Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression

Crude oil prices and clean energy stock indices: lagged and asymmetric effects with quantile regression

Abstract

Unlike previous studies examining the association between crude oil and renewable energy stock prices under average conditions, we employ a quantile-based regression approach offering a more comprehensive dependence structure under diverse market conditions. Using weekly data covering crude oil prices (WTI market) and three clean energy stock indices (the Wilderhill Energy Index, MAC Global Solar Energy Index, and S&P Global Clean Energy Index), quantile regression analyses provide solid evidence of the decreasing dependence of clean energy stock returns on crude oil returns. The lagged effect of WTI oil returns on clean energy stock returns is generally significant, which indicates that clean energy stock returns react differently to new information on oil returns under different market conditions. We further check for asymmetrical effects of oil returns on clean energy stock returns in various market conditions and find a strong effect of negative oil returns during bearish periods and an insignificant effect during bullish episodes.

Keywords: crude oil; clean energy stock indices; quantile regression; lagged and asymmetric effects

1. Introduction

Crude oil has been one of the most important fuels for energy creation over the past decades. However, due to concerns regarding deteriorating global climatic conditions, there is a drastic switch to renewable or clean energy sources (such as solar, wind etc.) [1-2]. Based on the latest report from the International Energy Agency (IEA), there will be a substantial fall in crude oil demand by the end of 2024 and, consequently, an upward shift in renewable energy usage. Luqman et al. [3] find evidence of asymmetric impacts of renewable energy on economic growth in Pakistan. Razmi et al. [4] examine the association of renewable energy consumption with stock market value and reveal evidence that stock market value influences renewable energies in the long term. Rahman and Velayutham [5] explore the association between renewable and non-renewable energy consumption and economic growth and show evidence of a one-way Granger causality flowing from economic growth to renewable energy consumption.

Recently, companies functioning in clean energy sectors have received considerable attention from investors not only because their stocks offer higher returns than general stocks but also because investments in clean energy companies have positive environmental and socio-economic impacts that potentially help ensure a certain degree of sustainability. Kumar et al. [6] argue that investments in renewable energy sectors increase due to concerns about climate change and oil price volatility. Reboredo [7] contends that uncertainty in oil market encourages investors to capitalize in renewable energy stocks.

Given the importance of the association between the crude oil and clean energy sectors, a major line of literature studies the correlations between these two assets. Sadorsky [8] finds that an upsurge in oil prices increases the risk associated with clean energy equities. Kumar et al. [6] document how stock prices of renewable energy firms are sensitive to oil price shocks. Employing a copula approach, Reboredo [7] shows that the dependence between oil and clean energy stock prices evolve over time. Bondia et al. [9] indicate a short-term linkage between oil and renewable energy equity markets and, more importantly, show that the Granger-causality runs from commodity to stock markets. Using wavelets, Reboredo et al. [10] demonstrate that, although the short-run connection between energy and clean energy stock prices appears to be weak, such a relationship seems strong in the long run. Ahmad [11] finds that oil prices and renewable energy stock returns move in tandem, implying that an upturn in energy prices leads to an increase in the stock prices of alternative energy firms. More recently, Ferrer et al. [12]

examine spillover measures between US clean energy stock returns and crude oil returns, and show that spillovers are significant in the short term and vary with time. Kocaarslan and Soytas [13] apply a nonlinear auto-regressive distributed lag (NARDL) model and report evidence of a nonlinear relationship and asymmetric effects between crude oil prices and clean energy stock prices. Xia et al. [14] examine the extreme connectedness between energy price and renewable energy stock indices, indicating evidence of a substitution relationship between dirty energy resources and renewable energy. Bouri et al. [1] show that crude oil acts as safe-haven asset for clean energy stocks during episodes of extreme market movement[1]. However, most of the above-mentioned studies overlook the possibility that the effect of crude oil prices on clean energy indices can vary across the various quantiles of the return distribution.

In this paper we examine the relationship between crude oil prices and clean energy stock indices, considering three aspects. First, we adopt a quantile regression model to examine how variations in crude oil prices impact clean energy stock returns under diverse market conditions. Second, we explore the lagged effect of the oil market on the stock index at various quantiles. Third, we investigate the nonlinear association between oil prices and clean energy stock indices. We contribute in two major ways. Firstly, unlike previous researchers who use the ordinary least squares (OLS) method to examine the relationship between crude oil and stock indexes under average conditions, we apply a quantile regression (QR), proposed by Koenker and Bassett [15], to reveal a more comprehensive picture of the relationship under diverse market conditions. Given that investors' heterogeneity is important to clean energy stock pricing, a heterogeneity-consistent approach such as the QR needs to be estimated[2]. This is based on the rationale that dependent variables across the return distribution might react differently to similar shocks given investors' heterogeneity in the market. Since the application of OLS regression, which focuses on variations in means only, would produce biased estimates, QR has recently been employed in several studies [9, 16-20]. Secondly, this is the first study to investigate whether the impacts of crude oil returns on clean energy stock indexes are persistent (i.e. have lags), which allows us to

[1] Another line of literature uses the information content of crude oil volatility index (OVX) to explore whether energy market uncertainty has any impact on clean energy stock indices. Dutta [21] finds a positive association between the levels of oil price volatility and the realized volatility of renewable energy stocks. Ahmad et al. [22] show that OVX and clean energy equities are negatively correlated, suggesting that the inclusion of OVX in a portfolio of clean energy equities reduces the risk associated with the alternative energy markets.

[2] As Badshah [17] notes: "Investors' heterogeneity leads to a multimodal and fat-tailed distribution of stock market returns".

make inferences regarding the gradual information diffusion hypothesis developed by Hong and Stein [23] and Hong et al. [24]. Motivated by this hypothesis, some studies document significant lagged effects of energy prices on conventional stock markets [25-26]. As Xiao et al. [26] claims: 'Investors in the stock market find it difficult to evaluate information from the oil market that they do not specialize in or that the responses of investors to information in the oil market appear at different points in time. Hence, investors in the stock market underreact to new information in the oil market.' Nevertheless, previous literature focusing on the association between oil and clean energy stock prices has ignored such lagged impacts. This paper aims to address this gap in the literature.

The main findings provide solid evidence for the decreasing dependence of clean energy stocks on oil price movements. Moreover, the results of the asymmetric test indicate strong effects of negative oil returns during bearish periods and an insignificant association throughout bullish episodes. The outcomes provide a base for future risk management decisions and policy implications. Our proposed analyses could be useful for developing future investment options under varied market conditions.

For the rest of the paper, Section 2 defines the dataset, Section 3 outlines the quantile regression, Section 4 discusses the results, and Section 5 concludes.

2. Data

We use the WTI crude oil index as the international benchmark for oil prices and three different indexes to track the equity prices of alternative energy firms: (1) the S&P Global Clean Energy Index (SPGCE); (2) the MAC Global Solar Energy Index (MAC); and (3) the WilderHill Clean Energy Index (ECO). These stock indexes measure the performance of the largest companies in global renewable energy industries. Our sample period spans 31 March 2005 to 21 June 2019, providing 743 weekly observations. We choose weekly data to the detriment of daily data to avoid possible biases due to overlapping trading hours. All the data series are sourced from the Bloomberg terminal. Figure 1 depicts the weekly prices of all three renewable energy stock indices and the WTI oil prices. It is evident from this graph that, during the 2008 financial crisis period, the SPGCE index exhibits the highest prices followed by the MAC index. The ECO index is uniformly consistent with the oil prices over the stress period.

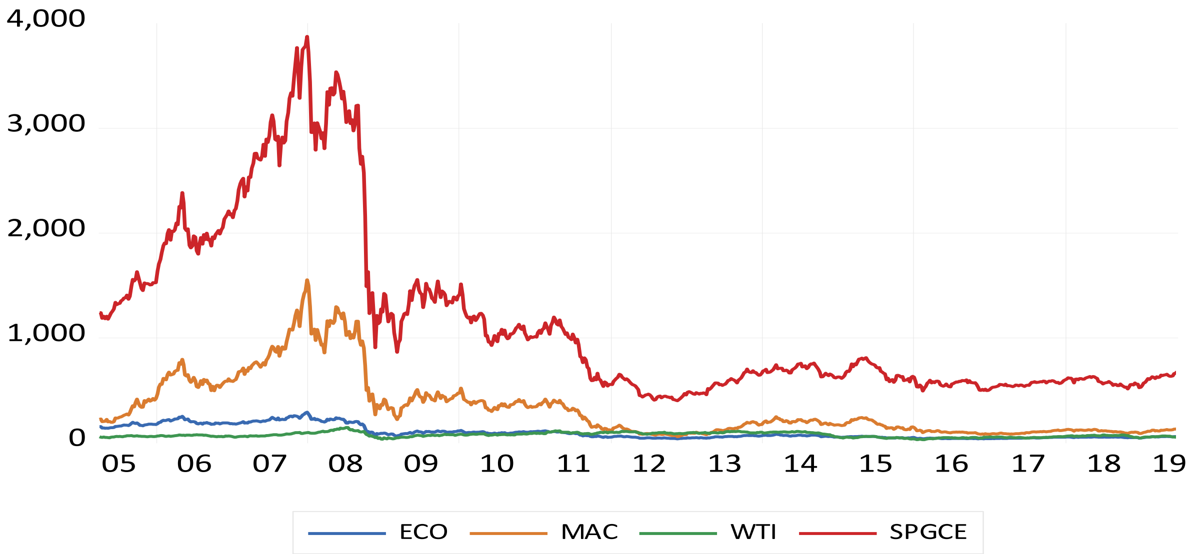

Figure 1. Plot of level series from 31/03/2005 to 21/06/2019

Table 1: Summary Statistics and stationary tests for the return series

Variables	ECO	SPGCE	MAC	WTI
Mean	-0.0012	-0.0008	-0.0006	0.0000
Std. Dev.	0.0453	0.0450	0.0643	0.0504
Median	0.0024	0.0019	0.0023	0.0019
Skewness	-0.5719	-1.2823	-0.4994	-0.2580
Kurtosis	6.9771	15.6250	7.2911	9.9309
Jarque-Bera	529.48***	5131.25***	600.14***	1493.41***
ADF	-26.59***	-27.59***	-26.03401***	-28.01***
PP	-26.58***	-27.70***	-26.19***	-28.14***

