Can clean energy stock price rule oil price? New evidences from a regime-switching model at first and second moments

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Year: 2021

Version: Accepted manuscript

Please cite the original version:

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. https://doi.org/10.1016/j.eneco.2021.105116

Title page

Can Clean Energy Stock Price Rule Oil Price? New Evidences From a Regime-Switching Model at First and Second Moments.

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Declaration of Interests: None

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- Evaluates price transmission mechanisms between BRENT and CEI in TVECM-DCC-GARCH
- Shows statistical coherency combining 1st and 2nd moments of nonstationary assets
- Price transmission of the assets is nonlinear and regime dependent
- CEI governs BRENT during post-crisis days, supporting the divestment thrust in oil
- The integrated model is capable to give higher returns than volatility models

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Abstract

The study evaluates nonlinear price transmission mechanisms between clean energy stock and crude oil price in levels, mean, and error variances. We propose a novel way of combining a two-regime threshold vector error correction with the DCC-GARCH model to demonstrate a statistical coherency. The study advances the literature by examining the long-and short-term dynamics of these assets in their levels where the information of nonstationarity in the first moment of these assets is preserved, which generally disappears or becomes a random walk process in the return series. The combined model is then applied to derive a regime dependent dynamic hedging strategy, which has been complemented by a wavelet-based hedging strategy. The data spans from 2nd April 2004 to 10th July 2020 is divided into sub-periods to incorporate the financial crisis and ongoing COVID pandemic. Our findings suggest a nonlinear regime-dependent long-term connectedness among the assets in the first and second moments. The study affirms that the price transmission path between the two asset classes is nonlinear. The research indicates that the clean energy index emerges as the dominant influencer on the crude oil price over the post-crisis subsample. A nonparametric nonlinear causality further validates the theoretical rationale of an integrated model. While examining the impact of several control variables on the relationship between these assets, we find that policy uncertainty is an important thread which further demonstrates the prominence of clean energy stocks. Our findings are in accordance with the global focus of divestment in the non-fossil fuel energy sector. This study differs from previous studies in its apt application of statistical modeling techniques on the theoretical and empirical ground. The outcomes are encouraging for the global investors' and traders' communities as the integrated model has the potential to fetch higher returns compared to commonly used volatility-based models.

Key Words: Clean Energy Stocks, Oil Price, Threshold Cointegration, TVECM, DCC-GARCH, Wavelet, Hedging Strategy

JEL Classification: G10, G12, G15, Q21, C58

1. Introduction

Is the clean energy stock going to be the critical economic indicator instead of oil? With the downfall in crude oil prices in the aftermath of the 2008 financial crisis and better awareness about the disastrous environmental impact of fossil fuels, the global focus has shifted towards clean energy sources (Lauri et al., 2014). The clean energy sector has seen a tremendous thrust of investment in the past decade. Two-thirds of the global energy investment is expected to absorb only by renewables in 2040 (IEA, 2018). The sector has witnessed investments of $279.8 billion as of 2017. The cumulative investments in the sector have increased to $2.9 trillion since 2004 (McCrone et al., 2018). The impulse is equally reflected in the financial market performance of clean energy stocks, which has received grand attention from global investors, practitioners, and policymakers in recent years (Ahmad, 2017; Ahmad et al., 2018; Elie et al., 2019; Rezec and Scholtens, 2017; Uddin et al., 2019). The Wilder Hill Clean Energy Index, one of the leading renewable energy stock indexes, had attained global attention when it fetched a recorded annual return of 35% in 2007, exceeding the benchmark indices of NASDAQ significantly. Returns have also been higher than the benchmark indices in the years 2013 and 2019 (Invesco, n.d.). Oil price, on the other hand, has exhibited a significant plunge in the year 2014 (-49.73%), 2015 (-32.55%) after attaining a historic low-price post-2008. It has followed the recovery of 52.41% in 2016 and another 17.44% in the year 2017. Later on, it has again slumped by 24.22% in 2018 and by more than 40% during the period of the pandemic in 2020 (Figure 1). Because of this, it is quite realistic to assume that the dynamics between clean energy index and crude oil are complex but transient, which passes through different market conditions, causing a persistent upturn or downturn in the underlying risk-return relationship. And the clean energy stock price may soon become the leading indicator representing the health of the global economy.

The literature, so far, has mostly advocated the dominance of crude oil over clean energy assets (Broadstock et al., 2012; Dutta, 2018; Dutta et al., 2020, 2018; Elie et al., 2019; Henriques and Sadorsky, 2008; Kang et al., 2017; Kocaarslan and Soytas, 2019a, 2019b; Kumar et al., 2012; Managi and Okimoto, 2013; Mei et al., 2018; Mishra et al., 2019; Pal and Mitra, 2017; Pandey and Vipul, 2018; Reboredo, 2015; Sadorsky, 2012; Uddin et al., 2019; Wen et al., 2014; Yahya et al., 2020). Recently, some studies have highlighted weak (Elie et al., 2019; Nasreen et al., 2020; Ripsy Bondia et al., 2016) or no association (Ferrer et al., 2018) between crude oil and clean energy stock price. Lundgren et al. (2018) report that oil is not the key influencer in the financial market.

The majority of previous researches have deployed variants of multivariate GARCH models (Ahmad, 2017; Ahmad et al., 2018; Broadstock et al., 2012; Dutta, 2017; Dutta et al., 2020; Elie et al., 2019; Reboredo, 2015; Sadorsky, 2012; Wen et al., 2014), cross-quantilograms (Uddin et al., 2019), or time-frequency spillover (Ferrer et al., 2018) to study the relationship of crude oil and clean energy price. A few recent studies have used a mix of parametric and nonparametric approaches (Ferrer et al., 2018; Lundgren et al., 2018; Nasreen et al., 2020; Zhang et al., 2020). The application of different linear and nonlinear cointegration techniques is also not rare (Ripsy Bondia et al., 2016; Henriques and Sadorsky, 2008; Kocaarslan and Soytas, 2019b; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo et al., 2017). While the latter group of researchers has focused on modelling the nonstationary assets in levels, thereby ignoring their heteroscedastic properties of error variances, the former has extensively dealt with the return and volatility aspects after making the assets stationary, disregarding the cointegration property. In this study, we adopt an integrated modelling approach where we preserve the information of nonstationarity and heteroscedasticity in examining the price transmission mechanism of crude oil and clean energy stock price. To the best of our knowledge, such an integrated modelling approach is nonexistent and makes novel additions to the literature. Our research contributes to the literature in many ways.

