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Examining crude oil price outlook amidst substitute energy price and household energy expenditure in the USA: A novel nonparametric multivariate QQR approach

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A R T I C L E I N F O

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A B S T R A C T

The outlook of crude oil prices has sparsely been empirically examined especially from the critical perspectives of energy expenditure per household, retail electricity prices, and environmental indicators. Given the enormous macroeconomic and socioeconomic effects of crude oil price amidst the fundamentals, this study examines the dynamics of the oil price outlook amidst energy demand (measured by energy expenditure per household), retail electricity price i.e., substitute price, and carbon dioxide (CO_2) emissions in the United States of America (USA) over the period 1970 to 2040. This study offers two main innovations: first, it extends the bivariate nonparametric Quantile-on-Quantile Regression (QQR) to the multivariate case. Second, the analysis incorporates projected data series, which provides useful policy insights. The empirical results show evidence of time-varying effects of energy expenditure per household, retail electricity price, and CO_2 emissions across the quantiles of crude energy prices. The results further show that the effect of energy demand through household energy expenditures is positive and stronger at the lower quantiles of crude oil price, which corresponds to periods of low crude oil prices. Furthermore, the effects of retail electricity price and CO_2 emissions are negative and stronger in the mid-quantiles of crude oil price. This suggests that retail electricity prices and environmental indicator dampen crude oil prices during periods of low crude oil prices. These findings are robust to multivariate Quantile regression and Kernel-based Regularized Least Squares (KRLS) estimates. Therefore, our study suggests time-varying policies to dampen the effects of energy demand, retail electricity price, and environmental indicator on crude oil prices in the USA.

1. Introduction

The decades of increasing development and expansion of alternative and clean energy sources in response to the global challenge of climate change and other environmental-related issues are yet to reduce the significance of crude oil and other fossil fuel sources. As a vital economic agent, energy sources, especially the crude oil market have remained an important determinant of economic buoyancy. This accounts for the evidence of a strong synchronization between the energy market vis-à-vis the global crude oil price and sector-wide economic, macroeconomic, and financial activities, thus explaining the vulnerability of the global economy amidst crude oil price fluctuations (Sadorsky, 1999; Shahbaz et al., 2017; Hammoudeh and Reboredo, 2018). Specifically, extant studies have explained the nexus between crude oil price dynamics and underlying fundamentals such as the macroeconomic indicators (Tvedt, 2002; Mallick et al., 2018; Balcilar et al., 2021a, 2021b), financial indicators (Wang and Li, 2021; Yang et al., 2021; Balcilar et al., 2022), energy aspects (Hassouneh et al., 2012; Kassouri et al., 2021; Alola, 2021 & Alola, 2022), and even the socioeconomic aspects (Dodson and Sipe, 2007; Akbari and Nurul Habib, 2014). Importantly, the dynamics of global crude oil price is not only explained by the above-mentioned factors but there is also increasing attention on other potential fundamentals such as energy access (Sinha et al., 2022).

Consequently, the curiosity to further uncover the significance of other underlying fundamentals of crude oil price is the main motivation and a major research question the current study seeks to answer. Given

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the potential fundamentals that are being scrutinized in this investigation, the revealing results ought to provide more assuring answers to some critical questions. For instance, and in a more practical term, how much of the 21st century's household-centered drivers of environmental sustainability and energy efficiency are impacting the global crude oil price? Additionally, how has or will the pursuit of the global goal such as the carbon neutral ambition (say net zero by 2050) influence the global crude oil price? Therefore, toward providing further revelation alongside answering the above-mentioned questions, the current study is objectively fashioned accordingly. Importantly, the roles of environmental indicator (measured by the level of CO_2 emissions and price of retail electricity (a proxy for crude oil price substitute) are both considered toward achieving the novel objective of further revealing the crude oil price effect of environmental and energy efficiency drive. Additionally, with the overarching objective of providing more answers about the role of carbon-neutral ambition, an extensive dataset covering until 2040 is utilized for the investigation. Moreover, the case of the United States of America (USA) is considered given both the country's carbon dioxide (CO_2) emissions and energy utilization profile i.e., the USA is a world-leading energy consuming and second highest carbon emitting economy in the world (United States Energy Information Administration, 2021). Interestingly, as an additional novelty, the study extends the bivariate nonparametric Quantile-on-Quantile Regression (QQR) while also utilizing energy expenditure per household as a proxy for energy demand. Given the justifications for considering the case of the USA, this potentially makes the results of the investigation a suitable template for policy recommendation and adoption across the globe.

Then, the other parts of the study are structured such that relevant previous studies are briefly discussed in section 2. In section 3, the dataset is described alongside the empirical methodology. While the results of the estimations are discussed in section 4, the conclusion alongside relevant policy insight is presented in section 5.

2. Theoretical consideration

The seminal work of Baily et al. (1978) is one of the studies that provide information about the dynamics of crude oil prices with respect to changes in economic activities. Therefore, economic, and macroeconomic indicators expectedly exert a causative effect on crude oil prices. Moreover, given that the global oil market is the central trading space for crude oil (a tradable good), macroeconomic indicators such as the exchange rate could directly impact crude oil prices (Blomberg and Harris, 1995). This reality as suggested by the relevant law of single price for tradable goods offer the intuitive background to suggest that economic fundamentals such as energy demand, electricity price, and other related factors potentially drive the dynamics of crude oil price.