Note. * Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 1 displays the descriptive statistics for all the weekly returns series. MAC is the most volatile. Each return series is negatively skewed and exhibits a leptokurtic distribution. The Jarque-Bera test confirms the violation of normality assumption. The outcomes of augmented Dickey-Fuller (ADF) and Phillips-Pearson (PP) tests suggest that the return series are stationary.

3. Quantile regression

To examine the dependence relationship between crude oil price changes and clean energy stock returns, we use the quantile regression approach. This model has been used extensively in the finance and economics literature, given its ability to uncover the asymmetric relationship between financial and economic variables and to model the quantiles of a random variable as functions of observed variables [16-17, 19]. Due to the fact that the estimates of QR process are robust to outliers, heteroskedasticity, and skewness on the dependent variables, this approach receives significant attention in previous studies [26].

The traditional regression equation is:

$$R_t = \alpha + \beta\, WTIRET_t + \theta R_{t-1} + \varepsilon_t \qquad (1)$$

where, R_t is the return of the clean energy stock index at time *t*, α is the constant, β is the coefficient of $WTIRET_t$ and $WTIRET_t$ refers to the return for the WTI index at time *t*, and θ is the coefficient of the lagged value of R_t. This relationship directly explains the dependence of clean energy stock index return on WTI oil prices.

To test for the gradual information diffusion hypothesis, the following regression model is estimated:

$$R_t = \alpha + \sum_{i=0}^{8} \beta_i\ WTIRET_{t-i} + \theta R_{t-1} + \varepsilon_t \qquad (2)$$

where R_t is the return of the clean energy stock index at time *t*, α is the constant, β is the coefficient of $WTIRET_{t-i}$ and $WTIRET_{t-i}$ refers to the lagged returns for the WTI index at time *t-i* with *i*= 0, 1, 2, ….8, and θ is the coefficient of the lagged value of R_t.

The above equation explains the lagged impact of crude oil on clean energy stock indices as proposed by Driesprong et al. [27] and Narayan and Narayan [28]. The lag length is 8, optimally chosen based on information criterion.

To investigate whether crude oil prices have any asymmetric effect on the clean energy stock indices, we estimate the following model:

$$R_t = \alpha + \beta_1 WTIRET_t^+ + \beta_2 WTIRET_t^- + \theta R_{t-1} + \varepsilon_t \quad (3)$$

where, $WTIRET_t^+ = \max(0, WTIRET_t)$ indicates positive oil returns and $WTIRET_t^- = \min(0, WTIRET_t)$ stands for negative oil returns.

Unlike the OLS regression, the QR method estimates the rates of change in all parts of the distribution of a dependent variable. Since one of our purposes is to examine the return linkage between oil prices and clean energy stock indexes under diverse market conditions, we apply the QR model.

For a given X_i, the quantile regression for a variable Y_i can be stated as:

$$Q_{y_i}(\tau|x) = \alpha(\tau) + X_i'\beta(\tau) \quad (4)$$

Following Koenkar and Bassett [15], $Q_{y_i}(\tau|x)$ signifies the τ conditional quantile of y_i. The value of τ lies between 0 and 1. Furthermore, $\alpha(\tau)$ accounts for the unobserved effect in the quantile model, *x* includes all the independent variables that are responsible for changes in *y*, and $\beta(\tau)$ is estimated as:

$$\hat{\beta}(\tau) = \arg min_{\beta \in R^P} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i'\beta(\tau) - \alpha(\tau)\right) \quad (5)$$

For $\beta(\tau)$, the check function is defined as $\rho_\tau(u) = u(\tau - I(u < 0))$, and the indicator function I(·) is given as $(u = y_i - x_i'\beta(\tau) - \alpha(\tau))$.

To investigate the association between crude oil and clean energy stock indexes, the following quantile regression is proposed:

$$Q_R(\tau|x) = \alpha(\tau) + \beta(\tau)WTIRET + \theta R_{t-1} \quad (6)$$

To check for the lagged effect, the following quantile regression is proposed:

$$Q_R(\tau|x) = \alpha(\tau) + \sum_{i=0}^{8} \beta_i(\tau)\ WTIRET_{t-i} + \theta(\tau) R_{t-1} \tag{7}$$

To test for asymmetry, the relationship between the two variables is modelled as:

$$Q_R(\tau|x) = \alpha(\tau) + \beta_1(\tau)\, WTIRET_t^{+} + \beta_2(\tau) WTIRET_t^{-} + \theta(\tau) R_{t-1} \tag{8}$$

A positive and statistically significant $\beta(\tau)$ indicates that an increase in crude oil prices leads to an upturn in the prices of clean energy stocks. However, if $\beta(\tau)$ is negative, there is an inverse relationship between the two assets.

We consider seven quantiles, τ = (0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95). The median (0.50) quantile reflects the normal market condition. Lower quantiles (i.e. 0.05, 0.10, 0.25) reflect bearish market states, whereas, higher quantiles (i.e. 0.70, 0.90, 0.95) reveal bullish market conditions.

Note that as stock markets tend to behave differently under diverse market conditions (bearish, normal and bullish), it is essential for market participants to understand how their investments react to oil price shocks under such conditions. To this end, the quantile regression approach is an effective tool for taking precise risk management decisions given that it allows us to investigate the effects of independent variables on the different distributions of dependent variables [29-30].

4. Empirical results[3]

4.1. Impacts of crude oil returns on clean energy stock returns

Table 2 Panel A presents the results of the relationship between WTI and ECO. The results of the OLS show that the average relationship is positive. However, the QR results show that the effect of WTI tends to decrease as quantiles decrease. The same goes for the adjusted R-squared values of the model. In fact, in lower quantiles the model fits much better, indicating that the impact of

[3] The models are estimated with EViews 10. However, we have run the regression using SPSS (as the reviewer suggests) and the results remain the same. The re-estimated results will be available from the authors upon request.

crude oil on the WilderHill Clean Energy Index is stronger in bearish market conditions but weaker in bullish market conditions. Figure 2 depicts this graphically.

Similar results are reported for the cases of the MAC and SPGCE indices in Panel B and Panel C, respectively. The impact of WTI is positive at the mean, as shown in the OLS results, whereas it diminishes during bullish states (τ =0.75, 0.90, 0.95). The adjusted R-squared values also suggest that the model fitness decreases in the upper quantiles. However, the impact of WTI on the MAC and SPGCE indices is significant in normal and bearish market conditions. Figures 3 and 4 demonstrate the quantile relationships inferred above.

Table 2. Impacts of WTI oil prices on clean energy stocks

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Panel A	ECO index							
Constant	-0.0729***	-0.0524***	-0.0231***	0.0014	0.0230***	0.0445***	0.0617***	-0.0012
WTIRET	0.3558***	0.3804***	0.2732***	0.2723***	0.2492***	0.2584	0.1455***	0.3297***
Lagged ECO	0.2844***	0.2782***	0.0607	-0.0477	-0.0617	-0.105**	-0.1579***	0.0241
Adjusted R^2	15.61%	10.95%	6.37%	5.06%	4.79%	3.87%	3.70%	13.27%
Panel B	MAC index							
Constant	-0.0981***	-0.074***	-0.0331***	0.0027	0.0322***	0.0665***	0.0879***	-0.0007
WTIRET	0.6107***	0.5371***	0.4308***	0.3449***	0.3553***	0.4096***	0.2930	0.4395***
Lagged MAC	0.3125***	0.2313***	0.0754	0.0346	-0.0158	-0.0694*	-0.1266***	0.0548
Adjusted R^2	16.82%	10.26%	5.74%	4.67%	4.67%	4.18%	3.73%	11.79%
Panel C	SPGCE index							
Constant	-0.0652	-0.046	-0.0196	0.0010	0.0215	0.0410	0.0559	-0.0008
WTIRET	0.5000***	0.3829***	0.3126***	0.2487***	0.2648***	0.2101	0.2395***	0.3336***
Lagged SPGCE	0.3709***	0.2238***	0.0785	0.0311	-0.042	-0.1777***	-0.1872***	0.0063
Adjusted R^2	14.19%	9.69%	6.39%	4.94%	5.25%	8.64%	10.48%	13.67%