First, the originality of this study is that it proposes a modelling technique where the first and second moments information of the assets are kept intact in exploring their mean and volatility transmission of clean energy stock price and the price of crude oil through an integrated research framework combining a regime-changing Threshold vector error correction model (hereafter: TVECM) (Hansen and Seo, 2002) with dynamic conditional correlation (DCC-GARCH) procedure of Engle (2002) together. The novelty of this modelling approach originates to some of the seminal works by (Gregory and Hansen, 1996; Hamilton, 1994; Hatemi-J, 2008) that recommended that investigating the non-linearity in mean returns, ignoring the impact of the spurious relationship, or the existence of structural breaks may lead to false inferences. From the theoretical standpoint, our study advances the literature by examining the long- and short-term dynamics of these assets in their levels where the information of the first moment of these assets is preserved and added to their second moment or heteroscedastic variance. The nonstationarity property often disappears after the first difference of the financial assets because they follow a random walk process (Fama, 1970). This means the return series becomes 'white noise' and bears no systematic information which can be modelled for. So, the first-order or mean modelling of assets is statistically meaningful if these assets are examined in levels as the information of 'nonstationarity' is appropriately leveraged. Earlier studies have remained silent and oblivious about these gaps. Our approach captures the dynamics of these assets in levels and their heteroscedastic variances by not working with the series, which are white noise to start with.

Second, we add to the literature by deploying a regime-based modelling framework in level and volatility with nonstationary assets. The rationale for adopting a regime-based approach can be explained by the continuous occurrence of upswing and downswing dynamics of the underlying variables. The price transmission mechanism between any two instruments never follows a linear or constant path due to changing market conditions. Thus, a chronological evolution of clean energy stock and crude oil prices must have witnessed different regimes or market conditions. The TVECM (Hansen and Seo, 2002; Seo, 2011, 2007) can aptly encapsulate two (three) regime-driven dynamics of assets that are nonstationary at levels. This feature differentiates a two (three) regime-TVECM from other parametric or nonparametric class of models, which can analyze the assets at various market states with only asset returns. A regime-switching dynamics is an endogenously determined phenomenon in a TVECM. The regime definitions of 'normal' or 'extreme', depend on the estimated threshold parameter, which determines the distribution of regimes (Hansen and Seo, 2002; Seo, 2011, 2007). One of the limitations of this model is that it cannot estimate the volatility transmission of two asset classes for separate market conditions. We address this gap by applying the DCC-GARCH (Engle, 2002) TVECM residuals to investigate the regime-dependent level and volatility transmission of prices.

Third, we have conducted a rigorous validation process and robustness check for the proposed model. The need for the integrated modelling approach (TVECM-DCC-GARCH) with nonstationary level variables is validated using a nonparametric causality of Diks and Panchenko (D&P) (2006). The D&P causality is tested on filtered residuals sequentially for i) VAR filtered residuals, ii) TVECM filtered residuals, iii) MEAN plus DCC-GARCH filtered residuals, and iv) TVECM-DCC-GARCH filtered residuals. This approach helps to reassess the information richness of each model by looking into the causal relationship between the assets at every stage. For example, if the null of no causal link between crude oil price and clean energy residuals obtained from the VAR estimation is rejected, then we could possibly infer that the residual is not white noise. This implies that the VAR model applied has not been able to arrest embedded information in the underlying variables completely. Similar conclusions hold true if the null of no causality gets rejected at other stages. We further tested the effectiveness of our proposed model empirically in a trading strategy.[1] We also perform the diagnostic tests by estimating wavelet-based portfolio weights and hedge ratios for the underlying assets to measure robustness checks.

Fourth, we have thoroughly examined the consistency of the regime driven relationship between crude oil price and clean energy stock price by adding many facets to the empirical analysis. We have divided the weekly data of Wilder Hill Clean Energy Index and Brent crude oil (BRENT) spanning from 2nd April 2004 to 10th July 2020 into seven different subperiods, which incorporate the effects of the 2008 financial crisis and ongoing COVID pandemic period. To examine the strength of the linkage between these two assets, we have checked the link of clean energy stock price with other variants of crude oil price like WTI (West Texas Intermediate), its futures (1,3,6,9,12 months), and S&P oil index using the TVECM-DCC-GARCH. Additionally, the nexus between these assets are modelled in a multivariate framework to test if the link withstands the impact of control variables like carbon price, policy uncertainty, and S&P volatility index in different subsample periods. The risk strategies are also examined for oil price with clean energy stock price, wherever appropriate.

This study offers some unique outcomes carrying practical implications for traders and market practitioners. This research establishes that the two nonstationary series, crude oil price, and clean energy stock price, share a two-regime nonlinear cointegrating relationship with a threshold effect. Our findings indicate a weak cointegration link before the financial crisis of 2008 between these assets, which become significantly stronger over the post-crisis subsample. The threshold cointegration link, however, breaks when the data period encompasses the COVID

[1] TVECM-DCC-GARCH is applied to Bollinger bands (Bollinger, 2001; Ramlall, 2016) trading strategy.

pandemic period. A similar finding is also uncovered when the threshold cointegration is examined for financial crisis days as well.

The causal dynamics from the TVECM indicates the dominance of crude oil over the clean energy stock price in the pre-crisis period. The dynamics reverse over the post-crisis period, where the clean energy stock emerges as a strong driver of crude oil price in a normal regime. Our findings deviate from the majority of earlier studies that advocate that the oil price governs over clean energy. However, the finding of 'the crude oil driving the clean energy stock is a rare phenomenon and observed only in extreme regimes' synchronizes with the research outcomes of (Dutta et al., 2020; Uddin et al., 2019; Zhang et al., 2020). Our study does differ from Ferrer et al. (2018) and Bouri et al. (2019), who showed a decoupling or a weak link between clean energy and oil price returns. This research extends the work of Lundgren et al. (2018) to some extent, who suggest clean energy stock is one of the net transmitters and oil is on the net recipient's side.[2]

In examining the relationship in a multivariate framework, policy uncertainty and S&P volatility index establish interesting characteristics in honing the connection between clean energy and crude oil price. We find that policy uncertainty and S&P volatility index (VIX) share a two-regime threshold cointegration with BRENT and clean energy stock price for the entire sample. In the post-financial crisis period, excluding the COVID pandemic, policy uncertainty exhibits a threshold cointegration link with BRENT, WTI, and clean energy stock price. These findings are consistent with Lundgren et al. (2018). Furthermore, the presence of policy uncertainty and the VIX has not altered the findings of clean energy stock price, becoming the key driver for the crude price since the onset of the financial crisis.

[2] These outcomes are validated for WTI, its futures, and the S&P oil index with clean energy stock price. While WTI and its futures have shown similar results as BRENT crude oil price for all subperiods, the S&P oil index has shown similar findings as BRENT only for pre-financial crisis days.

The DCC-GARCH analysis of TVECM residuals recommends that the volatility spillover among assets is statistically significant. The volatility association between crude oil and clean energy emerges to be more dynamic in the post-crisis days in a normal regime. The dynamic conditional correlation shows a wide range of variation from -0.05 to 0.4 as compared to the pre-crisis era, which has shown a weak association in volatility between these two assets varying from -0.1 to 0.1. The correlation, however, has stayed less than 0.5 in all cases suggesting CEI, a good instrument for hedging although weakened in comparison to the pre-crisis period. This finding is in line with Sadorsky (2012), who also argues that although clean energy and oil markets are positively correlated, it is still possible that investors holding assets in these sectors would receive portfolio diversification benefits. The obtained portfolio weights and hedge ratios affirm this association, indicating a significant difference in hedging effectiveness over the pre-and post-crisis period.

