional energy literature.

The existing literature consistently suggests that there are hysteresis effects in energy price transmission, albeit through different mechanisms. Kilian and Park (2009) [47] and Bernanke et al. (1997) [48] provide theoretical support for lagged responses, distinguishing short-term sentiment-driven responses from longer-term structural/policy-mediated adjustments. Radchenko (2005) [49] shows that gasoline price transmission is delayed by 2–3 months due to market perceptions of the transient nature of the shock, consistent with the observed lagged effects.

This study shows that the renewable energy industry's response to oil price shocks varies over time, due to three main factors: supply chain frictions, policy lags, and algorithmic trading dynamics. First, supply chain frictions slow cost changes: The renewable energy industry relies heavily on oil-based materials (32-45% of inputs such as plastics for solar panels). When oil prices rise, these material costs rise first and then slowly trickle through factories to the final product–a process that takes months. Second, policy stability amplify the impact: Sudden changes in oil prices can cause companies to pause decision-making and wait for governments to act. For example, solar companies may delay projects until subsidy rules are clear, while electric vehicle manufacturers speed up production to avoid future carbon taxes. Third, automated trading exacerbates market volatility: Computer programs used by large funds automatically sell renewable energy stocks when oil markets are volatile, causing short-term price deviations that may decouple from firm fundamentals.

In addition, this study innovatively uncovers distinct, sub-sector-specific temporal response patterns to oil price shocks. Wind energy is slower to respond due to its long project lifecycle. Lithium batteries experience delayed cost shocks due to the 3-5 years material contract period. Solar and electric vehicles adjust faster because they can be scaled up quickly and consumers turn directly to them when oil prices rise.

6 Conclusion and policy implications

This study provides key insights into the asymmetric, heterogeneous, and lagged effects of international oil price shocks on China's new energy sector and offers practical policy implications for mitigating systemic vulnerabilities. This study draws three core conclusions. First, oil price shocks are asymmetric - expected shocks dampen new energy returns through policy dependency and cost rigidity. For example, during periods of expected price increases, fixed price limits exacerbate profit squeezes, while unexpected shocks boost valuations through speculative narratives and delayed cost shifting. Second, there are significant differences in the responses of different sub-sectors. Downstream sectors are highly sensitive to expected shocks due to direct substitution effects, while upstream sectors face amplified lagged effects from institutional rigidities such as delayed infrastructure project implementation. Third, supply chain bottlenecks, policy adjustment lags, and algorithmic trading behavior lead to lagged transmission mechanisms, and cost pressures are present at different time points. These dynamic factors highlight the structural contradiction between market-driven energy transformation and institutional inertia.

To address these challenges, we propose three core policy strategies. First, dynamic policy adjustments should be implemented to address asymmetric shock impacts on renewables pricing stability. This is achieved by: establishing an oil price-linked subsidy system with tiered triggers that automatically raise solar/wind grid electricity prices when Brent crude volatility exceeds, for example, a daily fluctuation of 5 percent or prices breach a reference threshold such as 100 dollars per barrel, while funding temporary EV purchase subsidies through fossil fuel carbon taxes during spikes; expanding petrochemical derivatives markets for corporate hedging; and mandating financial safety nets for extreme price swings. Second, sector-specific governance mechanisms should be established to resolve fragmented risk exposure across energy value chains. For upstream renewables, integrate oil-cost sharing clauses into long-term power contracts, requiring grid operators to cover, for instance, approximately 30–40 percent of material cost overruns beyond agreed levels. For downstream sectors, tie infrastructure subsidies to regional charging network quality, penalizing underperforming areas by reducing support. For nuclear/hydropower, fast-track project approvals during volatile periods. Third, multi-layer risk management frameworks should be deployed to mitigate systemic vulnerability to supply disruptions. Maintain strategic material stockpiles sufficient to cover roughly 90 days of net imports, deploy AI-assisted oil-renewable risk monitoring systems to generate short-horizon shock forecasts, for example within a 72-hour window, and impose trading limits on automated systems. Ultimately, shifting from oil dependence requires transforming renewables from policy-guided price followers to technology-backed market anchors—a transition demanding flexible regulations and shared risk frameworks across stakeholders.

