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The Effects of Artificial Intelligence on Oil Shocks: Evidence from a Wavelet-Based Quantile-on-Quantile Approach

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ABSTRACT

This study examines the effects of artificial intelligence on oil shocks (supply, demand, and risk shocks) across different time scales and market conditions, using the wavelet-based quantile-on-quantile approach. The empirical results have discovered that in the short term, artificial intelligence exerts significant negative impacts on supply and risk shocks, with these adverse effects gradually diminishing over time. Notably, artificial intelligence begins to positively influence supply shock in the medium to long term. In contrast, demand shock is initially positively affected, but these benefits diminish over time. The outcomes gained from this study not only give policymakers valuable insights for developing more precise energy policies, but also provide investors with nuanced market perspectives and risk assessments.

KEYWORDS

Artificial intelligence; Oil shocks; Wavelet analysis; Quantile-on-quantile approach

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1. Introduction

With the arrival of the fourth industrial revolution, artificial intelligence (AI) has become a signature technology of this era, leading the charge in industrial upgrades and technological revolutions globally (Zorman et al., 2022; Li, 2023; Kuang et al., 2024). The rapid development and extensive application of AI have not only transformed the operational models in manufacturing, services, and healthcare but also provided new impetus for economic growth and social progress (Amjad et al., 2023; Ronaghi, 2023; Lee et al., 2024). The deep integration of AI technology is driving innovation in data analysis, machine learning, and automated decision-making, offering unprecedented possibilities for solving complex problems, optimizing operational efficiency, and enhancing creative capabilities (Saveliev & Zhurenkov, 2021; Nguyen et al., 2023; Singh et al., 2023).

AI has demonstrated its revolutionary potential in numerous fields and is playing an increasingly important role in the global financial and energy markets (Ahmad et al., 2021). Among them, the oil market, known for its high degree of globalization, extreme price volatility, and sensitivity to external events (Zhang & Chen, 2014), has become an important and complex area for the application of AI technology. The application of AI in this area, such as predicting price fluctuations through advanced data analysis and machine learning models, optimizing supply chain management, and improving exploration and production efficiency, can not only change the traditional operation of the oil market but also have profound impacts on the stability of oil prices and long-term market trends (Lu et al., 2019). Historically, severe oil price fluctuations have had significant impacts on the world economy, from the oil crisis in the 1970s to the financial crisis in 2008, and the unprecedented negative prices during the COVID-19 pandemic, each major fluctuation leaving profound effects on the global economy (Estrada et al., 2020; Almaskati, 2024; Mao et al., 2024). Therefore, given the far-reaching effects of the oil market on the global economy and the rapid development of AI in this market, this paper aims to delve into the impacts of AI on the oil market.

Although existing literature has made some progress in exploring the impacts of AI on different financial assets (stocks, bonds, commodity markets, etc.) (Demiralay et al., 2021; Abakah et al., 2023), it has neglected to investigate the effects of AI on various sources of oil shocks. The complexity of the oil market and its critical role in the global economy calls for a more refined analytical approach (He & Zhao, 2024). To bridge this gap, this study utilizes Ready (2018)'s decomposition approach to decompose the oil price series into supply, demand, and risk shocks and performs specific analyses across different time scales and market conditions to shed more light on the impacts of AI on various sources of oil shocks.

This paper contributes to existing research in several ways. Firstly, unlike previous studies that used AI-based methods to analyze energy-related data (Jabeur et al., 2021; Yin & Wang, 2022; Heidari et al., 2024), this paper is the first to investigate the impacts of AI on oil shocks from various sources. In this paper, the effects of AI on oil shocks are investigated after decomposing the oil price series to obtain various sources of oil shocks, which extends the related work of Liu et al. (2024), which only investigates the effects of AI on the overall oil price volatility.

Secondly, this study employs the wavelet-based quantile-on-quantile approach to examine the impacts of AI on various sources of oil shocks. This approach enables us to capture the impacts of AI on various sources of oil shocks across different time scales and market conditions. Our findings indicate that in the short term, AI shows significant negative impacts on supply and risk shocks. However, these adverse effects gradually diminish over time, and AI begins to positively influence supply shock in the medium to long term. Furthermore, regarding demand shock, AI shows positive effects in the short term, but these benefits tend to weaken over time. This paper confirms the robustness of the empirical results through an alternative estimation method, the quantile regression (QR) estimation approach.

Finally, as an indispensable key resource in global economic development, oil has become a significant driving force for industrial development and economic activities worldwide (Jahanger et al., 2022; Jie et al., 2023). The findings of this paper on the impacts of AI on various sources of oil shocks not only aid policymakers in formulating more precise and effective energy policies to ensure energy security and market stability but also provide investors with critical market insights and risk assessments, helping them make wiser investment decisions in the ever-changing energy sector.

The remainder of the study is organized as follows. Section 2 briefly reviews the relevant literature. Section 3 describes the econometric methods employed in this paper. The statistical data are detailed in Section 4. Section 5 presents the empirical results. Section 6 summarizes the findings of the research.

2. Literature review

As a strategic technology, AI is leading a new round of industrial upgrading and technological revolution, greatly impacting the global financial markets (Li et al., 2023a; Wang et al., 2023; Zou & Xiong, 2023). Based on this, existing literature extensively explores the effects of AI on various financial assets such as stocks, bonds, commodities, and cryptocurrencies. This paper will provide a brief review.