Our validation exercise has offered results in line with our expectations. The sequential D&P causality checks of filtered residuals for the TVECM-DCC-GARCH model has accurately justified the need for our integrated modelling approach. The trading strategy results also demonstrate that TVECM-DCC-GARCH outperforms DCC-GARCH in CAGR (cumulative annual growth rate) significantly. Finally, the analysis of robustness check using wavelet-based portfolio weights and hedge ratios further support this evidence. The outcomes of this study bear meaningful implications for academicians and market participants.

The introduction section follows five separate sections. Section 2 provides a survey of existing literature. Section3 explains data and variables. Section 4 illustrates the methodological setup. Section 5 reports empirical findings. Section 6 provides the conclusion and discussion.

2. A Brief Literature Survey

Empirical research on the dynamic interactions and price transmission mechanisms among clean energy and crude oil has mainly evolved around the work of a) cointegration and Granger causality (Ripsy Bondia et al., 2016; Henriques and Sadorsky, 2008; Kocaarslan and Soytas, 2019b; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo et al., 2017) and b) volatility transmission (Ahmad et al., 2018; Broadstock et al., 2012; Dutta, 2017; Reboredo, 2015; Sadorsky, 2012; Wen et al., 2014, Uddin et. al., 2019; Bouri et. al., 2019; Dutta et. al., 2020) and connectedness (Ferrer et al., 2018; Lundgren et al., 2018).

Before the onset of the 2008 financial crisis, studies carried out by Kumar et al. (2012), and Henriques and Sadorsky (2008) determine that the fluctuations in crude oil price and risk-free asset significantly impact the clean energy assets. In the aftermath of the financial crisis, studies (Bondia et al., 2016; Kocaarslan and Soytas, 2019; Managi and Okimoto, 2013; Reboredo et al., 2017, among others) evaluate the linkage among crude oil price and clean assets using cointegration and causality. Managi and Okimoto (2013) report a positive connectedness between clean energy and oil after the structural breaks found during the end of 2007. Bondia et al. (2016) establish a cointegration relation between assets by utilizing an endogenous regime-dependent cointegration test proposed by Gregory and Hansen (1996) and Hatemi-J (2008). Reboredo et al. (2017) and Kocaarslan and Soytas (2019) report nonlinear causal relationship and cointegration relationships between crude oil and clean assets, respectively, reaffirming earlier study by Kanjilal and Ghosh (2018).

In another strand of literature, the researchers (Ahmad, 2017; Ahmad et al., 2018; Broadstock et al., 2012; Dutta, 2017; Reboredo, 2015; Sadorsky, 2012; Wen et al., 2014¸ Uddin et. al., 2019; Bouri et. al., 2019; Dutta et. al., 2020) investigate the dynamic associations and volatility spillover between crude oil and clean energy assets. Sadorsky (2012) reports the time-varying relationship of clean energy assets with crude oil. Broadstock et al. (2012) evaluate the linkage structure of international crude oil and clean energy assets in China. Wen et al. (2014) report significant asymmetric spillover between the new energy index of China and that of coal and fuel index. Ahmad (2017) reports clean energy assets as net transmitters to crude oil. Reboredo (2015) examines the systemic risk and connectedness dynamics between renewables and crude oil. Dutta (2017) reports that the crude oil volatility index shocks significantly impact clean energy assets. Ahmad et al. (2018) determine that volatility index (VIX), crude oil, and crude oil volatility index (OVX) provide the best hedge for clean energy assets. Bouri et. al. (2019) suggest that crude oil and gold are the weak safe-haven assets for clean energy. Uddin et. al. (2019) show that RE stock returns have a strong positive dependence on oil price change. Dutta et. al. (2020) report the implied volatility index of crude oil as the most effective hedge against clean energy indexes.

Some recent studies have used wavelet (Nasreen et. al., 2020, Zhang et. al., 2020) and network connectedness (Lundgren et. al. 2018, Ferrer et. al. 2018) to study the price transmission dynamics of crude oil price and clean energy stocks. Ferrer et. al. (2018) provide evidence of decoupling between traditional and clean energy industries. Lundgren et. al. (2018) report that crude oil is a net receiver, while clean energy stocks as the third-largest net transmitter of spillover during the recent global financial crisis. Nasreen et. al. (2020) show a weak association between oil prices and clean energy stock returns. Zhang et. al. (2020) shows that oil price shocks on clean energy stocks vary across quantiles.

Thus, the dynamics of clean energy assets (clean technology stocks) and crude oil prices analyzed so far denied the statistical coherence because earlier studies have worked with return series ignoring their nonstationary property. The current study is an attempt to catalyze this change in the existing literature. It examines the price dynamics of crude oil and clean energy stock in level and variance, preserving the nonstationary and heteroscedastic properties of the assets in a TVECM-DCC-GARCH framework.

3. Data description

The data span considered ranges from 2nd April 2004 to 10th July 2020 on a weekly basis. The sample is divided into seven different subperiods to incorporate the effects of the 2008 financial crisis and the ongoing COVID pandemic.[3] These subperiods are Pre&at&post-crisis (April 2004 - July 2020), Pre&at&post-crisis-pre-COVID (April 2004 - Jan 2020), At&post-Crisis (Aug 2008 - July 2020), At&post-crisis-pre-COVID (Aug 2008 - Jan 2020), Post-crisis (Jan 2009 –July 2020), Post-crisis-pre-COVID (Jan 2009 - Jan 2020), and At crisis (Aug 2008 –Dec 2008).[4] The global clean energy index considered for this study is the WilderHill Clean Energy Index (CEI), which is an equally-weighted index of clean energy firms. This index is dedicated exclusively to registering clean energy firms' performance in renewable energy, energy storage and conservation, power delivery and conservation, and cleaner fuels. Most CEI stocks have a market capitalization of $200 million and above. The rationale for selecting BRENT is that in the trading world, "BRENT is one of the benchmarks for oil in the wider market whereas WTI is primarily a benchmark for the US oil market (Killian, 2020). Several studies consider Brent crude as the leading representative of the global oil market given that more than 65% of the world's crude oil markets have anchored this pricing system (Kanjilal and Ghosh, 2017; Lin and Li, 2015; Liu et al., 2020; Mensi et al., 2014; Zhang et al., 2018, 2020). To validate the results of BRENT and CEI,

[3] The data frequency is weekly, barring the "At crisis" (Aug-Dec'2008) period, where we have considered daily data to avoid small sample bias.