Note. This table presents the estimates of equation 6. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

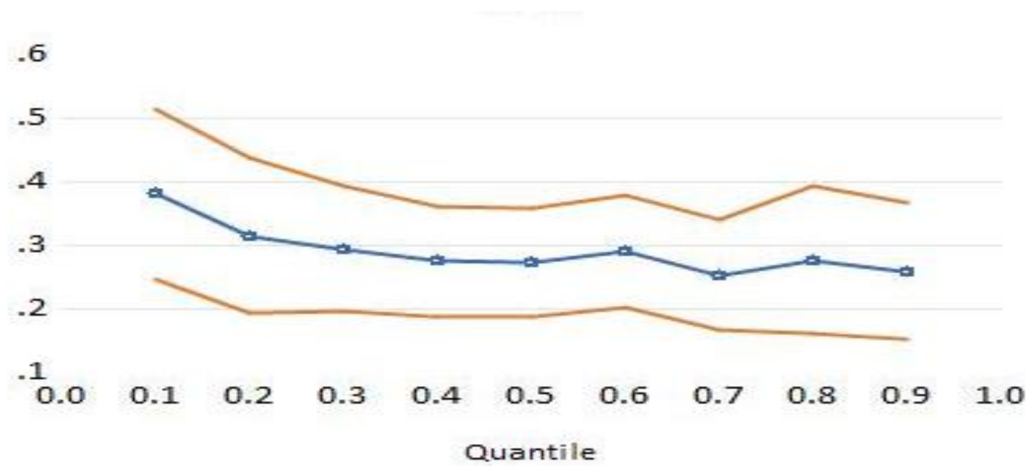

Figure 2. Quantile regression based on WTI and ECO indices

Notes: We plot the contemporaneous impacts of WTI on ECO across 10 quantiles. The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

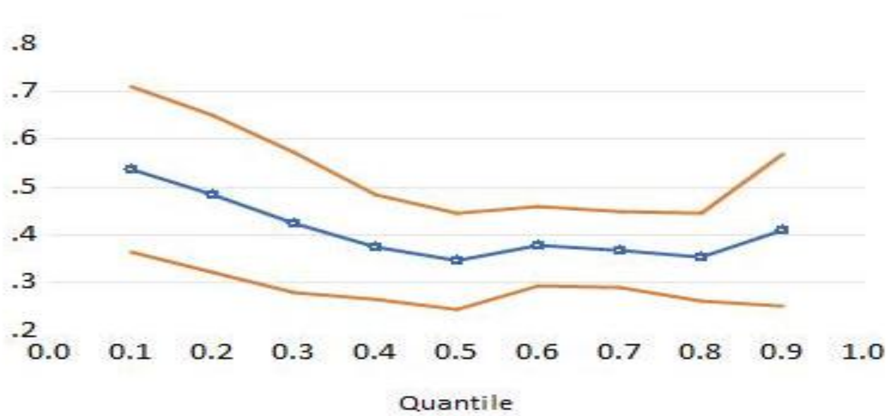

Figure 3. Quantile regression based on WTI and MAC indices

Notes: We plot the contemporaneous impacts of WTI on MAC across 10 quantiles. The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

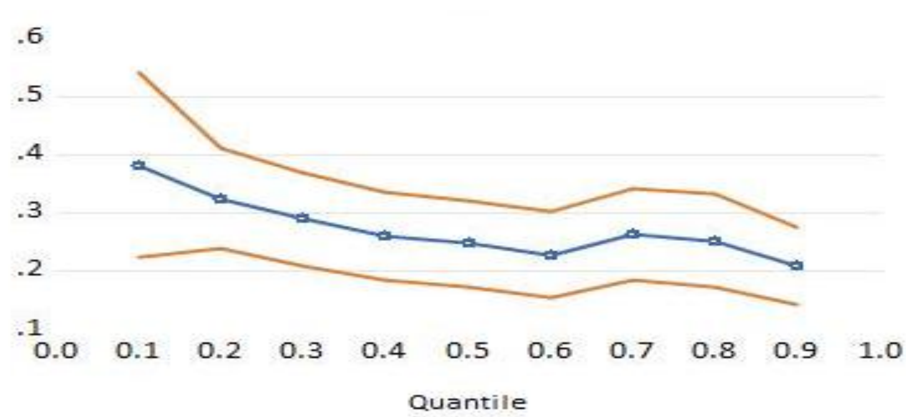

Figure 4. Quantile regression based on WTI and SPGCE indices

Notes: We plot the contemporaneous impacts of WTI on SPGCE across 10 quantiles. The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

It follows that the QR approach gives a solid dependence structure for the clean energy stock indices on crude oil prices. Previous results reveal a positive relationship between clean energy stock returns and oil returns. Furthermore, Henriques and Sardosky [31] document that oil returns are not as significant as technological stocks in explaining the movement of clean energy stock indices. Our results generally concord with previous findings as indicated by the average of 13% for R squared levels in our models.

Our above QR analysis complements previous studies [1, 6, 9, 11, 13, 21, 26]. These papers show that all clean energy stock indices under study have a positive impact under the mean-based regression, and the R-squared values are in line with the results from previous papers. However, using the quantile regression, we reveal the structure of the investment pattern of clean energy traders under different market conditions. In the upper quantiles, i.e., during upward market conditions, the dependency of clean energy stocks on crude oil prices decreases. This shows that when investor sentiment is highly positive, oil returns do not affect clean energy stock returns. However, during downturns market conditions, clean energy stock returns have high dependency on crude oil returns, suggesting that investors should develop an investment decision to invest in clean energy stocks in bearish market conditions. During the Global Financial Crisis of 2007-2008, the movements of crude oil price were very low but positive, and the movement of clean energy stock indices rose significantly. Our analysis helps break down the price change structure between crude oil and clean energy stock indices, as the rising oil price in the bearish period is one significant reason for the peaks in the clean energy stock indices.

4.2. Lagged impact of crude oil returns on clean energy stock returns

The gradual information diffusion hypothesis is accepted under two conditions: first, if the lagged effect of crude oil returns on clean energy stock returns has a similar or a larger magnitude than the contemporaneous effect of crude oil returns; and second, if the lagged effect peaks then declines as the lag length increases. Earlier studies [26-27, 32] have applied those two conditions for testing the gradual information diffusion hypothesis. We first consider the ECO index and the results of Equation (7) are shown in Table 3. The OLS results show that the effect of lag 1 is positive. The gradual information diffusion hypothesis is rejected given that the lagged effect (i.e. β_1) is lower than the contemporaneous effect (i.e. β_0). Furthermore, the effect of lag 5 is higher than the effect of lag 1. This suggests that investors have a delayed reaction to information about oil returns.

Furthermore, we notice that the estimated results for the QR are quite similar to the OLS results in extreme quantiles (τ =0.05, 0.1, 0.9, 0.95). The lagged effects are highly positive, specifically in bullish or bearish markets. Whereas, there is an inverse relationship between the first lag of WTI and ECO during normal market conditions (in the middle quantile). Checking for the diffusion hypothesis, the first condition is rejected. The second condition does not comply with our quantile regression model, given evidence that in lower quantiles the model fits perfectly to the condition that the first lag has the highest effect on ECO prices. At the median quantiles, however, the fifth and sixth lags have the highest effect, indicating that during normal market conditions investors take five to six weeks to react to changes in oil prices. Therefore, as the market conditions shift from bearish to bullish, the information diffusion shifts from t-1 to t-6 indicating that investors in ECO react late to WTI prices. Figure 5 shows the quantile lagged impacts of oil returns on ECO returns. These results are comparable to those reported in previous studies [26-27, 32].

