Connectedness and risk spillovers between crude oil and clean energy stock markets

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Abstract: This research investigates the relationship between clean energy stock and oil market returns utilizing Granger predictability in distribution and quantile impulse response analysis. We find that clean energy stock returns Granger predict oil price returns during "normal times" based on the distribution's center, but not vice versa. During bullish market episodes, there is bidirectional Granger predictability between the returns of clean energy stocks and oil market returns. Nonetheless, we find that clean energy stock returns Granger predict oil returns in bearish markets without any evidence of the contrary. This indicates that oil returns cannot be used to hedge the downside risk associated with renewable energy company purchases. Quantile impulse responses for the relationship between clean energy stocks and the crude oil market reveal bidirectional and significant responses, where a negative shock during an extremely down market reveals a negative response in the other market and a positive shock during an extremely up market reveals a significant positive response. This shows that neither market can be utilized to offset risks in the other market.

Keywords: Clean energy returns; oil returns; risk spillovers; the hedging

JEL classifications: G11; G32; Q42

1. Introduction

Since fossil fuels like coal, oil, and natural gas continue to be the main source of energy for industry, transportation, and heating, there is a wealth of empirical literature describing the significant effects of oil price shocks on post-World War II economic activity (Rasche and Tatom 1981; Bruno and Sachs, 1982; Hamilton, 1983; Hamilton, 1988; and Mork, 1989 among others). One of the topics that has received the most investigation in this area is how the price of oil affects financial markets and other economic activities. Based on this, Chen et al. (1986), Kaul and Jones (1996), Sadorsky (1999), Hammoudeh et al. (2004), Killian and Park (2009), Cevik et al. (2018), Kirci-Cevik et al. (2021), and Cevik et al. (2021) demonstrated the relationship between stock markets and oil prices.

Oil price shocks can have both direct and indirect effects on stock markets. While changes in the price of oil have an immediate effect on the present and future cash flows of businesses, the indirect effect is mediated by the interest rate channel (Ma et al. 2019). As a result, changes in the price of oil affect the interest rates used to discount businesses' future cash flows, which is expected to have a significant impact on stock prices. According to Zhang et al. (2020), there is a resemblance between the relationship between oil prices and stock indices for sustainable energy. However, as the number of petroleum-related derivative products has increased, particularly after the Global Financial Crisis (GFC), the link between oil prices and stock markets has grown stronger. Zhang (2018) claims that this is a result of the financialization of the oil market. However, according to Dutta (2017), the association between oil prices and the stock market is not uniform across all industries; as a corollary, there may be differences between the relationship between oil prices and the renewable or clean energy industry and other industries. This is because rising oil prices may encourage greater use of alternative energy sources. The use of alternative or renewable energy may have expanded recently due to environmental concerns.

Fluctuations in oil prices have an impact that goes beyond macroeconomic indicators and financial markets. Due to the negative environmental effects of using crude oil, there is a growing interest in alternative clean and sustainable energy sources. Consequently, an expanding corpus of research examines the relationship between these so-called clean energy sources and the financial markets, macroeconomic indices, and oil prices. Additionally, investments are being put more into renewable energy sources. For instance, between 2014 and 2018, $1.5 trillion was invested globally in the clean energy sector (Zhang et al. 2020). Furthermore, it is expected that by 2040, investments in renewable energy will make up two-thirds of all energy investments worldwide. (IEA, 2018). As a result, the stock markets for renewable energy have caught the attention of regulators as well as researchers and investors. According to Dutta et al. (2020), the growing demand for investments in environmentally friendly businesses is a result of the increasing popularity of companies that produce environmentally friendly goods and services.

The large fluctuations in oil prices and concerns about global warming causes have raised the popularity of clean energy sources and the companies that produce clean energy. As such, there has been an increase in the formation of stock market indexes to track the performance of clean energy firms such as the S&P Global Clean Energy Index, NASDAQ Clean Edge Green Energy, WilderHill Clean Energy Index, and FTSE Environmental Technology Index. These are the main indexes that track clean energy firms and their performances in stock markets. The studies that focus on the relationship between clean energy stock indexes and oil prices have gained momentum, especially after the GFC.

The literature is opaque on the consensus regarding the relationship between oil prices and stock prices for renewable energy sources. Bondia et al. (2016) and Dutta (2017) highlighted the substitution effect of clean energy sources due to rising oil prices, and therefore an inverse relationship between oil prices and clean energy stock prices, contrary to Zhang et al. (2020), Jiang et al. (2019), and Basher and Sadorsky (2006) who claim increasing oil prices decrease the cash flows of clean energy firms decreasing their stock prices. In other words, rising oil costs may lead to higher stock prices for clean energy companies. This is not unexpected given that the precise nature of the correlation between oil prices and the values of clean energy stocks may shift across the distribution. For instance, the substitution impact between oil prices and clean energy sources may cause an unbalanced link to exist between clean energy stocks and oil prices. Additionally, because the substitution effect can produce fluctuations in gains and losses in the crude oil and clean energy markets, the dynamic link between oil prices and clean energy stock prices may not be the same across the different parts of the distribution. Therefore, utilizing an econometric methodology that takes into account the relationship between the variables' right and left tails of distribution as well as their means is necessary to study the relationship between the price of renewable energy and the price of oil.

