

# Revisiting Crude Oil Prices and Energy Indices Returns Nexus



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**K Kokila**  
**Shaik Saleem**  
VIT University

(kokilakalimuthu@gmail.com)  
(saleemshaik57@gmail.com)

*Crude oil plays a crucial role in fueling the world economy and driving the global commodity market. This study focuses on examining how different energy indices retort to changes in WTI oil prices. The researchers utilized daily data of WTI crude oil and four energy stock indices: the Nifty Energy Index, BSE Energy Index, MSCI World Energy Index, and S&P Energy Index. The empirical findings reveal that the BSE energy and NSE energy indices are less sensitive to crude oil price changes compared to the MSCI World Energy Index and S&P 500 energy index.*

**Keywords:** WTI Crude Oil, BSE Energy Index, NSE Energy index, MSCI World Energy Index, S&P 500 Energy

## 1. Introduction

Energy is the core pillar of our world and a vital part of everyone's existence. Both industrialized and emerging market economies (Xi et al., 2019) have seen a major impact of energy on several economic factors. Oil has a vital role (Halttunen et al., 2022) in social and economic activities compared to other important energy sources like natural gas and coal since it is the most significant source of producing heat and electricity, the primary fuel for vehicles, ships, and airplanes; a vital raw ingredient for petroleum products; and an industry staple in the textile and chemical sectors. The global energy market is intricate and ever-changing, with crude oil at its core, often called "black gold" due to its essential role in driving economic activity. As a result, changes in crude oil prices can have profound and widespread effects on economic stability, energy security, and the financial performance of energy-related assets. So crude oil is highly valued in every country and is an important asset in many investors' portfolios (Ahmad, 2017). Energy indices, which track the performance of various energy-related assets, including stocks of energy companies, commodities, and other financial instruments, provide a comprehensive measure of the sector's health. These indices are used by investors, policymakers, and industry stakeholders to assess the energy market's performance and make informed decisions. Understanding the relationship between crude oil prices and these energy indices return is crucial for predicting market trends, managing risks, and developing strategic plans for investors. These indices serve as crucial tools for investors, to evaluate the energy market's performance and make well-informed decisions. Grasping the relationship between crude oil prices and these energy indices is essential for predicting market trends, mitigating risks, and developing effective strategic plans.

The paper aims to explore how crude oil prices affect energy indices, considering the growing consumption of crude oil worldwide. Specifically, it focuses on four energy indices: the Nifty Energy Index (NEI) and BSE Energy Index (BEI), (representing domestic energy indices), as well as the MSCI World Energy Index (MEI) and S&P 500 Energy Index (SEI) (representing global indices). The NEI is a thematic index listed on the NSE that tracks the performance of the energy sector within the Indian economy. This index is composed of various aspects of the energy industry, including petroleum, natural gas, power generation, and related sectors. The BEI is specifically crafted to serve as a benchmark for investors. It aims to mirror the performance of companies listed in the S&P BSE All Cap index that fall under the category of the energy sector. The MEI is constructed to encompass the significant and mid-sized companies operating within twenty-three Developed Markets countries. All the securities included in this index are categorized under the Energy sector according to the Global Industry Classification Standard. This index, therefore, provides a representation of the performance of energy-related companies across a wide range of developed economies. Finally, The SEI is composed of companies that are part of the S&P 500 and fall under the classification of the Global Industry Classification Standard energy sector. While previous studies have investigated the connection between crude oil prices and energy indices returns, this paper distinguishes itself by examining both domestic and global indices return. To achieve this, the study employs a quantile-based regression approach, which differs from previous research that primarily examined the connection between crude oil prices and energy indices. By utilizing this approach, the paper aims to provide a more comprehensive understanding of the dependence structure between the variables across different market conditions. The subsequent sections of the study are outlined as follows: Segment 2 provides a concise overview of relevant literature studies, Segment 3 discusses the research methods and data utilized, Segment 4 presents the empirical results, and Segment 5 concludes the study by summarizing key findings and policy implications.

## 2. Review of Literature

Crude oil is an unprocessed natural commodity sourced from the Earth, and it undergoes refinement to create various items like gasoline, aviation fuel, and additional petroleum-based products. It consists primarily of hydrocarbon deposits and organic substances derived from ancient plant and animal remains dating back millions of years. Additionally, it serves as a significant energy source, producing heat and propelling a wide range of vehicles and machinery. Furthermore, it plays a vital role as an ingredient in numerous everyday products, such as plastics, paints, and cosmetics. The influence of crude oil prices on the energy sectors has been examined in previous studies from a variety of angles. One area of study focused on crude oil prices and stock return link which is investigated by Chen et al. (2022); Rahman, (2022); Anand and Paul (2021); Alamgir and Amin (2021); Joo and Park (2021); Cevik et al. (2020); Salisu and Isah (2017); Ghosh and Kanjilal (2016); Zhu et al. (2016); Kang et al. (2015); Sim and Zhou (2015); Xu et al. (2019); You et al. (2017) and Driesprong et al. (2008). Other researchers have conducted analyses to understand the association between oil prices and alternative energy sources, such as the works of Maghyereh and Abdoh (2021); Geng et al. (2021); Nasreen et al. (2020); Kocaarslan and Soytas (2019); Xia et al. (2019); Ferrer et al. (2018); Abdallah and Ghorbela (2018); Reboredo et al. (2017) and Bondia et al. (2016). While others concentrated on the relationship between crude oil prices and energy-related commodities returns. This literature includes Babu et al. (2023); Ben Ameer et al. (2022); Asl et al. (2021); Mensi et al. (2021); Tiwari et al. (2021a); Tiwari et al. (2021b); Gatfaoui, (2016); Aloui et al. (2014) and Tong et al. (2013). Portfolio diversification and hedging strategies receive considerable attention from researchers. Several studies have specifically focused on calculating hedge ratios for clean energy stocks. Noteworthy among these works are Gustafsson et al. (2022); Antonakakis et al. (2020); Elsayed et al. (2020); Bunnag, (2015) and Hamma et al. (2014).