Table 3. Regression results for lagged effect between WTI and ECO

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.0773***	-0.0544***	-0.0244***	0.0012	0.0228***	0.0460***	0.0631***	-0.0012
$WTIRET_t$	0.3773***	0.3737***	0.2925***	0.2933***	0.2646***	0.3091***	0.2069**	0.3402***
$WTIRET_{t-1}$	0.2245**	0.0505	-0.0194	-0.0337	-0.0038	0.0197	0.0307	0.0053
$WTIRET_{t-2}$	0.1213***	0.0494	-0.0183	-0.0338	-0.0198	-0.0294	-0.0682	-0.0279
$WTIRET_{t-3}$	0.1517*	-0.0795	-0.0295	-0.0348	-0.0031	-0.0023	0.0317	-0.0155
$WTIRET_{t-4}$	0.0326	0.0534	0.0677	0.0287	0.0056	-0.0113	0.0455	0.0406
$WTIRET_{t-5}$	0.1815***	0.0977	0.0738	0.0460	-0.0002	0.0994*	0.1454*	0.0636**
$WTIRET_{t-6}$	0.0140	0.0457	0.0312	-0.0197	-0.0031	0.03045	0.0700	0.0083
$WTIRET_{t-7}$	0.0095	0.0166	0.0476	-0.0046	0.0284	-0.0084	-0.0300	0.0323
$WTIRET_{t-8}$	-0.0946*	-0.0622	-0.0417	-0.0614	-0.0663*	-0.0695	-0.1592	-0.0706**
Lagged ECO	0.2550***	0.2343***	0.0876	-0.0145	-0.0619	-0.1543*	-0.1953*	0.0178
$H_0: \beta_0 = \beta_1$	1.1468**	2.7675***	4.4503***	5.1846***	5.0505***	2.4749**	1.7105*	7.3209***
Adjusted R^2	19.354%	11.272%	6.304%	4.328%	4.571%	4.035%	6.259%	13.634%

Note. This table presents the estimates of equation 7 for the ECO index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

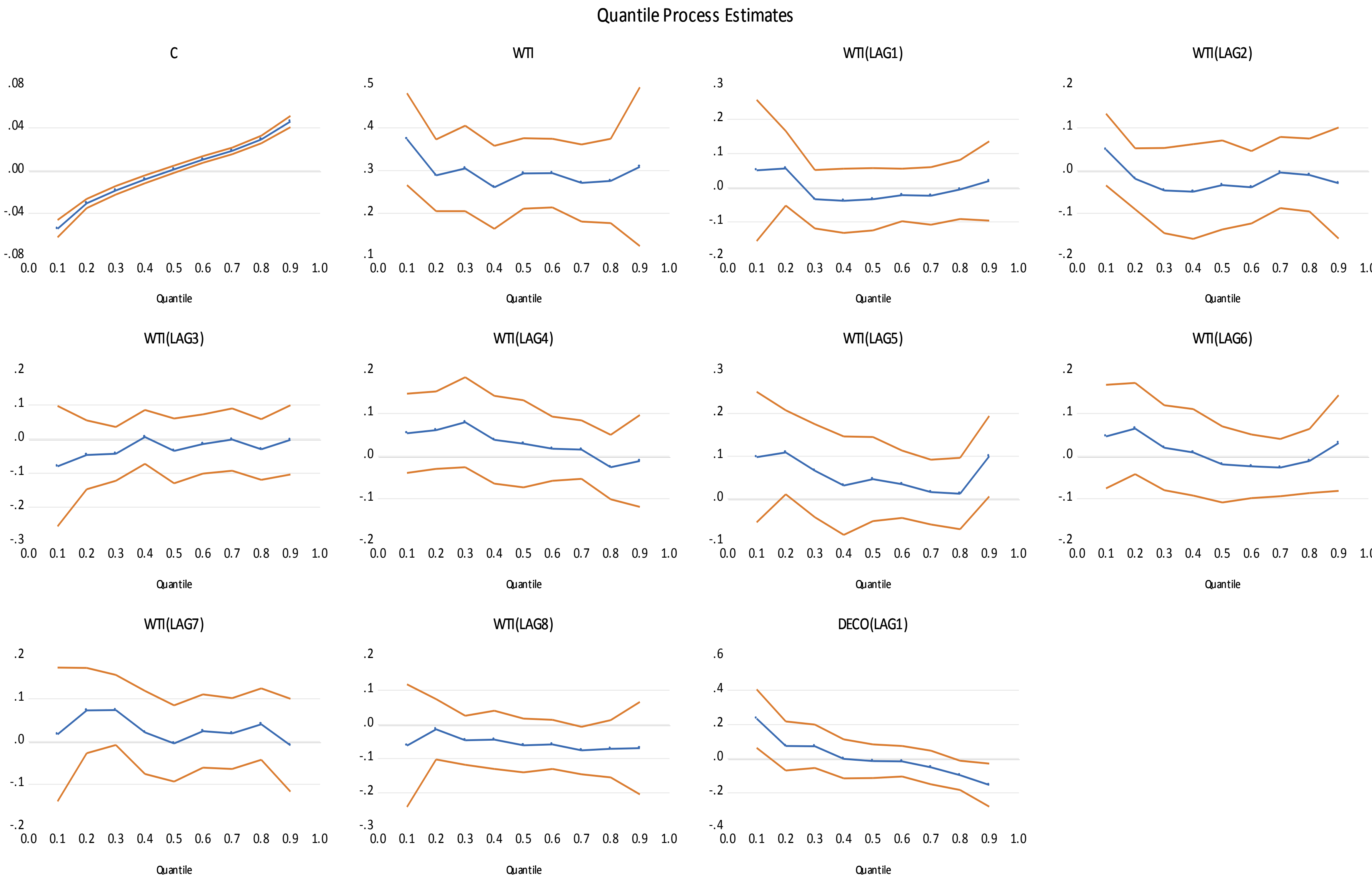

Figure 5. Quantile regression showing the lagged impact of WTI on ECO

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

The results for MAC are shown in Table 4. The OLS results indicate that the first lag effect of oil returns has a positive effect on MAC returns; however, it is significantly lower than the contemporaneous effect of oil returns. This result indicates that the first condition of the diffusion hypothesis is unsatisfied by the MAC index. For the second condition, the fifth lag of oil prices has the highest effect on MAC returns, inferring that the information diffusion takes place in the fifth lag and investors use the information to invest accordingly.

In low quantiles (τ=0.05, 0.1, 0.25), the first lagged has a positive relationship with MAC returns. In the median quantile (τ=0.5) and higher quantiles (τ =0.9, 0.95), the first lagged effect has a negative relation with MAC returns. We observe that during bearish and normal market conditions the information diffuses at the fifth lag, whereas in bullish market conditions, investors in MAC react at the third lag to the crude oil returns. Detailed results are shown in Figure 6.

Table 4. Regression results for lagged effect between WTI and MAC

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.1047***	-0.0752***	-0.0357***	0.0017	0.0334***	0.0668***	0.0916***	-0.0005
$WTIRET_t$	0.5366***	0.6103***	0.4193***	0.3527***	0.3769***	0.33087***	0.2239*	0.4566***
$WTIRET_{t-1}$	0.1880	0.1335	0.0204	-0.0416	0.0041	-0.0124	-0.0533	0.0325
$WTIRET_{t-2}$	0.1052	-0.0306	-0.1346**	-0.0283	-0.0451	-0.0735	-0.1682*	-0.0869*
$WTIRET_{t-3}$	0.1710*	0.0691	0.0308	0.0395	0.0211	0.12330**	0.1747**	0.0315
$WTIRET_{t-4}$	0.0213	0.0335	0.0470	0.0092	-0.004	0.01160	-0.0199	0.0250
$WTIRET_{t-5}$	0.2834***	0.2762***	0.1388*	0.0519	-0.0437	0.04737	0.0788	0.0959**
$WTIRET_{t-6}$	0.0635	0.1037	0.0702	-0.0456	-0.0376	0.08843	0.0455	0.0205
$WTIRET_{t-7}$	0.0541	0.1983**	0.0022	0.0261	0.1334**	0.01308	0.0386	0.0574
$WTIRET_{t-8}$	-0.0569	-0.1539**	-0.0869	-0.0637	-0.0583	-0.1226	-0.2454*	-0.1090**
Lagged MAC	0.3024***	0.2039***	0.0607	0.0377	-0.0053	-0.0961	-0.0895	0.0514
$H_0: \beta_0 = \beta_1$	1.9655**	2.5545**	5.0867***	5.2838***	4.6217***	2.6972***	2.0730**	6.5150***
Adjusted R^2	20.58%	12.28%	6.31%	4.63%	4.72%	4.90%	7.58%	13.06%

Note. This table presents the estimates of equation 7 for the MAC index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