The principal objective of this paper is to revisit the relationship between clean energy stocks and oil prices using Granger Predictability in the Distribution Test (hereafter GPDT) proposed by Candelon and Tokpavi (2016) [hereafter CT]. Even though there are empirical studies that focus on tail dependence between clean energy stocks and crude oil markets, these studies generally use a copula approach. However, as Elie et al. (2019) emphasized, using different copula functions may provide different results. Also, the copula approach allows for examining tail dependence between the variables where dependence in the mean of variables is ignored. CT’s (2016) approach can be used to investigate the existence of a relationship between the variables for the whole distribution. To the best of our knowledge, the paper is the first attempt to examine the presence of a dynamic relationship between oil prices and clean energy stock prices by using the predictability in the distribution test. Also, we consider the impacts of outliers and structural breaks in variance in the estimation since GARCH model parameters are sensitive to these are sensitive to outliers and structural breaks. Proper specification of the GARCH process is important not only for the predictability in the distribution test but also for the copula approach because the marginal distribution of the series is obtained by using the GARCH model in the copula approach. Finally, we also calculate the quantile impulse responses proposed by White et al. (2015) to ascertain the magnitude of responses of the clean energy stock market to a shock in the crude oil market for the different regions of distribution.

The rest of the paper is organized as follows: We provide a brief literature survey on the relation between the clean energy stock market and the crude oil market. We present econometric methodology in section 3 and empirical findings in section 4. Section 5 is the conclusion.

2. Brief Literature Review

The relationship between the stock markets for clean energy and crude oil has generally been examined in terms of causality, reliance, and volatility spillovers. The literature has employed a variety of methods for this purpose, including the VAR model, Markov Regime Switching, BEKK, DCC, Threshold cointegration, cointegration with structural breaks, Copula, and Wavelet methods. The relationship between alternative energy stock prices, technology stock prices, oil prices, and interest rates was examined using a VAR model by Henriques and Sadorsky (2008) and Kumar et al. (2012). According to Sadorsky's (2012) research, oil prices are not as closely associated with the stock prices of clean energy businesses as they are with technology stocks. Using asset pricing models and time-varying conditional correlation, Broadstock et al. (2012) examined how Chinese energy-related stock returns were affected by global oil prices.

Building on Henriques and Sadorsky (2008), Managi and Okimoto (2013) used a Markov Regime Switching Model to analyze the relationship between oil prices, clean energy stock prices, and technology stock prices. After controlling for structural breaks, they discover a positive relationship between oil prices and clean energy prices. According to Reboredo (2015), the volatility of oil prices accounts for about 30% of the upside and downside risk faced by renewable energy enterprises. The return and volatility spillover impact between the stock prices of Chinese new energy and fossil fuel businesses was examined by Wen et al. in 2014. They discovered that equities of fossil fuels and new energy are frequently viewed as rival investments. Oil prices, technology stocks, and the global stock market index were all examined by Inchauspe et al. (2015) in relation to their effects on renewable energy equities. The findings demonstrate a strong correlation between stock returns for renewable energy companies and those of technology companies, with some contribution from oil prices. According to Bondia et al. (2016), while oil prices, interest rates, and stock prices for technology companies have a short-term impact on the stock prices of alternative energy companies, there is no long-term causal relationship between these variables and the stock prices of alternative energy companies.

Dutta (2017) discovered that the crude oil volatility index (OVX) shocks had a significant impact on clean energy stock returns. Using wavelets and linear and nonlinear Granger causality tests, Reboredo et al. (2017) revealed that the reliance between oil and renewable energy returns is minimal in the short run but gradually becomes stronger in the long run. According to Ahmad's (2017) analysis of the directional spillover between crude oil prices and the stock prices of technology and renewable energy businesses, the two sectors are interdependent. According to Lundgren et al. (2018), the stock prices of renewable energy companies have a significant impact on the European stock market. As per Ahmad et al. (2018), VIX offers cleaner energy equities better hedging prospects than crude oil and OVX.

The temporal and frequency dynamics of the relationships between the stock prices of US clean energy businesses, crude oil prices, and many significant financial indicators were studied by Ferrer et al. in 2018. The empirical findings indicate that whereas return and volatility connectivity has a little impact over the long run, it has a major impact over the very short run. Crude oil and gold are both weak safe-haven assets for clean energy indexes, according to Elie et al. (2019). The cross-quantile reliance of stock returns for renewable energy sources on total stock returns, changes in the price of gold and oil, and exchange rates is examined by Uddin et al. (2019). The findings demonstrate that there is an imbalance in the relationship between the quantities, which is more pronounced at longer delays. Wavelet coherency was used by Nasreen et al. (2020) to establish the existence of a tenuous correlation between oil prices and renewable energy stock returns. According to Zhang et al. (2020), the effect of exogenous structural shocks to oil prices on clean energy equities differs by quantile and investment horizons, and is asymmetric at larger oil shock quantiles over the long term. In the first and second moments, Yahya et al. (2021) discovered evidence in support of a non-linear, regime-dependent long-term connection between renewable energy stock and crude oil price.

3. Econometric Framework

In order to examine the dependence between the clean energy stocks and the crude oil market, we first use the nonparametric GPDT proposed by CT (2016). We also calculate quantile impulse responses based on a multivariate quantile vector autoregression model suggested by White et al. (2015) to ascertain the size of tail dependence between clean energy stocks and the crude oil market.

3.1. Nonparametric Granger Predictability in Distribution Test

CT's (2016) test statistic is a multivariate generalization of the test procedure so-called predictability in risk proposed by Hong et al. (2009) in which the relationship between two random variables such as Y_t and X_t is examined in the left tail of the distribution. Since it is necessary identifying regions of the distribution for each series in the GPDT, CT (2016) suggested using a value-at-risk (VaR) approach at a specific risk level α.