Bouoiyour et al. (2023) investigated the connection between crude oil and various renewable energy sector stock indices. Their findings revealed that the relationship between crude oil and these renewable energy indices is characterized by non-linearity and complexity. Furthermore, their analysis led them to conclude that the strength of the relationship between crude oil and wind energy is weaker when compared to the relationships involving geothermal energy or bioenergy, and this variation varies across different scales. A separate study conducted by Troster et al. (2018) interrogated the association between renewable energy consumption, oil prices, and economic activity. Their research uncovered the relationship between shifts in renewable energy consumption and economic growth at the lower end of the distribution. Additionally, they observed that variations in renewable energy consumption drive economic progress at the higher end of the distribution. Zhang et al. (2020) examined the influence of exogenic shocks of oil prices on clean energy stocks. Their conclusions showed that these shocks had different consequences at different quantiles and investment horizons. They also noticed the influence was asymmetric, especially at higher quantiles, which suggests long-term impacts. Pham, (2019) explored the association between oil prices and clean energy stocks across various sub-sectors within the clean energy stock market. The study found that the relationship between oil prices and clean energy stocks was not consistent across all sectors. In fact, the findings indicated significant variations in this relationship across different clean energy-related stocks. Mainly, biofuel and energy management stocks demonstrated the highest level of correlation with oil prices, indicating a strong connection. On the other hand, wind, geothermal, and fuel cell stocks were among the sub-sectors with the least correlation to oil prices, suggesting a weaker connection between these stocks and oil price fluctuations. Mugaloglu et al. (2021) explored the connection between global oil prices, the stock market, and the returns of the FTSE Oil & Gas Index during the COVID-19 period. The study's findings suggested that global oil price shocks had a relatively limited impact on the returns of the FTSE Oil & Gas Index. However, it was observed that shocks in the stock market had a more pronounced effect, leading to increased variations in the returns of the FTSE Oil & Gas Index. In essence, this indicates that stock market movements played a more influential role in determining the performance of the FTSE Oil & Gas Index during the specified COVID-19 period. Corbet et al. (2020) in their study, investigated the presence of volatility spillovers and co-movements among energy-focused corporations during the covid-19 pandemic. They utilized the spillover index approach developed by Diebold and Yilmaz and employed the DCC-FIGARCH conditional correlation framework. Their findings revealed that there were significant and positive spillovers from declining oil prices to both the renewable energy and coal markets. This suggests that variations in oil prices had a notable impact on the volatility of these sectors. Additionally, the researchers highlighted the renewable energy sector as a more dependable means of generating long-term, stable, and cost-effective supply compared to other energy sources. Dutta, (2017) investigated the impact of oil price shocks on clean energy stock returns. The study concluded that there is a strong relationship between crude oil volatility and clean energy stock market returns. This indicates that the performance of clean energy stocks is highly sensitive to changes in crude oil prices and their associated volatility. There are some studies that concentrate on the small level, specifically company stock or indices (Tan et al., 2021; Niu et al., 2021; Ma et al., 2019; Song et al., 2019). However, some studies discussed the crude oil return in view of positive and negative returns to analyse their differences with regard to data spillover to diverse clean energy companies. Singhal and Ghosh (2016) delved into the relationship between crude oil movements and returns in the Indian stock market. The study's findings discovered that there is not a significant direct transfer of shocks from the oil market to the overall Indian stock market. However, the significance becomes apparent when focusing on specific sectors, particularly the automobile, power, and finance sectors. This research underscores the importance of volatility as a factor for investors seeking to diversify their portfolios with the aim of optimizing returns and mitigating risks.

Most existing research tends to aggregate energy indices or focus on broad measures of market performance, without delving into how specific energy indices—such as those tracking oil and gas companies, renewable energy sources, or energy commodities—respond differently to fluctuations in crude oil prices. This lack of detailed analysis highlights a significant gap

in understanding how different segments of the energy sector are individually affected by changes in crude oil prices. Addressing this gap requires a more nuanced investigation into which specific energy indices are most sensitive to these price fluctuations. By exploring this area, the study aims to provide valuable insights for investors, policymakers, and industry professionals seeking to understand the varied impacts of crude oil price changes across different energy sector segments.

### 3. Methodology

The study uses the WCO (WTI crude oil price) and four energy indices namely, the NEI, BEI, MEI, and SEI. The sample period ranges from 1 January 2013 to 31 May 2023, providing 2483 daily observations which are sourced from BSE and NSE official websites (BSE Energy Index, Nifty Energy Index), Federal Reserve Bank of St. Louis (MSCI World Energy Index), and investing.com (S&P500 Energy Index). The data was filtered to correspond to the trading days in all markets. The assessment of variable stationarity in the model is conducted through the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests applied to each individual series. The results indicate that the alternative hypothesis is supported, affirming that the series exhibits stationarity at the base level.

#### 3.1 Quantile Regression

The study employed the quantile regression approach to investigate the association between crude oil price fluctuations and the earnings of four energy indices. The linear model-based ordinal least squares (OLS) regression focuses on estimating the conditional mean of the dependent variable  $y$  given the explanatory variable  $x$ . Quantile regression, initially developed by Koenker and Bassett in 1978, offers a technique for estimating conditional quantiles of the variable  $y$  based on one or more explanatory factors. Its robustness in estimating the quantile regression process sets it apart, even when dealing with challenges like outliers, heteroskedasticity, and skewness in the dependent variables. This method has been widely utilized in finance and economics research (Anguyo et al., 2020; Ma et al., 2019; Gupta et al., 2017; Fenget al., 2008; Ma et al., 2008; Englet al., 2004).

The basic Quantile Regression equation is as follows

$$Q_{\tau}(Y_i/X) = \beta_{0i} + \beta_{1i}X + \epsilon_{\tau i} \quad (1)$$

Here

- $Q_{\tau}(Y_i/X)$  is the  $\tau^{\text{th}}$  conditional quantile of the energy indices,  $Y_i$ , given the independent variable  $X$  (crude oil).
- $\beta_{0i}$  is the intercept for the quantile regression of the  $i^{\text{th}}$  energy indices.
- $\beta_{1i}$  is the slope coefficient for crude oil in the quantile regression of the  $i^{\text{th}}$  energy indices.
- $X$  is the crude oil price.
- $\epsilon_{\tau i}$  is the error term for the  $\tau^{\text{th}}$  quantile regression of the  $i^{\text{th}}$  energy indices.

