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Time-Varying Correlation and Quantile Relationship between Oil Prices and Regional Green Markets

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Abstract: This study examines the time-varying equicorrelation and tail dependence between global oil prices and regional green markets. We use novel approaches, namely the GARCH-DECO model, Quantile-on-Quantile Regression (QQR), and Granger-causality in quantiles. The empirical findings show that global oil prices and renewable energy stock markets are inextricably linked. Specifically, there is a positive equicorrelation between global oil prices and clean energy stock markets. During times of turmoil, these trends become more pronounced, fostering contagion effects that diminish the benefits of diversification between renewable energy stocks and oil portfolios. The outcomes of the QQR technique reveal a heterogeneous interdependence structure between the oil and renewable energy stock markets across the entire distribution. Our results have significant implications for policymakers, investors and traders, as they may assist in understanding the behaviour of renewable energy and oil markets during periods of extreme market stress.

Keywords: GARCH-DECO and regional analysis, oil prices, quantile dependence, renewable energy equities
JEL classification: C58, G10, R11

1. Introduction

In recent decades, meeting the increasing demand for energy has become one of the major challenges for future generations. According to recent predictions, global energy demand is expected to rise by 28% between 2015 and 2040, with non-OECD nations contributing significantly to this increase (Liu & Hamori, 2020). This trend may threaten climate and energy security unless a substantial portion of this demand is met by renewable energy sources (Ferrer et al., 2018; Kocaarslan & Soytas, 2019).

Supporting policies, laws, incentives and technologies integrated into the power sectors of many forward-thinking countries have recently driven a surge in renewable energy installations (Shah et al., 2018; Tien et al., 2024; Urom et al., 2021). Although countries differ significantly in their capacity to invest in sustainable energy systems, legislative frameworks and market mechanisms play a crucial role in reallocating

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private resources toward renewable energy investments (Lee & Baek, 2018; Paiva et al., 2018; Urom et al., 2021). The success of green energy projects depends on raising awareness about environmental pollution and enforcing regulations to reduce fossil fuel consumption. Additionally, the impact of rising oil prices on economic development and increasing energy consumption is a critical factor influencing the profitability of renewable energy projects (Urom et al., 2021).

Investors have recently been paying close attention to companies in the clean energy sector, attracted not only by the environmental and socioeconomic benefits of clean energy investments but also by their potential for higher returns compared to general equities (Elie et al., 2019; Xia et al., 2019; Zhao, 2020). According to Reboredo et al. (2017) and Urom et al. (2021), uncertainty in the oil market motivates investors to allocate funds to renewable energy equities, leading to increased investments in this sector. Policymakers must evaluate both the dependence of regional renewable energy returns on market-based fossil energy costs and their integration with these costs. The influence of crude oil prices could incentivise more investment in renewable energy projects, thereby prompting the creation of new financial incentives. While investors seeking diversification across different time horizons need to understand how regional green energy returns are affected by global financial market volatility, they must also navigate the negative correlation between global renewable energy development and financial market instability.

Given the significance of the relationship between crude oil and clean energy stock markets, our research analyses the equicorrelations and quantile relationships between crude oil prices and the NASDAQ OMX Green Economy US Index, the NASDAQ OMX Green Economy Europe Index, and the NASDAQ OMX Green Economy Asia Index from February 2011 to December 2023. This analysis takes into account both the onset of the COVID-19 pandemic and the period of extraordinary volatility when crude oil prices turned negative. Although Urom et al. (2021) use spillover index and wavelet analysis to describe the lead-lag connection in these regional energy stock markets, these techniques, while providing valuable insights into the time-frequency relationship between variables, do not capture the dependency patterns between distinct quantiles of both the conditional and conditioned variables (Naeem et al., 2020).

This paper first adopts the dynamic conditional equicorrelation (DECO) model by Engle and Kelly (2012) to identify co-movements across green energy stock markets. We then employ the quantile-on-quantile approach developed by Sim and Zhou (2015) to enhance our understanding of the tail dependence between oil prices and selected green energy stock markets. These methods allow us to examine the interdependence structure over various time horizons, helping economic agents such as investors and portfolio managers navigate different investment horizons and market conditions. Specifically, we aim to answer the following research questions: (1) How intertwined are crude oil and regional green energy stock markets? (2) How have these co-movements evolved over time, particularly in response to the COVID-19 crisis? (3) How do these markets compare in terms of tail dependence?

Our study contributes to the existing literature in several ways. First, we provide robust evidence of the time-varying equicorrelation between crude oil prices and regional renewable energy equity markets. Unlike previous studies that used a single stock index to represent the overall green equity market, we divide the green equity market into three regions − the United States, Asia and Europe − and analyse their links to global oil prices across different quantiles. This approach allows us to assess the impact of crude oil price shocks and fluctuations on each regional green energy market over various time horizons and understand investors' perceptions of long-term financial market conditions. Second, the quantile-on-quantile technique, unlike the standard quantile regression model, can explore tail dependence patterns in typical market conditions (middle quantiles), bullish market conditions (higher quantiles), and bearish market conditions (lower quantiles) (Hung, 2021b; Jiang et al., 2020; Naeem et al., 2020). As a result, our findings are more dynamic and detailed, providing significant policy implications regarding the heterogeneous behaviour of crude oil prices and regional renewable energy equity markets across space and time. Finally, we also employ Troster et al.'s (2018) nonlinear quantile Granger causality estimation method. This method complements the quantile-on-quantile approach by identifying causal relationships between the two variables at the median, lower and upper tails of the distribution. The outcomes derived from this asymmetric causality analysis provide additional support and validation for the quantile-on-quantile results.

The remainder of this paper is organised as follows. Section 2 reviews the related literature. Section 3 outlines our methodology. Section 4 presents our empirical results and discussions. Section 5 concludes the paper.

2. Literature Review

There is a substantial body of literature exploring the interdependence between renewable energy, oil prices and stock markets, including evidence of causal relationships, interdependence and transmission effects. Oil markets, being a significant and sometimes contentious factor, are considered one of the most critical determinants influencing the returns of renewable energy firms. Given the scope of our research, we specifically focus on the literature concerning the oil-renewable energy relationship in three regions: the United States, Europe, and Asia.

Oil prices are closely related to financial markets, and this relationship is one of the most extensively studied areas in research (Ferrer et al., 2018; Kocaarslan and Soytas, 2019; Shah et al., 2018; Uddin et al., 2019; Zhao et al., 2021). Additionally, fluctuations in the oil market driven by economic growth can also stimulate the development of green markets (Urom et al., 2021; Zhao, 2020). As a result, examining the connection between oil prices and regional green markets is a common focus. For example, Dominioni et al. (2019) argued that the total price and volatility spillovers from oil prices to renewable stock markets are greater in the United States than in Europe. Ma et al. (2019) highlighted the importance of industrial-level common information in understanding the oil-stock nexus. Similarly, Urom et al. (2021) found a significant relationship between regional energy equities across all wavelet scales, with strong medium- and long-term dependence observed among regional clean energy equity markets, particularly between the US and European markets. Shah et al. (2018) demonstrated notable differences between countries, such as a strong correlation between oil prices and renewable energy in the US and Norway, while no such correlation is found in the UK. Kocaarslan and Soytas (2019) indicated significant asymmetric effects between clean energy stock prices and technology firms relative to crude oil markets.