2.1. Empirical literature: a synopsis

In the literature, the is empirical evidence affirming that crude oil price is associated with electricity price and energy consumption (Mohammadi, 2009; Nakajima and Hamori, 2012; Bernal et al., 2019). For instance, Mohammadi (2009) considered the case of the USA while investigating the relationship between electricity prices and three fossil fuel prices (coal, natural gas, and crude oil). By employing the dataset that spread over 1960–2007, the investigation only revealed a statistically significant relationship between coal prices and electricity prices. Specifically, coal prices and real electricity prices are found to exhibit a stable long-run association, and as well both exhibits long-run bi-directional causality. Moreover, the study also failed to establish asymmetric evidence between electricity prices and fossil fuel prices. Similarly, Bernal et al. (2019) adopted the approach of Mohammadi (2009) for the case of Mexico over the period of January 2006 to January 2016. Contrarily, the result from Bernal et al. (2019) revealed that all the fossil fuel prices (coal, natural gas, and crude oil) showed a significant and positive association with domestic electricity price rates, especially in the short-run. For the industrial and commercial electricity price rates, both relationships with crude oil and natural gas prices are also found to be significantly positive. Additionally, the study of Nakajima and Hamori (2012) used the case of Japan to investigate the nexus of electricity price and crude oil price alongside the role of the exchange rate vis-à-vis the yen-to-US-dollar exchange rate. The study employed the novel causality-in-mean and causality-in-variance through the approach of the cross-correlation function. Importantly, Nakajima and Hamori (2012)'s study found no evidence of both Granger-causality-in-mean and Granger-causality-in-variance between the electricity and crude oil markets. Contrarily, through the Granger-causality-in-variance, the result established that there is a combined effect of the yen-to-US-dollar exchange rate and crude oil price on electricity prices in the examined country.

Though still not widely covered in the literature, crude oil prices are now being increasingly linked with carbon emission and environmental-related factors (Payne, 2012; Kassouri et al., 2022; Umar et al., 2022; Wei et al., 2022). The recent study by Kassouri et al. (2022) implemented a wavelet-based approach to examine the relationship between oil price shock and carbon emission in the USA over the period of February 1975 to July 2018. The study utilized disaggregated demand and supply oil price shocks to provide interesting insight into the oil price shock and carbon emission nexus. Interestingly, the result revealed that neither the shock in oil demand (due to high energy demand) nor the shock in oil supply is able to trigger a decline in carbon emission. From a different perspective, Wei et al. (2022) employed the economic input-output life cycle method (EIO-LCA) approach to investigate the interlinkage between crude oil price uncertainty and corporate carbon emission (from 1089 Chinese companies). Desirably, the investigation found that corporate carbon emissions in the examined companies could be mitigated when there is an experience of high uncertainty in international crude oil prices. However, the result further implies that an increase in carbon emission intensity triggers global oil market uncertainty while causing a decline in different frequency bands of oil inventory. Meanwhile, Payne (2012) employed the Toda-Yamamoto approach to examine the Granger causality between real oil prices, carbon emission, gross domestic product, and renewable energy consumption. By using the dataset that spread over 1949–2009, the study failed to establish significant Granger causality between carbon emission and oil price.

While the above-reviewed studies explain the dynamics of oil prices from the perspectives of energy consumption, electricity prices, and carbon emission, the role of household energy expenditures remained unexplored in the literature. Moreover, the dataset covering the period 1970–2040 is employed in this study by also extending the bivariate nonparametric Quantile-on-Quantile Regression (QQR) to the multivariate case.

3. Econometric model, data, and methodology

This section provides information on the dataset under investigation alongside the procedures and justification for the novel empirical approach being implemented.

3.1. Econometric model and data

To investigate the dynamics of crude oil prices in the USA from the perspective of household energy expenditure, substitute energy price, and environmental factors, the deployed econometric approach has an underlying economic model written as:

$$\mathrm{COP} = \mathrm{f}\,(\mathrm{ED}, \mathrm{Z}) \tag{1}$$

where COP represents crude oil prices, ED is energy demand, and Z stands for other factors such as prices of other goods (retail electricity