A set of $A = \{\alpha_1, \ldots, \alpha_{m+1}\}$ of m+1 VaR risk levels cover the distribution support of both variables X_t and Y_t with $0 \leq \alpha_1 < \ldots < \alpha_{m+1} \leq 100\%$. The relevant VaRs at time t for the X_t are $VaR^X_{t,s}(\theta^0_X, \alpha_s)$ $s = 1, \ldots, m+1$, with

$$VaR^X_{t,1}(\theta^0_X, \alpha_1) < \cdots < VaR^X_{t,m+1}(\theta^0_X, \alpha_{m+1}) \tag{1}$$

where the vector θ^0_X is the true unknown finite-dimensional parameter set related to the VaR model for X_t. If the distribution support of X_t is divided into m disjoint regions, each region associated with the indicator variable may be stated following:

$$Z^X_{t,s}(\theta^0_x) = \begin{cases} 1 & if\ X_t \geq VaR^X_{t,s}(\theta^0_X, \alpha_s)\ and\ X_t \leq VaR^X_{t,s+1}(\theta^0_X, \alpha_{s+1}) \\ 0 & else \end{cases} \tag{2}$$

where $s = 1, \ldots, m$. If $m+1 = 5$, the set A is $A = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5\} = \{0\%, 20\%, 40\%, 60\%, 80\%\}$. Let $H^X_t(\theta^0_X)$ be vector (m, 1) and components of the m event variables

$$H^X_t(\theta^0_X) = \left\{Z^X_{t,1}(\theta^0_X),\ Z^X_{t,2}(\theta^0_X), \ldots, Z^X_{t,m}(\theta^0_X)\right\}^T \tag{3}$$

Similarly, the vector of $H^Y_t(\theta^0_Y)$ is written for the Y_t following:

$$H^Y_t(\theta^0_Y) = \left\{Z^Y_{t,1}(\theta^0_Y),\ Z^Y_{t,2}(\theta^0_Y), \ldots, Z^Y_{t,m}(\theta^0_Y)\right\}^T \tag{4}$$

The null hypothesis of no Granger predictability from Y_t to the X_t in distribution is written following:

$$\mathbb{H}_0: E\left[H^X_t(\theta^0_X) \,\middle|\, \mathcal{F}^{X\&Y}_{t-1}\right] = E\left[H^X_t(\theta^0_X) \,\middle|\, \mathcal{F}^X_{t-1}\right] \tag{5}$$

Suppose $\widehat{H}^X_t \equiv H^X_t(\hat{\theta}_X)$ and $\widehat{H}^Y_t \equiv H^Y_t(\hat{\theta}_Y)$ are the estimated counterparts of the multivariate process of event variables $H^X_t(\theta^0_X)$ and $H^Y_t(\theta^0_Y)$ respectively and $\hat{\theta}_X$ and $\hat{\theta}_Y$ are $\sqrt{T}$ consistent estimators of the true unknown parameter vectors θ^0_X and θ^0_Y. Let $\hat{\Lambda}(j)$ be the sample cross-covariance matrix between $\widehat{H}^X_t$ and $\widehat{H}^Y_t$ with

$$\hat{\Lambda}(j) \equiv \begin{cases} T^{-1}\sum_{t=1+j}^{T}\left(\widehat{H}^X_t - \widehat{\Pi}_X\right)\left(\widehat{H}^Y_{t-j} - \widehat{\Pi}_Y\right)^T & 0 \leq j \leq T-1 \\ T^{-1}\sum_{t=1-j}^{T}\left(\widehat{H}^X_{t+j} - \widehat{\Pi}_X\right)\left(\widehat{H}^Y_t - \widehat{\Pi}_Y\right)^T & 1-T \leq j \leq 0 \end{cases} \tag{6}$$

where the vector of $\widehat{\Pi}_X$ (or $\widehat{\Pi}_Y$) of length m is the sample mean of $\widehat{H}^X_t$ (or $\widehat{H}^Y_t$). $\widehat{\Pi}_X$ and $\widehat{\Pi}_Y$ are replaced by $\Pi_X = E\left(H^X_t(\theta^0_X)\right)$ and $\Pi_Y = E\left(H^X_t(\theta^0_Y)\right)$, respectively. The sample cross-correlation matrix is written following:

$$\hat{R}(j) = D\left(\hat{\Sigma}_X\right)^{-1/2}\hat{\Lambda}(j)D\left(\hat{\Sigma}_Y\right)^{-1/2} \tag{7}$$

with D (.) is the diagonal form of a matrix and $\hat{\Sigma}_X$ and $\hat{\Sigma}_Y$ are the sample covariance matrices of $\hat{H}_t^X$ and $\hat{H}_t^Y$. The test statistic can be expressed in weighted quadratic form that relates the current value of $\hat{H}_t^X$ and the lagged values of $\hat{H}_t^Y$

$$\hat{\mathcal{T}} = \sum_{j=1}^{T-1} \kappa^2 \left(\frac{j}{M}\right) \hat{Q}(j) \tag{8}$$

where κ (.) is a kernel function, and M is the truncation parameter. $\hat{Q}(j)$ is obtained by:

$$\hat{Q}(j) = Tvec\left(\hat{R}(j)\right)^T \left(\hat{\Gamma}_X^{-1} \otimes \hat{\Gamma}_Y^{-1}\right) vec\left(\hat{R}(j)\right) \tag{9}$$