AI can have impacts on stock and bond markets. Using the wavelet coherence approach, Demiralay et al. (2021) observe that AI affects the S&P 500 index and U.S. government bonds across different time scales, with the COVID-19 pandemic amplifying the effects. Abakah et al. (2023) explore the impacts of AI on the Islamic stock market by using the cross-quantilogram method and find that AI negatively affects the Islamic stock market returns and the negative effects are strongest during market downturns. Through the generalized forecast error variance decomposition method, Huynh et al. (2020) identify that there are tail risk spillover effects of AI on green bonds, and the tail risk spillover effects are strongest in the short term and weaken in the long term.

Furthermore, AI also affects commodity and cryptocurrency markets. Using the cross-quantilogram method and the quantile connectedness approach, Liu et al. (2024) discover that the negative impacts of AI on traditional energy markets like oil and gas, are strongest in the short term and disappear over the long term. Chen & Wang (2018), utilizing the quantile generalized autoregressive conditional heteroskedasticity (GARCH) approach, explore the effects of AI on gold. They find that AI can have impacts on gold, and therefore gold cannot be used as a safe haven for AI. Through the multivariate VAR-GARCH model, Symitsi & Chalvatzis (2018) investigate the risk spillover effects of AI on Bitcoin, noting significant return and volatility spillovers. Le et al. (2021), employing the generalized forecast error variance decomposition method, investigate the changes in AI's influence on Bitcoin before and after the COVID-19 pandemic outbreak, finding that the onset of the COVID-19 pandemic intensifies the impacts of AI on Bitcoin.

As mentioned above, although existing studies have extensively focused on the impacts of AI on different financial assets, they have neglected to investigate the effects of AI on various sources of oil shocks. Kilian (2009) highlighted that various sources of oil shocks differently affect economic development, oil prices, and inflation. Therefore, considering only the effects of AI on the change in overall oil prices leads to biased conclusions. To address this gap in the literature, this research examines the impacts of AI on various sources of oil shocks across different time scales and market conditions.

3. Methodology

3.1. Identification of oil shocks

Kilian (2009) initially suggests decomposing the structural shocks in the international oil market from both supply and demand angles. However, Ready (2018) points out the limitations of this approach, noting that it does not consider the dynamic changes in oil prices, both present and future. As a result, Ready (2018) introduces a new method for decomposing oil shocks. This method, employing the structural vector autoregressions (SVAR) model based on the price changes of financial assets, generates daily data on oil shocks from various sources, reflecting more information (Chatziantoniou et al., 2023). This approach receives widespread application in the literature on the impacts of oil price volatility (Zheng et al., 2021; Chen & Zhang, 2023; Li et al., 2023b). Based on the orthogonality assumption of three types of oil shocks, the decomposition equation by Ready (2018) can be expressed as:

$$X_t \equiv \begin{bmatrix} \Delta P_t \\ R_t^{Prod} \\ \varepsilon_{VIX,t} \end{bmatrix}, Y_t \equiv \begin{bmatrix} ss_t \\ ds_t \\ rs_t \end{bmatrix}, M \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{1}$$

where ΔP_t represents fluctuations in oil prices, R_t^{Prod} stands for the stock return index of oil production companies, and $\varepsilon_{VIX,t}$ represents unexpected changes in the VIX. Y_t is a 1 x 3 vector, where ss_t, ds_t and rs_t respectively represent supply, demand and risk shocks. The three shocks are mapped by the matrix M :

$$X_t = MY_t \tag{2}$$

To establish orthogonality among the three shocks derived from the decomposition, the following condition must be satisfied:

$$M^{-1} \Sigma_X \left(M^{-1}\right)^T = \begin{bmatrix} \sigma_{ss}^2 & 0 & 0 \\ 0 & \sigma_{ds}^2 & 0 \\ 0 & 0 & \sigma_{rs}^2 \end{bmatrix} \tag{3}$$

where Σ_X denotes the covariance matrix of the observable X_t. σ_{ss}^2, σ_{ds}^2 and σ_{rs}^2 correspond to the variances of supply, demand, and risk shocks.

3.2. Wavelet transform approach

The wavelet transform method not only allows for the acquisition of data at different time scales but also helps reduce noise interference, aiding in more accurately capturing the underlying trends in the data (Kumah & Mensah, 2022). The wavelet decomposition approach works by segmenting time series data into orthogonal time frames and then transforming it through the following two functions:

$$\int^{\alpha}(t)dt = 1 \tag{4}$$

$$\int^{\beta}(t)dt = 0 \tag{5}$$

where α and β respectively denote father wavelet and mother wavelet. Father wavelet captures low-frequency series, while mother wavelet captures high-frequency series. Based on the aforementioned equation, the generated wavelets can be represented as:

$$\alpha_{u,s}(t) = 2^{u/2}\alpha(2^u t - s) \tag{6}$$

$$\beta_{u,s}(t) = 2^{u/2}\beta(2^u t - s) \tag{7}$$

where u signifies the scale and s indicates the continuous translation. Notably, the chosen number of observations limits the maximum number of scales. Based on Pang et al. (2022), this paper employs the wavelet method to decompose research variables into three frequencies: 2-16, 32-128, and 256-1024, corresponding respectively to short-, medium-, and long-term temporal dimensions.