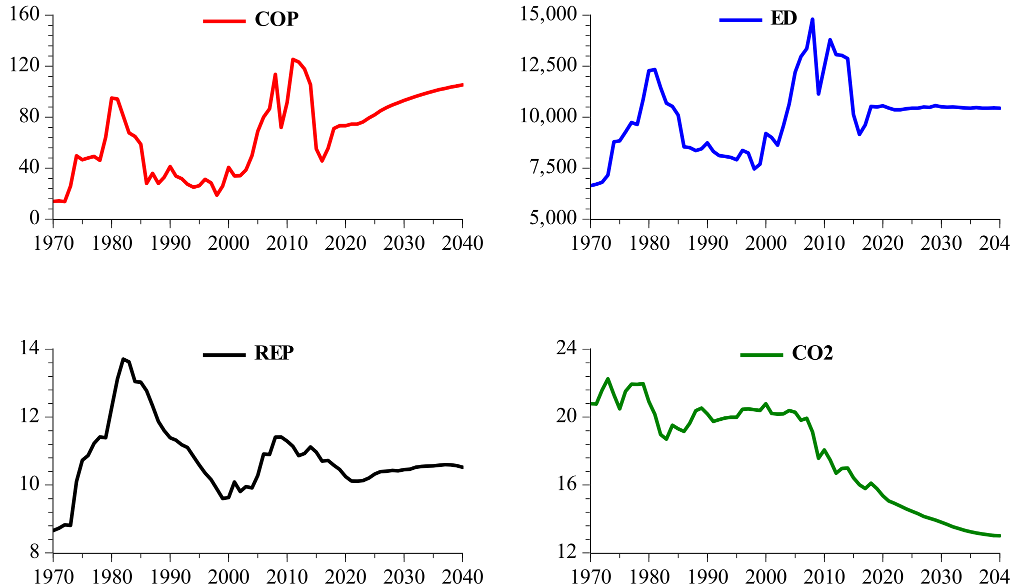

Fig. 1. Annual values of the variables from 1970 to 2040.

price, denoted as REP) and environmental factors (CO_2 emission). In this context, this study employs 71 years of time-series data covering 1970–2040. Annual crude oil price is measured as 2018 USA dollars per barrel (bbl). Additionally, energy expenditures per household (2018 USA dollars) are employed as a proxy for energy demand. Furthermore, the prices of other (substitute) goods which are represented by retail electricity prices and measured in 2018 USA cents per kilowatt hour (kWh) are also added as a variable of interest. Finally, for an environmental factor, energy-related CO_2 emissions per capita measured in metric tons are also employed. The entire data was freely retrieved from the Global Energy Institute of the United States Chamber of Commerce (Global Energy Institute, 2020).

The annual values of the variables during the sample period can be seen in Fig. 1. By following the study of Hassan et al. (2023), variables are first transformed into their logarithm to ensure homoscedasticity and data smoothening. The annual frequency logarithmic series are converted to the quarterly frequency via the quadratic match-sum method in order to obtain a sufficient number of observations in the empirical analysis as in the studies of Liguo et al. (2022), Razzaq et al. (2022), and Shahbaz et al. (2022).

3.2. Methodology

Sim and Zhou (2015) stated that the relationship between two variables may change at different points in their respective distributions, and therefore, they proposed a nonparametric approach, namely quantile-on-quantile regression (QQR), to assess the relationship between the quantile of a dependent variable and the quantile of an independent variable. Assuming x is the independent variable and y the dependent variable, the QQR model for the relationship between the quantile of y and quantile of x can be written as follows:

$$\underbrace{y_t = \beta_0(\theta, \Phi) + \beta_1(\theta, \Phi)(x_t - x^{\Phi}) + \propto^{\theta} y_{t-1} + {}^{\theta}_{t}}_{*} \tag{2}$$

where θ and Φ represent the quantiles (0,05-0,95) of the dependent and independent variables, respectively, and ϵ_t^{θ} is the error term with a zero θ–quantile. Additionally, part (*) of Eq. (1) captures the overall dependence structure between y and x through the dependence between their respective distributions.[1]

As can be seen from the above-mentioned information, the QQR is a single-variate-based technique. This leads to the ignoring of other important factors that may have effects on the dependent variable in the analysis performed with this technique. Therefore, we have modified the QQR method to include more than one independent variable. Our novel nonparametric multivariate QQR method can assess the relationship between the quantile of the dependent variable and the quantiles of any number of independent variables, thus allowing us to see the pure effect of each variable adjusted for the effects of other variables.

Assuming x_1, $x_2 \ldots x_n$ are the independent variables and y the dependent variable, our multivariate QQR model for the relationship between y and $x's$ across various quantiles (0,05-0,95) can be written as follows:

$$y_t = \beta_0(\theta, \Phi_1, \Phi_2 \ldots \Phi_n) + \beta_1(\theta, \Phi_1)(x_{1t} - x_1^{\Phi_1}) + \beta_2(\theta, \Phi_2)(x_{2t} - x_2^{\Phi_2}) + + \beta_n(\theta, \Phi_n)\left(x_{nt} - x_n^{\Phi_n}\right) + \propto^{\theta} y_{t-1} + \epsilon_t^{\theta} \tag{3}$$

where $\Phi_1, \Phi_2, \ldots, \Phi_n$ represent the quantiles of $x_1, x_2 \ldots x_n$, respectively, θ indicates the quantile of y. Furthermore, the shaded area captures the relationship between the quantile of the dependent variable and the quantiles of the independent variables. However, since the QQR method requires the bandwidth size to be determined optimally, we set the bandwidth to 0.05 for our multivariate QQR method. This process follows the study of Sim and Zhou (2015).

4. Empirical results

In this part of the study, the results of the empirical analysis, the steps of which are shown in Fig. 2, are reported and discussed.

[1] For more details, please see Sim and Zhou (2015).

Fig. 2. Empirical analysis steps.

Table 1
Results of the unit root tests.