Ferrer et al. (2018) examined the time and frequency relationships between US energy stock markets, crude oil prices and several key financial variables, finding that price and volatility spillovers occur in the very short run. Dawar et al. (2021) extended Ferrer et al.'s research by providing a more comprehensive analysis of the interdependence between the oil market and renewable energy stock prices under various market conditions. They found that new information about oil returns significantly impacts renewable energy stock prices. Zhao et al. (2021) demonstrated that simulating scenarios combining oil price volatility with renewable energy policies underscores the important role of these policies.

Additionally, Uddin et al. (2019) investigated the cross-quantile dependency of green energy equity markets on aggregate stock indexes, oil and gold prices, and exchange rate returns. Using a cross-quantilogram technique, they found that renewable stock returns positively impact oil prices and the aggregate stock index, with this relationship being asymmetric across quantiles. Xia et al. (2019) employed a network technique to analyse how changes in fossil energy prices affect renewable energy stock returns. Their findings revealed a relatively high level of intercorrelation within fossil and renewable energy network systems. In their return connectedness network, the electricity market is the largest contributor to changes in renewable energy returns, while oil and coal are also major contributors. Their time-varying analysis showed that the impact of fossil energy price changes on renewable energy returns follows a distinct time-varying pattern with significant volatility. During the COVID-19 pandemic, Corbet et al. (2020) found that declining oil prices have favourable and economically significant spillovers to renewable energy and coal markets.

While many studies have explored the relationship between oil prices and various traditional assets (Dutta, 2017; Elie et al., 2019; Lee & Baek, 2018; Mejdoub & Ghorbel, 2018; Troster et al., 2018; Xia et al., 2019; Zhao, 2020), only a few have examined the connections between oil prices and regional green markets (Urom et al., 2021). Understanding this relationship is crucial for investors seeking to hedge against climate risks in their green investments and for policymakers aiming to decarbonise stock markets by promoting the use of green technologies for climate change mitigation.

Given the above developments, this study aims to extend existing research by investigating the intensity and extreme dependence structure between crude oil prices and the NASDAQ OMX Green Economy US Index, NASDAQ OMX Green Economy Europe Index and NASDAQ OMX Green Economy Asia Index. We offer a fresh perspective on the interdependence structure between oil and regional green energy stock markets, contrasting with previous approaches that explore equicorrelations and tail dependencies (Dutta, 2018; Elie et al., 2019; Paiva et al., 2018; Reboredo, 2015; Reboredo et al., 2017). This study builds on prior research that utilises the GARCH-DECO model and quantile-on-quantile regression to capture the interdependence of crude oil and regional green energy stock markets. Our goal is to provide valuable insights for assessing and comparing investments in these regions across various time frames.

3. Methodology

We begin by measuring equicorrelation and volatility transmission across global oil and regional renewable energy equity prices using the GARCH-DECO model introduced by Engle and Kelly (2012). Engle (2002) introduced the DCC-GARCH model, which allows for flexible modelling of multivariate conditional volatility and dynamic correlations over time. However, estimating the DCC model involves calculating correlations for a large number of pairs, n (n − 1)/2, which can be complex to interpret (Kang et al., 2019). To address these challenges, Engle and Kelly (2012) developed the DECO-GARCH model, where the average of the conditional correlations is equal to the average of all pairwise correlations. The DECO model provides a single dynamic correlation coefficient that reflects the overall correlation level among assets. This feature enables the analysis of market integration across selected variables using a single figure, eliminating the need to analyse each pairwise correlation individually to understand market co-movements.

Additionally, we utilise the quantile-on-quantile regression (QQR) introduced by Sim and Zhou (2015) to explore the tail dependence between the selected variables. Finally, we apply the Granger-causality approach based on different quantiles, developed by Troster et al. (2018), to capture the causal connections between oil prices and green energy stock markets. Combining these methods enables us to systematically understand both the interactions between quantiles of the regressor and the causal associations between variables, providing more detailed insights than traditional regression frameworks (Hung et al., 2021a; Iqbal et al., 2021).

3.1 The GARCH-DECO Model

We have a return series and its vector is $r_t = [r_{1,t}, \cdots, r_{n,t}]'$. The framework of ARMA (1,1) model is written as follows:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t + \xi \varepsilon_{t-1}, \text{ with } \varepsilon_t = u_t h_t \tag{1}$$

where constant vector is presented by μ, and $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]'$ is a vector of residuals.

The dynamic conditional correlation (DCC) method is employed to reflect the time-varying behaviour of conditional covariance. This estimator, proposed by Engle (2002), captures the dynamic correlations between multiple time series. The conditional covariance matrix H_t now has the following definition:

$$H_t = D_t R_t D_t \tag{2}$$

where R_t is the time-varying correlation matrix, and we denote diagonal matrix with conditional variances along the diagonal as $D_t = diag\sqrt{\{H_t\}}$.

Each conditional variance's GARCH (1,1) specification is expressed as follows:

$$h_{ii,t} = c + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1} \tag{3}$$

$$h_{ij,t} = \rho_{ij}\sqrt{h_{ii,t} h_{jj,t}}\ ,\ i, j = \overline{1,n} \tag{4}$$

$$E_{t-1} e_t e_t' = D_t^{-1} H_t D_t^{-1} = R_t = \left[\rho_{ij,t}\right] \tag{5}$$

The mean-reverting conditionals with the GARCH(1,1) specification is:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{6}$$

where

$q_{ij,t} = \bar{\rho}_{ij}(1-\alpha-\beta) + \alpha e_{i,t-1}e_{j,t-1} + \beta q_{ij,t-1}$

$\bar{\rho}_{ij}$ denotes the correlation between $e_{i,t-1}$ and $e_{j,t-1}$. The coefficients of α and β must hold, $\alpha \geq 0,\ \beta \geq 0,$ and $\alpha + \beta < 1$

The presence of a value of $(\alpha + \beta)$ close to one indicates that the conditional variance is persistent.

In the matrix,

$$Q_t = \bar{Q}(1-\alpha-\beta) + \alpha e_{t-1}e_{t-1}^{'} + \beta Q_{t-1} \tag{7}$$

$\bar{Q}$ is written as

$$\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} e_t e_t^{'} \tag{8}$$

We can get R_t from (9)

$$R_t = \left(Q_t^*\right)^{1/2} Q_t \left(Q_t^*\right)^{1/2} \tag{9}$$

where $Q_t^* = diag\{Q_t\}$.

Nonetheless, Aielli (2013) claimed that estimating the covariance matrix Q_t is incoherent because $E[R_t] \neq E[Q_t]$. The author uses the correlation-driving process (cDCC) to illustrate the following consistent model:

$$Q_t = (1-\alpha-\beta)S^* + \alpha\left(Q_{t-1}^{*1/2}\varepsilon_{t-1}\varepsilon_{t-1}^{'}Q_{t-1}^{*1/2}\right) + \beta Q_{t-1} \tag{10}$$

where S^* is the unconditional covariance matrix of $Q_t^{*1/2}\varepsilon_t$.