3.3. Quantile-on-quantile (QQ) method

This paper further adopts the QQ approach proposed by Sim & Zhou (2015) to examine the impacts of artificial intelligence on various sources of oil shocks. The QQ method is an enhancement derived from the quantile regression method and non-parametric technique (Duan et al., 2023). This method captures the actual marginal impacts and effectively identifies responses across different distributions (Feng et al., 2023). Firstly, the three types of oil shocks ($Shocks_t$) in time are set as the function of artificial intelligence (AI_t) as follows:

$$Shocks_t = \varphi^{\theta}\left(AI_t\right) + \varepsilon_t^{\theta} \tag{8}$$

where φ^{θ} represents the effects of artificial intelligence. θ denotes the quantile of the variable. ε_t^{θ} represents the residual term. To explore how the γ -quantile of artificial intelligence impacts the θ -quantile of three types of oil shocks, this research performs a first-order Taylor expansion of function φ^{θ} around AI^{γ} :

$$\varphi^{\theta}\left(AI_t\right) \approx \varphi^{\theta}\left(AI^{\gamma}\right) + \dot{\varphi}^{\theta}\left(AI^{\gamma}\right)\left(AI_t - AI^{\gamma}\right) \equiv b_0\left(\theta,\gamma\right) + b_1'\left(\theta,\gamma\right)\left(AI_t - AI^{\gamma}\right) \tag{9}$$

Through Equations (4) and (5), the final equation can be derived:

$$Shocks_t = \varphi^{\theta}\left(AI^{\gamma}\right) + \dot{\varphi}^{\theta}\left(AI_t - AI^{\gamma}\right) + \varepsilon_t^{\theta} \tag{10}$$

The parameters in Equation (6) are derived by solving the equation below:

$$\begin{pmatrix} \hat{b}_0\left(\theta,\gamma\right) \\ \hat{b}_1\left(\theta,\gamma\right) \end{pmatrix} = \arg \min_{b_0, b_1, \varphi^{\theta}} \sum_{t=1}^{T} \mu_{\theta}\left[Shocks_t - b_0 - b_1\left(AI_t - AI^{\gamma}\right)\right] W\left(\frac{F\left(AI_t\right) - \gamma}{h}\right) \tag{11}$$

where $W\left(\bullet\right)$ denotes the Gaussian kernel function and $\mu_{\theta}\left(m\right) = m\left(\theta - p_m\right)$. $\left\{p_m\right\}$ stands for the indicator function of “ m ”. The empirical distribution function gets defined as $F\left(AI_t\right) = \frac{1}{L}\sum_{n=1}^{L} p\left(AI_n - AI_{L-1}\right)$. h means the bandwidth.

4. Variables and data

This paper deals with three sets of raw data for the decomposition of oil shocks, namely the NYMEX crude-light sweet oil futures Index, the S&P Commodity Producers Oil and Gas Exploration and Production Index, and the CBOE volatility index. Additionally, to measure the development of the artificial intelligence industry, this paper utilizes the NASDAQ Global CAT Artificial Intelligence & Robotics Index. This index aims to track companies involved in the development and application of artificial intelligence and robotics technology, reflecting the performance of the AI industry (Zeng et al., 2024a). The paper considers the log returns of the AI index and uses the SVAR model to decompose the three sets of primary data to obtain various sources of oil shocks. Daily data for each variable are retrieved from DataStream.

Figure 1 shows the time series graphs of the research variables from December 20, 2017, to February 29, 2024. The reason for choosing this period is that the data of the AI index starts from that date. The figure shows that the volatility of each research variable has distinct characteristics. Notably, there is a spike in the change of each variable series at the onset of the COVID-19 pandemic outbreak, indicating a good alignment of these graphs with reality. Figure 2 presents the specific effects of wavelet transformation on the research variables across multiple time scales. The figure illustrates that from short-term to long-term, the noise gradually diminishes, and the data series become smoother. These decomposed series enable the paper to study the impacts of artificial intelligence on various sources of oil shocks from different time dimensions.

The descriptive statistics of these data series are displayed in Table 1. The table presents that from short-term to long-term, the standard deviation of the data series corresponding to each research variable significantly decreases, making the data series smoother. Moreover, the skewness and kurtosis values for each research variable deviate from zero across different time scales, indicating that these time series are non-normally distributed. The Jarque-Bera test results also confirm this conclusion. Lastly, the Elliott Rothenberg Stock test results indicate that the AI index and the three types of oil shocks are stationary, implying that the application of the quantile-on-quantile approach is appropriate.