The Quantile regression model for each energy indices is as follows.

$$Q_{\tau}(NEI/X) = \beta_{0NEI}(\tau) + \beta_{1NEI}(\tau)X + \epsilon_{\tau NEI} \quad (2)$$

$$Q_{\tau}(BEI/X) = \beta_{0BEI}(\tau) + \beta_{1BEI}(\tau)X + \epsilon_{\tau BEI} \quad (3)$$

$$Q_{\tau}(MEI/X) = \beta_{0MEI}(\tau) + \beta_{1MEI}(\tau)X + \epsilon_{\tau MEI} \quad (4)$$

$$Q_{\tau}(SEI/X) = \beta_{0SEI}(\tau) + \beta_{1SEI}(\tau)X + \epsilon_{\tau SEI} \quad (5)$$

The nine quantiles (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9) were taken into account in the study. The normal market situation is represented by the median (0.5) quantile. Lower quantiles, such as 0.1, 0.2, 0.3, and 0.4, show bearish market conditions, whereas higher quantiles, such as 0.6, 0.7, 0.8, and 0.9, show bullish market trends. Under various market scenarios (bearish, normal, and bullish), oil prices have a tendency to behave differently; therefore, it is crucial to know how energy indices retort to oil price surprises under these circumstances. In order to achieve this, the quantile regression method is a useful tool since it enables to explore of the impact of independent factors on various distributions of dependent variables.

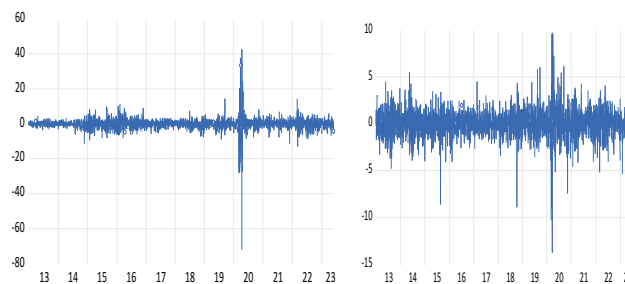


Figure 1 WTI Crude Oil Return

Figure 2 BSE Energy Indices Return

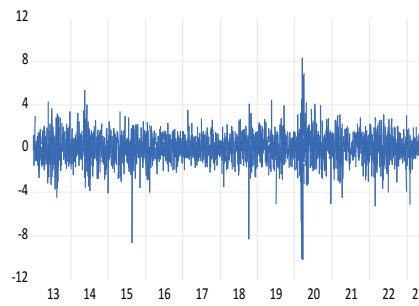


Figure 3 NSE Energy Indices Return

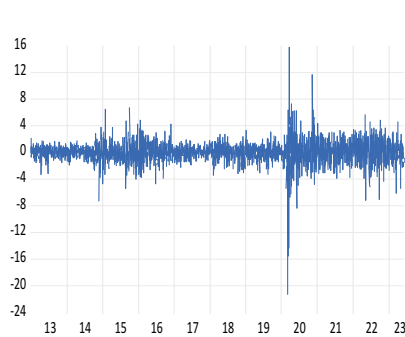


Figure 3 MSCI Energy Indices Return

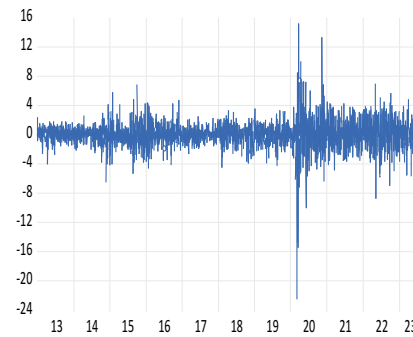


Figure 3 S&P 500 Energy Indices Return

#### 4. Results and Discussion

The quantile regression approach offers a more comprehensive examination of the entire conditional distribution, in contrast to the conditional mean regression analysis, which concentrates solely on a specific part of the conditional distribution. Moreover, a quantile causal relationship can differ from causality in the mean of the conditional distribution. This study investigates the association between crude oil prices and the returns of energy indices. Table 1 displays the descriptive statistics for WCO price and four energy indices' average daily returns. WCO return and MEI return are volatile compared to the NEI, BEI, and SEI. All the return series are negatively skewed and show a Leptokurtosis distribution. The outcome of the ADS and PP tests indicates that the return sequence is stationary at a 5% level of significance

Table 1 Summary of Statistics and Stationarity test of the Indices

Variables	NEI	BEI	MEI	SEI	WCO
Mean	0.045	0.051	-0.003	0.005	-0.011
Median	0.073	0.086	0.011	0.028	0.080
Standard Deviation	1.347	1.479	1.663	1.881	3.493
Kurtosis	5.766	8.763	22.185	16.372	98.543
Skewness	-0.596	-0.445	-1.138	-0.831	-2.513
ADF test	-49.188*	-49.762*	-28.064*	-29.265*	-25.342*
PP test	-49.206*	-49.773*	-47.815*	-51.428*	-56.876*

Source: Author's Computation

Note: \*Statistically Significant at 5% level

Table 2 illustrates the association between the WCO price and the returns of energy indices. A 1% increase in the median crude oil price corresponds to a 34% increase in the median value of the SEI. The Pseudo R<sup>2</sup> is recorded at 16.4%, and the adjusted R-squared mirrors this figure, signifying that approximately 16.4% of the variations in the conditional median of the SEI can be attributed to fluctuations in WCO prices. The quasi-LR statistics value stands at 821.285, and its associated p-value is below 0.05, indicating the stability of the model.

Table 2 WTI Crude Oil Price and Energy Indices Return

Variables	BEI	NEI	MEI	SEI
WCO	0.037	0.030*	0.315*	0.340*
Constant	0.083	0.060	0.010	-0.008
Pseudo R <sup>2</sup>	0.033	0.004	0.186	0.164
Adjusted R <sup>2</sup>	0.002	0.003	0.185	0.164
Q-LR stat.	12.083	14.614	954.446	821.285

Source: Author's Computation.