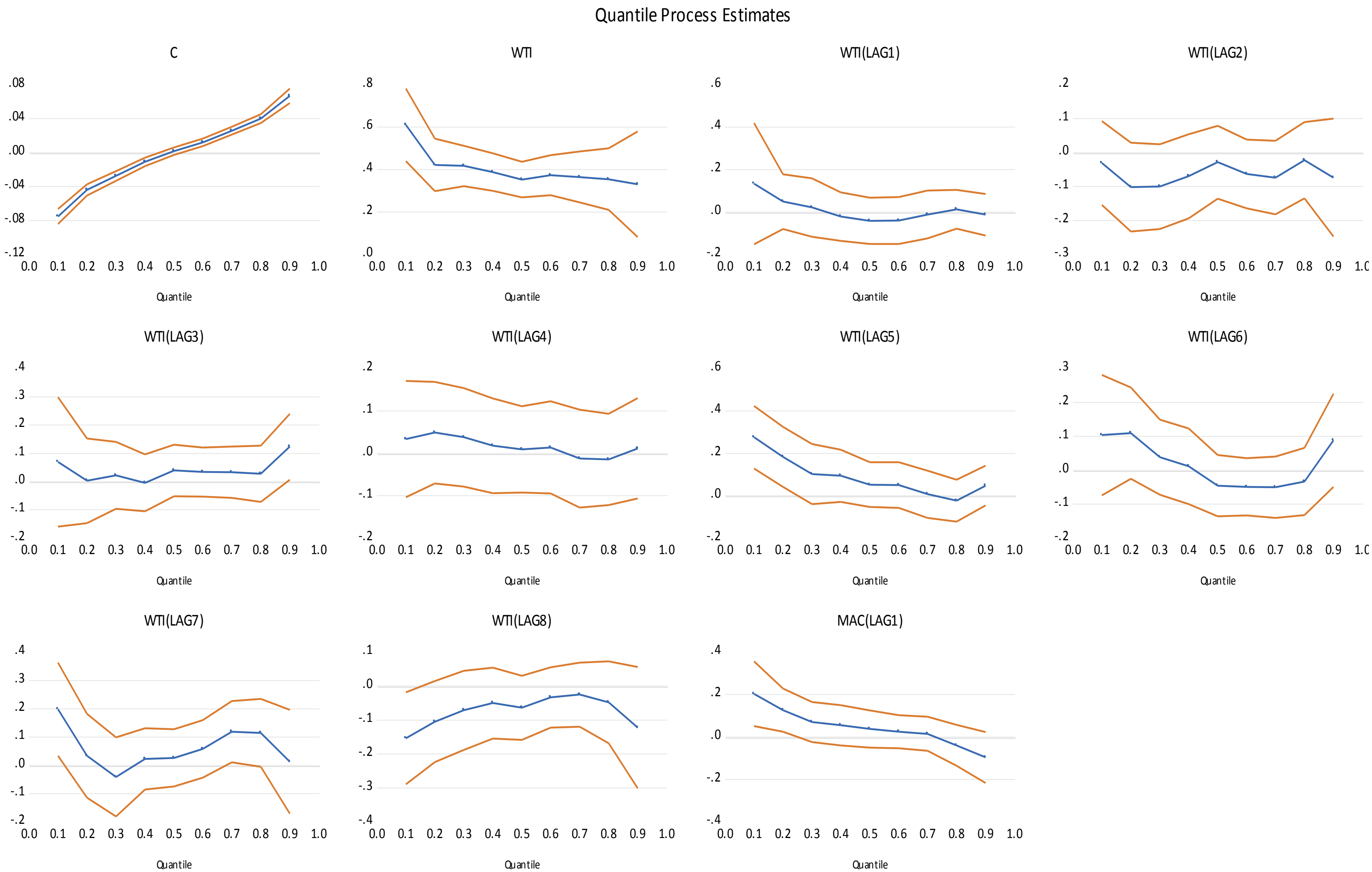

Figure 6. Quantile regression showing the lagged impact of WTI on MAC

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

For the SPGCE, the OLS regression displays a positive effect of the first lag of WTI returns. Testing for the gradual information diffusion hypothesis, the contemporaneous effect of crude oil is about 9 times the effect of the first lag, which defies the first condition. After incorporating all 8 lags of oil returns, we note that the highest effect is at lag 5, which indicates a rejection of the second condition. Thus, based on the OLS model, the gradual information diffusion hypothesis is rejected. Table 5 shows the results for the first lag effect of WTI returns in each quantile to be highly scattered with both negative and positive correlation with SPGCE returns. As the contemporaneous effect is very high compared to the first lagged effect of oil returns, the first condition is rejected. The second condition is also rejected. Figure 7 shows the quantile regression for each of the eight lags taken into account for the SPGCE.

Table 5. Regression results for lagged effect between WTI and SPGCE

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.0730***	-0.0467***	-0.0203**	0.0022	0.0209**	0.0408**	0.0565***	-0.0008
$WTIRET_t$	0.5088***	0.3619***	0.3178***	0.2715***	0.2772***	0.2101***	0.2048***	0.3511***
$WTIRET_{t-1}$	0.0873	-0.0073	0.0033	-0.0155	0.0110	0.0267	-0.0054	0.0406
$WTIRET_{t-2}$	0.0548	-0.0347	-0.0684	-0.0445	-0.0311	-0.0465	-0.1325*	-0.0534
$WTIRET_{t-3}$	0.1078	0.0288	-0.0015	0.0486	0.0090	0.0259	0.0679	0.0087
$WTIRET_{t-4}$	0.1225*	0.0833	-0.0184	-0.0075	-0.0192	0.0037	0.0270	0.0143
$WTIRET_{t-5}$	0.2114***	0.14678*	0.0879	0.0334	-0.0008	0.0290	0.0437	0.0634
$WTIRET_{t-6}$	0.0050	0.0526	0.0210	-0.0527	-0.0040	0.0509	0.0353	0.0042
$WTIRET_{t-7}$	0.1069*	0.08157	-0.0178	0.0531	0.0749	0.0337	0.0273	0.0523
$WTIRET_{t-8}$	-0.1324**	-0.0388	-0.0680	-0.0404	-0.0749	-0.0389	-0.1381**	-0.1002
Lagged SPGCE	0.3205***	0.2918***	0.0486	0.0591	-0.0281	-0.1887	-0.1690**	-0.0051
$H_0: \beta_0 = \beta_1$	2.4352**	2.8333***	6.7964***	5.9895***	4.8884***	4.1476***	2.4425**	6.7781***
Adjusted R^2	18.12%	10.43%	6.31%	4.63%	5.74%	9.33%	13.32%	15.31%

Note. This table presents the estimates of equation 7 for the SPGCE index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

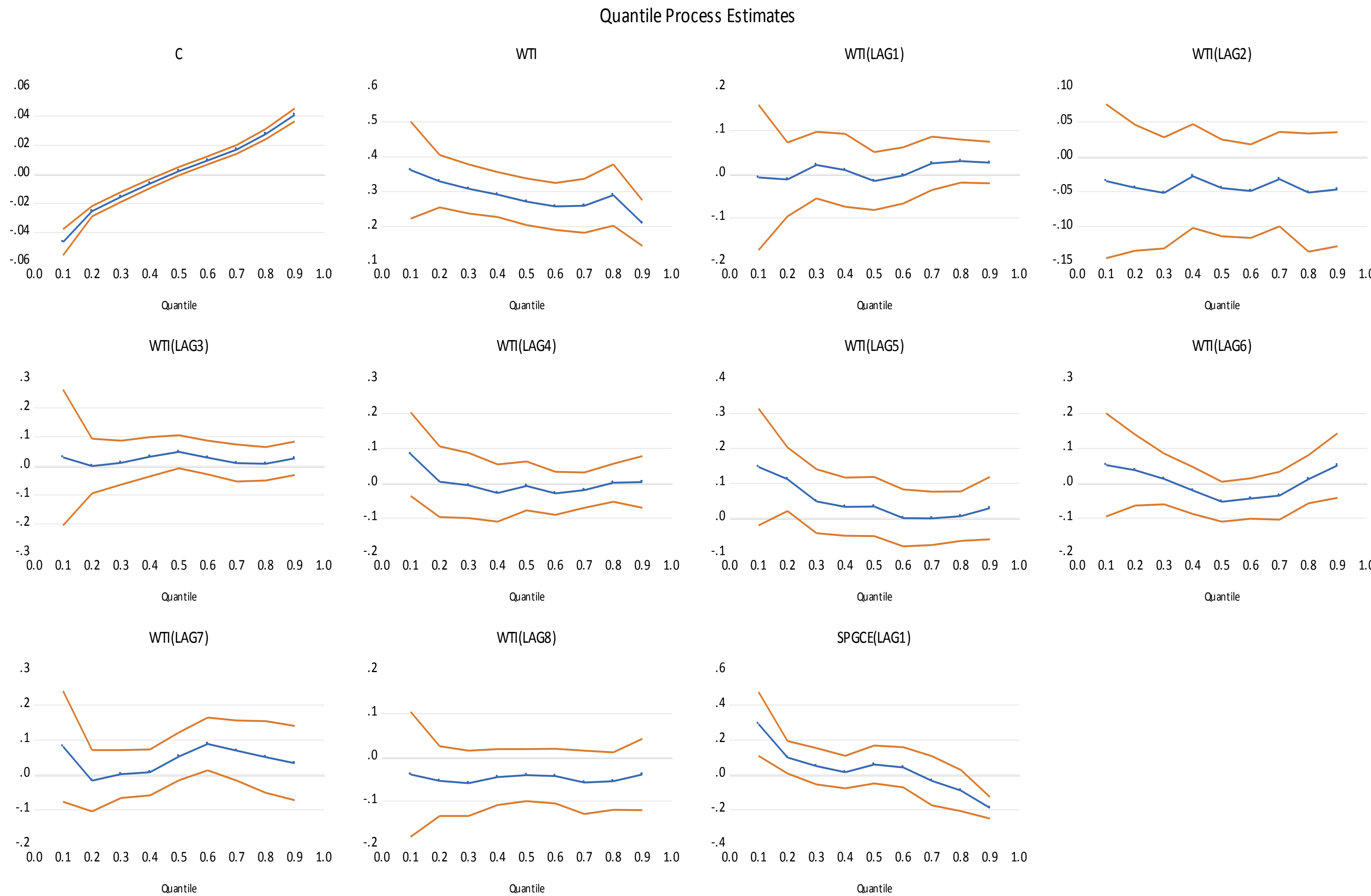

Figure 7. Quantile regression showing the lagged impact of WTI on SPGCE

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

To summarize, the various clean energy stock returns react differently to the lagged effects of crude oil returns. The contemporaneous effects are always larger for WTI returns than the first lagged effect, which rejects the gradual information diffusion hypothesis. For the three stock indices, the major lagged effect takes place at either the third or fifth lag, depending on the market condition. The effect is statistically significant and thus influences investing decisions. These results agree with the earlier finding of Peng and Ng [33] that the return effects transmit slowly. Thus, when the market is bullish or bearish, the major reason for slower lag effect is not justified by the diffusion hypothesis. The analysis also confirms the findings of Driesprong et al. [27] that because these lagged effects occur at different times there is a lagged response of clean energy stock returns to oil returns. The effect of new information continues for a long time in the case of oil markets returns [29] which would compel clean energy stock returns to react differently to new information in oil returns under different market conditions.