	Variables							
	COP		ED		REP		CO_2	
Tests	$\mathscr{L}$	$\triangle$	$\mathscr{L}$	$\triangle$	$\mathscr{L}$	$\triangle$	$\mathscr{L}$	$\triangle$
ADF	-2.740^{*}	-4.650^{***}	-2.859^{*}	-3.810^{***}	-3.389^{**}	-3.253^{**}	-0.101	-4.003^{***}
PP	-2.524	-8.290^{***}	-2.657^{*}	-8.238^{***}	-2.527	-6.857^{***}	0.245	-8.244^{***}
GLS	-0.332	-4.641^{***}	-0.767	-3.802^{***}	-1.063	-3.236^{***}	0.956	-3.070^{***}
ERS	20.250	0.398^{***}	9.384	0.677^{***}	8.150	1.285^{***}	87.865	0.652^{***}

Note: ADF, PP, GLS, and ERS symbolize the t-statistics of the Augmented Dickey-Fuller (Dickey and Fuller, 1979), adjusted t-statistics of the Phillips-Perron (Phillips and Perron, 1988), t-statistics of the Dickey-Fuller Generalized Least Squares (Elliott et al., 1996), and P-statistics of the Elliott-Rothenberg-Stock point-optimal (Elliott et al., 1996) unit root tests, respectively. $\mathscr{L}$ and $\triangle$ represent the level and first difference, respectively. ***, **, and * indicate the rejection of the null hypothesis that the relevant series has a unit root at 1%, 5%, and 10% levels, respectively.

4.1. *Stationarity tests*

In the first stage of the empirical analysis, we try to determine the stationarity levels of the variables. To obtain robust results, we apply four different unit root tests, namely Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Dickey-Fuller Generalized Least Squares (GLS), and Elliott-Rothenberg-Stock (ELS). The results of all unit root tests reported in Table 1 show that the null hypothesis cannot be rejected for the level series but rejected at the 1% significance level for the first difference series. This unveils that each variable has a unit root at level; however, these variables turn stationary at the first difference. Considering these results, the other stages of the empirical analysis will be carried out on the first difference series.

4.2. *Descriptive statistics*

After determining the stationarity properties of the variables, we start to examine the statistical properties of the variables through descriptive statistics. Table 2 exhibits the descriptive statistics of the first difference series. From the table, it is seen that the average of quarterly CO_2 values in the sample period is negative, while that of other variables is positive. Standard deviation values indicate that crude oil has the most volatility during the sample period. The results of the D'Agostino test demonstrate that all variables except CO_2 are statistically skewed. Moreover, the Anscombe and Glynn test results indicate that all variables have excess kurtosis. The results of the Jarque-Bera test also support the results of skewness and excess kurtosis; that is, study variables are non-normally distributed. Finally, the values of the Ljung-Box Q test of order 10 indicate that autocorrelation does not exist in either the first difference or squared first difference series.

Table 2
Descriptive statistics of the first difference series.

	COP	ED	REP	CO_2
Observation	283	283	283	283
Mean	0.002	0.000	0.000	-0.000
Std. Dev.	0.019	0.006	0.002	0.002
Skewness	-0.884^{***}	-1.381^{***}	2.252^{***}	-0.071
ρ value	0.000	0.000	0.000	0.620
Ex. Kurtosis	8.358^{***}	16.093^{***}	13.493^{***}	7.022^{***}
ρ value	0.000	0.000	0.000	0.000
J-B	860.565^{***}	3143.843^{***}	2385.867^{***}	581.715^{***}
ρ value	0.000	0.000	0.000	0.000
Q(10)	163.792^{***}	158.961^{***}	277.855^{***}	187.899^{***}
ρ value	0.000	0.000	0.000	0.000
$Q^2(10)$	44.854^{***}	28.008^{***}	46.682^{***}	55.382^{***}
	0.000	0.000	0.000	0.000

Notes: Skewness represents the D'Agostino (1970) test, Ex. Kurtosis indicates the Anscombe and Glynn (1983) test, J-B stands for the Jarque and Bera (1980) normality test, and Q(10) and $Q^2(10)$ demonstrate the Ljung and Box (1978) serial autocorrelation test. ***, **, and * stand for significance at 1%, 5%, and 10% levels, respectively.

4.3. *(Non)linearity test*

The use of non-linear models on the linear series or linear models on the non-linear series can produce misleading results. In this regard, we employ the Broock-Dechert-Scheinkman [BDS] (Broock et al., 1996) test to investigate (non)linearity characteristics of the variables by following the studies of Dergiades et al. (2013), Galadima and Aminu (2020), Baz et al. (2021), Kassouri et al. (2021), Lahiani et al. (2021), Alola (2022), Oryani et al. (2022), and Wang et al. (2023). The results of the BDS test in Table 3 divulge that the null hypothesis is rejected at the 1% significance level for all variables in all embedded dimensions. This indicates that the study variables exhibit non-linearity. In terms of variable characteristics, it can be concluded that our nonparametric multivariate

Table 3
The results of the BDS test.

Variables	$\mathscr{M} = 2$	$\mathscr{M} = 3$	$\mathscr{M} = 4$	$\mathscr{M} = 5$	$\mathscr{M} = 6$
COP	10.301^{***}	9.395^{***}	8.933^{***}	10.599^{***}	11.810^{***}
ED	11.521^{***}	10.855^{***}	10.706^{***}	11.807^{***}	12.677^{***}
REP	15.473^{***}	15.424^{***}	15.451^{***}	16.801^{***}	18.063^{***}
CO_2	11.370^{***}	10.236^{***}	9.512^{***}	10.901^{***}	11.903^{***}

Note: $\mathscr{M}$ denotes the embedding dimension. ***, **, and * indicate the rejection of the null hypothesis that the relevant series is independent and identically distributed at 1%, 5%, and 10% levels, respectively.