[4] We have presented the empirical results of three subperiods i) Pre&at&post-crisis-pre-COVID, ii) Pre-crisis, and iii) Post-crisis-pre-COVID in the text because the threshold cointegration becomes statistically insignificant when the COVID pandemic period is included and second these three subperiods encompass the entire data span and pre- and post- financial crisis and hence they are sufficient to address the research objectives. This also maintains brevity. Results for other subperiods are available on request. In accordance with this, the descriptive statistics are produced for the three subperiods in Table 1.

we also used WTI, its futures (1,3,6,9,12 months), and the S&P oil index for various sample subperiods. All the data has been sourced from the Bloomberg terminal. CEI, BRENT, WTI, WTI futures, and S&P oil index are represented as *lnCEI*, *lnBRENT*, *lnWTI lnWTI_F1, lnWTI_F3, lnWTI_F6, lnWTI_F9, lnWTI_F12,* and *lnS&POI* after the logarithmic transformation. We have also considered control variables like carbon price (CO_2), US economic policy uncertainty index (uncertainty), and S&P volatility index (SPXVOL) to examine their effects on the relationship between crude oil and clean energy stock price. A logarithmic transformation is also applied to these control variables. A graphical representation of the CEI and BRENT series is exhibited in Figure 1 for the entire sample period. Table 1 provides the preliminary statistics of both assets for three sample periods. The nonstationary properties of underlying variables *lnCEI* and *lnBRENT* are checked by ADF, PP, and KPSS tests and a test evaluating structural shifts (Bai and Perron, 2003a, 2003b, 1998). Both underlying assets are $I(1)$ and possess structural breaks for all three subperiods.[5]

Table 1. Descriptive statistics

	Pre-crisis		Post-crisis-pre-COVID		Pre&at&post-crisis-pre-COVID	
	lnBRENT	*lnCEI*	*lnBRENT*	*lnCEI*	*lnBRENT*	*lnCEI*
Mean	4.14	5.23	4.29	4.09	4.25	4.43
Maximum	4.95	5.68	4.84	4.77	4.95	5.68
Minimum	3.47	4.83	3.32	3.59	3.32	3.60
Std. Dev.	0.32	0.18	0.35	0.31	0.35	0.58
Skewness	0.32	0.01	-0.23	0.49	-0.07	0.45
Kurtosis	2.92	2.23	2.06	2.14	2.12	1.82
Jarque-Bera	3.89	5.64	26.13^{***}	41.59^{***}	27.57^{***}	75.18^{***}

Notes: Authors' Calculation. Descriptive statistics are based on the logarithmic transformed series.

[5] For the sake of brevity, we chose not to report these estimates, but are available upon request.

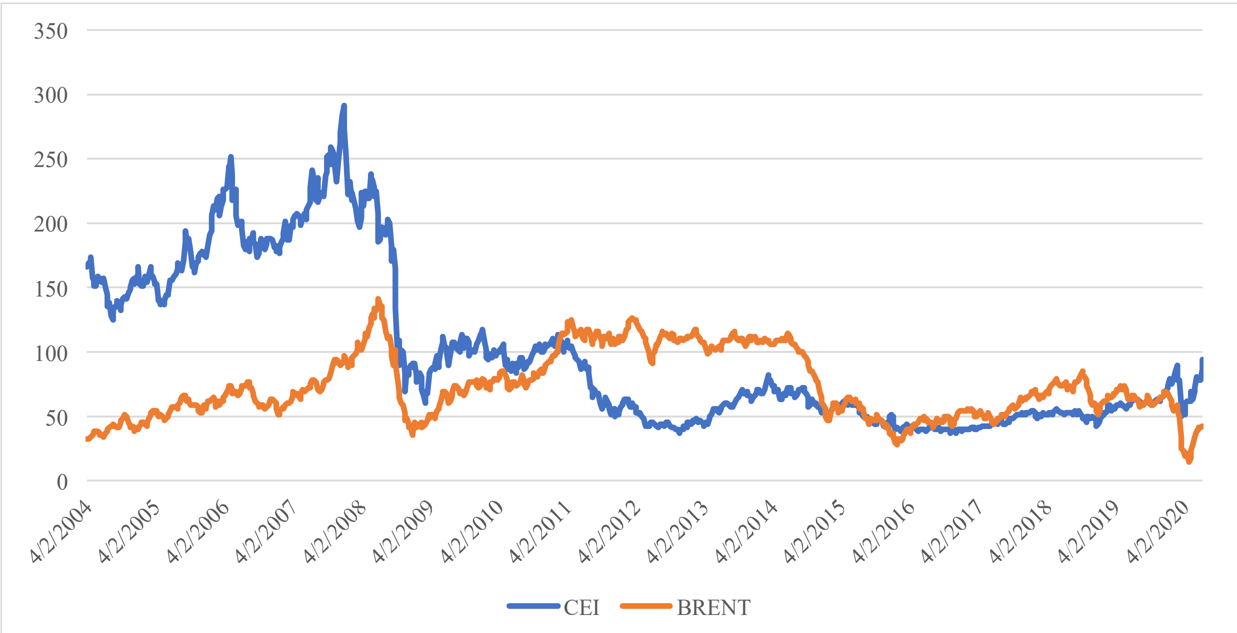


Figure 1. Graphical illustration of the development of the underlying series.

4. Empirical framework

This section discusses the estimation methodologies of the Threshold vector error correction model (TVECM) and DCC-GARCH highlighting the main equations in light of the underlying assets being used for this study. The variables under study are represented by Y_t (*lnBRENT*) and X_t (*lnCEI*).

4.1. Threshold Vector Error Correction Model (TVECM):

Following Hansen and Seo (2002), we express a two-regime TVECM of order *(p+1)* as:

$$\Delta z_t = \begin{cases} C_1' z_{t-1}(\beta) + u_t \text{, if } \eta_{t-1}(\beta) \leq \lambda, \\ C_2' z_{t-1}(\beta) + u_t \text{, if } \eta_{t-1}(\beta) > \lambda, \end{cases} \tag{1}$$

where λ corresponds to the threshold coefficient. z_t is a q −dimensional $I(1)$ assets, *lnBRENT,* and *lnCEI* cointegrated of $(q \times 1)$ vector β. $\eta_t(\beta) = \beta' z_t$ represents the $I(0)$ error correction term (ECT). $z_{t-1}(\beta)$ represent a matrix of $(k \times 1)$ terms represented as:

$$z_{t-1}(\beta) = \begin{pmatrix} 1 \\ \eta_{t-1}(\beta) \\ \Delta z_{t-1} \\ \Delta z_{t-2} \\ \vdots \\ \Delta z_{t-p} \end{pmatrix} \quad 2$$

Let C represents $(k \times q)$ output matrix where $k = q \cdot p + 2.$, and v_t corresponds to normally distributed error vector, $(k \times q)$, with covariance matrix represented as $\sum = E(v_t v_t')$. We may rewrite Equation 1 as:

$$\Delta z_t = C_1' z_{t-1}(\beta) d_{1t}(\beta, \lambda) + C_2' z_{t-1}(\beta) d_{2t}(\beta, \lambda) + v_t \quad 3$$

where,

$$d_{1t}(\beta, \lambda) = I(\eta_{t-1}(\beta) \leq \lambda),$$

$$d_{2t}(\beta, \lambda) = I(\eta_{t-1}(\beta) > \lambda),$$

with $I(\cdot)$ representing indicator function. C_1 and C_2 represent the coefficient matrices in two discrete regimes. $\eta_{t-1}(\beta)$ corresponds to the ECT. The parameters, $l_n = (C_{1,} C_{2,} \sum, \beta, \lambda)$, is estimated using a constrained ML estimation process. [6] We may define the threshold cointegration hypothesis by utilizing Lagrange-Multiplier (LM) test as:

$$SupLM = \sup_{\lambda_L \leq \lambda \leq \lambda_u} LM(\hat{\beta}, \lambda) \quad 4$$

where λ_L represents the π_0 percentile of $\hat{\eta}_{t-1}$ and λ_U corresponds to $(1 - \pi_0)$ percentile, and $\pi_0 < P(\eta_{t-1} \leq \lambda) < 1 - \pi_0$; $\pi_0 > 0$; and $0 < P(\eta_{t-1} \leq \lambda) < 1$.