4.3. Asymmetric impacts of crude oil returns on clean energy stock returns

We examine the asymmetric impacts of positive and negative WTI returns on clean energy stock returns using QR, given that the OLS regression is unable to do the same. The results are reported in Tables 6-8, based on Equation (8). $WTIRET_t^+$

Table 6. Regression results for asymmetric impacts between WTI and ECO

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.0524***	-0.0331***	-0.0151***	0.0061***	0.0230***	0.0422***	0.0522***	0.0049**
$WTIRET_t^+$	-0.0065	-0.1017*	0.0158	0.0930**	0.2484**	0.3724***	0.5259***	0.1435**
$WTIRET_t^-$	0.8628***	0.9134***	0.6656***	0.3796***	0.2494***	0.2113**	0.0216	0.4888***
Lagged ECO	0.2067***	0.1541***	0.0490	-0.0224	-0.0611	-0.1524**	-0.1102**	0.01917
$H_0: \beta_1 = \beta_2$	-5.7963***	-5.9276***	-2.6694***	-2.9397***	-0.0068	0.8753	2.7023***	-3.9413***
Adjusted R^2	23.03%	17.36%	8.42%	5.75%	4.66%	3.90%	5.95%	14.94%

Note. This table presents the estimates of equation 8 for the ECO index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 7. Regression results for asymmetric impacts between WTI and MAC

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.0715***	-0.0502***	-0.0178***	0.0066*	0.0331***	0.0653***	0.0761***	0.0063**
$WTIRET_t^+$	-0.0536	0.0143	-0.0773	0.1992	0.3470***	0.4297*	0.6118**	0.2263***
$WTIRET_t^-$	1.2970***	1.2869***	0.9951***	0.4522***	0.4137***	0.3855***	-0.1104**	0.6213***
Lagged MAC	0.1999***	0.1928***	0.1132***	0.0342	0.0014	-0.0786*	-0.0873**	0.0515
$H_0: \beta_1 = \beta_2$	-4.7523***	-3.7271***	-4.0139***	-1.2899	-0.6371	0.1376	2.3879	-3.1375***
Adjusted R^2	23.66%	15.36%	7.32%	4.78%	4.61%	4.05%	4.68%	12.84%

Note. This table presents the estimates of equation 8 for the MAC index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 8. Regression results for asymmetric impacts between WTI and SPGCE

Quantile →	0.05	0.1	0.25	0.5	0.75	0.9	0.95	OLS
Constant	-0.0406***	-0.0257**	-0.0093	0.0052	0.0207*	0.0361**	0.0437**	0.0042*
$WTIRET_t^+$	-0.1518	-0.1115	-0.0111	0.1569***	0.3092***	0.3650***	0.6335***	0.1807***
$WTIRET_t^-$	1.2979***	1.0111***	0.6493***	0.3572**	0.2352**	0.1166**	0.0105	0.4641***
Lagged SPGCE	0.1492***	0.1756***	0.0837*	0.0632	-0.0683	-0.1714***	-0.1400***	0.0043
$H_0: \beta_1 = \beta_2$	-3.7105***	-4.3476***	-3.3371***	-1.5493	0.8953	1.0565	2.3047***	-3.2499***
Adjusted R^2	23.27%	16.33%	8.43%	5.13%	5.23%	9.20%	12.59%	14.77%

Note. This table presents the estimates of equation 8 for the SPGCE index. OLS stands for the ordinary least squares regression. WTIRET refers to the return for the WTI index. Logarithmic returns are used for all the indexes. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Starting with the results reported in Table 6, which involves the ECO index. The OLS regression results show that both positive and negative WTI returns have a positive effect on ECO, although negative WTI returns have a stronger effect. However, the QR results show that in the lower quantiles, positive WTI returns have an inverse relationship with ECO returns. As we move towards the median and upper quantiles, positive WTI returns have a high positive effect. Negative WTI returns have a positive effect across all quantiles, but the effect is much higher in lower quantiles. These results are useful for decisions regarding investment strategies in various market conditions. Positive WTI returns affect investment decisions more in bullish periods, whereas in bearish markets, negative WTI returns are more important for making investment decisions in ECO. The results of the Wald test for asymmetry show that the null hypothesis of asymmetry is rejected under the OLS model. However, the same test under quantile regression is not rejected in bearish market conditions only. Asymmetry seems to exist in the model in both bearish and normal market conditions.

Moving to the results of MAC and SPGCE, reported in Table 7 and Table 8, respectively. The OLS regression results show that both positive and negative WTI returns have a positive effect. However, the effect of negative WTI returns is much stronger and the asymmetric effect is insignificant. The QR results show that positive WTI returns have a negative effect in lower quantiles and are highly positive in upper quantiles. In contrast, negative WTI returns are positively significant in lower quantiles and negatively significant in upper quantiles. This suggests that positive WTI returns have a positive explanatory power for the returns of MAC and SPGCE in bullish market conditions, whereas in extreme bearish market conditions the explanatory power of positive WTI returns is negative. Furthermore, negative WTI returns positively affect the returns of MAC and SPGCE in upper quantiles, whereas negative WTI returns have a negative effect in extreme upper quantiles. The Wald test rejects the null hypothesis of asymmetry under the OLS model. However, the quantile regression results show that the Wald test rejects the null hypothesis in the median quantile and extreme high quantiles for MAC, and in median and high quantiles for SPGCE. Figures 8-10 show the quantile regression for investigating the asymmetric impact of WTI on the clean energy stock indices.