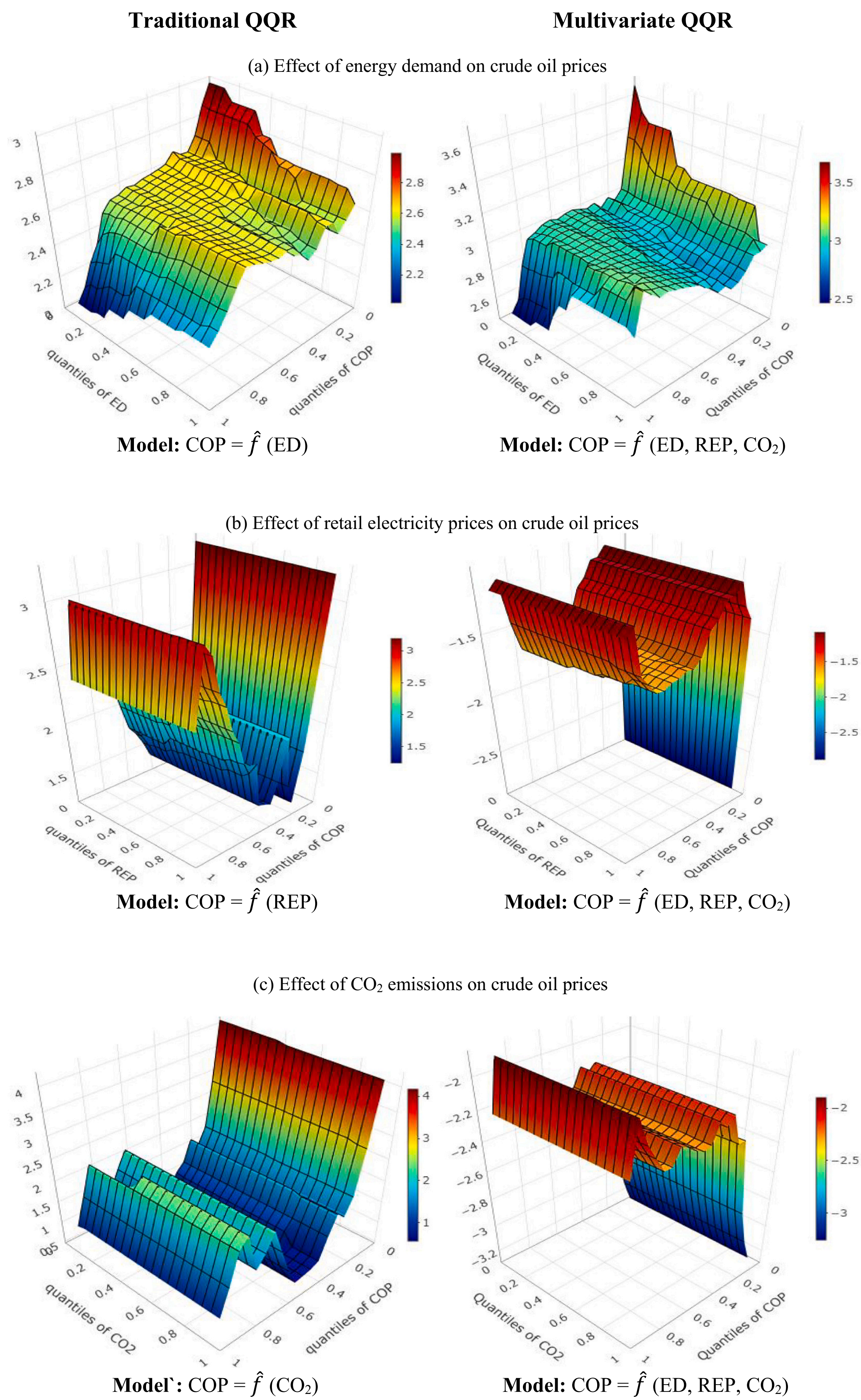

Fig. 3. Traditional and multivariate QQR results.