where $\hat{\Gamma}_X$ and $\hat{\Gamma}_Y$ are the sample correlation matrices of $\hat{H}_t^X$ and $\hat{H}_t^Y$ respectively. Noted that the constraints for M and the κ (.) are identical as in Hong et al. (2009). CT (2016) establihed the test statistic following:

$$V_{Y \to X} = \frac{\hat{\mathcal{T}} - m^2 C_T(M)}{\left(m^2 D_T(M)\right)^{1/2}} \tag{10}$$

where $C_T(M)$ and $D_T(M)$ are:

$$C_T(M) = \sum_{j=1}^{T-1} (1 - j/T) \kappa^2 (j/M) \tag{11}$$

$$D_T(M) = 2 \sum_{j=1}^{T-1} (1 - j/T)(1 - (j+1)/T) \kappa^4 (j/M) \tag{12}$$

CT (2016) indicated that the test statistic follows a standard Gaussian distribution.

3.2. Quantile Impulse Responses Analysis

White et al. (2015) proposed a multivariate regression quantile model called the VAR for VaR model to investigate tail dependency between variables using impulse-response analysis. The multivariate quantile regression model is based on estimating the following multivariate multi-quantile conditional autoregressive value at risk framework (MVMQ-CAViaR), which is a bivariate modification of Engle and Manganelli's (2004) CAViaR model:

$$q_{Y,t} = c_1(\theta) + a_{11}(\theta)|Y_{t-1}| + a_{12}(\theta)|X_{t-1}| + b_{11}(\theta) q_{Y,t-1} + b_{12}(\theta) q_{X,t-1} \tag{13}$$

$$q_{X,t} = c_2(\theta) + a_{21}(\theta)|Y_{t-1}| + a_{22}(\theta)|X_{t-1}| + b_{21}(\theta) q_{Y,t-1} + b_{22}(\theta) q_{X,t-1} \tag{14}$$

where θ is the risk level. Y_t and X_t are e.g., clean energy stock returns and oil returns respectively and q_Y and q_X are the quantile functions at the risk level θ for clean energy stock index and oil returns series.

Equation (13) and (14) can be represented in matrix notation as follows:

$$q_t = c + A|Z_{t-1}| + Bq_{t-1} \tag{15}$$

such that q_t, Z_{t-1}, and c are vectors where $q_t = (q_Y, q_X)$, $Z_t = (Y_t, X_t)$, and $c = (c_1, c_2)$. A and B indicate the coefficients matrix for a_{ii} and b_{ii} that are defined in Equations (13) and (14). Equation (15) shows that quantiles of clean energy stock (oil) returns can be estimated by using its lag, lag of oil (clean energy stock index) returns, and also lag of the quantiles of clean energy stock index (oil) returns. Note that, whereas the diagonal members of matrix B indicate persistency in the risk at a certain risk level, the off-diagonal members show risk spillovers across the clean energy and crude oil markets.

Quantile impulse response functions (QIRF) are calculated via the estimated parameter in Eq. (15). The QIRF assumes that there is one intervention δ in the observable Y_t at time t

only $\left(\tilde{Y}_t \coloneqq Y_t + \delta\right)$. $\{\ldots, Y_{t-2}, Y_{t-1}, Y_t, Y_{t+1}, Y_{t+2}, \ldots\}$ and $\{\ldots, Y_{t-2}, Y_{t-1}, \tilde{Y}_t, Y_{t+1}, Y_{t+2}, \ldots\}$ indicate the time-series properties of Y_t with and without intervention respectively.

The pseudo QIRF is defined by White et al (2015) following:

$$\Delta_{i,s}\left(\tilde{Z}_{it}\right) = \tilde{q}_{i,t+s} - q_{i,t+s}, \;\; s = 1, 2, 3, \ldots \tag{16}$$

where $\tilde{q}_{i,t+s}$, and $q_{i,t+s}$ are the conditional quantiles of the affected and unaffected series respectively. The pseudo QIRF for the first and second variables is defined following:

$$\Delta_{Y,1}\left(\tilde{Y}_t\right) = a_{11}\left(\left|\tilde{Y}_t\right| - |Y_t|\right) + a_{12}\left(\left|\tilde{X}_t\right| - |X_t|\right), \;\; for\ s = 1 \tag{17}$$

$$\Delta_{Y,s}\left(\tilde{Y}_t\right) = b_{11}\Delta_{Y,s-1}\left(\tilde{Y}_t\right) + b_{12}\Delta_{X,s-1}\left(\tilde{Y}_t\right), \;\; for\ s > 1 \tag{18}$$

$$\Delta_{X,1}\left(\tilde{Y}_t\right) = a_{21}\left(\left|\tilde{Y}_t\right| - |Y_t|\right) + a_{22}\left(\left|\tilde{X}_t\right| - |X_t|\right), \;\; for\ s = 1 \tag{19}$$

$$\Delta_{X,s}\left(\tilde{Y}_t\right) = b_{21}\Delta_{Y,s-1}\left(\tilde{Y}_t\right) + b_{22}\Delta_{X,s-1}\left(\tilde{Y}_t\right), \;\; for\ s > 1 \tag{20}$$

We can define the QIRF as:

$$\Delta_s\left(\tilde{Y}_t\right) := \begin{bmatrix} \Delta_{Y,s}\left(\tilde{Y}_t\right) \\ \Delta_{X,s}\left(\tilde{Y}_t\right) \end{bmatrix} \tag{21}$$

If we define D_t as $\left|\tilde{Y}_t\right| - |Y_t|$, after that the pseudo QIRF is following:

$$\Delta_s\left(\tilde{Y}_t\right) = AD_t, \;\; for\ s = 1 \tag{22}$$

$$\Delta_s\left(\tilde{Y}_t\right) = B^{(s-1)}AD_t, \;\; for\ s > 1 \tag{23}$$

We employed the Cholesky decomposition for orthogonalizing the shocks.