Note: \*Statistically Significant at 5% Level

Similarly, a 1% increase in the median crude oil price predicts a roughly 31.5% increase in the median value of the MEI. The Pseudo R<sup>2</sup>, representing the model's goodness of fit, is 18.6%, while the adjusted R-squared closely aligns at 18.5%. This implies that about 18.5% of the variability in the conditional median of the MEI can be attributed to shifts in WCO prices. The quasi-LR statistics value is calculated as 954.446, and the associated p-value is less than 0.05, confirming the statistical reliability of the model.

However, it is imperative to note that the impacts of WCO changes on the BEI and NEI differ from those on the MEI and SEI. These two indices exhibit a lesser influence from crude oil price fluctuations. All indices show positive and statistically significant effects except for the BEI, suggesting that the BEI and NEI are less susceptible to changes in crude oil prices compared to the MEI and SEI.

Table 3 Quantile Regression Results

Quantile	Low			Medium			High		
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
<b>BEI</b>									
WCO ret.	0.064*	0.039*	0.040*	0.038*	0.037	0.025	0.016*	0.019*	0.027*
Constant	-1.563	-0.925	-0.502	-0.222	0.083	0.367	0.664	1.069	1.635
<b>NEI</b>									
WCO ret.	0.331*	0.341*	0.338*	0.326*	0.315*	0.317*	0.323*	0.322*	0.305*
Constant	-1.317	-0.763	-0.443	-0.208	0.010	0.214	0.457	0.769	1.308
<b>MEI</b>									
WCO ret.	0.068*	0.059*	0.040*	0.037*	0.030*	0.028*	0.030*	0.036*	0.036*
Constant	-1.498	-0.904	-0.497	-0.190	0.060	0.346	0.662	1.031	1.586
<b>SEI</b>									
WCO ret.	0.351*	0.370*	0.368*	0.348*	0.340*	0.348*	0.343*	0.340*	0.321*
Constant	-1.542	-0.898	-0.523	-0.237	-0.008	0.263	0.540	0.875	1.572

Source: Author's Computation.

Note: \*Statistically Significant at 5% Level.

Table 3 reveals that various energy indices respond contrarily to the lagged value of crude oil returns. The results from the Quantile Regression analysis indicate that the influence of WCO tends to diminish as we move to lower quantiles. In fact, the model fits much better in lower quantiles (0.1, 0.2, 0.3, 0.4), suggesting that the influence of crude oil on the Energy Indices is more pronounced during bearish market conditions but less significant during bullish market conditions (higher quantiles). Nevertheless, the influence of WCO on the NEI, MEI, and SEI remains significant across normal, bullish, and bearish market conditions. For the BEI, significance is observed in most quantiles except for 0.5 and 0.6 quantiles. However, in the higher quantiles, specifically during rising market conditions, the reliance of energy stocks on crude oil prices appears to diminish. This indicates that when market conditions are improving, changes in crude oil prices have a lesser impact on energy stock returns. Conversely, during market downturns, the reliance of energy stocks on crude oil prices increases.

In summary, the consequence of crude oil on energy indices is more pronounced in bearish market conditions but feebler in bullish market conditions. Visual representations of these findings can be seen in Figures 6,7,8 and 9.

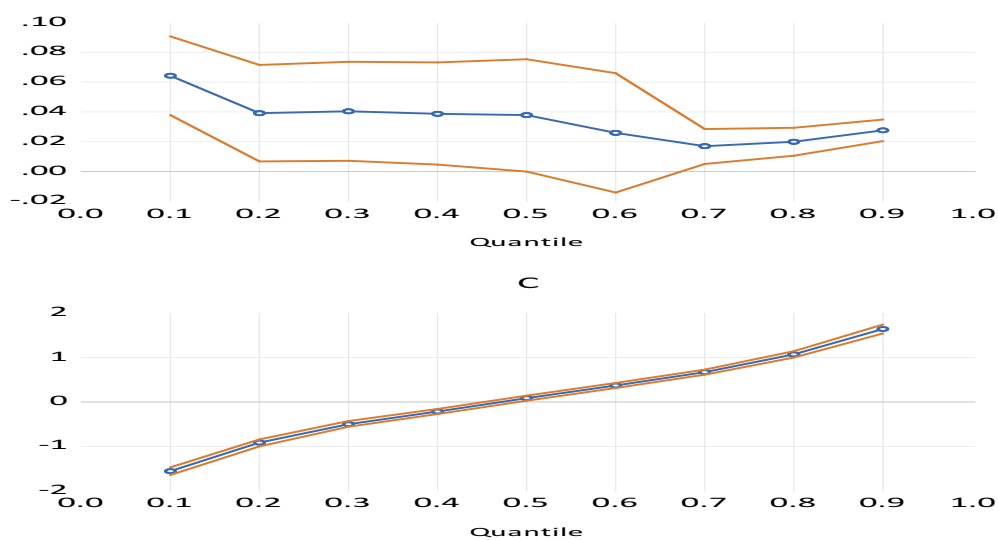


Figure 6 Quantile Estimates -WTI Crude Oil and BSE Energy Index

Note: The above figure depicts the influence of West Texas Intermediate (WTI) on the BSE Energy index, organized into ten quantiles. The thin blue line denotes the estimated values, and the red lines represent the 95% confidence interval.

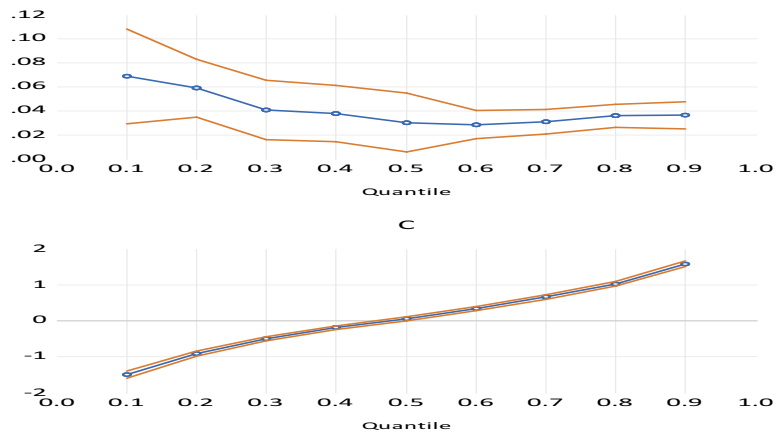


Figure 7 Quantile Estimates - WTI crude oil and NSE Energy

**Note:** The above figure depicts the influence of West Texas Intermediate (WTI) on the NSE Energy index, organized into ten quantiles. The thin blue line denotes the estimated values, and the two red lines represent the 95% confidence interval.