4.2. DCC-GARCH approach

The mean-equation in GARCH process specified as:

$$R_t = L + \tau R_{t-1} + \varepsilon_t \quad 5$$

$$\varepsilon_t = H_t^{1/2} \eta_t \quad 6$$

[6] We refer to Hansen and Seo (2002) for detailed discussion of the estimation procedure.

where R_t represents the log-difference of both assets, L represents intercept, τ represents the impact of lagged returns, ε_t corresponds to error term, η_t represents innovations matrix, and $H_t^{1/2}$ represents conditional volatility, which can be decomposed as:

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag\left(\sqrt{h_t^s}, \sqrt{h_t^o}\right) \tag{8}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{9}$$

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \xi_{t-1} \xi'_{t-1} + \theta_2 Q_{t-1} \tag{10}$$

where in equation 8, h_t^s and h_t^o correspond to conditional variances from *lnCEI* and *lnBRENT*, respectively.

4.3. Portfolio weights, hedge ratios, and hedging effectiveness

We utilize the DCC-GARCH process to examine whether the inclusion of these assets, *lnCEI* and *lnBRENT*, together in a portfolio, would result in risk minimization. Following Kroner and Ng (1998), we defined the weights of the optimal portfolio as:

$$\omega_t^{so} = \frac{h_t^s - h_t^{so}}{h_t^o - 2h_t^{so} + h_t^s} \tag{11}$$

$$\omega_t^{so} = \begin{cases} 0, & if \quad w_t^{so} < 0 \\ w_t^{s0}, & if \quad 0 \le w_t^{so} \le 1 \\ 1, & if \quad w_t^{so} > 1 \end{cases} \tag{12}$$

where ω_t^{so} corresponds to the weight of \$1 portfolio to be invested in crude oil at time t, and the weight of clean energy equities amounts to $(1 - \omega_t^{so})$. Following Kroner and Sultan (1993), we estimate the optimal hedge ratios for a \$1 long position in crude oil and \$$\beta_t$ short of CEI as:

$$\beta_t^{so} = \frac{h_t^{so}}{h_t^s} \tag{13}$$

Following Ku et al. (2007), we estimate the hedging effectiveness (HE) as:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \quad (14)$$

where $Var_{unhedged}$ represents CEI variance and Var_{hedged} corresponds to portfolio variance. The higher values of HE suggest a greater portfolio uncertainty reduction, thereby favoring the underlying portfolio strategy (Arouri et al., 2011).

5. Results and Discussions

We organize the structure of this section as follows. First, we discuss the results of threshold cointegration, its parameter estimation, and short-and long-run dynamics of TVECM. In the next step, we present the results of the DCC-GARCH of TVECM residuals and the hedging statistics. Finally, we discuss the results of validation and robustness checks.

5.1. Threshold cointegration, threshold parameter estimation, and TVECM

The estimation process of TVECM involves three major steps; first, testing for the presence of threshold cointegration, where the underlying variables are integrated of order one. The threshold cointegration ('SupLM' test) tests for linear cointegration as null against threshold cointegration. Second, it estimates the threshold parameter that determines the sample distribution in two or three discrete regimes. Finally, it estimates coefficient matrices in these regimes, which control the dynamics of the regimes as defined by the threshold parameter. After examining the threshold cointegration, we have applied statistical tests to determine the appropriate number of thresholds which would determine the regime driven dynamics of the variables.

Table 2 reports the results of threshold cointegration between *lnBRENT* and *lnCEI* for three subperiods, i) Pre-crisis, ii) Post-crisis-pre-COVID, and iii) Pre&at&post-crisis-pre-COVID. Before discussing the results of these three subperiods, it is critical to take a closer look at the threshold cointegration results for seven subperiods and understand the reasons for the selection of these sample periods. Table A6 in the Appendix presents a summary result of threshold cointegration of clean energy with BRENT, WTI, its futures, and S&P oil index across all subperiods. Results indicate that the threshold cointegration becomes statistically insignificant when the COVID pandemic period is included in the data span. Similar is the case when the financial crisis period is scanned for a threshold cointegration. The findings for WTI and CEI are consistent with BRENT and CEI. Based on the summary results, we have selected three sample periods to examine the linkage between clean energy and crude oil price in TVECM-DCC-GARCH. The selection serves to attain the larger objectives of this study.

Coming back to the results of Table 2, we find that the SupLM test statistic is statistically significant at the 5% level for the subperiods, Post-crisis-pre-COVID and Pre&at&post-crisis-pre-COVID period, whereas, for the pre-crisis subsample, this estimate is significant at the 10%. This confirms that *lnCEI* and *lnBRENT* are linked by a cointegrating relationship that witnessed threshold(s). This implies a weak cointegration link before the financial crisis of 2008 between these assets, which become significantly stronger over the post-crisis subsample. To understand the short-term deviations and asymmetric adjustments towards the cointegrating relationship, the tests of equality of i) Error correction Model (ECM) parameters and ii) dynamic parameters across two regimes are examined. Results indicate that the null-hypothesis for the Wald equality test of ECM parameters between *lnBRENT* and *lnCEI* is rejected at a 5% threshold level for the second and third subperiods. However, it is rejected at a 10% threshold for the pre-crisis period. This implies that the ECM adjustment parameter across two regimes is asymmetric and regime dependent. However, the impact is stronger for the post-crisis subsample. The Wald equality test of dynamic coefficients is rejected at the 5% threshold for the pre-crisis subsample, indicating short-term dynamics of *lnBRENT* and *lnCEI* in two regimes are dissimilar.

Table 2: Threshold cointegration test

	Pre-crisis	Post-crisis-pre-COVID	Pre&at&post-crisis-pre-COVID
SupLM Test Statistic	13.25*	19.28***	23.03***
	(0.06)	(0.01)	(0.00)
Linear Cointegrating Vector Estimate	2.10	1.54	0.095
	(0.66)	(0.60)	(0.32)
Wald Test for Equality of Dynamic Coefficients	10.30**	26.35***	15.10**
	(0.03)	(0.00)	(0.02)
Wald Test for Equality of ECM Coefficients	4.52*	7.41**	10.80***
	(0.10)	(0.02)	(0.00)

Notes: '*,' '**,' and '***' imply significance at 10%,5%, and 1% level of significance.
Figures in (*) represent p-values.