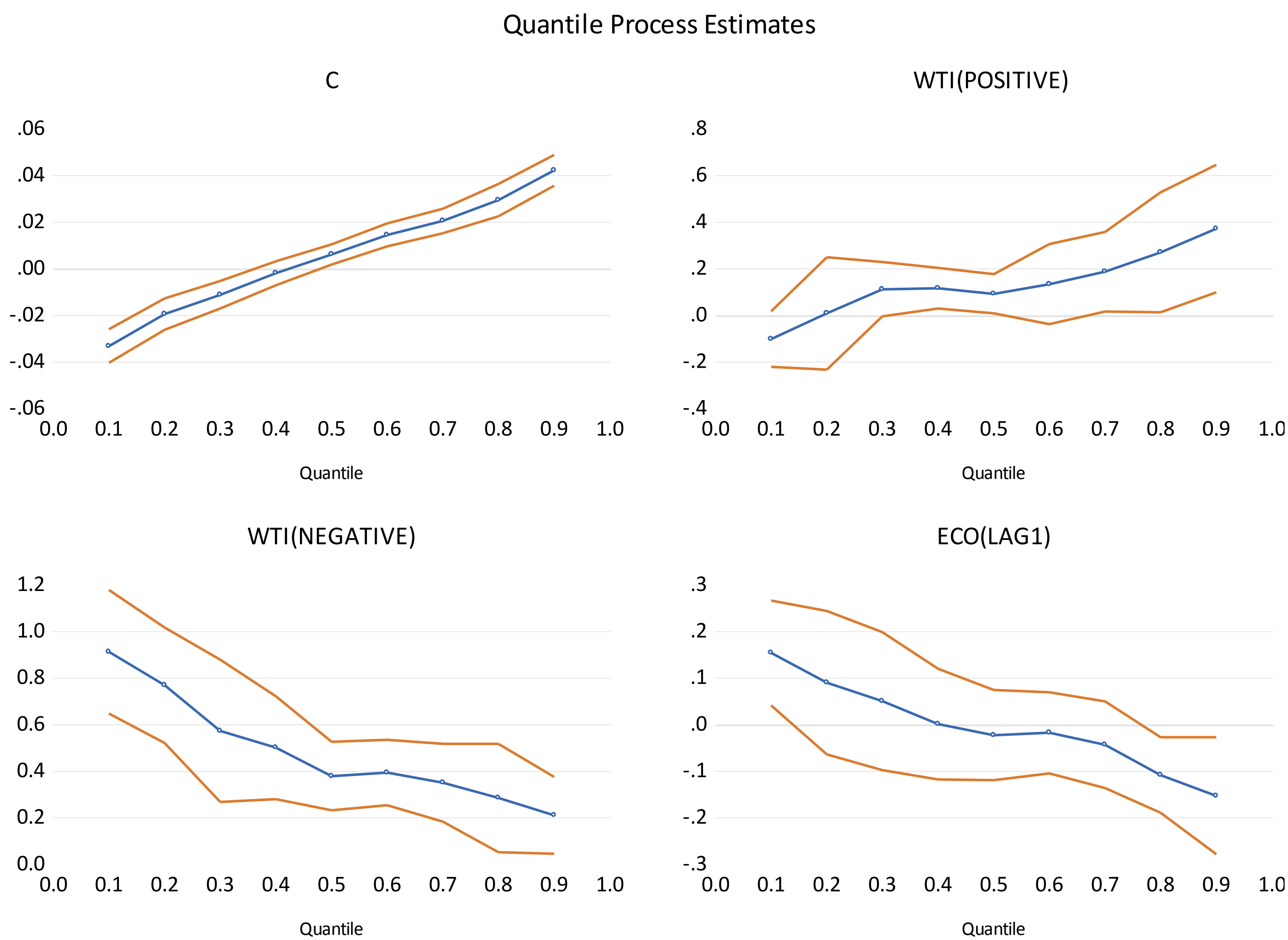

Figure 8. Quantile regression investigating the asymmetric impact of WTI on ECO

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

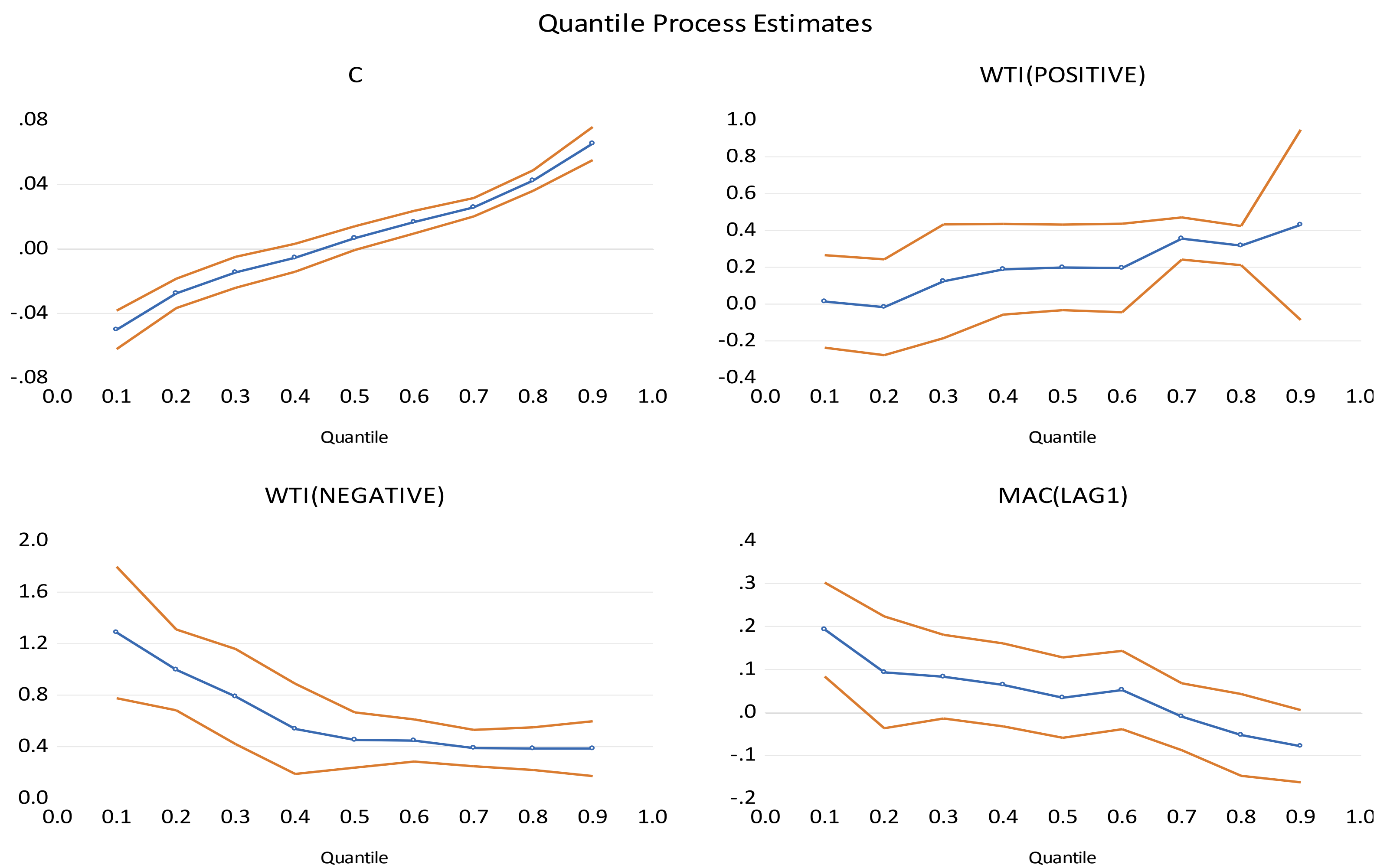

Figure 9. Quantile regression investigating the asymmetric impact of WTI on MAC

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

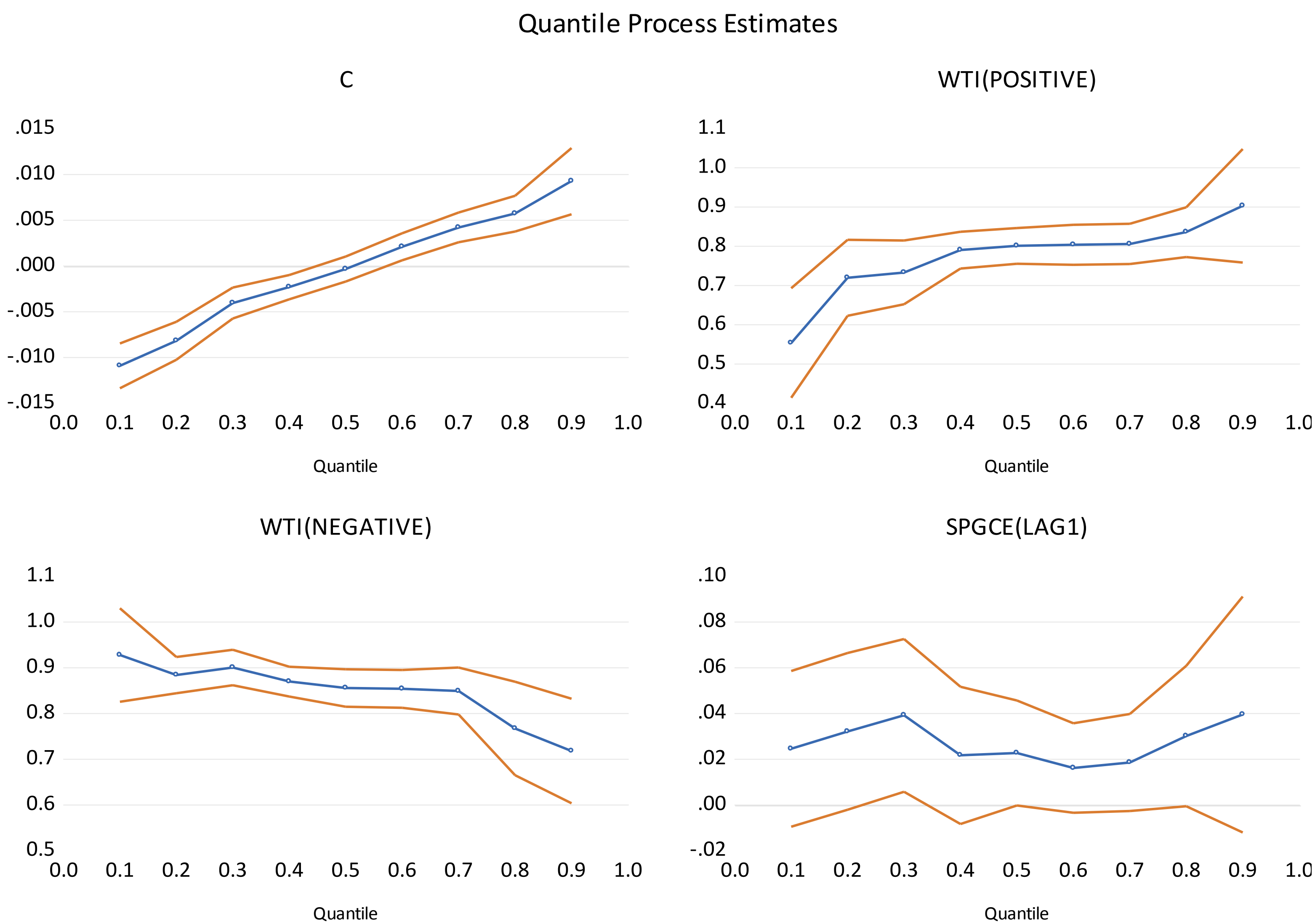

Figure 10. Quantile regression investigating the asymmetric impact of WTI on SPGCE

Notes: The blue line represents the point estimates whereas the two orange lines represent the 95 percent confidence bands.