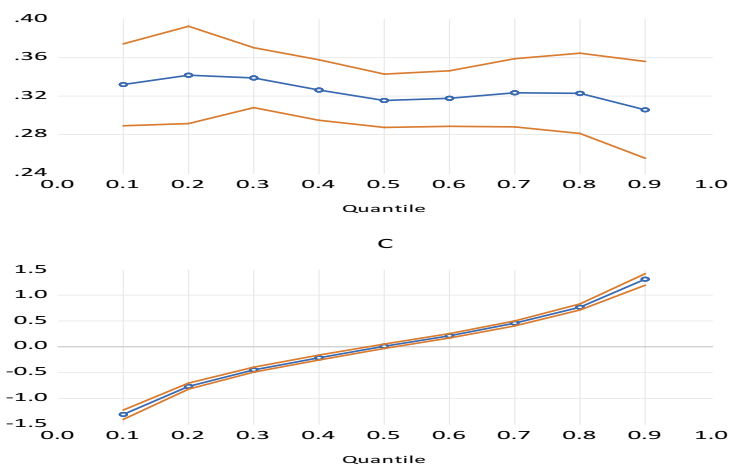


Figure 8 Quantile Estimates - WTI crude oil and MSCI World Energy

**Note:** The above figure depicts the influence of West Texas Intermediate (WTI) on the MSCI World Energy Index, organized into ten quantiles. The thin blue line denotes the estimated values, and the two red lines represent the 95% confidence interval.

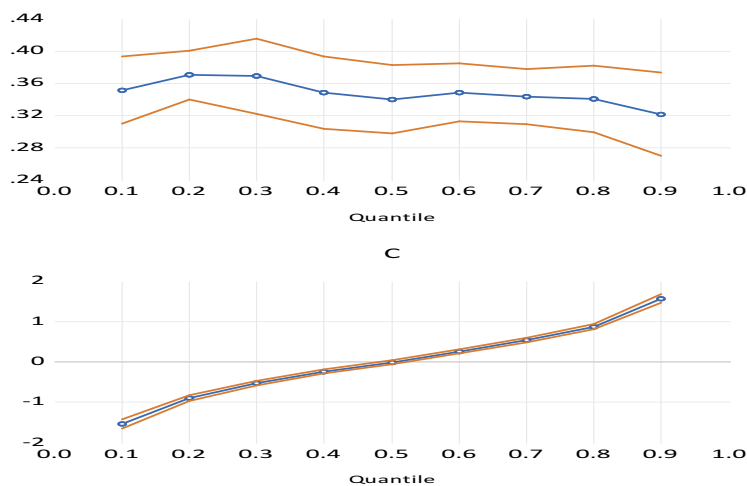


Figure 9 Quantile Estimates - WTI crude oil and S&P 500 Energy

**Note:** The above figure depicts the influence of West Texas Intermediate (WTI) on the S&P Energy index, organized into ten quantiles. The thin blue line denotes the estimated values, and the two red lines represent the 95% confidence interval.



**Table 4** *Quantile Slope Equality Test*

Indices	BEI		NEI		MEI		SEI	
	Chi squ.	P	Chi squ.	P	Chi squ.	P	Chi squ.	P
<b>Across quartiles</b>	20.942	0.007*	11.032	0.199	4.616	0.797	6.187	0.626
<b>Wald test</b>	20.942	0.007*	11.032	0.199	4.616	0.797	6.187	0.626
<b>Inter quantiles</b>	Res.val.	Prob.	Res.val.	Prob.	Res.val.	Prob.	Res.val.	Prob.
<b>0.1, 0.2</b>	0.025	0.045*	0.009	0.515	-0.010	0.607	-0.018	0.248
<b>0.2, 0.3</b>	-0.001	0.910	0.018	0.034*	0.002	0.861	0.001	0.932
<b>0.3, 0.4</b>	0.001	0.880	0.002	0.704	0.012	0.209	0.020	0.167
<b>0.4, 0.5</b>	0.001	0.922	0.007	0.316	0.010	0.239	0.008	0.532
<b>0.5, 0.6</b>	0.011	0.334	0.001	0.839	-0.002	0.798	-0.008	0.489
<b>0.6, 0.7</b>	0.009	0.569	-0.002	0.513	-0.005	0.578	0.005	0.647
<b>0.7, 0.8</b>	-0.003	0.415	-0.005	0.142	0.001	0.952	0.002	0.832
<b>0.8, 0.9</b>	-0.007	0.029*	-0.001	0.942	0.016	0.391	0.019	0.343

**Source:** Authors Computation.

**Note:** \*Statistically Significant at 5% Level.

Table 4 presents the results of the Quantile Slope Equality Test. According to the Wald test, the Chi-square statistic for the slope equality test regarding BEI is 20.942, indicating statistical significance. This suggests that the equality of slopes varies across different quantile levels. Specifically, the BEI inter-quantile range, except for the 0.1-0.2 and 0.8-0.9 quantiles, fails to reject the null hypothesis of equality at a 5% significance level. This implies that there is no significant difference in slope equality across these quantile levels. On the other hand, for NEI, MEI, and SEI, the Wald test results do not achieve statistical significance. Therefore, we can conclude that there is no significant difference in slope equality across quantile levels for these indices. Similarly, when examining inter-quantile results, it is found that for NEI (except for the 0.2 and 0.3 quantiles), MEI, and SEI, the results are not statistically significant. Consequently, we can conclude that the slope equality for these indices does not differ significantly across inter-quantile ranges.

This study investigates the symmetrical impacts of WCO returns on the returns of various energy indices through Quantile Regression. The findings are presented in Table 6. The Wald test reveals that the Chi-square statistics for the symmetric quantiles of BEI (11.658), NEI (11.122), MEI (4.384), and SEI (9.452) are not statistically significant. This lack of statistical significance indicates evidence of symmetry since the p-values are greater than 0.05.