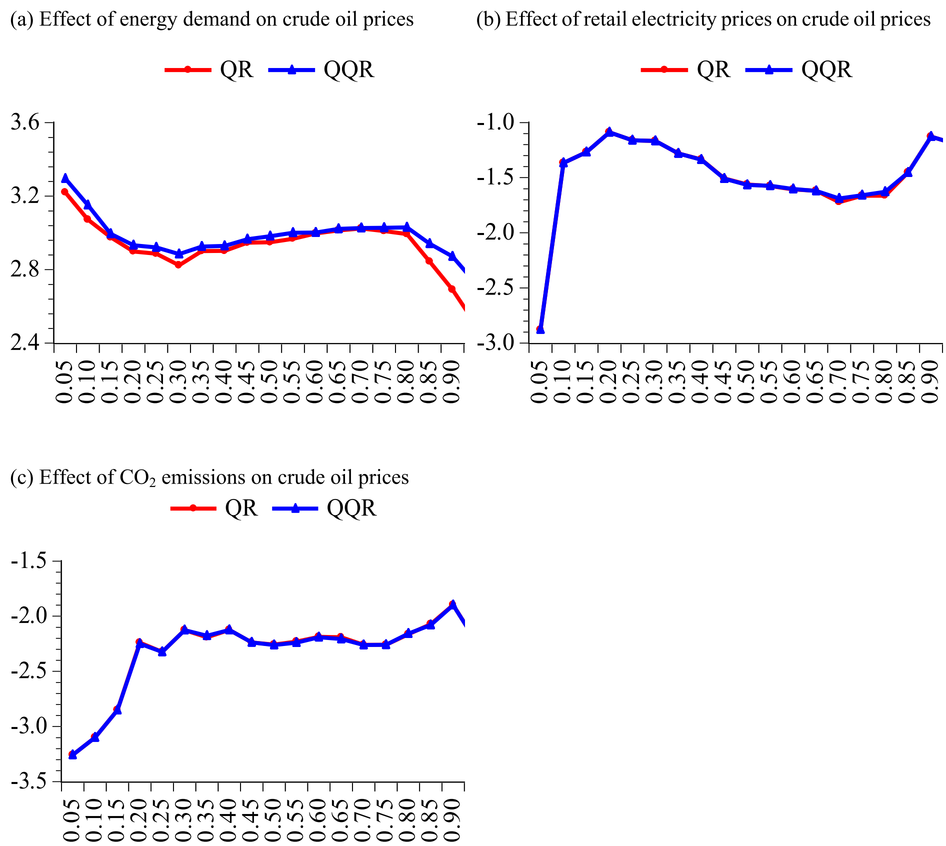

Fig. 4. Multivariate QQR and QR comparison.

QQR is one of the best approaches for this study because it simultaneously accounts for both non-normality and nonlinearity.

4.4. Multivariate quantile-on-quantile regression

This study employs the multivariate QQR to investigate the effect of energy demand on crude oil prices by controlling the effects of retail electricity prices and CO_2 emissions. For the sake of comparison, we also employ the traditional QQR. Both the traditional and our multivariate QQR results are plotted in Fig. 3. The graphs in Fig. 3 clearly show that although both the traditional and multivariate QQR results are similar for the effect of energy demand on crude oil prices, their results are totally different for the effects of retail electricity prices and CO_2 emissions. These results obviously reveal how misleading results can be if the effects of other factors are not considered. Therefore, this finding is consistent with Balcilar et al. (2021a, 2021b) who argued that multivariate nonparametric causality provided better outcomes of the causality relationship because of the incorporation of other dimensions of economic policy uncertainties, namely, global, regional, and advanced markets.

Turning to the multivariate QQR estimations, the results reveal that the effects of energy demand (measured by energy expenditure per household), retail electricity prices, and CO_2 emissions on crude oil prices in the USA vary across quantiles. That is, the effects of these variables on crude oil prices are non-linear. Fig. (3a) shows that the effect of energy demand on crude oil prices is positive, and this effect is quite strong at lower quantiles (0.05–0.15) of crude oil prices, whereas it decreases at higher quantiles (0.80–0.95) of crude oil prices. This result empirically reveals that an increase in energy demand raises crude oil prices in the USA, especially during lower crude oil price periods. This finding which aligns with the result of Wei et al. (2022) implies that prices of crude oil determine the level of the demand for energy in the USA. Therefore, the government can regulate the demand for energy by putting the underlying drivers of prices of crude oil under regulatory check. On the other hand, Figs. (3b) and (3c) demonstrate that the effect of both retail electricity prices and CO_2 emissions on crude oil prices is negative in the USA. A strong negative relationship is evident in the areas which merge all quantiles of retail electricity prices and CO_2 emissions with the lowest quantile of crude oil prices (i.e., 0.05). These imply that the effects of retail electricity prices and environmental indicator are stronger during periods of low crude oil prices. These results empirically divulge that an increase in retail electricity prices and CO_2 emissions declines crude oil prices in the USA, especially during periods when crude oil prices are very low. This result possibly explains that electricity prices are closely associated with crude oil prices in the USA. Therefore, the current results which contradict the findings of Kassouri et al. (2022), are consistent with the study of Ike et al. (2020) that found a causal relationship between oil production and electricity prices in 15 countries that are producing oil in the world and the analogue of energy consumption synchronization in Kassouri et al. (2023). Similarly, the decreasing effect of CO_2 emissions on crude oil energy prices is consistent with Rafindadi and Usman (2021) who found evidence that emissions led to a fall in electricity energy consumption. Meanwhile, environmental, and fiscal policies such as environmental-related taxes and clean energy credits could effectively incentivize the nexus of carbon emissions and energy prices (Doğan et al., 2022).