It should be noted that we have previously conducted a qualitative discussion on the phenomenon explanation and transmission mechanism of the impact of international oil price jumps on China's new energy. We did not quantitatively isolate the specific contributions of mechanisms such as policy inertia and supply chain resilience due to the lack of high-frequency policy data. Quantitative methods such as MIDAS, a mixed data sampling approach, merit further investigation as a means of incorporating low-frequency policy variables like feed-in tariff adjustments into a more granular analysis. In addition, this study focuses exclusively on China's new energy industry given its unique market-policy dual structure. Future research could expand this framework to cross-national panel data, comparing the heterogeneity of oil price volatility transmission across different regulatory regimes to enhance the generalizability of the findings.

Acknowledgements

This research is supported by the National Social Sciences Fund of China (No. 24AJL007).

Author contributions

Chuanguo Zhang: Investigation, Methodology, Supervision, Visualization, Project administration, Funding acquisition.

Yujie Du: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing-original draft, Writing-review & editing.

All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The author declares that there is no conflict of interest.

References

[1] Barndorff-Nielsen OE. Power and Bipower Variation with Stochastic Volatility and Jumps. Journal of Financial Econometrics. 2004, 2(1): 1-37.
https://doi.org/10.1093/jjfinec/nbh001

[2] Lee SS, Mykland PA. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. Review of Financial Studies. 2007, 21(6): 2535-2563.
https://doi.org/10.1093/rfs/hhm056

[3] Lee YH, Hu HN, Chiou JS. Jump dynamics with structural breaks for crude oil prices. Energy Economics. 2010, 32(2): 343-350.
https://doi.org/10.1016/j.eneco.2009.08.006

[4] Bjursell J, Gentle JE, Wang GHK. Inventory announcements, jump dynamics, volatility and trading volume in U.S. energy futures markets. Energy Economics. 2015, 48: 336-349.
https://doi.org/10.1016/j.eneco.2014.11.006

[5] Dutta A, Bouri E, Roubaud D. Modelling the volatility of crude oil returns: Jumps and volatility forecasts. International Journal of Finance & Economics. 2020, 26(1): 889-897.
https://doi.org/10.1002/ijfe.1826

[6] Dutta A, Soytas U, Das D, et al. In search of time-varying jumps during the turmoil periods: Evidence from crude oil futures markets. Energy Economics. 2022, 114: 106275.
https://doi.org/10.1016/j.eneco.2022.106275

[7] Zhang L, Chen Y, Bouri E. Time-varying jump intensity and volatility forecasting of crude oil returns. Energy Economics. 2024, 129: 107236.
https://doi.org/10.1016/j.eneco.2023.107236

[8] Deng X, Xu F. Connectedness between international oil and China's new energy industry chain: A time-frequency analysis based on TVP-VAR model. Energy Economics. 2024, 140: 107954.
https://doi.org/10.1016/j.eneco.2024.107954

[9] Su X, He J. Does the crude oil return matter for the new energy vehicle-related industry markets? — A comparison of complete vehicles, energy systems, and raw materials. Energy Economics. 2025, 144: 108339.
https://doi.org/10.1016/j.eneco.2025.108339

[10] Askari H, Krichene N. Oil price dynamics (2002–2006). Energy Economics. 2008, 30(5): 2134-2153.
https://doi.org/10.1016/j.eneco.2007.12.004

[11] Larsson K, Nossman M. Jumps and stochastic volatility in oil prices: Time series evidence. Energy Economics. 2011, 33(3): 504-514.
https://doi.org/10.1016/j.eneco.2010.12.016