**Table 5** *Symmetric Quantiles Test*

Symmetric qua. test	BEI		NEI		MEI		SEI	
	Chi squ.	P	Chi squ.	P	Chi squ.	P	Chi squ.	P
<b>Across quartiles</b>	11.658	0.167	11.122	0.194	4.384	0.820	9.452	0.305
<b>Wald test</b>	11.658	0.167	11.122	0.194	4.384	0.820	9.452	0.305
<b>Inter quantiles</b>	Int.qua.	Prob.	Int.qua.	Prob.	Int.qua.	Prob.	Int.qua.	Prob.
<b>0.1, 0.9</b>	0.016	0.635	0.044	0.082	0.006	0.840	-0.006	0.870
<b>C</b>	-0.094	0.170	-0.033	0.621	-0.030	0.670	0.046	0.550
<b>0.2, 0.8</b>	-0.016	0.607	0.034	0.085	0.033	0.246	0.030	0.363
<b>C</b>	-0.022	0.656	0.005	0.909	-0.015	0.690	-0.007	0.871
<b>0.3, 0.7</b>	-0.018	0.506	0.011	0.513	0.031	0.096	0.032	0.243
<b>C</b>	-0.003	0.919	0.043	0.235	-0.007	0.800	0.033	0.308
<b>0.4, 0.6</b>	-0.010	0.541	0.005	0.656	0.013	0.307	0.019	0.380
<b>C</b>	-0.020	0.424	0.035	0.160	-0.015	0.427	0.022	0.060

**Source:** Authors Computation.

**Note:** \*Statistically Significant at 5% Level.

Furthermore, the individual coefficient restriction tests provide no indications of asymmetry within the selected indices across the quantiles. For instance, when examining BSE energy across the quantile levels ranging from 0.1 to 0.9, there is no statistically significant evidence of asymmetry.

## 5. Conclusion

The swift ascent of emerging markets and the growing significance of developing countries have led to an amplified demand for crude oil. According to assessments by the 'International Energy Agency' and the 'International Monetary Fund', fluctuations in crude oil prices have generated more pronounced economic shocks in developing economies compared to developed ones. This study delves into the impact of shifts in WTI crude oil prices on the returns of energy indices. The approach employed to assess the distribution of the dependent variable (energy indices return) involves the utilization of quantile regression. This technique offers a comprehensive insight into how independent variables influence the dependent variable. Unlike conventional OLS regression, which examines average effects, quantile regression unveils the asymmetric consequences of changes in crude oil prices on energy indices returns across assorted market conditions, encompassing bearish, bullish, and normal periods.

Drawing on daily data spanning from January 1, 2013, to May 31, 2023, the empirical findings highlight that the BEI and NEI exhibit comparatively lower susceptibility to fluctuations in crude oil prices when contrasted with the MEI and SEI. The

quantile regression outcomes reveal that the impact of WCO tends to weaken as quantiles decrease, suggesting that the influence of crude oil on Energy Indices is more pronounced amid bearish market conditions but less so during bullish market conditions (higher quantiles). These conclusions align with and complement earlier research conducted by Xia et al. (2019); Bondia et al. (2016) and Henriques and Sadorsky (2008).

For NEI, MEI, and SEI, the outcomes of the Wald test lack statistical significance, implying that there is no substantial variance in slope equality across quantile levels. Symmetry is observed across the quantiles of BEI, NEI, MEI, and SEI. The study is focused exclusively on examining how crude oil prices affect selected energy indices return. In future studies, there is an opportunity to explore more deeply how crude oil influences the performance of renewable energy stocks in India and stocks from various other countries across a range of market conditions. Additionally, further enhancements can be made by employing advanced statistical methods. With the rising concerns surrounding climate change and energy security, there is a potential for investigation into the association between investments in green technologies and the occurrence of oil price shocks. Overall, this research delivers valuable insights to decision-makers across diverse sectors. It equips investors and portfolio managers with the knowledge to make informed decisions that protect their investments during episodes of oil price fluctuations. Simultaneously, policymakers can formulate strategies to encourage energy efficiency and diversification, thereby mitigating the overall influence of oil price changes on energy indices and fostering a more stable economic environment.

## 6. References

1. Abdallah, A., & Ghorbela, A., (2018) Hedging Oil Prices with Renewable Energy Indices A Comparison between Various Multivariate Garch Versions, *Biostatistics and Biometrics Open Access Journal*, Vol. 6, No. 3, pp.74-86, <https://doi.org/10.19080/BBOAJ.2018.06.555687>.
2. Ahmad, W., (2017) On the dynamic dependence and investment performance of crude oil and clean energy stocks, *Research in International Business and Finance*, Vol.42, pp.376-389, <https://doi.org/10.1016/j.ribaf.2017.07.140>.
3. Alamgir, F., & Amin, S. B., (2021) The nexus between oil price and stock market: Evidence from South Asia, *Energy Reports*, Vol.7, pp.693-703, <https://doi.org/10.1016/j.egy.2021.01.027>.
4. Aloui, R., Aissa, M. S. B., Hammoudeh, S., & Nguyen, D. K., (2014) Dependence and extreme dependence of crude oil and natural gas prices with applications to risk management, *Energy Economics*, Vol. 42, pp.332-342, <https://doi.org/10.1016/j.eneco.2013.12.005>.
5. Anand, B., & Paul, S., (2021) Oil shocks and stock market: Revisiting the dynamics, *Energy Economics*, Vol. 96, pp.105111, <https://doi.org/10.1016/j.eneco.2021.105111>.
6. Anguyo F. L., Gupta, R., & Kotze, K., (2020) Inflation dynamics in Uganda: a quantile regression approach, *Macroeconomics and Finance in Emerging Market Economies*, Vol. 13, No. 2, pp.161-187, <https://doi.org/10.1080/17520843.2019.1596963>.
7. Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & de Gracia, F. P., (2020) Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness, *Energy Economics*, Vol. 91, pp.104762.
8. Asl, M. G., Canarella, G., & Miller, S. M., (2021) Dynamic asymmetric optimal portfolio allocation between energy stocks and energy commodities: Evidence from clean energy and oil and gas companies, *Resources Policy*, Vol. 71, pp.101982, <https://doi.org/10.1016/j.resourpol.2020.101982>.
9. Babu, M., Hariharan, C., Srinivasan, S., Shimny, P. S., Jayapal, G., Indhumathi, G., ... & Kathiravan, C., (2023) Return and Volatility Spillovers of Asian Pacific Stock Markets' Energy Indices, *International Journal of Energy Economics and Policy*, Vol. 13, No. 1 (61), <https://doi.org/10.32479/ijeeep.13492>.
10. Ben Ameer H., Ftiti, Z., Jawadi, F., & Louhichi, W., (2022) Measuring extreme risk dependence between the oil and gas markets, *Annals of Operations Research*, Vol. 313, No. 2, pp.755-772, <https://doi.org/10.1007/s10479-020-03796-1>.
11. Bondia, R., Ghosh, S., & Kanjilal, K., (2016) 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*, 101, pp.558-565, <https://doi.org/10.1016/j.energy.2016.02.031>.
12. Bouoiyour, J., Gauthier, M., & Bouri, E., (2023) Which is leading: Renewable or brown energy assets? *Energy Economics*, 117, pp.106339, <https://doi.org/10.1016/j.eneco.2022.106339>.
13. Bunnag, T., (2015) Hedging petroleum futures with multivariate GARCH models, *International Journal of Energy Economics and Policy*, Vol. 5, No. 1, pp.105-120, <https://dergipark.org.tr/en/pub/ijeeep/issue/31912/350868>
14. Cevik, N. K., Cevik, E. I., & Dibooglu, S. (2020) Oil prices, stock market returns and volatility spillovers: Evidence from Turkey, *Journal of Policy Modeling*, Vol. 42, No. 3, pp.597-614, <https://doi.org/10.1016/j.jpolmod.2020.01.006>.
15. Chen, Y., Qiao, G., & Zhang, F., (2022) Oil price volatility forecasting: Threshold effect from stock market volatility, *Technological Forecasting and Social Change*, 180, pp. 121704, <https://doi.org/10.1016/j.techfore.2022.121704>.
16. Corbet, S., Goodell, J. W., & Günay, S. (2020) Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19, *Energy economics*, 92, pp.104978, <https://doi.org/10.1016/j.eneco.2020.104978>.
17. Driesprong G., Jacobsen, B., & Maat, B., (2008) Striking oil: another puzzle? *Journal of financial economics*, Vol. 89, No. 2, pp.307-327, <https://doi.org/10.1016/j.jfineco.2007.07.008>.