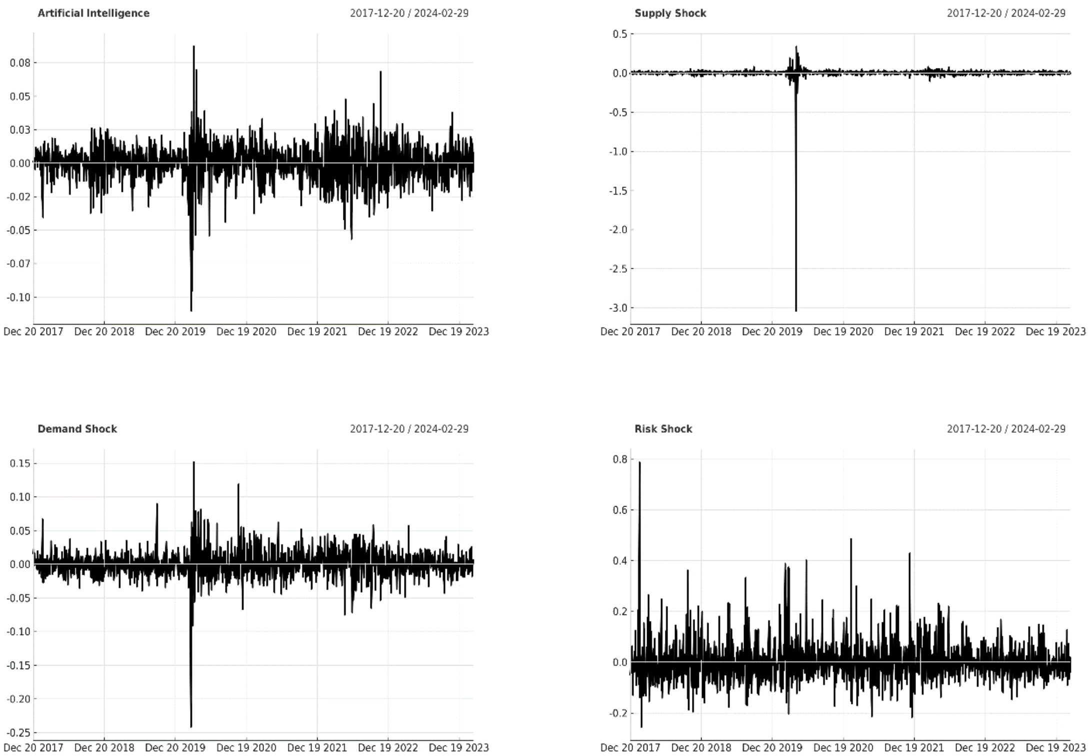
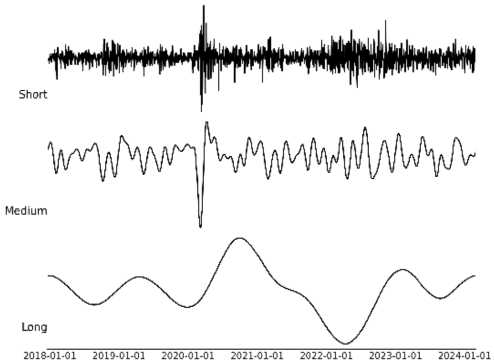
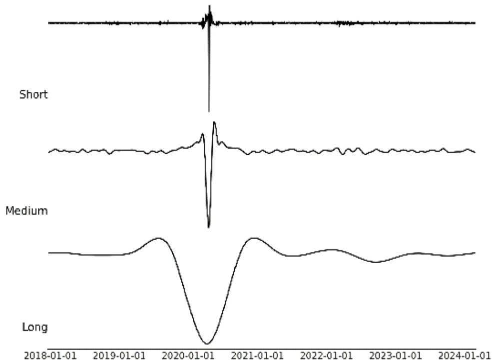


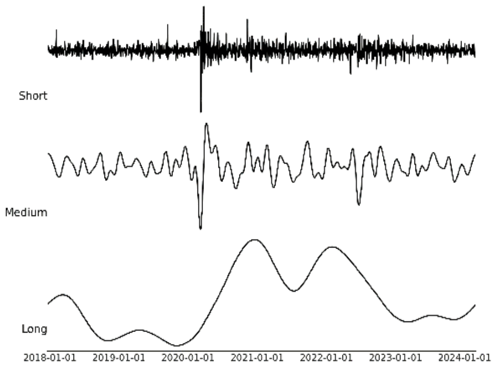
Figure 1. Times series plots of main variables.



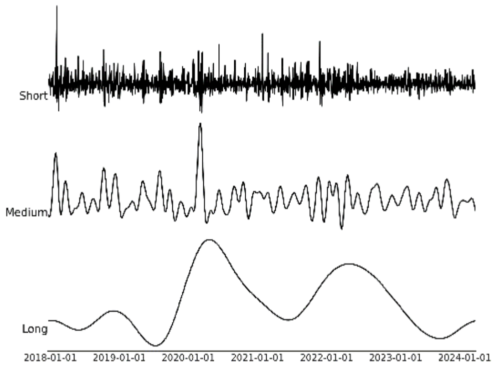
(a) Artificial intelligence



(b) Supply shock



(c) Demand shock



(d) Risk shock

Figure 2. Times series plots of main variables after wavelet transform.

Table 1. Descriptive statistic.