Engle and Kelly (2012) proposed modelling ρ_t by obtaining the conconditional correlation matrix Q_t via the cDCC method and then taking the mean of its off-diagonal members. The estimating time is cut in half thanks to the DECO specification. The scalar equicorrelation can be expressed in the following way:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(K_n^{'}R^{cDCC}K_n - n\right) = \frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{11}$$

where $q_{ij,t} = \rho_t^{DECO} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \rho_t^{DECO}\right) + \beta_{ECO}\left(q_{ij,t} - \rho_t^{DECO}\right)$

This indicates that an ARMA (1,1) mean equation will be included in each GARCH model to account for potential autocorrelation of returns. In line with Kang et al. (2019), we will apply a multivariate Student t-distribution for the DECO model.

3.2 Quantile on Quantile Approach

Sim and Zhou (2015) introduced the quantile-on-quantile regression (QQR) approach, which extends quantile regression by examining how the quantiles of an independent variable influence the quantiles of the dependent variable. The QQR method integrates nonparametric and quantile regression techniques to provide insights into the relationship between different quantiles of the variables.

The equation for nonparametric quantile regression is as follows:

$$O_t = \gamma^{\sigma}(RE_t) + \mu_t^{\sigma} \tag{12}$$

where RE_t represents renewable energy stock prices at time t, O_t represents oil prices at time t, σ is the σ^{th} quantile of the renewable energy stock prices, and the quantile error term μ_t^{σ} has a conditional σ^{th} quantile that is equal to zero. The unidentified function is γ^{σ} because we do not have previous knowledge of the nexus across the markets under consideration.

3.3 Quantiles Granger-Causality Approach

Granger (1969) asserted that a time series Y_i does not Granger-cause another series X_i if the previous Y_i does not aid in forecasting X_i, assuming the former X_i.

Assume a describing vector exists $\left(M_i = M_i^X, M_i^y\right)' \in \mathbb{R}^e, e = o + q$, where M_i^y is the former evidence set of $Y_i M_i^y \coloneqq \left(Y_{i-1}, \dots, Y_{i-q}\right)' \in \mathbb{R}^q$. We write the null hypothesis of Granger-non-causality running from Y_i to X_i as:

$$H_o^{Y \nrightarrow X}: F_X\left(x \middle| M_i^X, M_i^y\right) = F_X\left(x \middle| M_i^X\right), \text{for all } x \in \mathbb{R} \tag{13}$$

where the conditional scattering function of X_i is $F_X(.\,|M_i^X, M_i^Y)$, given (M_i^X, M_i^Y).

Following Troster et al. (2018), the present paper employs the D_T test by determining the quantile autoregressive function $m(\cdot)$ for all $\pi \in \Gamma \subset [0,1]$,

$$AR(1): m^1\left(M_i^X, \partial(\pi)\right) = \lambda_1(\pi) + \lambda_2(\pi)\, X_{i-1} + \mu_t \Omega_{\Upsilon}^{-1}(\pi) \tag{14}$$

where the values $\partial(\pi) = \lambda_1(\pi), \lambda_2(\pi)$ and μ_t are computed by supreme probability in a grid of quantiles of the same size. The antithesis of a standard ordinary scattering function is $\Omega_{\Upsilon}^{-1}(.)$. To correct the causal causality sign between the series, we compute the (QAR) frameworks in equation (14) with a lagged variable to another variable. Finally, using equation (14) as a guide, the equation for the QAR (1) model is as follows:

$$Q_\pi^X\left(X_i \middle| M_i^X, M_i^Y\right) = \lambda_1(\pi) + \lambda_2(\pi)\, X_{i-1} + \eta(\pi) Y_{i-1} + \mu_t \Omega_{\Upsilon}^{-1}(\pi) \tag{15}$$

3.4 Data

We use daily data from Datastream for the NASDAQ OMX Green Economy Index Family, which includes regional renewable energy equity indices. The NASDAQ OMX Green Economy US Index (US), NASDAQ OMX Green Economy Europe Index (EURO) and NASDAQ OMX Green Economy Asia Index (ASIA) measure the performance of renewable energy equity markets in the US, Europe and Asia, respectively. These indices track firms across various sectors closely tied to sustainable economic development, providing a comprehensive view of the green equity markets in these regions.

In this study, we analyse the relationship between global oil prices and regional green energy equity indices using the global crude oil market index (OIL). We transform all daily data series into log-returns by calculating the logarithmic difference of index values. The sample period for the analysis spans from July 28, 2011 to December 30, 2023, based on data availability.

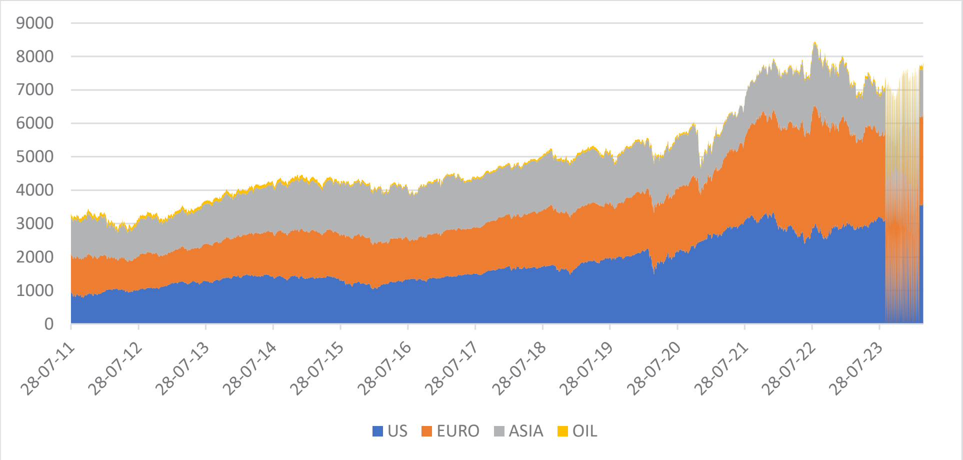

Figure 1. Daily prices of regional clean energy stocks and oil prices

Figure 1 displays the daily series for each variable over the sample period. All three green energy stock indices exhibited an upward trend, whereas oil prices show less volatility. Notably, both the green energy indices and oil prices experience significant declines during the COVID-19 pandemic and the Ukraine-Russian conflict. Despite these downturns, all variables eventually recover to their pre-crisis levels.

Table 1. Descriptive statistics

	US	EURO	ASIA	OIL
Mean	0.0459	0.0359	0.0007	-0.0321
Maximum	10.4123	8.1019	7.6834	40.3524
Minimum	-12.2917	-14.6407	-10.4786	-40.4629
Standard Deviation	1.3310	1.2230	1.4023	2.6127
Skewness	-0.4941	-1.0465	-0.3313	-1.2356
Kurtosis	13.2732	15.4080	7.6233	63.6670
Jarque-Bera	11703.39***	17397.60***	2396.868***	405065.3***
ADF	-19.1367***	-51.0197***	-43.0307***	-46.3132***
ARCH-LM	587.4440***	36.1582***	69.2162***	244.6258***

Notes: ADF is test statistics of the augmented Dickey and Fuller unit root test. US is the NASDAQ OMX Green Economy US Index, EURO represents NASDAQ OMX Green Economy Europe Index, ASIA is NASDAQ OMX Green Economy Asia Index, and OIL represents global crude oil market index. *** denotes significance at the 1% level.