18. Dutta, A. (2017) Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index, *Journal of Cleaner Production*, 164, pp.1157-1166, <https://doi.org/10.1016/j.jclepro.2017.07.050>.
19. Engle, R. F., & Manganelli, S. (2004) CAViaR: Conditional autoregressive value at risk by regression quantiles, *Journal of business & economic statistics*, Vol. 22, No. 4, pp.367-381, <https://doi.org/10.1198/073500104000000370>.
20. Elsayed, A. H., Nasreen, S., & Tiwari, A. K., (2020) Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies, *Energy Economics*, 90, pp.104847, <https://doi.org/10.1016/j.eneco.2020.104847>.
21. Feng, Y., Chen, R., & Basset, G. W., (2008) Quantile momentum, *Statistics and its interface*, Vol.1, pp.243-254.
22. Ferrer, R., Shahzad, S. J. H., Lopez, R., & Jareno, F., (2018) Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices, *Energy Economics*, 76, pp.1-20, <https://doi.org/10.1016/j.eneco.2018.09.022>.
23. Gatfaoui, H., (2016) Linking the gas and oil markets with the stock market: Investigating the US relationship, *Energy Economics*, 53, pp.5-16, <https://doi.org/10.1016/j.eneco.2015.05.021>.
24. Geng, J. B., Liu, C., Ji, Q., & Zhang, D. (2021) Do oil price changes really matter for clean energy returns?, *Renewable and Sustainable Energy Reviews*, 150, pp.111429, <https://doi.org/10.1016/j.rser.2021.111429>.
25. Ghosh, S., & Kanjilal, K. (2016) Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests, *Energy Economics*, 53, pp.111-117, <https://doi.org/10.1016/j.eneco.2014.11.002>.
26. Gustafsson, R., Dutta, A., & Bouri, E., (2022) Are energy metals hedges or safe havens for clean energy stock returns? *Energy*, 244, pp.122708, <https://doi.org/10.1016/j.energy.2021.122708>.
27. Gupta, R., Jooste, C., & Ranjbar, O., (2017) South Africa's inflation persistence: A quantile regression framework, *Economic Change and Restructuring*, 50, pp.367-386, <https://doi.org/10.1007/s10644-016-9192-z>.
28. Halttunen, K., Slade, R., & Staffell, I., (2022) What if we never run out of oil? From certainty of "peak oil" to "peak demand", *Energy Research & Social Science*, 85, pp. 102407, <https://doi.org/10.1016/j.erss.2021.102407>.
29. Hamma, W., Jarbouli, A., & Ghorbel, A., (2014) Effect of oil price volatility on Tunisian stock market at sector-level and effectiveness of hedging strategy, *Procedia Economics and Finance*, Vol.13, pp.109-127, [https://doi.org/10.1016/S2212-5671\(14\)00434-1](https://doi.org/10.1016/S2212-5671(14)00434-1).
30. Henriques, I., & Sadorsky, P. (2008) Oil prices and the stock prices of alternative energy companies, *Energy Economics*, Vol. 30, No. 3, pp.998-1010, <https://doi.org/10.1016/j.eneco.2007.11.001>.
31. Joo, Y. C., & Park, S. Y. (2021) The impact of oil price volatility on stock markets: Evidences from oil-importing countries, *Energy Economics*, 101, pp.105413, <https://doi.org/10.1016/j.eneco.2021.105413>.
32. Kang, W., Ratti, R. A., & Yoon, K. H., (2015) The impact of oil price shocks on the stock market return and volatility relationship, *Journal of International Financial Markets, Institutions and Money*, 34, pp.41-54, <https://doi.org/10.1016/j.intfin.2014.11.002>.
33. Kocaarslan, B., & Soytaş, U. (2019) Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis, *Energy Reports*, Vol. 5, pp.117-125, <https://doi.org/10.1016/j.egyr.2019.01.002>.
34. Koenker, R., & Bassett Jr, G. (1978) Regression quantiles, *Econometrica: journal of the Econometric Society*, pp.33-50, <https://doi.org/10.2307/1913643>.
35. Ma L., & Pohlman, L., (2008) Return forecasts and optimal portfolio construction: a quantile regression approach, *The European Journal of Finance*, Vol. 14, No. 5, pp.409-425, <https://doi.org/10.1080/13518470802042369>.
36. Ma Y. R., Zhang, D., Ji, Q., & Pan, J. (2019) Spillovers between oil and stock returns in the US energy sector: does idiosyncratic information matter? *Energy Economics*, 8, pp.536-544, <https://doi.org/10.1016/j.eneco.2019.05.003>.
37. Maghyreh A., & Abdoh, H. (2021) The impact of extreme structural oil-price shocks on clean energy and oil stocks, *Energy*, 225, pp.120209, <https://doi.org/10.1016/j.energy.2021.120209>.
38. Mensi, W., Rehman, M. U., Hammoudeh, S., & Vo, X. V. (2021) Spillovers between natural gas, gasoline, oil, and stock markets: Evidence from MENA countries, *Resources policy*, 71, pp.101983, <https://doi.org/10.1016/j.resourpol.2020.101983>.
39. Mugaloglu, E., Polat, A. Y., Tekin, H., & Dogan, A. (2021) Oil price shocks during the COVID-19 pandemic: evidence from United Kingdom energy stocks, *Energy Research Letters*, Vol. 2, No. 1, <https://doi.org/10.46557/001c.24253>.
40. Nasreen, S., Tiwari, A. K., Eizaguirre, J. C., & Wohar, M. E., (2020) Dynamic connectedness between oil prices and stock returns of clean energy and technology companies, *Journal of Cleaner Production*, 260, pp.121015, <https://doi.org/10.1016/j.jclepro.2020.121015>.
41. Niu, H. (2021) Correlations between crude oil and stocks prices of renewable energy and technology companies: A multiscale time-dependent analysis, *Energy*, 221, pp.119800, <https://doi.org/10.1016/j.energy.2021.119800>.
42. Pham, L. (2019) Do all clean energy stocks respond homogeneously to oil price? *Energy Economics*, 81, pp.355-379, <https://doi.org/10.1016/j.eneco.2019.04.010>.
43. Rahman, S., (2022) The asymmetric effects of oil price shocks on the US stock market, *Energy Economics*, 105, pp.105694, <https://doi.org/10.1016/j.eneco.2021.105694>.
44. Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A., (2017) Wavelet-based test of co-movement and causality between oil and renewable energy stock prices, *Energy Economics*, 61, pp.241-252, <https://doi.org/10.1016/j.eneco.2016.10.015>.