Variable	Obs	Mean	Std.Dev	Kurtosis	Skewness	J-B Stat.	ERS Stat.
Artificial intelligence							
Raw data	1,559	0.000	0.014	9.155	-0.647	2,569.3***	-16.614***
Short-term	1,559	0.000	0.014	7.866	-0.199	1,548.3***	-27.938***
Medium-term	1,559	0.000	0.004	7.611	-1.116	1,704.6***	-43.918***
Long-term	1,559	0.000	0.001	3.432	-0.134	16.779***	-40.560***
Supply shock							
Raw data	1,559	0.000	0.088	970.971	-28.913	61,081,097***	-15.788***
Short-term	1,559	0.000	0.083	847.816	-25.306	46,528,118***	-32.693***
Medium-term	1,559	0.000	0.022	59.119	-6.177	214,486***	-46.408***
Long-term	1,559	0.000	0.007	8.039	-2.421	3,172.4***	-43.318***
Demand shock							
Raw data	1,559	0.000	0.020	20.213	-0.590	19,336***	-11.713***
Short-term	1,559	0.000	0.019	17.211	-0.298	13,142***	-27.869***
Medium-term	1,559	0.000	0.005	7.198	-0.668	1,260.6***	-34.251***
Long-term	1,559	0.000	0.002	1.971	0.450	121.44***	-26.456***
Risk shock							
Raw data	1,559	0.001	0.079	12.714	1.740	6,915.7***	-14.029***
Short-term	1,559	0.000	0.076	11.550	1.380	5,243.6***	-19.444***
Medium-term	1,559	0.000	0.016	8.119	1.504	2,289.4***	-35.793***

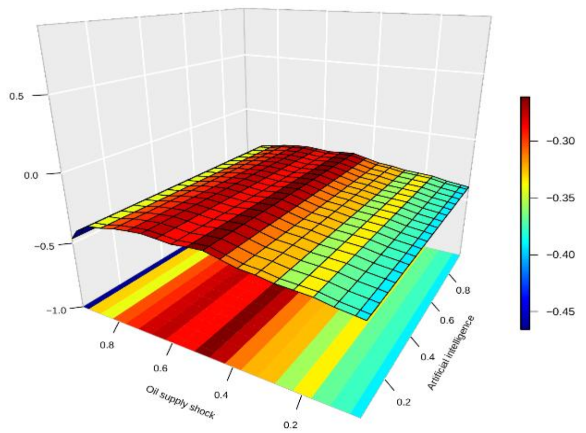
Long-term	1,559	0.000	0.006	2.248	0.608	132.65***	-37.253***

*Notes: *** denotes statistical significance at the 1% level.*

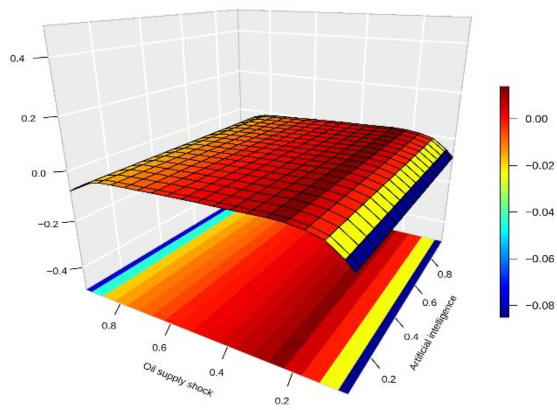
5. Empirical results

5.1. Quantile-on-quantile results

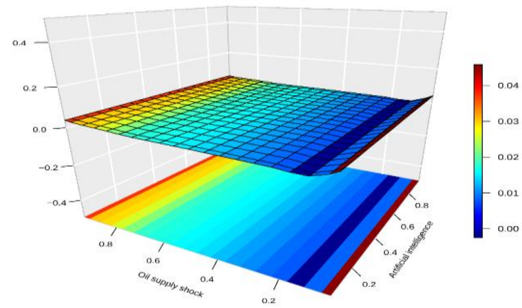
This section investigates the effects of AI on various sources of oil shocks across multiple time scales using the QQ method, with results shown in Figures 3 to 5. Figure 3(a) displays the short-term impacts of AI on supply shock. It is observed that AI exerts negative impacts on supply shock in the short term. This is attributed to the rise of AI, where capital and resources may shift from traditional energy sectors, such as oil and gas, to the development and application of AI and related technologies (Ernst et al., 2019). This shift could lead to reduced investment in oil exploration and drilling activities, thus negatively affecting supply shock in the short term. As shown in Figures 3(b) and (c), it is found that the negative impacts of AI on supply shock gradually weaken and start to become positive in the medium to long term. This finding aligns with the conclusions of Koroteev & Tekic (2021). This is because, over time, the application of AI in oil and gas exploration and drilling becomes more mature, and AI can help more accurately predict oil field locations, optimize drilling processes, and improve recovery rates (Sircar et al., 2021).



(a) Short-term



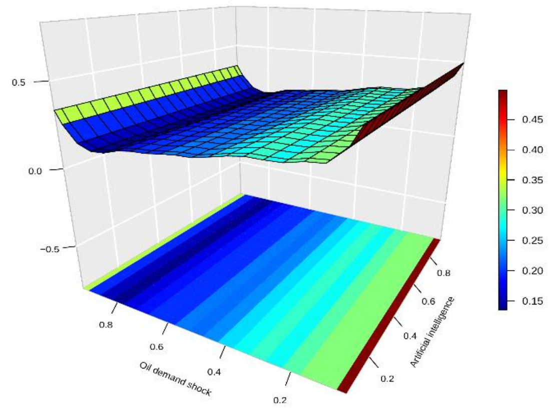
(b) Medium-term



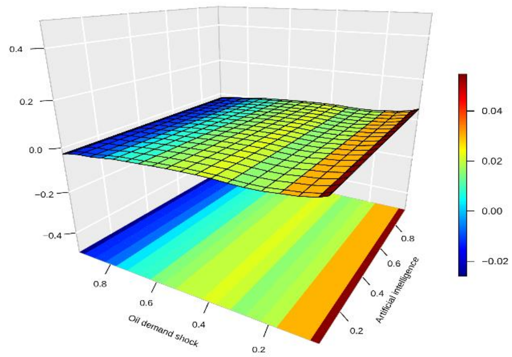
(c) Long-term

Figure 3. QQ regression results for the effects of artificial intelligence on supply shock.