[12] Baum CF, Zerilli P. Jumps and stochastic volatility in crude oil futures prices using conditional moments of integrated volatility. Energy Economics. 2016, 53: 175-181.
https://doi.org/10.1016/j.eneco.2014.10.007

[13] Bollerslev T. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. 1986, 31(3): 307-327.
https://doi.org/10.1016/0304-4076(86)90063-1

[14] Gronwald M. A characterization of oil price behavior – Evidence from jump models. Energy Economics. 2012, 34(5): 1310-1317.
https://doi.org/10.1016/j.eneco.2012.06.006

[15] Wilmot NA, Mason CF. Jump Processes in the Market for Crude Oil. The Energy Journal. 2013, 34(1): 33-48.
https://doi.org/10.5547/01956574.34.1.2

[16] Du L, Yanan H, Wei C. The relationship between oil price shocks and China's macro-economy: An empirical analysis. Energy Policy. 2010, 38(8): 4142-4151.
https://doi.org/10.1016/j.enpol.2010.03.042

[17] Taghizadeh-Hesary F, Yoshino N, Mohammadi Hossein Abadi M, et al. Response of macro variables of emerging and developed oil importers to oil price movements. Journal of the Asia Pacific Economy. 2015, 21(1): 91-102.
https://doi.org/10.1080/13547860.2015.1057955

[18] Zhao L, Zhang X, Wang S, et al. The effects of oil price shocks on output and inflation in China. Energy Economics. 2016, 53: 101-110.
https://doi.org/10.1016/j.eneco.2014.11.017

[19] Yildirim Z, Guloglu H. Macro-financial transmission of global oil shocks to BRIC countries — International financial (uncertainty) conditions matter. Energy. 2024, 306: 132297.
https://doi.org/10.1016/j.energy.2024.132297

[20] Kim WJ, Hammoudeh S, Hyun JS, et al. Oil price shocks and China's economy: Reactions of the monetary policy to oil price shocks. Energy Economics. 2017, 62: 61-69.
https://doi.org/10.1016/j.eneco.2016.12.007

[21] Togonidze S, Kočenda E. Macroeconomic responses of emerging market economies to oil price shocks: An analysis by region and resource profile. Economic Systems. 2022, 46(3): 100988.
https://doi.org/10.1016/j.ecosys.2022.100988

[22] Lee K, Ni S. On the dynamic effects of oil price shocks: a study using industry level data. Journal of Monetary Economics. 2002, 49(4): 823-852.
https://doi.org/10.1016/s0304-3932(02)00114-9

[23] Cong RG, Wei YM, Jiao JL, et al. Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy. 2008, 36(9): 3544-3553. https://doi.org/10.1016/j.enpol.2008.06.006

[24] Zhang C, Qu X. The effect of global oil price shocks on China's agricultural commodities. Energy Economics. 2015, 51: 354-364. https://doi.org/10.1016/j.eneco.2015.07.012

[25] Zhu H, Guo Y, You W, et al. The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. Energy Economics. 2016, 55: 30-41. https://doi.org/10.1016/j.eneco.2015.12.027

[26] Zhu X, Liao J, Chen Y. Time-varying effects of oil price shocks and economic policy uncertainty on the nonferrous metals industry: From the perspective of industrial security. Energy Economics. 2021, 97: 105192. https://doi.org/10.1016/j.eneco.2021.105192

[27] Sun Z, Cai X, Huang WC. The Impact of Oil Price Fluctuations on Consumption, Output, and Investment in China's Industrial Sectors. Energies. 2022, 15(9): 3411. https://doi.org/10.3390/en15093411

[28] Wang KH, Su CW, Xiao Y, et al. Is the oil price a barometer of China's automobile market? From a wavelet-based quantile-on-quantile regression perspective. Energy. 2022, 240: 122501. https://doi.org/10.1016/j.energy.2021.122501

[29] Henriques I, Sadorsky P. Oil prices and the stock prices of alternative energy companies. Energy Economics. 2008, 30(3): 998-1010. https://doi.org/10.1016/j.eneco.2007.11.001