4. Data and Empirical Results

We use daily data for clean energy stock indexes and crude oil prices from November 21, 2003 to August 6, 2021 where total number of observations is 4621. We consider S&P Global Clean Energy Index (GCE), WilderHill Clean Energy Index (ECO), and FTSE Environmental Technologies Index (ET50) as a benchmark for clean energy stocks and spot prices of West Texas Intermediate (WTI) and Brent for the crude oil market. All data are collected from Refinitive Eikon Datastream. We calculate daily log difference for each series to obtain returns series.

We start our empirical analysis by first investigating the presence of outliers in the data because large number of studies showed that the GARCH model parameters are adversely affected from outliers (see Charles and Darne, 2005; Franses and van Dijk, 2011; Behmiri and Manevra, 2015 and Grane and Veiga, 2014). We use an outlier detection test suggested by Bruffaerts et al. (2014) which depends on calculating the box plot for the return series (and hence its simplicity). The test performs reasonably well for series that have skewed or heavy-tailed distributions. The latter is very important because the distribution of financial return series is generally leptokurtic. The test results indicate 62 outliers in the GCE returns, 53 outliers in the ECO returns, and 45 outliers in the ET50 return series. On the other hand, we find 58 and 39 outliers in WTI and Brent return series, respectively. We follow Bodart and Candelon (2009) and Warshaw (2020) and adjust the returns by considering outlier dates where each outlier is replaced by a 10-day average centered around the abnormal observation.

We present descriptive statistics for adjusted returns in Table 1. The mean returns are positive for all series during the sample except for ECO and WTI. Crude oil returns are more volatile than clean energy stock returns according to standard deviations. The skewness and kurtosis statistics indicate that the distributions for all returns are leptokurtic. This is confirmed by the Jarque-Bera normality test where the null hypothesis of normality is rejected at the 1% significance level. The ARCH LM test and the Box-Pierce *Q* statistics suggest volatility clustering in all returns. Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) unit root test results indicate all returns are stationary in levels.

<Insert Table I here>

The well-documented literature reveals that the structural breaks in variance cause to overestimation of the GARCH parameters (Ewing and Malik, 2017 and Malik, 2021). Therefore, we examine regime changes in variance of returns by using structural breaks in variance test suggested by Sanso et al. (2004). We present the test results in Table 2 and Figure 1. According to the results in Table 2, we find three regime shift points in the variance of ET50 return series. ECO has eight sudden change points between 2007 and 2021 where most are related to the GFC and the Covid-19 outbreak. Brent has nine sudden change points. The highest regime shifts in the variance of returns are in GCE and WTI where 12 sudden change points are statistically significant. Indeed, results in Table 2 point to two global episodes where structural breaks occur, and these are clustered around the GFC and the Covid-19 global pandemic. Also, ET50 index seems to have the lowest number of structural breaks and more stable than the other clean energy indexes.

<Insert Table II here>

<Insert Figure I here>

Since the Granger predictability in distribution test relies on calculating VaR for each return series, we first use a GARCH class model to estimate the time-varying VaR. In this regard, we consider several volatility models such as GARCH, EGARCH, GJR-GARCH, IGARCH, APARCH, FIGARCH, FIEGARCH, FIAPARCH and HYGARCH and find out that the FIAPARCH model provides a better fit for clean energy stock returns according to the Akaike Information Criterion (AIC). On the other hand, the FIEGARCH model outperforms others for oil returns. As in Ewing and Malik (2017) and Malik (2021), we construct dummy variables according to structural break dates and include these dummies in the variance equations to account for structural breaks. Hence, we estimate two volatility models (with and without dummy variables) for each return series and present the results in Table 3. The results in Table 3 show that the beta parameter (measuring persistence in volatility) and the long memory parameter (d) decrease substantially when the effect of structural breaks is considered and these results are in line with the empirical literature. According to a likelihood ratio (LR) test results in Table 3, the null hypothesis of no systematic difference between parameters of volatility models with and without dummy variables is rejected in favor of volatility models with dummy variables at the 1% significance level. As such, taking into account structural breaks significantly improves model fit. It is evident that the existence of structural breaks causes to overestimate of GARCH parameters and hence they can cause to spurious integrated GARCH and long memory processes.

<*Insert Table III here*>

Before proceeding with the GPDT, we define the borders of tails and the center of the distribution. We follow CT (2016) and set as A^L = {0%, 1%, 5%, 10%} and A^R = {90%, 95%, 99%, 100%} for the left and right tail of the distribution respectively. For the center of distribution, the VaR risk levels are set as A^C = {20%, 30%, …, 70%, 80%}. As in CT (2016), the truncation parameter is calculated as $[1.5T^{0.3}]$ which corresponds to 19 and a Daniel kernel is used for the weighting scheme. The test results in Table 4 show that the relationship between clean energy stocks and the crude oil market varies not only depending on the regions of the distribution but also the clean energy stock index used. For example, while we find only unidirectional Granger predictability from GCE and ECO to WTI in the center of distribution, we cannot detect a predictability between ET50 and WTI. On the other hand, there is unidirectional Granger predictability from all clean energy indexes to WTI in the left tail of distribution. Also, there is strong bidirectional Granger predictability between clean energy indexes and WTI in the right tail of the distribution. Furthermore, we find similar results for Brent where there is strong feedback between clean energy stock returns and Brent in the right tail of distribution. However, the test results show that all clean energy stock indexes Granger predict Brent in the left tail of distribution. In the center of distribution, only GCE returns Granger predict Brent returns.