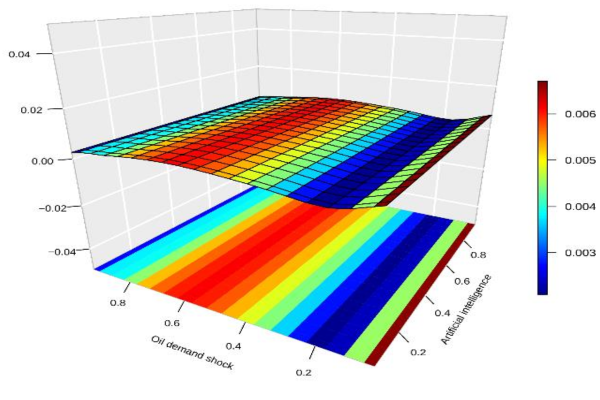
Regarding demand shock, as illustrated in Figure 4(a), AI has positive impacts on demand shocks in the short term. This is due to the rapid development and widespread application of artificial intelligence technology in the short term, which necessitates significant electricity consumption in related industries such as data centers and cloud computing services (Zeng et al., 2024b). In many regions, electricity production still relies on fossil fuels, thereby positively affecting demand shock. Furthermore, as shown in Figures 4(b) and (c), the positive impacts of AI on demand shock gradually diminish in the medium to long term. This attenuation is attributed to the maturation of AI technology, which enhances the efficiency and reliability of electricity supply in intelligent grid management (Ali & Choi, 2020), consequently reducing the positive effects on demand shock. Notably, in Figure 4(b), AI negatively affects demand shock when they are in the very large quartile (above 0.75), i.e., when demand shock is in the sharp increase in demand shock. The negative effects arise because AI enhances energy efficiency in industrial and production processes, reduces waste through intelligent management systems, and optimizes production flows, thus lowering consumption when demand shock surge (Sarvestani et al., 2024).



(a) Short-term



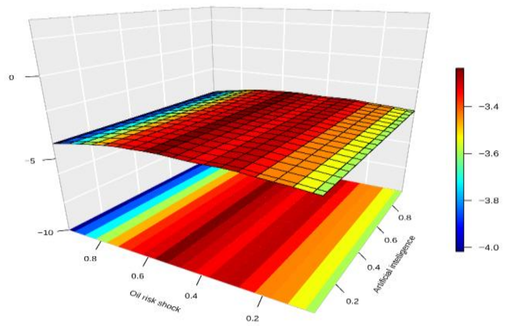
(b) Medium-term



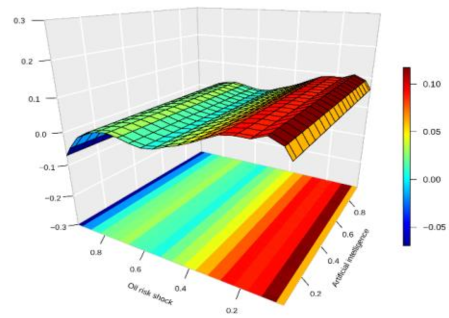
(c) Long-term

Figure 4. QQ regression results for the effects of artificial intelligence on demand shock.

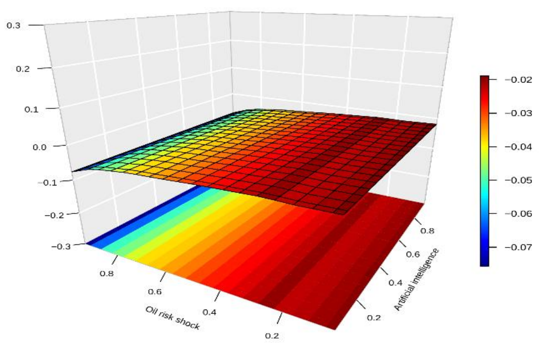
Figure 5 illustrates the impacts of AI on risk shock. It is evident from Figure 5(a) that AI has negative effects on risk shock in the short term. This is attributed to AI's capability to analyze news and social media, which aids in more accurately assessing market sentiment and reducing overreactions due to misinformation (Ahmed et al., 2022). Additionally, AI's ability to rapidly analyze vast amounts of data and make trading decisions contributes to a reduction in market uncertainty (Ashta & Herrmann, 2021), thereby negatively impacting risk shock. Figures 5(b) and (c) depict the influence of AI on risk shock in the medium and long term, respectively. AI has weaker positive effects on risk shock at most quantiles in the medium term. This phenomenon is likely due to market participants gradually adapting to AI technology and possibly identifying AI trading patterns, leading to the adoption of strategies to counteract, thereby increasing uncertainty (Papagiannidis et al., 2023) and resulting in positive impacts on risk shock. In the long term, AI exhibits slight negative effects on risk shock. The explanation for this finding is that with further advancements in AI technology, new technological challenges may arise, such as algorithmic biases and data security issues (Rodrigues, 2020). Risk shock represents a psychological anticipation of market investors, which can rapidly change with external factors (Li et al., 2023b). The emergence of these AI-related issues could influence market expectations, thus diminishing the negative effects of AI on risk shock. The results of the above QQ regressions across multiple time scales are briefly summarized in Table 2.