In addition, we have applied three different statistical tests; namely, i) BBC (Bec et al., 2004) (Panel A of Table 3), ii) KS (Kapetanios et al., 2003) test (Panel B of Table 3), and iii) Seo (2011, 2006) (Table A2, Appendix) TVECM model to test if two or three regimes TVECM is the best fit for our sample periods. The sample subperiods for the BBC and KS tests across all variables are applied for those cases where the threshold cointegration is found to be statistically significant at the 5% level (Table A6, Appendix). In summary, the test results demonstrate that a one threshold model or a two-regime TVECM is more appropriate for our data. For example, the BBC test results in panel A of Table 3 fail to reject the null of unit root for symmetric three-regimes at 5% significance level. KS test also cannot reject the null of unit root for symmetric three regimes for any variables across all subperiods (panel B of Table 3). To further investigate the possibility of the presence of three regimes between crude oil and clean energy price, we estimate Seo's (Seo, 2011, 2006) three-regime TVECM model.[7]

[7] TVECM is estimated pairwise for BRENT and WTI with CEI at 'Pre&at&post-crisis-pre-COVID' and 'At&post-crisis-pre-COVID' subperiods as the BBC test rejects the null for BRENT and WTI in these two cases. Results are reported in the Appendix, Table A2. The results (Table A2) show evidence of the statistical significance of ECT consistently across two regimes. The outcomes are in line with the finding of BBC (2004). Thus, a two-regime (one threshold) is the best choice for our data.

Table 3: TVECM regime selection tests

Panel A: BBC-SETAR test

Max Wald Test	Pre-crisis	Post-crisis-pre-COVID	Pre&at&post-crisis-pre-COVID
lnBRENT	5.03	16.02	17.25*
lnCEI	12.19	14.22	14.41

Panel B: KS test

Avg(W) Test	Pre-crisis	Post-crisis-pre-COVID	Pre&at&post-crisis-pre-COVID
lnBRENT	0.202	0.033	0.067
lnCEI	0.056	0.016	0.029

Notes: '*,' '**,' and '***' imply significance at 10%,5%, and 1% level of significance. Further details are given in Table A6, Appendix

Having established the suitability of a two-regime TVECM for our data, we present the estimation of a two-regime TVECM in Table 4 for three subperiods i) Pre-crisis, ii) Post-crisis-pre-COVID, and iii) Pre&at&post-crisis-pre-COVID. A two-regime TVECM is also estimated for all subperiods.[8]

Regime switching dynamics are endogenously determined phenomenon in a TVECM. The regime definition depends on the estimated threshold parameter, which determines the distribution of two or three regimes. For instance, for the post-crisis period excluding the COVID 19 pandemic days, the estimated threshold parameter is $\lambda = -1.9079$. The estimated cointegrating parameter is C = 1.3386. So, normal and extreme regimes are identified based on the formula, $ECT(\eta_{t-1}) = lnBRENT_{t-1} - C * lnCEI_{t-1} <= \lambda_t$ where C is the cointegrating parameter, and λ is the threshold parameter. The estimated cointegrating relationship is $\eta_{t-1} = lnBRENT_{t-1} - 1.3386\ (lnCEI_{t-1})$, implying that a 1 percent increase in clean energy stock price brings a 1.33 percent increase in crude oil price. The threshold parameter estimate is -1.9079. Based on this value, the threshold vector error correction model is divided into two regimes. The first regime occurs when $\eta_{t-1} \leq -1.9079$, i.e. $lnBRENT_{t-1} \leq 1.3386(lnCEI_{t-1}) - 1.9079$. In other words, the crude oil price falls below

[8] The result is reported in the Appendix (Table A3) to maintain succinctness.

the clean energy stock price less 1.9079 percent. This seems to be an extreme phenomenon in the commodity market as it is reasonably unusual or rare. This regime has 18 percent of observations. So, this regime is termed as an "extreme regime." On the other hand, the second regime occurs when $\eta_{t-1} > -1.9079$. This means crude oil price exceeds clean energy stock price less 1.9079 percent. This seems to be more usual or normal. Hence the second regime can be labelled as a "normal regime" with 82 percent observations. Similarly, the threshold parameter defines the distribution of normal and extreme regimes in the other two subperiods. The distribution of sample observations in subperiods suggests that Brent crude oil price has remained higher than the CEI in most cases over this study period. The proportion of the distribution of sample observations into two regimes falls in line with previous works (Ghosh and Kanjilal, 2020; Güriş and Kiran, 2014; Hansen and Seo, 2002; Kanjilal and Ghosh, 2017; Rapsomanikis and Hallam, 2006). The existence of the threshold parameter indicates that the price transmission between the two variables is different in two regimes, and hence, it is regime-dependent.

Table 4. Vector error correction model of threshold cointegration

	Regime1 ($\eta_{t-1} \leq \lambda$)		*Regime II* ($\eta_{t-1} > \lambda$)	
Variables	$\Delta lnBRENT$	$\Delta lnCEI$	$\Delta lnBRENT$	$\Delta lnCEI$
Panel A: Pre-crisis Period Threshold Estimate (λ) = -6.5520; Cointegrating Vector Estimate = (1, -2.0252)				
$(ECT)_{t-1}$: η_{t-1}	-0.0235 [0.0367]	0.1147** [0.0464]	-0.0160 [0.0159]	0.0101 [0.0179]
Constant	-0.1491 [0.2469]	0.7637** [0.3098]	-0.1003 [0.1006]	0.0664 [0.1137]
$\Delta lnBRENT_{t-1}$	0.0247 [0.1114]	0.1542 [0.1461]	0.3174** [0.0732]	0.0516 [0.0731]
$\Delta lnCEI_{t-1}$	0.1392 [0.1031]	0.1958 [0.1429]	-0.0850 [0.0739]	-0.0178 [0.0814]
Sample size (%)	33%	33%	66%	66%
Panel B: Post-crisis-pre-COVID Period Threshold Estimate (λ) = -1.9079; Cointegrating Vector Estimate = (1, -1.3386)				
$(ECT)_{t-1}$: η_{t-1}	-0.1486 [0.0979]	0.2077** [0.1070]	-0.0069** [0.0035]	0.0005 [0.0048]
Constant	-0.2901 [0.1982]	0.2575 [0.2163]	-0.0075** [0.0037]	0.0006 [0.0055]
$\Delta lnBRENT_{t-1}$	-0.2903** [0.1245]	-0.3974** [0.1469]	0.2249** [0.0477]	0.0241 [0.0507]
$\Delta lnCEI_{t-1}$	0.2540 [0.1519]	0.4321** [0.1512]	0.1745** [0.0426]	-0.0155 [0.0530]
Sample size (%)	18%	18%	82%	82%
Panel C: Pre&at&post-crisis-pre-COVID Period Threshold Estimate (λ) = 4.3388; Cointegrating Vector Estimate = (1, 0.1008)				
(ECT)t-1 : η_{t-1}	-0.0783** [0.0409]	0.0325 [0.0327]	-0.0016 [0.0048]	-0.0167** [0.0059]
Constant	0.3339 [0.1724]	-0.1366 [0.1372]	0.0075 [0.0237]	0.0793** [0.0287]
$\Delta lnBRENT_{t-1}$	0.1485** [0.0794]	-0.0929 [0.0750]	0.2297** [0.0465]	0.0578 [0.0747]
$\Delta lnCEI_{t-1}$	0.0213 [0.1148]	-0.1307 [0.1311]	0.1888** [0.0392]	0.0512 [0.0673]
Sample size (%)	20%	20%	80%	80%

Notes: Figures in parenthesis show Eicker-White standard errors. *, ** and *** imply significance at 10%, 5%, and 1% level of significance. .Δ is the first differenced operator. The lag structure has been selected based on the lowest AIC and SC criteria. Regime I and II represent extreme and normal regimes, respectively.