Table 1 presents the descriptive statistics for oil and selected green stock market returns. The mean values of green energy stock returns are positive and close to zero, while the mean return for oil is negative. Oil prices also exhibit greater volatility compared to the three clean energy stock markets, as indicated by the standard deviation of daily returns. The skewness and kurtosis values deviate from normal distribution, as confirmed by the Jarque-Bera test, suggesting that none of the selected series follow a normal distribution. Given the distribution characteristics, we use the Student's t-distribution, rather than the Gaussian error distribution, for estimating all univariate and multivariate GARCH models. The unit root test results, also shown in Table 1, indicate that at the 1% significance level, the ADF test confirms the stationarity of the log levels of all indices. Additionally, the ARCH-LM test reveals the presence of an ARCH effect in both oil price and clean energy stock market returns. Consequently, we apply the GARCH-DECO model to account for this ARCH effect in the selected market returns.

Figure 2 illustrates the overall distribution of the data and the pairwise correlations between oil prices and clean energy stock market performance. The figure confirms that

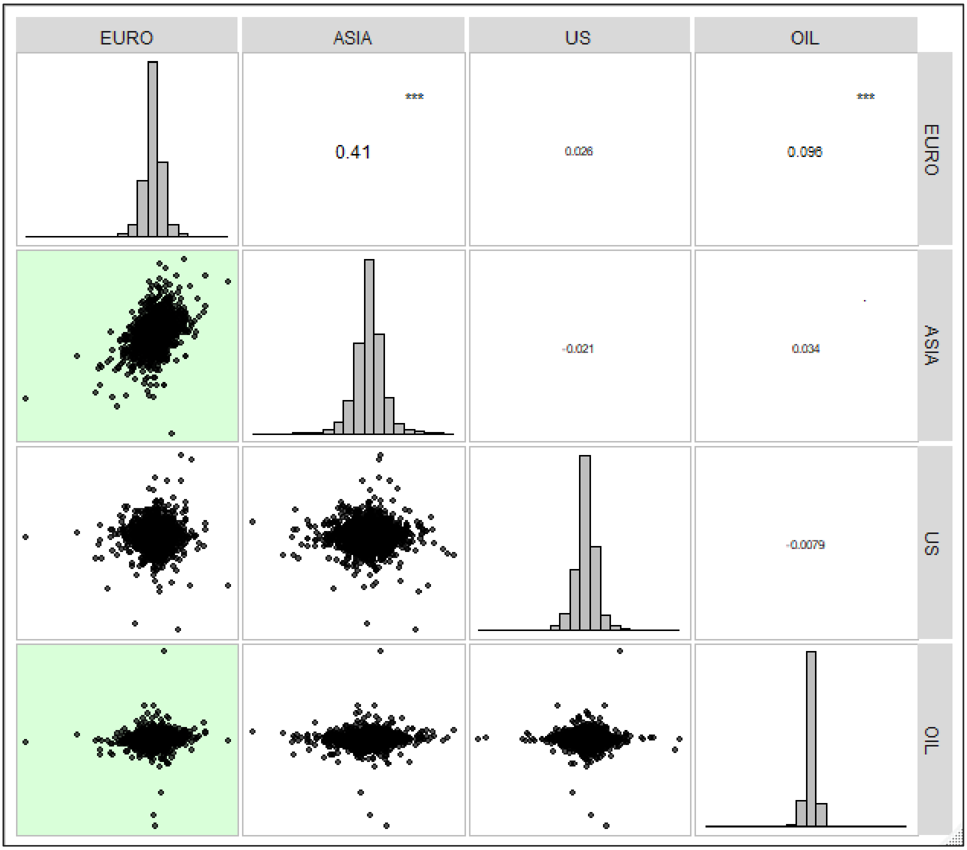

Figure 2. Plots of the distribution and pair-wise correlations

the data is not normally distributed. Among the observed correlations, the highest is 0.098 between OIL and EURO, followed by 0.034 between OIL and ASIA. Overall, Figure 2 provides a clear depiction of both the data distribution and the correlation structure among the main variables.

4. Empirical Results

4.1 GARCH-DECO Findings

The model primarily aims to estimate various versions of the multivariate GARCH model, each including a constant in the mean equation along with a GARCH(1,1) variance equation. Modifications are made to incorporate an ARMA(1,1) term in the mean equation and to select the appropriate distribution. The model selection criteria indicate that the DECO model, featuring an ARMA(1,1) term in the mean equation and estimated using a multivariate distribution, offers the best fit with the lowest AIC and BIC. Table 2 details the identification of the most suitable GARCH model for each asset. The empirical results of the first-step univariate ARMA(1,1)-GARCH(1,1) framework, based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC), are presented in Table 2.

Table 2. Identification of best-fitted GARCH-model

EURO		1	2	3	4	5	6
ARMA	(p, q)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)
GARCH	LOG	10798.93	10802.09	10789.28	10789.81	10794.93	10798.33
	AIC	-6.523981	-6.523922	-6.513590	-6.520442	-6.519597	-6.524989
	BIC	-6.514757	-6.514700	-6.502522	-6.511216	-6.510376	-6.513918
ASIA		1	2	3	4	5	6
ARMA	(p, q)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)
GARCH	LOG	9614.008	9612.224	9465.09	10452.76	10456.04	10465.05
	AIC	-5.807255	-5.806177	-5.321603	-6.316662	-6.314828	-6.323486
	BIC	-5.801722	-5.800644	-5.310534	-6.307436	-6.305606	-6.312415
US		1	2	3	4	5	6
ARMA	(p, q)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)
GARCH	LOG	3896.708	3896.708	3894.209	3896.712	3896.706	3896.710
	AIC	-2.347161	-2.352694	-2.252090	-2.352692	-2.352692	-2.352091
	BIC	-2.347161	-2.347161	-2.244713	-2.347160	-2.347160	-2.344713
OIL		1	2	3	4	5	6
ARMA	(p, q)	(1,0)	(0,1)	(1,1)	(2,0)	(0,2)	(2,1)
GARCH	LOG	7437.401	7436.937	7414.366	7426.868	7426.804	7437.906
	AIC	-4.492085	-4.491805	-4.462668	-4.485721	-4.485682	-4.491786
	BIC	-4.486552	-4.486272	-4.480091	-4.480188	-4.480149	-4.484409

Notes: This table identifies the best fitted GARCH model based on the values of Akaike information criterion (AIC) and Bayesian information criterion (BIC). LOG refers to the log-likelihood.