The above analysis gives a solid proof of our results in section 4.1 that in periods of lower returns, oil movements have a better explaining power for clean energy stock movements. The asymmetrical tests show that negative oil movements are more useful than positive movements in periods of high market distress. The lower explaining power in bullish or median periods, shown in section 4.1, is due to the asymmetry exhibited by positive and negative oil returns.

4.4. Implications of the results

We have revealed that oil price shocks have a strong positive impact on clean energy stock indices at lower quantiles, which complements previous findings [1, 9, 12-14, 31]. Furthermore, the impact tends to decrease at upper quantiles, which suggests a strong association between oil prices and clean energy stock indices during bearish market periods. Economically speaking, the implication of this result matters to the investors operating in clean energy markets who should be highly concerned about variations in the global oil price index when the market is bearish. Given that bearish market conditions refer to periods of low or negative returns, shifting towards clean energy investment in response to oil price movements appears to be common for hedging purposes.

To further explain the reason behind such high dependency of clean energy stock movements on oil prices during bearish periods, we examine the asymmetric relationship to check the nonlinear association between clean energy stock indices and crude oil prices and show evidence of high asymmetries in the lower quantiles and insignificant asymmetries in the upper quantiles. Accordingly, there is evidence of high dependence on negative oil movements in bearish periods for each of the clean energy indices whereas there is a high dependency on positive oil movements during bullish periods. Economically speaking, a potential explanation for these results is that the high negative oil returns in bearish market conditions seem to decrease the investment in crude oil and thus investors choose better assets to hedge market risk. As negative market movement has a high impact on clean energy sources, investors put more money into clean energy sources to hedge their portfolios. However, during bullish market conditions, rising oil prices move symmetrically with clean energy stocks implying the importance of alternative energy as a superior source of energy.

The results of this empirical research have significant implications to investors, financial managers, and portfolio managers who intend to estimate portfolio risk during the episodes of oil price shocks. Our results are also important for detecting hedging and arbitrage opportunities in alternative energy firms. To this end, investors holding assets in crude oil and clean energy markets could use those findings when constructing minimum risk portfolios. Policymakers could also make use of our outcomes while formulating effective strategies to moderate the impact of oil price shocks on clean energy stocks. One such policy could be encouraging industries to improve efficiency in the usage of crude oil and to employ alternative sources to evade oscillations in clean energy stock prices. In sum, active measures should be taken into account for avoiding the contagion risk originating from the unstable crude oil market.

5. Conclusions and implications for sustainability

Unlike previous researchers who mostly apply mean-based models, we examine the dependence structure between WTI prices and renewable energy equity indexes using quantile regression to offer a more comprehensive dependence structure under diverse market conditions. Our empirical analyses provide solid evidence for the decreasing dependence of clean energy stocks on oil price movements. Additionally, the lagged effect of WTI prices on clean energy equity returns is generally significant, which indicates that clean energy stock returns react differently to new information on oil returns under different market conditions. Further analyses involving the presence of asymmetry in the relationship between crude oil returns on the returns of clean energy stock indices in various market conditions show strong effects of negative oil returns during bearish periods and an insignificant effect during bullish periods.

Understanding the connectedness between renewable energy stocks and traditional energy prices is of paramount importance to ethical investors, as this information is essential for gaining superior risk-adjusted returns through proper allocation of clean energy assets to a portfolio. Such knowledge further helps to identify whether and to what extent these stocks are sensitive to shocks emanating from other allied markets. It is worth mentioning that although ethical investors aim at decarbonizing their portfolios, they still attempt to receive healthy returns from their investments. If decarbonizing portfolios does not provide incentives for switching over to renewable energy sources, investors would be reluctant to green their portfolios which will hamper the migration towards a low-carbon economy. Our findings will be of particular interest to those participants who want to invest in eco-friendly firms. Overall, these results could be useful in outlining sustainable business strategies and designing optimal portfolios.

Given earlier evidence from the academic literature that investments in clean energy stocks have positive environmental and socio-economic impacts that potentially help ensure a certain degree of sustainability, it is thus important to consider the application of modern portfolio theory with a view to gaining proper knowledge of stock market strategies. Accordingly, our current empirical analysis is of interest to institutional investors who aim at detecting the clean energy market risk via proper financial modelling. Furthermore, and given the growing interest in both alternative fuel sources and alternative investments, understanding the relationship between oil and clean energy stock markets is always crucial for making investment and risk management decisions.

For future research, it would be interesting to examine the impact of crude oil implied volatility on the return behaviour of renewable energy stocks under diverse market conditions. Other extensions could involve the potential association between critical metals and the markets of clean energy technologies [34] or the application of the approach of Kazemilari et al. [2] on the oil-clean energy nexus.

References

1. Bouri E., Jalkh N., Dutta A., Uddin, G.S. (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: blended copulas approach. Energy, 178, 544-53.

2. Kazemilari, M., Mardani, A., Streimikiene, D., & Zavadskas, E. K. (2017). An overview of renewable energy companies in stock exchange: Evidence from minimal spanning tree approach. Renewable energy, 102, 107-117.

3. Luqman, M., Ahmad, N., & Bakhsh, K. (2019). Nuclear energy, renewable energy and economic growth in Pakistan: Evidence from non-linear autoregressive distributed lag model. Renewable energy, 139, 1299-1309.

4. Razmi, S. F., Bajgiran, B. R., Behname, M., Salari, T. E., & Razmi, S. M. J. (2020). The relationship of renewable energy consumption to stock market development and economic growth in Iran. Renewable Energy, 145, 2019-2024.

5. Rahman, M. M., & Velayutham, E. (2020). Renewable and non-renewable energy consumption-economic growth nexus: New evidence from South Asia. Renewable Energy, 147, 399-408.

6. Kumar, S., Managi, S., Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Economics, 34(1), 215-226.

7. Reboredo, J.C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32-45.

8. Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics, 34(1), 248-255.

9. 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, 558-565.

10. 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, 241-252.

11. Ahmad, W. (2017). On the dynamic dependence and investment performance of crude oil and clean energy stocks. Research in International Business and Finance, 42, 376-389.

12. Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Economics, 76, 1-20.

13. Kocaarslan, B., & Soytas, U. (2019). Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis. Energy Reports, 5, 117-125.

14. 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, 118338.

15. Koenker, R., Bassett, G., (1978). Regression quantiles. Econometrika: journal of the Econometric Society, 46, 33–50.

16. Anguyo, F. L., Gupta, R., & Kotzé, K. (2019). Inflation dynamics in Uganda: a quantile regression approach. Macroeconomics and Finance in Emerging Market Economies, 1-27.

17. Badshah, I.U. (2012). Quantile regression analysis of the asymmetric return-volatility relation. Journal of Futures Markets, 33(3), 235-265.

18. Bouri E., Jalkh N., Roubaud D. (2017). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. Resources Policy, 61, 385-392.

19. Gupta, R., Jooste, C., & Ranjbar, O. (2017). South Africa's inflation persistence: a quantile regression framework. Economic Change and Restructuring, 50(4), 367-386.

20. 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, 30-41.

21. Dutta, A. (2017). Oil Price Uncertainty and Clean Energy Stock Returns: New Evidence from Crude Oil Volatility Index. Journal of Cleaner Production, 164: 1157-1166.

22. Ahmad, W., Sadorsky, P., Sharma, A. (2018). Optimal hedge ratios for clean energy equities. Economic Modelling, 72, 278-295.

23. Hong, H., Stein, J.C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance, 54(6), 2143-2184.

24. Hong, H., Torous, W., Valkanov, R. (2007). Do industries lead stock markets? Journal of Financial Economics, 83(2), 367-396.

25. Narayan, P.K., Sharma, S.S. (2011). New evidence on oil price and firm returns. Journal of Banking & Finance, 35(12), 3253-3262.

26. Xiao, J., Hu, C., Ouyang, G., Wen, F. (2019). Impacts of oil implied volatility shocks on stock implied volatility in china: Empirical evidence from a quantile regression approach. Energy Economics, 80, 297-309.

27. Driesprong, G., Jacobsen, B. Maat, B. (2008). Striking oil: another puzzle?. Journal of financial economics, 89(2), 307-327.

28. Narayan, P.K., Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. Applied energy, 87(1), 356-361.

29. Xiao, J., Zhou, M., Wen, F., Wen, F. (2018). Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: Evidence from oil volatility index. Energy Economics, 74, 777-786.

30. Batten, J. A., Ciner, C., Kosedag, A., & Lucey, B. M. (2017). Is the price of gold to gold mining stocks asymmetric?. Economic Modelling, 60, 402-407.

31. Henriques, I., Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. Energy Economics, 30(3), 998-1010.

32. Lu, H., Jacobsen, B. (2016). Cross-asset return predictability: Carry trades, stocks and commodities. Journal of International Money and Finance, 64, 62-87.

33. Peng, Y., Ng, W.L. (2012). Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. Annals of Finance, 8(1), 49-74.

34. Grandell, L., Lehtilä, A., Kivinen, M., Koljonen, T., Kihlman, S., & Lauri, L. S. (2016). Role of critical metals in the future markets of clean energy technologies. Renewable Energy, 95, 53-62.