The estimation results of TVECM indicate that while in the pre-financial crisis crude oil price has led the clean energy price, the influence of crude oil price reduces in the post-crisis days, excluding pandemic period with clean energy price becoming the main driver. A closer look into

Table 4 suggests that the ECT, η_{t-1}, is significant for the pre-crisis period in Regime I (extreme regime) when the explained asset is $\Delta lnCEI$. The ECT becomes significant over the Post-crisis-pre-COVID subsample when $\Delta lnBRENT$ is the explained asset in Regime II (normal regime). In the short-term as well, $\Delta lnCEI$ caused $\Delta lnBRENT$ in both extreme and normal regimes. For the entire sample excluding COVID19, we find the dominance of *lnCEI* over *lnBRENT,* where ECT is significant in the extreme regime when $\Delta lnBRENT$ is estimated. In the short-term, $\Delta lnCEI$ causes $\Delta lnBRENT$ in a normal regime. In the pre-crisis period, however, clean energy stock price is not found to bring any impact on crude oil prices, confirming a dominance of crude oil in the market. The dynamics reverse over the post-crisis period, where the clean energy stock emerges as a strong driver of crude oil price in a normal regime. Our findings differ from earlier studies that recommend that the oil price governs over clean energy. However, the result that crude oil drives the clean energy stock in extreme regimes falls in line with research outcomes (Uddin et. al., 2019; Dutta et. al., 2020; Zhang et. al., 2020). Our study also deviates from Ferrer et. al. (2018) and Bouri et. al., (2019), who showed a decoupling or a weak link between clean energy and oil price returns. However, this research is in accordance with Lundgren et. al. (2018) to some extent, who suggest clean energy stock is one of the net transmitters, and oil is a net receiver. Table 4 further establish a bidirectional association between crude oil price and clean energy stock price in a normal regime for the entire sample (including the financial crisis of 2008 but excluding COVID days). The error correction effects are stronger in Regime I than Regime II across all subperiods. The estimated ECT coefficients suggest the adjustment speed towards long-run equilibrium. These findings confirm the existence of a nonlinear regime-based adjustment process between these two assets.

The above causal dynamics are further validated for WTI, its futures, and the S&P oil index with clean energy stock price. Results (Table A3, Appendix) directs that WTI and its futures have shown similar results as BRENT crude oil price for all subperiods. The S&P oil index, however, has shown similar findings with BRENT only for pre-financial crisis days. We have also examined the presence of threshold cointegration and studied the causal dynamics between crude oil and clean energy stock prices after controlling the effect of the carbon price, uncertainty, and volatility index in a two-regime TVECM. Tables A4 and A5 in the Appendix present the summary of empirical findings, which indicate that the relationship of crude oil price and clean energy withstand the effect of control variables. We find that policy uncertainty and S&P volatility index share a two-regime threshold cointegration with BRENT and clean energy stock price for the entire sample. In the post-financial crisis period, excluding the COVID pandemic, policy uncertainty exhibits a threshold cointegration link with BRENT, WTI, and clean energy stock price. These outcomes are consistent with Lundgren et. al. (2018), as they report policy uncertainty is the main volatility transmitter. It is critical to note that the presence of policy uncertainty and the S&P volatility index has not altered the findings of clean energy stock price becoming the key driver for the crude price since the onset of the financial crisis.

5.2 TVECM-DCC-GARCH

Before analyzing TVECM-DCC-GARCH results, we test the presence of the ARCH effect in the TVECM residuals of *lnBRENT* and *lnCEI* for short-, medium, and long-term lag orders. Table 5 suggests that the ARCH effect is statistically significant in both regimes for the entire sample. In the Post-crisis-pre-COVID period, the ARCH effect is present only in the normal regime. DCC-GARCH is then estimated for the cases where the ARCH effect is significant. In view of the above findings, we estimate the TVECM-DCC-GARCH model with the mean equation obtained from the TVECM for i) Pre&at&post-crisis-pre-COVID and ii) Post-crisis-pre-COVID days. The DCC-GARCH analysis of TVECM residuals recommends that the volatility spillover among assets is statistically significant.[9] Figure 2 depicts the dynamic conditional correlation in variance between $\Delta lnBRENT$ and $\Delta lnCEI$ for the three subperiods, and the regime DCC-GARCH has been estimated for. The volatility association between crude oil and clean energy emerges to be more dynamic in the post-crisis days in a normal regime. The dynamic conditional correlation varies from -0.05 to 0.4 in the post-crisis days. The pre-crisis era has shown a weak association in volatility between these two assets varying from -0.1 to 0.1. The correlation is found to be less than 0.5 in all cases. This finding is in line with Sadorsky (2012), who also argues that although clean energy and oil markets are positively correlated, it is still possible that investors holding assets in these sectors would receive portfolio diversification benefits.

Table 5: ARCH-LM test

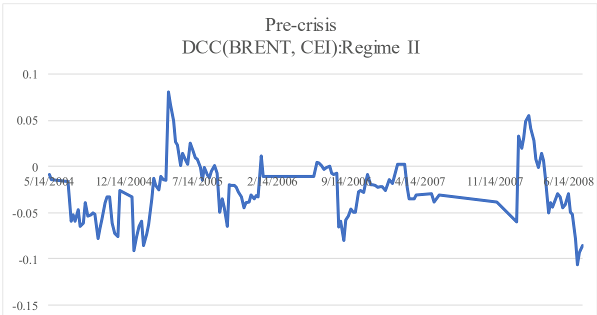
	Regime I		Regime II	
χ^2 Stat (p-value)	*Res ($\Delta lnBRENT$)*	*Res ($\Delta lnCEI$)*	*Res ($\Delta lnBRENT$)*	*Res($\Delta lnCEI$)*
Panel A. Pre-crisis				
Lag 5	NA		**	*
Lag 10			**	**
Lag 15			**	**
Lag20			***	**
Panel B. Post-crisis-pre-COVID				
Lag 5	NA		***	***
Lag 10			***	***
Lag 15			***	***
Lag 20			***	***
Panel C. Pre&at&post-crisis-pre-COVID				
Lag 5	***	**	***	***
Lag 10	**	**	***	***
Lag 15	*	**	***	***
Lag 20	**	**	***	***

Notes: The table presents the statistical significance of the ARCH effect at 5% level. NA indicates the ARCH effect is not statistically significant. Regime I and II represent normal and extreme regimes, respectively.