Panel A of Table 3 shows that the AR(1) and MA(1) coefficients are statistically significant for the Asian clean energy stock market, indicating that essential market information is promptly reflected in the prices. The ARCH and GARCH coefficients are also significant at conventional levels, suggesting that past shocks and volatilities have a strong influence on current conditional volatility (Demiralay & Golitsis, 2021;

Table 3. ARMA-GARCH with DECO specification

	EURO	US	ASIA	OIL
Panel A: Univariate ARMA-GARCH model				
Const (M)	0.0543***	0.0801***	0.0242	0.0383
(0.0186)	(0.0182)		[0.0297]	[0.0299]
AR (1)	0.3835	-0.0052	0.3068**	-0.5827
	(0.4359)	(1.5025)	[0.1010]	[0.5054]
MA (1)	-0.3692	-0.0087	-0.1188	0.5685
	(0.4392)	(1.5046)	[0.1060]	[0.5123]
Const (V)	0.0307***	0.0672***	0.0494***	0.1531***
	(0.0041)	(0.0082)	[0.0081]	[0.0224]
ARCH	0.0959***	0.1570***	0.0998***	0.2066***
	(0.0068)	(0.0136)	[0.0091]	[0.0073]
GARCH	0.8822***	0.7997***	0.8750***	0.7946***
	(0.0089)	(0.0154)	[0.0111]	[0.0109]
Univariate diagnostic tests				
Q(10)	12.715	3.6779	3.7408	7.3501
	[0.122]	[0.885]	[0.442]	[0.270]
$Q^2(10)$	13.257	9.3442	13.702	5.0611
	[0.210]	[0.500]	[0.187]	[0.887]
ARCH-LM	2.0249	0.0342	0.0994	0.0476
	[0.1547]	[0.8533]	[0.7525]	[0.8273]
Panel B: DECO model				
Average p_{ij}	0.0785***			
	(0.0390)			
A_{DECO}	0.0115**			
	(0.0046)			
B_{DECO}	0.9765***			
	(0.0109)			
Multivariate diagnostic tests				
Hosking (20)	245.01			
	[0.147]			
Li-McLeod (20)	256.33			
	[0.251]			

Notes: Q(10) and $Q^2(10)$ are the Ljung-Box test statistics used to the standard residuals and the squared standardised residuals, respectively. Hosking (20) and Li-McLeod (20) are the multivariate versions of Ljung–Box statistic of McLeod and Li (1983), up to 20 lags. p-values are in brackets and the standard errors are in parentheses. The asterisks *, **, *** represent significance at the 10%, 5% and 1% levels, respectively.

Hung, 2021a; Hung, 2021b). Diagnostic tests confirm that all univariate models are appropriate. The Ljung-Box test and ARCH-LM test reject the null hypotheses of no serial correlation and homoscedasticity, respectively. This rejection indicates that there is no serial correlation in the standardised residuals and no residual ARCH effects, demonstrating that the univariate models are adequately specified.

The DECO parameters are documented in Panel B of Table 3. The estimates of the DECO model are all statistically significant, indicating a significant dynamic relationship between oil prices and the selected energy stock markets. With a value of 0.0785, the coefficient average equicorrelation DECO is positive and significant, indicating a contagion effect across these markets. At the 5% level, the parameter of standardised residuals is positive and statistically significant, implying that shocks significantly affect equicorrelations. The parameter A_{DECO} is highly significant, indicating the importance of oil price shocks on clean energy stock markets. The parameter B_{DECO} is significant and close to one in all cases, implying that time-varying equicorrelation exists and is slowly mean-reverting across these markets. These findings suggest that market equicorrelations will be stable. Multivariate portmanteau tests are also used to assess the DECO model's validity. In the multivariate model, the Hosking and Li-McLeod tests do not reject the null hypothesis of no serial connection, suggesting well-specification. The diagnostic tests, as well as the statistical significance of the estimations, support our adoption of the GARCH-DECO model.

Next, we conduct a detailed examination of the correlation between oil prices and clean energy stock returns. The results, derived from the ARMA-GARCH model with the DECO specification, provide dynamic bilateral conditional correlations. Figure 3 illustrates the time evolution of these time-varying equicorrelations. The fitted equicorrelations range from 0.025 to 0.225. Starting at approximately 0.075 at the beginning of the sample period, the equicorrelations nearly reach 0.15 by the end of the sample period. There is a noticeable upward trend in equicorrelations, which spike significantly during the European debt crisis (2014) and the COVID-19 pandemic. This rise in equicorrelations is likely due to increased trading activity, particularly by institutional investors, leading to greater interconnectedness between the markets.

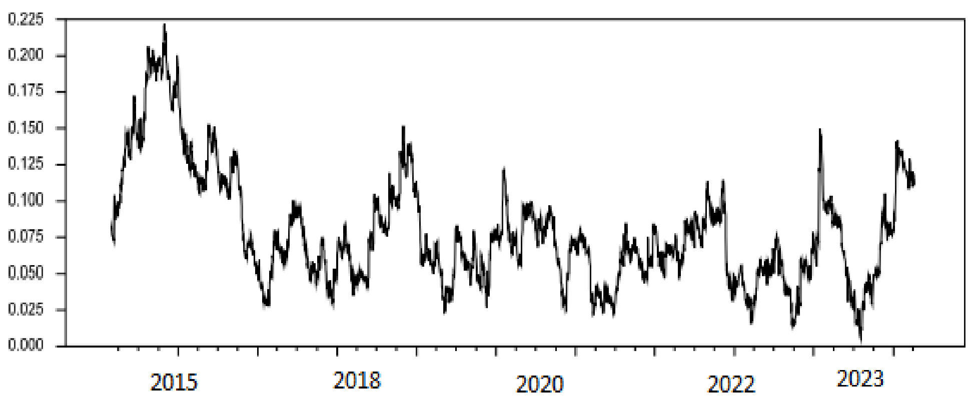

Figure 3. Time-varying equicorrelations of regional clean energy stocks and oil returns

Toward the end of our sample period, there is a notable shift, with a significant increase in the small interconnectivity between the markets under study.

During this period, short-run market integration exceeds long-run levels, indicating a heightened degree of co-movement between oil prices and green energy stock markets. This trend is attributed to significant fluctuations in global oil markets and the downward pressure on stock prices due to the war and the global economic collapse associated with the COVID-19 pandemic. Although medium- and long-run integration