45. Salisu, A. A., & Isah, K. O., (2017) Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach, *Economic Modelling*, 66, pp.258-271, <https://doi.org/10.1016/j.econmod.2017.07.010>.
46. Singhal, S., & Ghosh, S. (2016) Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models, *Resources Policy*, 50, pp.276-288, <https://doi.org/10.1016/j.resourpol.2016.10.001>.
47. Sim, N., & Zhou, H., (2015) Oil prices, US stock return, and the dependence between their quantiles, *Journal of Banking & Finance*, 55, pp.1-8, <https://doi.org/10.1016/j.jbankfin.2015.01.013>.
48. Song, Y., Ji, Q., Du, Y. J., & Geng, J. B. (2019) The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets, *Energy Economics*, 84, pp.104564, <https://doi.org/10.1016/j.eneco.2019.104564>.
49. Tan, X., Geng, Y., Vivian, A., & Wang, X. (2021) Measuring risk spillovers between oil and clean energy stocks: Evidence from a systematic framework, *Resources Policy*, 74, pp.102406, <https://doi.org/10.1016/j.resourpol.2021.102406>.
50. Tiwari, A. K., Boachie, M. K., Suleman, M. T., & Gupta, R., (2021a) Structure dependence between oil and agricultural commodities returns: The role of geopolitical risks, *Energy*, 219, pp.119584, <https://doi.org/10.1016/j.energy.2020.119584>.
51. Tiwari, A. K., Nasreen, S., Hammoudeh, S., & Selmi, R. (2021b) Dynamic dependence of oil, clean energy and the role of technology companies: New evidence from copulas with regime switching, *Energy*, 220, pp.119590, <https://doi.org/10.1016/j.energy.2020.119590>.
52. Tong, B., Wu, C., & Zhou, C. (2013) Modeling the co-movements between crude oil and refined petroleum markets, *Energy Economics*, 40, pp.882-897, <https://doi.org/10.1016/j.eneco.2013.10.008>.
53. Troster, V., Shahbaz, M., & Uddin, G. S. (2018) Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis, *Energy Economics*, 70, pp.440-452, <https://doi.org/10.1016/j.eneco.2018.01.029>.
54. Xia T., Ji, Q., Zhang, D., & Han, J. (2019) Asymmetric and extreme influence of energy price changes on renewable energy stock performance, *Journal of Cleaner Production*, 241, pp.118338, <https://doi.org/10.1016/j.jclepro.2019.118338>.
55. Xi, X., Zhou, J., Gao, X., Liu, D., Zheng, H., & Sun, Q. (2019) Impact of changes in crude oil trade network patterns on national economy, *Energy Economics*, 84, pp.104490, <https://doi.org/10.1016/j.eneco.2019.104490>.
56. Xu W., Ma, F., Chen, W., & Zhang, B. (2019) Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States, *Energy Economics*, 80, pp.310-320, <https://doi.org/10.1016/j.eneco.2019.01.014>.
57. You W., Guo, Y., Zhu, H., & Tang, Y. (2017) Oil price shocks, economic policy uncertainty and industry stock returns in China: Asymmetric effects with quantile regression, *Energy Economics*, 68, pp.1-18, <https://doi.org/10.1016/j.eneco.2017.09.007>.
58. Zhang H., Cai, G., & Yang, D. (2020) The impact of oil price shocks on clean energy stocks: Fresh evidence from multi-scale perspective, *Energy*, 196, pp.117099, <https://doi.org/10.1016/j.energy.2020.117099>.
59. Zhu, H., Guo, Y., You, W., & Xu, Y. (2016) The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach, *Energy Economics*, 55, pp.30-41, <https://doi.org/10.1016/j.eneco.2015.12.027>.