The GPDT results show that unexpected gains in the clean energy stock return Granger predict unexpected gains in oil returns and vice versa. Therefore, the link between clean energy stock market and crude oil market is very strong during bullish market episodes. On the other hand, unexpected loses in clean energy stocks Granger predict unexpected loses in the oil market, which indicates that clean energy stocks are more dominant in the price transmission process in bearish market episodes. This finding is very important in terms of risk management because investors are keen on the relationship between the variables in the left tail of distribution to minimize portfolio risk. In this vein, the empirical result implies that oil returns cannot be used to hedge the downside risk of clean energy stock investments and it is consistent with empirical findings of Elie et al. (2019) found that WTI is weak safe haven for clean energy stock return.

The test results for the center of distribution indicate the Granger predictability in the mean of the variables where clean energy stock prices have an edge in affecting oil prices and this finding is consistent with empirical results of Geng et al. (2021) and Yahya et al. (2021). Specifically, Yahya et al. (2021) indicated that while crude oil market plays a dominant role on the clean energy market before the GFC period, clean energy market is the main driver of crude oil prices after the GFC period.

<*Insert Table IV here*>

Note that the structural break in variance tests in Table 2 shows both clean energy stocks and crude oil are affected by the GFC and the recent Covid-19 global pandemic because the breaks dates are related to these global developments. Hence, it is noteworthy to examine predictability between clean energy stock returns and crude oil returns during the GFC, and the Covid-19 global pandemic. To that end, we split the sample accordingly and employ GPDT.

The findings in Table 5 indicate that the predictability link at the center of the distribution depends on the particular clean energy stock index used during the GFC. For example, we find Granger predictability running from GCE to WTI, but not the other way around. However, neither ECO nor ET50 Granger predicts WTI at the center of the distribution while WTI Granger predicts ECO. On the other hand, we cannot find any Granger predictability between ET50 and WTI. Similarly, the mixed results during the GFC for BRENT and clean energy stocks are obtained at the center of the distribution. Although it is determined bidirectional Granger predictability between GCE and BRENT, there is unidirectional Granger predictability from BRENT to ECO. However, ET50 Granger predicts BRENT during the GFC according to the center of the distribution. However, the relationship in the tails between the variables is consistent for all the clean energy indexes and oil prices during the GFC with bidirectional Granger predictability.

When we look at the results for the Covid-19 global pandemic, there is unidirectional Granger predictability from clean-energy stock indexes to oil prices at the center and left tail of the distribution. The test results for the right tail of distribution suggest bidirectional Granger predictability between clean-energy stock indexes and oil prices during the Covid-19 global pandemic. It seems the relationship between the oil market and clean energy stocks is different during the most recent global crises. This is not surprising because the origins and consequences of these two global crises are different. While the GFC emerged due to lax lending standards and risk management in the financial system, the Covid-19 global pandemic emerged severe threat to public health. Since the financial system collapsed during the GFC, our results show bidirectional Granger predictability between clean energy stocks and oil markets in the left tail of the distribution. As such, unexpected losses in the stock market can be predicted by unexpected losses in the crude oil market during the GFC and vice versa. On the other hand, the Covid-19 global pandemic first affected financial markets negatively due to investor concerns, then commodity markets were affected due to the disruptions in the supply chain. Therefore, unexpected losses in stock return preceded oil market developments during the Covid-19 global pandemic.

<Insert Table V here>

Finally, we use quantile impulse responses for the relationship between clean energy stocks and the crude oil market and present the results in Figure 2 and Figure 3. Note that although the studies in the literature have generally used quantile impulse response analysis to examine tail dependence between the variables, we consider the whole distribution in estimating impulse responses to better describe the relationship between clean energy and crude oil markets. [1] The results in Figure 2 and Figure 3 give the cumulative responses of oil returns (clean energy) to a 2-standard-deviation shock in clean energy returns (oil returns).[2]

While the left panel of Figure 2 and Figure 3 show the responses of WTI and Brent to a shock in clean energy returns at different quantiles, the responses of clean energy returns to a shock in WTI and Brent returns are given in the right panel of Figure 2 and Figure 3, respectively. The results in Figure 2 show that the relationship between clean energy and the crude oil market is symmetric in right and left of distribution as the responses of WTI to an unexpected extreme negative (positive) shock in clean energy returns at lower (higher)

[1] The impulse response results with confidence bands for the left and right tails are available upon request.
[2] The QIRF is calculated by using bivariate VAR for VaR model. To estimate the responses of oil returns to a shock in clean energy returns, the quantile of clean energy return series is estimated in the first equation and the quantile of oil return series is estimated in the second equation. To estimate the responses of clean energy returns to a shock in oil returns, the quantile of oil return series is estimated in the first equation and the quantile of clean energy return series is estimated in the second equation.

quantiles are negative (positive) and statistically significant. Similarly, clean energy returns react negatively (positively) and significantly to an unexpected negative (positive) shock in the WTI at lower (higher) quantiles. This finding is consistent with all clean energy stock returns. When we look at the center of distribution (50th quantile), the responses of WTI to a shock in clean energy returns are generally positive but statistically insignificant. Similarly, the responses of clean energy returns to a WTI shock are not statistically significant at the median.