4.5. Robustness tests

To check the validity of our multivariate QQR estimates, we perform two different robustness tests. First, we utilize the widely employed quantile regression (QR) method for the reliability of traditional QQR estimates (see e.g., Adebayo et al., 2022; Chang et al., 2022; Liu et al., 2022; Pang et al., 2022; Xie and Tang, 2022; Yu et al., 2022). It should be noted that while the single-variate QR method can be applied for the robustness of the traditional QQR, we employ the multivariate QR based

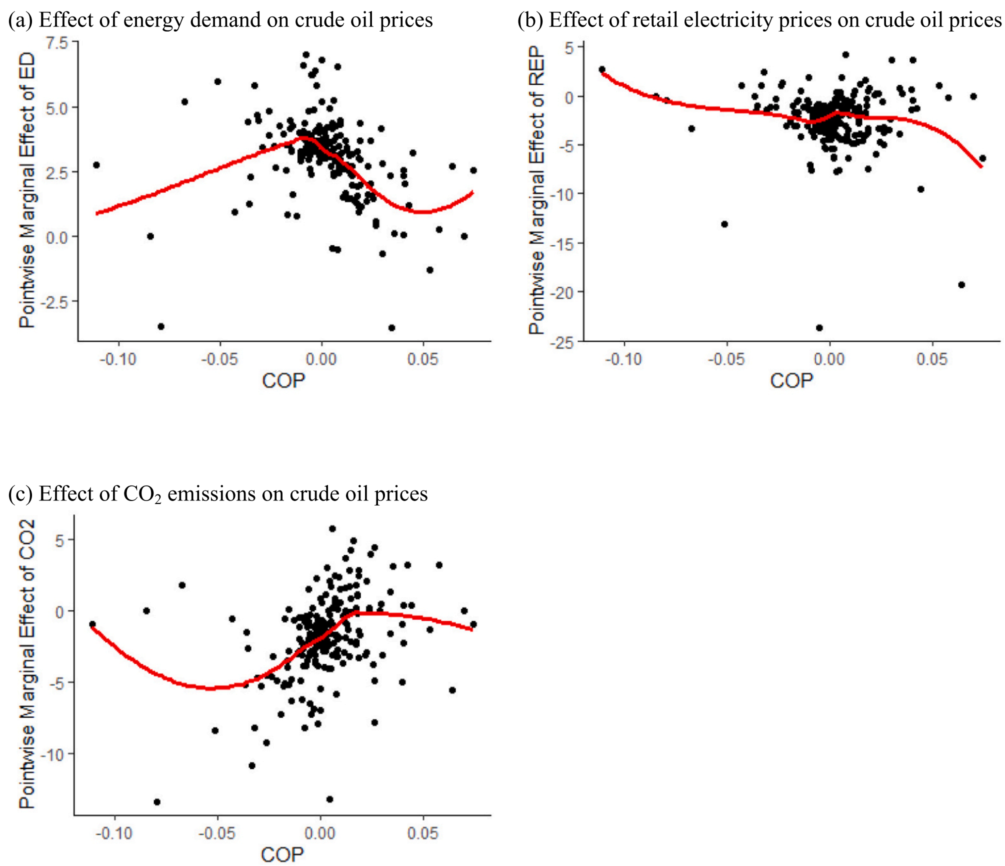

Fig. 5. KRLS pointwise marginal effect plots.

Table 4
KRLS average marginal effect results.

COP	Avg.	Std. error	t-value	ρ value	25%	50%	75%
ED	3.081***	0.145	21.200	0.000	2.979	3.144	3.511
REP	−2.024***	0.370	−5.462	0.000	−3.012	1.371	−0.913
CO_2	−1.834***	0.442	−4.145	0.000	−2.605	−1.846	−1.846
Diagnostics							
R^2	0.904	Lambda	0.172	Sigma	3	Looloss	2.576

Note: ***, **, and * stand for significance at 1%, 5%, and 10% levels, respectively. 25%, 50%, and 75% represent quartiles of marginal effects.

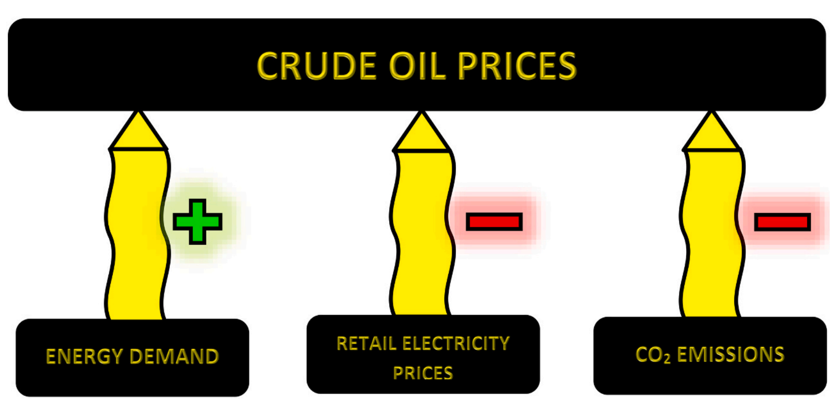

Fig. 6. Summary of the findings.

on the model of COP $=\widehat{f}$ (ED, REP, CO_2) for the robustness of our multivariate QQR. Fig. 4 illustrates the multivariate QR and the average of the multivariate QQR estimates across the quantiles of crude oil prices. It is observed that the trend of both multivariate QR and QQR estimates is quite the same, and this confirms the validity of our multivariate QQR results.