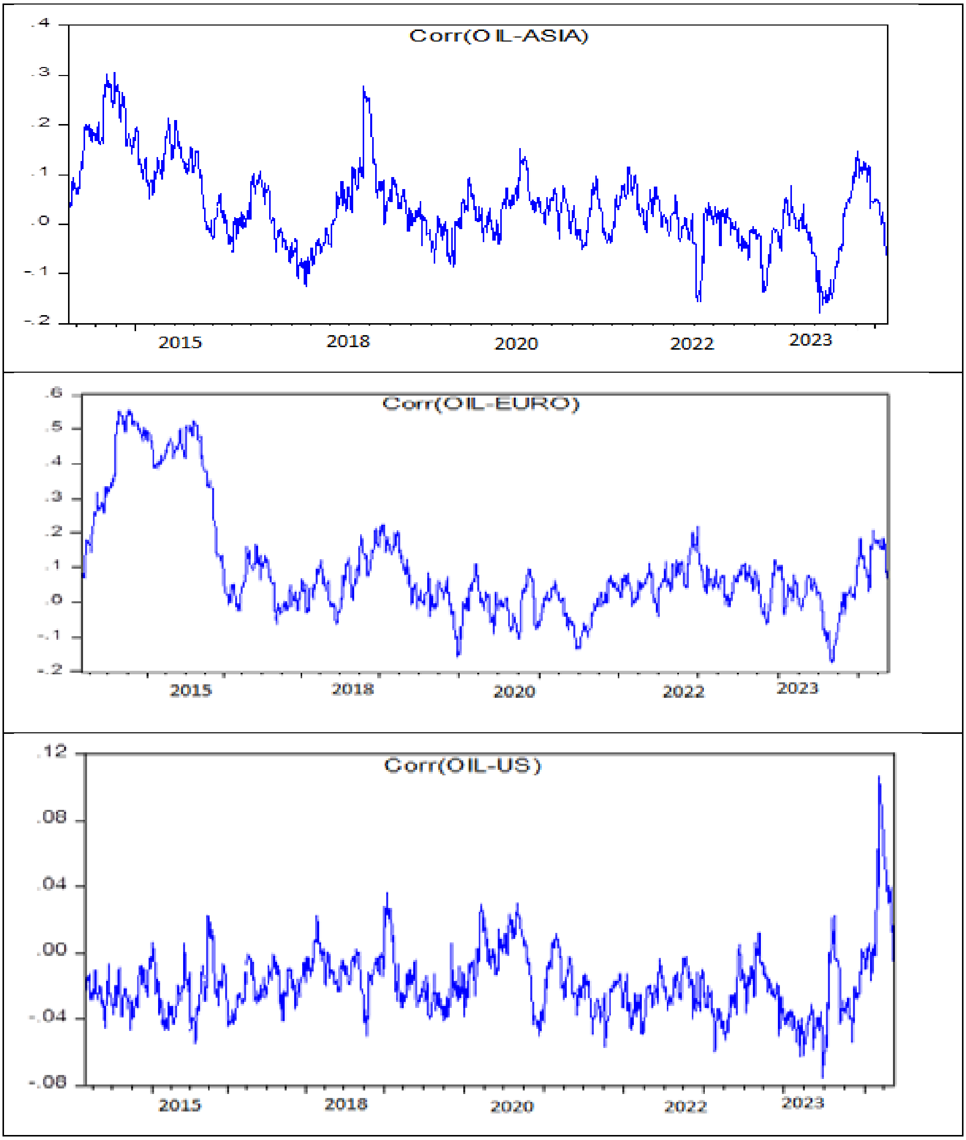

Figure 4. Dynamic condition correlation between oil and regional clean energy stock returns

levels are generally similar, the long-run level is notably higher than the medium-run level at the beginning of the sample period. However, during the COVID-19 outbreak and the Ukraine crisis, the medium-run integration level surpasses the long-run level. This shift may reflect the epidemic's long-term effects, with persistent market fears extending into the medium term, at least until the global economy begins to recover.

In summary, as evidenced by the strengthened DECO model over time, the selected markets have become increasingly integrated, supporting Hung's (2021a) recent conclusions. This increased integration, particularly during periods of instability, reduces the benefits of international portfolio diversification for investors. To test for robustness, we estimate dynamic conditional correlation models between oil prices and regional clean energy stock returns from 2011 to 2023. Figure 4 demonstrates that the pairwise dynamic conditional correlation results align with the DECO estimates presented in Figure 3.

4.2 Quantile on Quantile Estimation

We utilise the quantile-on-quantile regression (QQR) framework developed by Sim and Zhou (2015) to explore the heterogeneous dependence structure between clean energy stock markets and oil prices. This technique effectively captures the varying interdependence across different quantiles while preserving the characteristics of quantile regression (Hung, 2021a; Naeem et al., 2020). Figure 5 presents the QQR results in three dimensions, illustrating the quantile-on-quantile estimates of the slope coefficients as functions of the quantile parameters for both the dependent and independent variables. The plots show the estimated slope coefficient $\beta_1(\theta,\tau)$ in the z-axis versus the quantile of the oil price θ in the x-axis and the quantile of energy stock returns τ in the y-axis. The two generate nonlinear coefficients in the models, as we can observe.

Figure 5 illustrates the QQR findings of oil prices relative to the selected regional clean energy stock markets. It reveals a heterogeneous co-movement between these variables. Generally, the middle return quantiles of oil prices show a weak positive correlation with the returns of clean energy stock markets throughout the sample period, with the exception of ASIA. The QQR estimates reveal that the influence of crude oil markets on the European clean energy markets varies across different quantiles of both dependent and independent variables. Specifically, upper quantiles (0.80−0.95) of oil prices positively affect the lower quantiles (0.05−0.25) of clean energy stock returns in Europe, indicating that negative changes in oil prices have a positive impact on the EURO index during bearish market conditions. Conversely, during moderate quantiles (0.35−0.70), there is a negative relationship between oil prices and clean energy stock returns. A similar pattern is observed in the US markets, where the interdependence is positive across both lower and upper quantiles, but moderate quantiles of oil prices negatively affect the US clean energy stock market. Overall, the results suggest that both European and US clean energy stock markets are positively influenced by global oil price changes at extreme quantiles but experience a negative impact at moderate quantiles. These findings are consistent with the studies by Ma et al. (2019) and Urom et al. (2021).

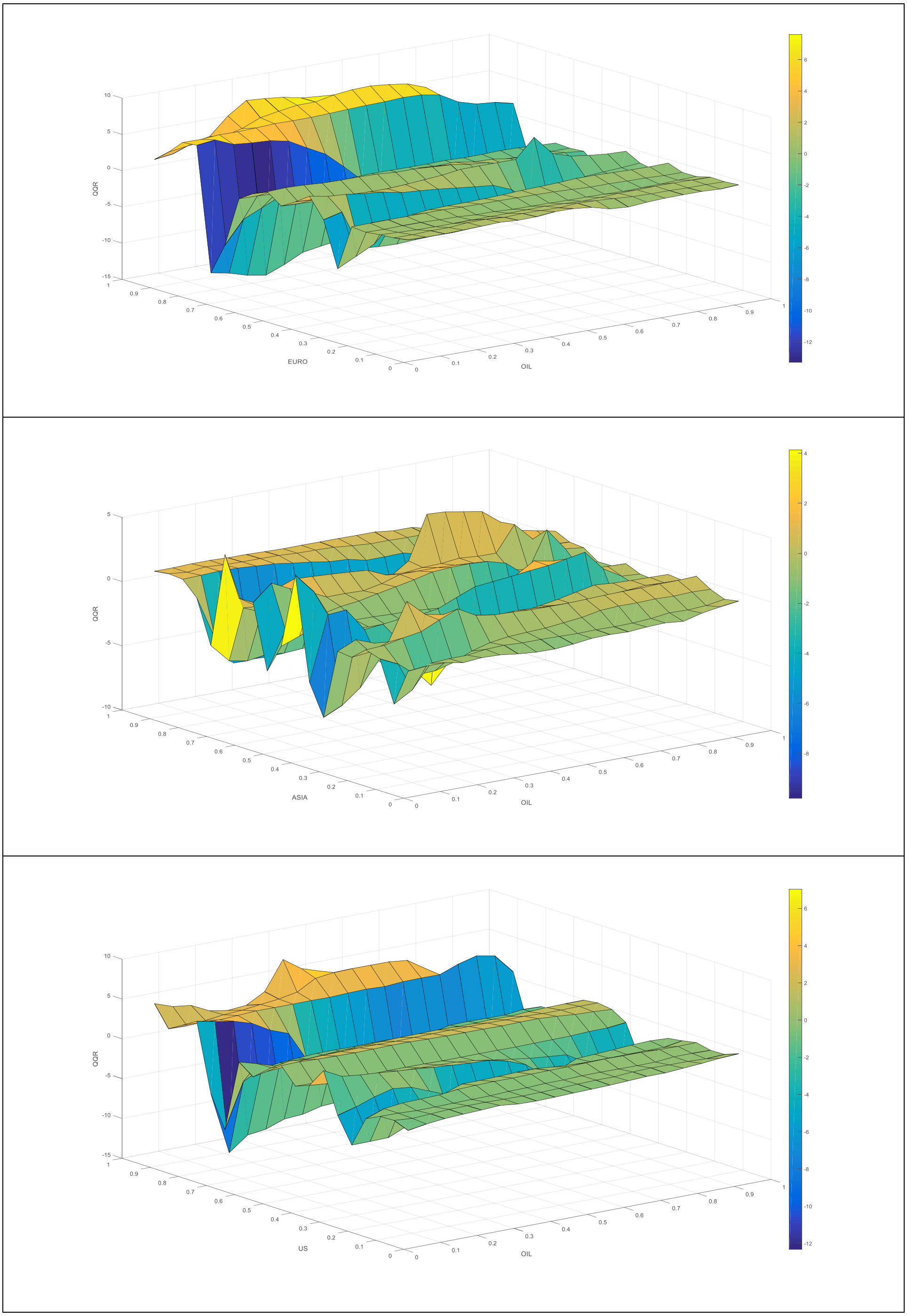

Figure 5. QQR estimates between regional clean energy stock markets and oil returns