<Insert Figure II here>

The results in Figure 3 show similar relationships to those in Figure 2. For example, the responses of Brent to an extreme negative (positive) shock in clean energy returns at lower (higher) quantiles are negative (positive) and statistically significant. Also, clean energy returns react negatively (positively) and significantly to a negative (positive) shock in Brent at lower (higher) quantiles. These results confirm a bidirectional relationship between clean energy returns and Brent returns.

<Insert Figure III here>

The impulse responses for the relationship between clean energy and crude oil markets indicate the responses of oil returns to unexpected losses in clean energy returns are negative and vice versa. Also, the responses of oil returns to unexpected gains in clean energy returns are positive and vice versa. Impulse responses show bidirectional relationship between clean energy stock returns and oil returns in the left tail of the distribution. In addition, impulse responses show the effects of shocks are long-lasting in the right tail of distribution as the responses in the left tail die out after the 15th lag but remain statistically significant up to the 30th lag in the right tail. By way of comparison, the effects of unexpected losses in clean energy markets on the losses in crude oil markets are temporary but the impact of unexpected gains in clean energy markets on the gains in the crude oil market is somewhat persistent and vice versa. The responses of the variables to an extreme shock in the left tail of distribution are considerably higher than the responses to an extreme shock in the right tail. As such, the link between crude oil and clean energy markets is stronger in bearish markets than bullish markets.

5. Conclusion and Policy Implications

The paper aims to revisit the relationship between clean energy stocks and oil prices using GPDT and the QIR analysis based on the multivariate quantile vector autoregression. Our results can be summarized as follows: there is some evidence that clean energy stock returns Granger predict oil price returns during "normal times" but not the other way around. During bullish market episodes, we determine bidirectional Granger predictability between clean energy stock returns and oil market returns. However, we find clean energy stock returns Granger predict oil returns in bearish markets with no evidence of reverse predictability. This implies that oil returns cannot be used to hedge the downside risk of clean energy stock investments. Focusing on the GFC and the recent Covid-19 pandemic, the right tail of the distribution shows bidirectional predictability during both the GFC and the Covid-19 pandemic. However, we find bidirectional predictability during the GFC but predictability running from clean energy stock returns to oil returns during the Covid-19 pandemic at the lower quantiles of the distribution. Again, oil returns cannot be used to hedge the downside risk of clean energy stock investments during extreme bearish market episodes. We also use quantile impulse responses for the relationship between clean energy stocks and the crude oil market. Impulse responses indicate bidirectional and significant responses where a negative shock during an extremely down market elucidates a negative response in the other market and a positive shock in an extreme upside market elucidates a significant positive response. This indicates that neither market can be used to hedge risks in the other market.

The empirical results of the study provide several implications for both policymakers and investors. First, at the center of the distribution, we find unidirectional Granger predictability from the clean energy stock index to the crude oil price. Since the Granger predictability at the center of distribution means predictability in the mean of variables, movements in the oil price are affected by clean energy investments. Therefore, the change in clean energy investments has a direct effect on oil prices. Secondly, we obtain different results at the tails of the distribution and this finding implies that the relationship between clean energy investments and oil prices changes during the bullish and bearish market periods, and hence the relationship between the variables changes according to the market conditions. The presence of unidirectional Granger predictability from the clean energy stock market to the crude oil price at the left tail of distribution indicates that unexpected losses in the clean energy stock market can be used to predict unexpected losses in the crude oil market. We determine bidirectional Granger predictability between clean energy stock market and crude oil market at the right tail of the distribution and this finding suggests the presence of comovement between the markets. These findings are important for policymakers to conduct sustainable energy policies because policy implications require taking market conditions into account. Finally, our results are important for investors their investment decisions and to reduce their portfolio risk. Hence, investors should use a dynamic risk management practice closely watching market conditions.

References

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.

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

Basher, S. A., & Sadorsky, P. (2006). Oil price risk and emerging stock markets. *Global finance journal*, *17*(2), 224-251.

Behmiri, N. B., & Manera, M. (2015). The role of outliers and oil price shocks on volatility of metal prices. *Resources Policy*, *46*, 139-150.

Bodart, V., & Candelon, B. (2009). Evidence of interdependence and contagion using a frequency domain framework. *Emerging Markets Review, 10*(2), 140–150.

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.

Broadstock, D. C., Cao, H., & Zhang, D. (2012). Oil shocks and their impact on energy related stocks in China. Energy Economics, 34(6), 1888-1895.

Bruffaerts, C., Verardi, V., & Vermandele, C. (2014). A generalized boxplot for skewed and heavy-tailed distributions. *Statistics & probability letters, 95*, 110-117.

Bruno, M., & Sachs, J. (1982). Input price shocks and the slowdown in economic growth: the case of UK manufacturing. *The Review of Economic Studies, 49*(5), 679-705.

Candelon, B., & Tokpavi, S. (2016). A nonparametric test for granger causality in distribution with application to financial contagion. *Journal of Business & Economic Statistics, 34*(2), 240-253.

Cevik, E., Atukeren, E., & Korkmaz, T. (2018). Oil Prices and Global Stock Markets: A Time-Varying Causality-In-Mean and Causality-in-Variance Analysis. *Energies, 11*(10), 2848.