[30] Kumar S, Managi S, Matsuda A. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Economics. 2012, 34(1): 215-226. https://doi.org/10.1016/j.eneco.2011.03.002

[31] Managi S, Okimoto T. Does the price of oil interact with clean energy prices in the stock market? Japan and the World Economy. 2013, 27: 1-9. https://doi.org/10.1016/j.japwor.2013.03.003

[32] Bondia R, Ghosh S, Kanjilal K. International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy. 2016, 101: 558-565. https://doi.org/10.1016/j.energy.2016.02.031

[33] Reboredo JC, Rivera-Castro MA, Ugolini A. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Economics. 2017, 61: 241-252. https://doi.org/10.1016/j.eneco.2016.10.015

[34] Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics. 2012, 34(1): 248-255. https://doi.org/10.1016/j.eneco.2011.03.006

[35] He X, Mishra S, Aman A, et al. The linkage between clean energy stocks and the fluctuations in oil price and financial stress in the US and Europe? Evidence from QARDL approach. Resources Policy. 2021, 72: 102021. https://doi.org/10.1016/j.resourpol.2021.102021

[36] Reboredo JC. Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics. 2015, 48: 32-45. https://doi.org/10.1016/j.eneco.2014.12.009

[37] Elie B, Naji J, Dutta A, et al. Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. Energy. 2019, 178: 544-553. https://doi.org/10.1016/j.energy.2019.04.155

[38] Broadstock DC, Cao H, Zhang D. Oil shocks and their impact on energy related stocks in China. Energy Economics. 2012, 34(6): 1888-1895. https://doi.org/10.1016/j.eneco.2012.08.008

[39] Wen X, Guo Y, Wei Y, et al. How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Economics. 2014, 41: 63-75. https://doi.org/10.1016/j.eneco.2013.10.018

[40] Chan WH, Maheu JM. Conditional Jump Dynamics in Stock Market Returns. Journal of Business & Economic Statistics. 2002, 20(3): 377-389. https://doi.org/10.1198/073500102288618513

[41] Engle RF, NG VK. Measuring and Testing the Impact of News on Volatility. The Journal of Finance. 1993, 48(5): 1749-1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

[42] Maheu JM, McCurdy TH. News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns. The Journal of Finance. 2004, 59(2): 755-793. https://doi.org/10.1111/j.1540-6261.2004.00648.x

[43] Kilian L. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. American Economic Review. 2009, 99(3): 1053-1069. https://doi.org/10.1257/aer.99.3.1053

[44] Zhang H, Cai G, Yang D. The impact of oil price shocks on clean energy stocks: Fresh evidence from multi-scale perspective. Energy. 2020, 196: 117099. https://doi.org/10.1016/j.energy.2020.117099

[45] Zhang Y, Tang G, Li R. Spillover effects between China's new energy and carbon markets and international crude oil market: A look at the impact of extreme events. International Review of Economics & Finance. 2025, 98: 103939.
https://doi.org/10.1016/j.iref.2025.103939

[46] Reboredo JC, Ugolini A. The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach. Energy Economics. 2018, 76: 136-152.
https://doi.org/10.1016/j.eneco.2018.10.012

[47] Kilian L, Park C. The Impact of Oil Price Shocks on the U.S. Stock Market. International Economic Review. 2009, 50(4): 1267-1287.
https://doi.org/10.1111/j.1468-2354.2009.00568.x

[48] Bernanke BS, Gertler M, Watson M, et al. Systematic Monetary Policy and the Effects of Oil Price Shocks. Brookings Papers on Economic Activity. 1997, 1997(1): 91.
https://doi.org/10.2307/2534702

[49] Radchenko S. Lags in the response of gasoline prices to changes in crude oil prices: The role of short-term and long-term shocks. Energy Economics. 2005, 27(4): 573-602.
https://doi.org/10.1016/j.eneco.2005.04.004