Notes: This figure describes the estimates of the slope coefficient, $\beta(\tau, \theta)$ which is placed on the z-axis against the quantiles of the stock returns (θ) x-axis and quantiles of the OIL (θ) on the y-axis. The different shaded bars measure the degree of the co-movement or correlation between variables under investigation.

Next, we examine the results for clean energy stock markets in Asia, which reveal differing findings compared to the other regions. In Asia, oil prices have a positive impact on the clean energy stock markets across various quantiles. However, during intermediate quantiles of both stock and oil prices, the associations between these variables are negligible. The observed significant positive impact in Asia may be attributed to the region's status as a net oil importer, characterised by a relatively inflexible domestic demand for oil and heightened sensitivity to oil price fluctuations (Jiang et al., 2020).

The results indicate that oil price volatility significantly affects investor sensitivity across various clean energy stock markets. The impact of low oil-specific demand shocks varies depending on the conditions within the energy stock markets (Jiang et al., 2020). High oil prices generally have a more pronounced positive effect on stock prices when the market is managed by more confident investors, compared to when less confident individuals are in control. This effect is particularly evident when both the green energy stock markets and oil prices are relatively stable. Overall, high oil prices tend to positively influence clean energy equity markets in most regions (Ferrer et al., 2018; Ma et al., 2019; Urom et al., 2021).

4.3 Granger Causality in Quantiles

We now present the results of Granger causality tests in quantiles, which assess the causal effects of oil prices on energy stock markets across different regions using a grid of 19 quantiles. Table 4 shows that fluctuations in global oil prices Granger-cause

Table 4. Granger-causality between OIL and regional energy stock markets

τ	*OIL→EURO*	*EURO→OIL*	*OIL→ASIA*	*ASIA→OIL*	*OIL→US*	*US→OIL*
0.05	0.9980	0.2806	0.9980	0.5755	0.9980	0.3417
0.10	**0.0036**	0.3129	**0.0036**	0.2230	**0.0036**	**0.0036**
0.15	**0.0036**	**0.0144**	**0.0036**	0.4388	**0.0036**	0.1223
0.20	0.1691	**0.0252**	0.1691	**0.0791**	0.1691	**0.0324**
0.25	**0.0180**	**0.0036**	**0.0180**	**0.0216**	**0.0180**	**0.0216**
0.30	0.1007	**0.0036**	0.1007	**0.0072**	**0.1007**	**0.0036**
0.35	**0.0036**	**0.0468**	**0.0036**	**0.0036**	**0.0036**	**0.0036**
0.40	**0.0504**	**0.0396**	**0.0504**	**0.0791**	**0.0504**	**0.0036**
0.45	**0.0252**	0.1799	**0.0252**	**0.0647**	**0.0252**	**0.0036**
0.50	**0.0072**	0.9980	**0.0072**	0.3957	**0.0072**	**0.0216**
0.55	0.2770	0.4353	0.2770	**0.0036**	0.2770	0.3058
0.60	0.9137	0.6151	0.9137	0.9980	0.9137	0.9980
0.65	0.6079	0.8381	0.6079	**0.2770**	0.6079	**0.0216**
0.70	0.8381	0.8022	0.8381	0.0935	0.8381	**0.0036**
0.75	**0.0288**	**0.0036**	**0.0288**	0.1871	**0.0288**	**0.0036**
0.80	0.3993	**0.0108**	0.3993	**0.0036**	0.3993	**0.0036**
0.85	**0.0036**	**0.0036**	**0.0036**	**0.0036**	**0.0036**	**0.0036**
0.90	**0.0036**	0.2014	**0.0036**	**0.0360**	**0.0036**	**0.0072**
0.95	0.5791	0.3094	0.5791	0.3633	0.5791	0.6331

Note: Bold *p*-values denote rejection of the null hypothesis at the 10% significance level.

increases in the EURO, US and ASIA indices at the 10% significance level across all distribution quantiles for the selected clean energy stock markets. However, except for the quantiles between [0.50–0.70], the EURO, US and ASIA indices also Granger-cause oil prices at the 10% significance level. This indicates a bidirectional causal relationship between oil prices and the selected clean energy stock markets at the 10% significance level.

Our approach aligns with the strategies of institutional investors, who manage diversified asset portfolios rather than focusing on individual stocks. This perspective helps us gain a deeper understanding of the relationship between oil prices and clean energy stock markets. Given the strong connection between these equity markets, analysing the interactions between oil price variations and clean energy stock markets, along with spillover effects at different frequencies, is crucial for making informed strategic investment decisions across various time horizons. Furthermore, oil prices can impact engagement in clean energy through both supply and demand-side motivations, affecting both the short and long run. Policymakers are thus keen to understand the dynamics between oil prices and green energy stock markets, including the transmission effects between them.

The observed positive and significant relationships across regional green energy stock markets indicate potential challenges for portfolio managers and investors seeking diversification among regional renewable energy equities, particularly during periods of heightened financial turbulence (Lee & Baek, 2018; Reboredo, 2015; Reboredo et al., 2017; Uddin et al., 2019).

Additionally, the negative relationship between global oil prices and renewable energy stock prices in the United States and Europe suggests that oil could serve as a hedge for investments in regional renewable energy. This is particularly relevant for short-term investors aiming to mitigate portfolio volatility.

5. Conclusion

In this paper, we first investigate the tail dependence structure and equicorrelations between regional clean energy stock markets (NASDAQ OMX Green Economy US Index, NASDAQ OMX Green Economy Europe Index and NASDAQ OMX Green Economy Asia Index) and global oil prices. Our analysis employs both the multivariate GARCH-DECO model and the quantile-on-quantile regression model, covering the period from July 28, 2011 to December 30, 2023.

These novel frameworks allow us to examine the behaviour of the intercorrelation structure between renewable energy markets and oil prices across various time horizons. The following is a summary of our empirical findings.

First, we find a positive association between clean energy stock markets and global oil prices. These trends are more pronounced during periods of market turmoil, supporting contagion effects that reduce the benefits of portfolio diversification between renewable energy markets and oil. Second, the results from the QQR technique reveal a heterogeneous interdependence structure between oil prices and renewable energy stock markets throughout the entire distribution during the research period. However, there is a weak relationship between the examined variables at the middle quantiles. In other words, the findings confirm that global oil price effects are positive on renewable energy markets at the lower and upper quantiles but have a negative impact on energy stock markets at the middle quantiles.