Cevik, E. I., Dibooglu, S., Awad Abdallah, A., & Al-Eisa, E. A. (2021). Oil prices, stock market returns, and volatility spillovers: evidence from Saudi Arabia. *International Economics and Economic Policy, 18*, 157–175.

Charles, A., & Darné, O. (2005). Outliers and GARCH models in financial data. *Economics Letters, 86*(3), 347-352.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, *59*(3), 383-403.

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.

Dutta, A., Jana, R. K., & Das, D. (2020). Do green investments react to oil price shocks? Implications for sustainable development. *Journal of Cleaner Production, 266*, 121956.

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.

Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of business & economic statistics, 22*(4), 367-381.

Ewing, B. T., & Malik, F. (2017). Modelling asymmetric volatility in oil prices under structural breaks. *Energy Economics, 63*, 227-233.

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.

Franses P.H., van Dijk D. (2011). GARCH, Outliers, and Forecasting Volatility. In: Gregoriou G.N., Pascalau R. (eds) Nonlinear Financial Econometrics: Forecasting Models, Computational and Bayesian Models. Palgrave Macmillan, London.

Geng, J. B., Liu, C., Ji, Q., & Zhang, D. (2021). Do oil price changes really matter for clean energy returns?. *Renewable and Sustainable Energy Reviews, 150*, 111429.

Grané, A., & Veiga, H. (2014). Outliers, GARCH-type models and risk measures: A comparison of several approaches. *Journal of Empirical Finance, 26*, 26-40.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of political economy, 91*(2), 228-248.

Hamilton, J. D. (1988). A neoclassical model of unemployment and the business cycle. *Journal of political Economy, 96*(3), 593-617.

Hammoudeh, S., Dibooglu, S., & Aleisa, E. (2004). Relationships among US Oil Prices and Oil Industry Equity Indices. *International Review of Economics and Finance*, 13: 427-453.

Hong, Y., Liu, Y., & Wang, S. (2009), Granger Causality in Risk and Detection of Extreme Risk Spillover Between Financial Markets. *Journal of Econometrics, 150*, 271–287.

IEA, International Energy Agency, https://www.iea.org/data-and-statistics/data-tables?country=WORLD&energy=Renewables%20%26%20waste&year=2018

Inchauspe, J., Ripple, R. D., & Trück, S. (2015). The dynamics of returns on renewable energy companies: A state-space approach. Energy Economics, 48, 325-335.

Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. *Energy, 166*, 577-586.

Kaul, G., & C. M. Jones (1996). Oil and the stock markets. *Journal of Finance, 51*, 463–491.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review, 50*(4), 1267-1287.

Kirci Cevik, N., Cevik, E. I., & Dibooglu, S. (2020). Oil Prices, Stock Market Returns and Volatility Spillovers: Evidence from Turkey. *Journal of Policy Modeling, 42*, 597-614.

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.

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.

Liu, Z., Tseng, H. K., Wu, J. S., & Ding, Z. (2020). Implied volatility relationships between crude oil and the US stock markets: Dynamic correlation and spillover effects. *Resources Policy, 66*, 101637.

Lundgren, A. I., Milicevic, A., Uddin, G. S., & Kang, S. H. (2018). Connectedness network and dependence structure mechanism in green investments. Energy Economics, 72, 145-153.

Maghyereh, A., & Abdoh, H. (2021). The impact of extreme structural oil-price shocks on clean energy and oil stocks. *Energy, 225*, 120209.

Malik, F. (2021). Volatility spillover among sector equity returns under structural breaks. *Review of Quantitative Finance and Accounting*, 1-18.

Managi, S., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market?. *Japan and the World Economy, 27*, 1-9.

Mazzarisi, P., Zaoli, S., Campajola, C., & Lillo, F. (2020). Tail Granger causalities and where to find them: Extreme risk spillovers vs spurious linkages. *Journal of Economic Dynamics and Control, 121*, 104022.

Mork, K. A. (1989). Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. *Journal of political Economy, 97*(3), 740-744.

Nasreen, S., Tiwari, A. K., Eizaguirre, J. C., & Wohar, M. E. (2020). Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. Journal of Cleaner Production, 260, 121015.

Pham, L. (2019). Do all clean energy stocks respond homogeneously to oil price?. *Energy Economics, 81*, 355-379.

Rasche, R. H., & Tatom, J. A. (1981). Energy price shocks, aggregate supply and monetary policy: The theory and the international evidence. *In Carnegie-Rochester Conference Series on Public Policy* (Vol. 14, pp. 9-93). North-Holland.

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

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.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics, 21*(5), 449-469.

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.

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.

Warshaw, E. (2020). Asymmetric volatility spillover between European equity and foreign exchange markets: Evidence from the frequency domain. *International Review of Economics & Finance*, *68*, 1-14.

Wen, X., Guo, Y., Wei, Y., & Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics*, 41, 63-75.

White, H., Kim, T. H., & Manganelli, S. (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics, 187*(1), 169-188.

Yahya, M., Kanjilal, K., Dutta, A., Uddin, G. S., & Ghosh, S. (2021). Can clean energy stock price rule oil price? New evidences from a regime-switching model at first and second moments. *Energy Economics, 95*, 105116.

Zhang, H., Cai, G., & Yang, D. (2020). The impact of oil price shocks on clean energy stocks: Fresh evidence from multi-scale perspective. *Energy, 196*, 11709.