(a) Short-term



(b) Medium-term



(c) Long-term

Figure 5. QQ regression results for the effects of artificial intelligence on risk shock.

Table 2. Summary of QQ regression results.

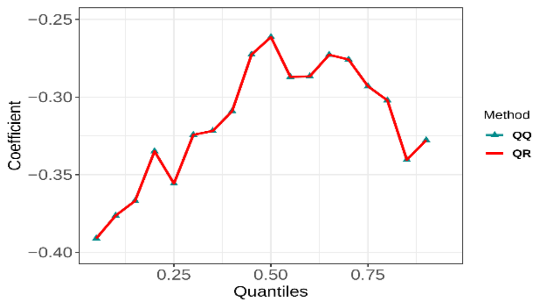
	Short-term	Medium-term	Long-term
AI → supply shock	Negative impacts in all quantiles	Negative impacts in extreme quantiles and positive impacts in other quantiles	Positive impacts in all quantiles
AI → demand shock	Positive impacts in all quantiles	Negative impacts in extreme upper quantiles and positive impacts in other quantiles	Positive impacts in all quantiles
AI → risk shock	Negative impacts in all quantiles	Negative impacts in extreme upper quantiles and positive impacts in other quantiles	Negative impacts in all quantiles

5.2. Robustness

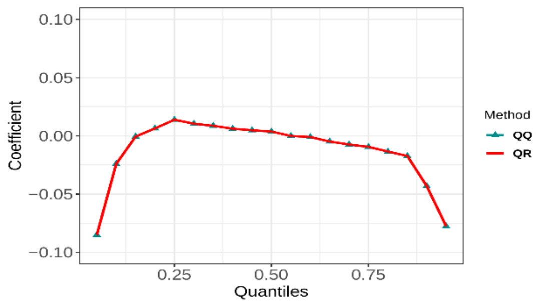
To assess the robustness of empirical results, this research conducts additional analyses by replacing the estimation methodology. The QQ approach might be viewed as a decomposition of the quantile regression (QR) approach (Pang et al., 2022). Therefore, following Feng et al. (2023), this paper compares the γ-averaged of QQ parameters with QR parameters to test the robustness of benchmark results. The γ-averaged of QQ parameters is defined as follows:

$$\xi_1(\varphi) \equiv \bar{\hat{b}}_1(\varphi) = \frac{1}{d}\sum_{\gamma}\hat{b}_1(\varphi,\gamma) \tag{12}$$

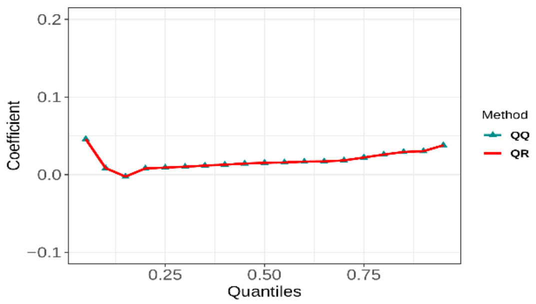
where d denotes the number of grid points. Figures 6 to 8 present the comparison results between the γ-averaged of QQ parameters and QR parameters. The figures show that the outcomes obtained using these two methods exhibit similar trends, thereby confirming the robustness of the main results of this paper.



(a) Short-term

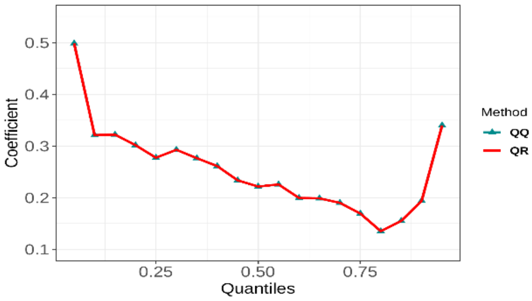


(b) Medium-term

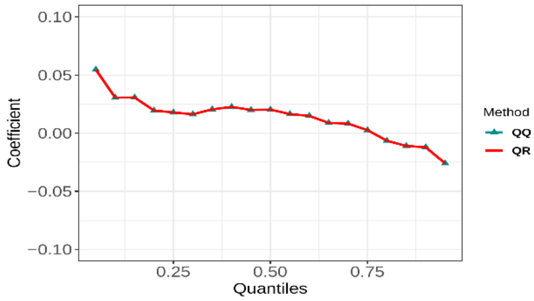


(c) Long-term

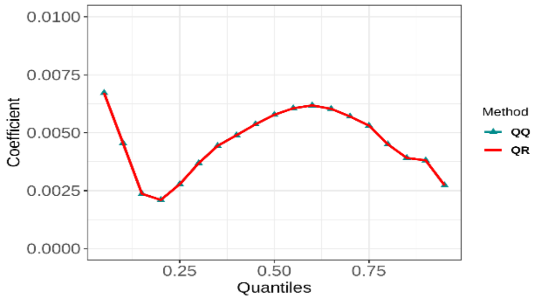
Figure 6. The robustness check: Comparisons of the results from QR and QQ estimates of the effects of artificial intelligence on supply shock.