Second, we employ Kernel-based Regularized Least Squares (KRLS) of Hainmueller and Hazlett (2014), a machine-learning algorithm that allows us to detect a non-linear association between the variables by considering the marginal effects of the independent variables at each data point in the covariate space. Fig. 5 shows the pointwise marginal effects of energy demand, retail electricity prices, and CO_2 emissions across data points of crude oil prices, and Table 4 demonstrates the average marginal effect of these variables on crude oil prices. The plots in Fig. 5 indicate that the marginal effects of energy demand, retail electricity prices, and CO_2 emissions vary based on crude oil prices, implying these factors have non-linear effects on crude oil prices. The plots also depict that the effect of energy demand on crude oil prices is positive, while the effect of retail electricity prices and CO_2 emissions is negative in the USA. Table 4 reveals that, on average, a 1% increase in energy demand increases crude oil prices by 3.081%, whereas a 1% surge in retail electricity prices and CO_2 emissions decreases crude oil prices by −2.024% and − 1.834% in the USA, respectively. It is observed that the results of the KRLS also support our multivariate QQR results.

Finally, we summarize the study findings in Fig. 6. From the figure, it is observed that energy demand has a non-linear positive effect on crude oil prices in the USA, while retail electricity prices and CO_2 emissions have a non-linear negative effect on crude oil prices. A 1% increase in energy demand escalates crude oil prices. Conversely, a 1% increase in retail electricity prices and CO_2 emissions have lowered crude oil prices. Consistent with these findings, we offer several policy implications for the USA.

5. Conclusion and policy implications

Over the years, economists and researchers have unanimously accepted that the shocks to crude oil prices determine the state of a country's economy. In other words, crude oil prices significantly affect macroeconomic variables. To this extent, this paper examines the dynamics of crude oil price outlook amidst energy price substitutes such as retail electricity prices and environmental indicators in the USA over the period 1970–2040. One advantage of this paper is its capacity to explain changes in crude oil prices by incorporating forecasted data series. In addition, our study applies the usual bivariate QQR and compared the results with the estimates of a novel multivariate QQR. The empirical results suggest that the effect of energy demand is quite indifferent across different quantiles both in the bivariate and multivariate QQR results. However, for the multivariate QQR, significant differences exist regarding the effects of retail electricity prices and environmental indicators on crude oil prices across quantiles with evidence of stronger effects noticed in the lower quantiles. This suggests that the negative effects of retail electricity prices and environmental indicators are stronger during periods of low crude oil prices in the USA. Furthermore, from the multivariate QQR, it is found that energy demand, retail electricity prices, and CO_2 emissions have time-varying effects across quantiles. While energy demand increases crude oil prices with a stronger effect at the lower quantiles and decreases at higher quantiles, retail electricity prices and retail electricity prices and CO_2 emissions exert a negative effect on crude oil prices with evidence of a stronger effect in the mid quantiles. In addition, an increase in retail electricity prices and CO_2 emissions decreases the U.S. crude oil prices during periods crude oil prices are very low. These results are robust to the Kernel-based Regularized Least Squares (KRLS) and the quantile regression (QR).

5.1. Policy implication

Based on the findings of this paper, the following policy implications are crafted to mitigate the effects of shocks to energy demand, retail electricity price, and environmental indicators on crude oil price in the USA: First, the fact that energy demand, retail electricity price, and environmental indicator have different effects across the quantiles suggest the need for the government and policymakers to carefully address the macroeconomic effects of these variables on crude oil price based on time variances. In other words, policy thrusts of the government should be dependent on the direction and size of the effect of energy demand, retail electricity price, and environmental indicators on crude oil prices at a time. Therefore, this finding calls for time-varying policies to adequately reduce and stabilize crude oil prices. Second, the positive effect of energy demand on crude oil prices suggests that changes in crude oil prices are positively dependent on the level of energy expenditures in the USA. Therefore, to reduce the price of crude oil in the country without reducing energy demand, governments and policymakers need to design policies that encourage energy production and consumption such as providing incentives for energy production and consumption. Once incentives are provided in the energy sector, crude oil prices can be fixed by the government or allow market forces to determine the price of crude oil. Third, since retail electricity price has a negative effect on crude oil prices, it shows that to reduce the impact of volatility in crude oil prices, macroeconomic policies should be focused on stimulating retail electricity, especially from alternative energy sources in the USA. For instance, the proportion of electricity utilization from the total electricity generated in the USA could be increased through scaling up investment in clean and renewable energy sources such as wind, solar, nuclear, and hydropower. Fourth, the negative effect of CO_2 emissions on the price of crude oil during the period of low prices of crude oil suggests the effectiveness of policies of decoupling environmental degradation from crude oil production in the country. Thus, the pathway to carbon neutrality which supposedly offers a niche in the energy transition plan in the country should be strengthened through more stringent environmental-related policies such as clean energy credit and environmental tax.

5.2. Limitation and future implementation

Despite the exciting policy recommendations that emanate from this investigation, there are visible limitations that could be improved upon in future implementation. For instance, there is a limited number of variables that span the 2040 period which restricts the control for relevant factors such as economic and financial uncertainties in the model. Thus, while the future study could consider and control for other factors, two sub-periods such as 1970–2022 and 1970–2040 could also be employed for sensitivity checking and the reason for temporal insights. Lastly, the current study implements CO_2 emissions, except for data availability issues, future studies could consider other environmental indicators such as ecological footprint and greenhouse gas (GHG) emissions.

CRediT authorship contribution statement

Andrew Adewale Alola: Data curation, Writing – original draft, Writing – review & editing, Validation, Conceptualization. **Oktay Özkan:** Writing – original draft, Investigation, Methodology, Formal analysis. **Ojonugwa Usman:** Writing – original draft, Formal analysis, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106613.

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