Another goal of our research is to determine whether global oil prices have a causal influence on renewable energy market prices in the United States, Europe, and Asia, using the recently proposed Granger causality in quantiles analysis (Troster et al., 2018). From 2011 to 2023, the results of the robust Granger causality in quantiles analysis reveal a bidirectional causal association between oil prices and renewable energy markets. However, there is only a unidirectional causal relationship from clean energy market prices to crude oil markets.

Our results may be useful to investors seeking to hedge or diversify renewable energy stock market risk with oil, as well as those looking to develop strategies to manage portfolio risk on both the downside and the upside. In particular, our findings provide clear insights for investors operating across various time horizons and market conditions.

References

Aielli, G.P. (2013). Dynamic conditional correlation: On properties and estimation. *Journal of Business & Economic Statistics, 31*(3), 282−299. https://doi.org/10.1080/07350015.2013.771027

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*, Article 104978. https://doi.org/10.1016/j.eneco.2020.104978

Dawar, I., Dutta, A., Bouri, E., & Saeed, T. (2021). Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression. *Renewable Energy, 163*, 288−299. https://doi.org/10.1016/j.renene.2020.08.162

Demiralay, S., & Golitsis, P. (2021). On the dynamic equicorrelations in cryptocurrency market. *The Quarterly Review of Economics and Finance, 80*, 524−533. https://doi.org/10.1016/j.qref.2021.04.002

Dominioni, G., Romano, A., & Sotis, C. (2019). A quantitative study of the interactions between oil price and renewable energy sources stock prices. *Energies, 12*(9), Article 1693. https://doi.org/10.3390/en12091693

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. https://doi.org/10.1016/j.jclepro.2017.07.050

Dutta, A. (2018). Oil and energy sector stock markets: An analysis of implied volatility indexes. *Journal of Multinational Financial Management, 44*, 61−68. https://doi.org/10.1016/j.mulfin.2017.12.002

Elie, B., Naji, J., Dutta, A., & Uddin, G.S. (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. *Energy, 178*, 544−553. https://doi.org/10.1016/j.energy.2019.04.155

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339−350. https://doi.org/10.1198/073500102288618487

Engle, R., & Kelly, B. (2012). Dynamic equicorrelation. *Journal of Business & Economic Statistics, 30*(2), 212−228. https://doi.org/10.1080/07350015.2011.652048

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. https://doi.org/10.1016/j.eneco.2018.09.022

Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424−438. https://doi.org/10.2307/1912791

Hung, N.T. (2021a). Bitcoin and CEE stock markets: Fresh evidence from using the DECO-GARCH model and quantile on quantile regression. *European Journal of Management and Business Economics, 30*(2), 261−280. https://doi.org/10.1108/EJMBE-06-2020-0169

Hung, N.T. (2021b). Directional spillover effects between BRICS stock markets and economic policy uncertainty. *Asia-Pacific Financial Markets, 28*, 429−448. https://doi.org/10.1007/s10690-020-09328-y

Iqbal, N., Fareed, Z., Wan, G., & Shahzad, F. (2021). Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market. *International Review of Financial Analysis, 73*, Article 101613. https://doi.org/10.1016/j.irfa.2020.101613

Jiang, Y., Tian, G., & Mo, B. (2020). Spillover and quantile linkage between oil price shocks and stock returns: New evidence from G7 countries. *Financial Innovation, 6*, Article 42. https://doi.org/10.1186/s40854-020-00208-y

Kang, S.H., Uddin, G.S., Troster, V., & Yoon, S.M. (2019). Directional spillover effects between ASEAN and world stock markets. *Journal of Multinational Financial Management, 52−53*, Article 100592. https://doi.org/10.1016/j.mulfin.2019.100592

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. https://doi.org/10.1016/j.egyr.2019.01.002

Lee, D., & Baek, J. (2018). Stock prices of renewable energy firms: Are there asymmetric responses to oil price changes? *Economies, 6*(4), Article 59. https://doi.org/10.3390/economies6040059

Liu, G., & Hamori, S. (2020). Can one reinforce investments in renewable energy stock indices with the ESG index? *Energies, 13*(5), Article 1179. https://doi.org/10.3390/en13051179

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, 81*, 536−544. https://doi.org/10.1016/j.eneco.2019.05.003

McLeod, A.I., & Li, W.K. (1983). Diagnostic checking ARMA time series models using squared-residual autocorrelations. *Journal of Time Series Analysis, 4*(4), 269−273. https://doi.org/10.1111/j.1467-9892.1983.tb00373.x

Mejdoub, H., & Ghorbel, A. (2018). Conditional dependence between oil price and stock prices of renewable energy: A vine copula approach. *Economic and Political Studies, 6*(2), 176−193. https://doi.org/10.1080/20954816.2018.1463600

Naeem, M A., Hasan, M., Arif, M., Balli, F., & Shahzad, S.J.H. (2020). Time and frequency domain quantile coherence of emerging stock markets with gold and oil prices. *Physica A: Statistical Mechanics and its Applications, 553*, Article 124235. https://doi.org/10.1016/j.physa.2020.124235

Paiva, A.S.S., Rivera-Castro, M.A., & Andrade, R.F.S. (2018). DCCA analysis of renewable and conventional energy prices. *Physica A: Statistical Mechanics and its Applications, 490*, 1408−1414. https://doi.org/10.1016/j.physa.2017.08.052

Reboredo, J.C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics, 48*, 32−45. https://doi.org/10.1016/j.eneco.2014.12.009

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. https://doi.org/10.1016/j.eneco.2016.10.015

Shah, I.H., Hiles, C., & Morley, B. (2018). How do oil prices, macroeconomic factors and policies affect the market for renewable energy? *Applied Energy, 215*, 87–97. https://doi.org/10.1016/j.apenergy.2018.01.084

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance, 55*, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Tien, H.T., Dang, N.M.B., & Hung, N.T. (2024). An empirical analysis of the dynamic impact of DeFi on GCC foreign exchange forward markets: Portfolio implication. *International Journal of Islamic and Middle Eastern Finance and Management, 17*(1), 170–194. https://doi.org/10.1108/IMEFM-06-2023-0228

Troster, V., Shahbaz, M., & Uddin, G.S. (2018). Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis. *Energy Economics, 70*, 440–452. https://doi.org/10.1016/j.eneco.2018.01.029

Uddin, G.S., Rahman, M.L., Hedström, A., & Ahmed, A. (2019). Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. *Energy Economics, 80*, 743–759. https://doi.org/10.1016/j.eneco.2019.02.014

Urom, C., Mzoughi, H., Abid, I., & Brahim, M. (2021). Green markets integration in different time scales: A regional analysis. *Energy Economics, 98*, Article 105254. https://doi.org/10.1016/j.eneco.2021.105254

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*, Article 118338. https://doi.org/10.1016/j.jclepro.2019.118338

Zhao, X. (2020). Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? *Journal of Economic Structures, 9*(1), 1–16. https://doi.org/10.1186/s40008-020-00229-x

Zhao, Y., Zhang, Y., & Wei, W. (2021). Quantifying international oil price shocks on renewable energy development in China. *Applied Economics, 53*(3), 329–344. https://doi.org/10.1080/00036846.2020.1808173