(a) Short-term

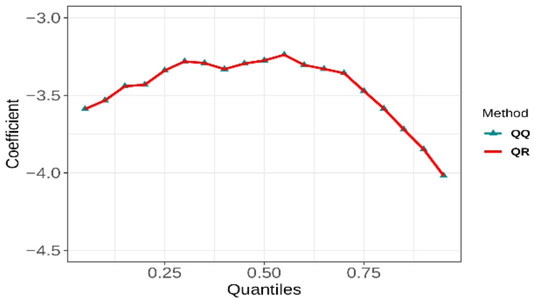


(b) Medium-term

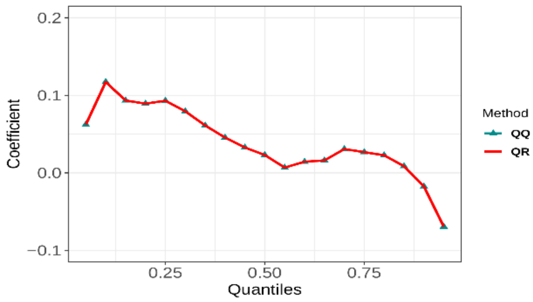


(c) Long-term

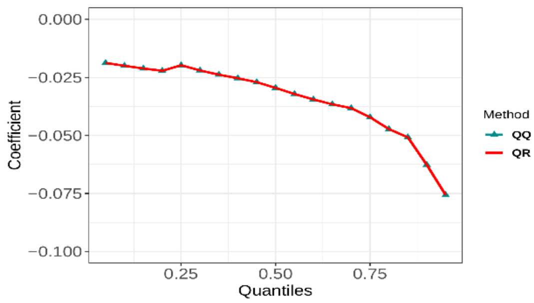
Figure 7. The robustness check: Comparisons of the results from QR and QQ estimates of the effects of artificial intelligence on demand shock.



(a) Short-term



(b) Medium-term



(c) Long-term

Figure 8. The robustness check: Comparisons of the results from QR and QQ estimates of the effects of artificial intelligence on risk shock.

6. Conclusion

An increasing number of studies focus on AI, investigating its impacts on the energy market (Zeng et al., 2024a; Zhang et al., 2024). However, the current literature does not take into account the study of AI's effects on various sources of oil shocks. To address the gaps in the existing literature, this paper initially applies the method proposed by Ready (2018) to decompose oil price changes into supply, demand, and risk shocks. Subsequently, we employ the wavelet-based quantile-on-quantile approach to examine the impacts of AI on various sources of oil shocks across different time scales and market conditions.

This study utilizes the dataset spanning from December 20, 2017, to February 29, 2024. By employing the QQ regression method, the findings of this paper indicate that in the short term, AI exhibits significant negative impacts on supply shock. However, as time progresses, the adverse effects diminish, and AI begins to exert positive effects on supply shock in the medium to long term. With respect to demand shock, AI demonstrates positive impacts in the short term, but the beneficial effects show a weakening trend in the medium to long term. Regarding risk shock, AI also presents negative impacts in the short term, but the effects gradually lessen over time. This paper validates the robustness of the empirical results using the QR estimation method, thereby enhancing the reliability of the research results.

The findings of the article hold significant value for both policymakers and investors. For policymakers, the first concern needs to be that AI may cause some disruption in the short term. They need to implement transitional support measures, which may include offering subsidies or tax incentives, to foster a smoother adjustment period and mitigate the direct adverse effects. Moreover, as AI begins to reveal its advantages over time, policymakers must prioritize long-term strategic planning. This entails investing in AI research and development, education, and infrastructure to fully capitalize on the potential benefits of AI for economic stability and growth (Babina et al., 2024). For investors, in the short term, it is prudent to invest cautiously in sectors that are highly affected by oil supply and risk shocks that are negatively impacted by AI. Investors should create a diversified portfolio and pay attention to industries that may benefit from the initial positive impacts of AI on oil demand shock. Additionally, investors may consider a long-term investment strategy, as industries initially setback by AI could adapt and start benefiting from its positive impacts over time, thus becoming profitable investment opportunities. While this study provides valuable insights into the effects of AI on various types of oil shocks across different time scales and market conditions, there are several limitations that warrant further investigation. Firstly, the study's reliance on the wavelet-based quantile-on-quantile approach, while robust, may not capture all the dynamic interactions between AI and oil shocks. Future research could explore alternative methodologies, such as machine learning models, to validate and extend these findings. Additionally, the analysis is confined to specific time periods and markets; expanding the scope to include more diverse datasets and global markets could yield more comprehensive results. Lastly, the study does not account for potential feedback loops where oil market fluctuations might influence AI development and deployment. Addressing these limitations in future research could provide a more holistic understanding of the interplay between AI and the energy sector.

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Conflict of interest

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

Author contributions

Conceptualization: Pengchao He; Data curation: Pengchao He; Formal analysis: Pengchao He, Nuan Zhao; Funding acquisition: Pengchao He; Investigation: Pengchao He; Methodology: Pengchao He, Nuan Zhao; Project administration: Pengchao He; Resources: Nuan Zhao; Software: Pengchao He; Supervision: Pengchao He; Validation: Pengchao He; Visualization: Nuan Zhao; Writing – original draft: Pengchao He, Nuan Zhao; Writing – review & editing: Pengchao He, Nuan Zhao. All authors have read and agreed to the published version of the manuscript.

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