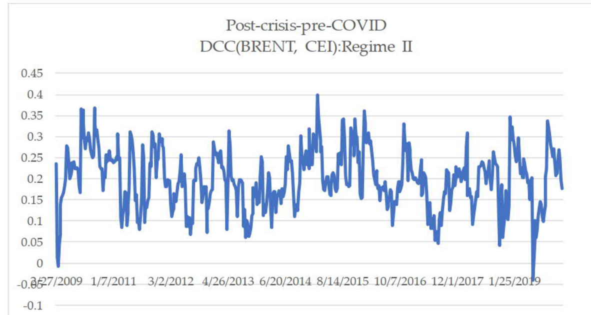
[9] Estimation results are available on request.

Figure 2. Development of dynamic conditional correlation in variance between $\Delta lnBRENT$ and $\Delta lnCEI$

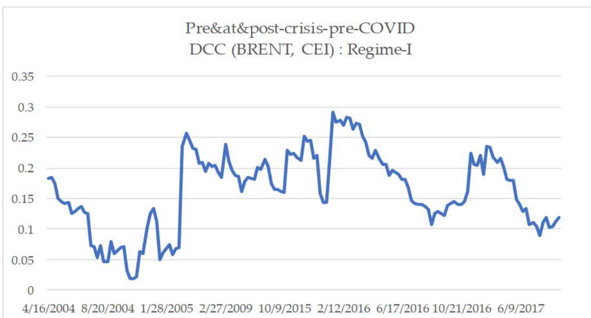
Panel A: DCC Pre-crisis -Regime II



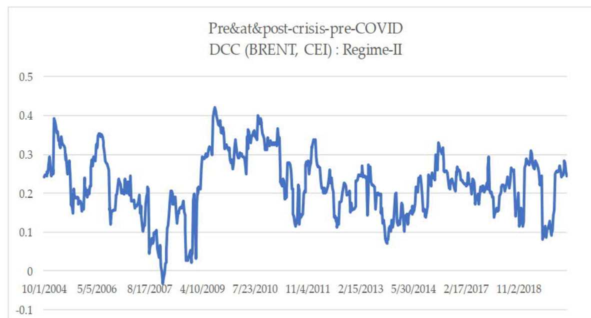
Panel B: DCC Post-crisis-pre-COVID-Regime II



Panel C: DCC Pre&at&post-crisis-pre-COVID – Regime I



Panel D: DCC Pre&at&post-crisis-pre-COVID – Regime II



We now discuss the results of optimal portfolio weights and hedge ratios. Table 6 provides the statistics of time-varying optimal weights (ω_t^{so}) and hedge ratios (β_t^{so}) for the sample subperiods based on the dependence structure estimated in TVECM-DCC-GARCH. The optimal weights indicate the proportion of investment that should be distributed among the two underlying assets. Looking at Table 6, which exhibits the hedging effectiveness of BRENT and CEI index, we find that the risk-minimizing hedge ratios, β_t, take similar values across the regimes and subsamples, although the corresponding value for the pre-crisis subsample in regime II appears to be negative.[10] The hedging has become more expensive ($0.18) in the post-crisis days compared

[10] In addition, we have also evaluated the hedging effectiveness of WTI and its futures with CEI. The results are not reported to maintain brevity. Results are available on request.

to the pre-crisis era where it was \$0.02 in absolute terms, the negative sign in $\beta_t$indicates a reverse position. Taking the Post-crisis-pre-COVID subsample in regime II as an example, we observe that a \$1 long position in crude oil can be hedged by an 18 cents short position in CEI. The portfolio optimum weights, on the other hand, are considerably different across the regimes. For instance, the weights for regime I and regime II amount to 0.39 and 0.61 for Pre&at&post-crisis-pre-COVID subsamples. These estimates suggest that in regime I, 39 cents should be invested in clean energy assets, while the corresponding amount in regime II is 61 cents. Hence, hedging can be considered effective in the markets considered in this empirical work.

The estimates of hedging effectiveness (HE) across the regimes indicate that maintaining the BRENT-CEI portfolio results in a noticeable reduction of portfolio risk. For example, the uncertainty reduction with the incorporation of BRENT in the portfolio with CEI varies from 28% to 53% over two different regimes during the Pre&at&post-crisis-pre-COVID period. In the Post-crisis-pre-COVID period, the maximum hedging effectiveness attains 78% and has exceeded the 60% cut-off in 12 percent cases. In the pre-crisis days, the average HE statistics is more consistent due to the less volatile association between these assets. Overall, the inclusion of crude oil, together with clean energy in a portfolio, leads to higher risk-adjusted-performance.[11]

Table 6: Portfolio weights, hedge ratios, and hedging effectiveness (HE) from TVECM-DCC-GARCH

	Regime I			Regime II		
lnBRENT Vs *lnCEI*	Pre-crisis	Post-crisis-pre-COVID	Pre&at&post-crisis-pre-COVID	Pre-crisis	Post-crisis-pre-COVID	Pre&at&post-crisis-pre-COVID
$\boldsymbol{\beta_t^{so}}$			0.20	-0.02	0.18	0.18
$\boldsymbol{\omega_{t12}^{so}}$			0.39	0.55	0.56	0.61
% of cases HE > 60%	NA		30%	0%	12%	2.7%
Average(HE)			0.53	0.47	0.35	0.28
Max(HE)			0.75	0.51	0.78	0.70

[11] To empirically examine the information richness of our integrated modelling approach, we apply Bollinger Bands trading strategy (Bollinger, 2001; Ramlall, 2016) for TVECM-DCC-GARCH and DCC-GARCH for an initial capital amount of \$1000. Results suggest a significant increase in CAGR (13.70%) when TVECM-DCC-GARCH is applied as compared to DCC-GARCH (5.20%) indicating an effective trading strategy for the market practitioners. We chose not to report the results to maintain brevity. The results are available on request.

Min (HE)	0.08	0.41	0.00	0.01

Notes: The table presents the hedging effectiveness of BRENT and CEI. NA implies not applicable as the ARCH effect is not statistically significant. Regime II presents a normal regime.

5.3 Validation and robustness checks

We corroborate the empirical findings using D&P causal test, Hill's rolling window causality and finally evaluate the robustness of hedging strategies using wavelet methods for three subperiods.

5.3.1. D&P Causality Test

The D&P causality is examined for $\Delta lnBRENT$ and $\Delta lnCEI$ for the subperiods and regimes where ARCH effect is statistically significant. The D&P causal test is carried out at four stages

i) VAR-filtered residuals

ii) TVECM- filtered residuals

iii) MEAN-DCC-GARCH filtered residuals

iv) TVECM-DCC-GARCH filtered residuals

This approach corroborates the need for mean plus variance modelling by looking into the causal relationship between $\Delta lnBRENT$ and $\Delta lnCEI$ for our data. The causality is tested sequentially on filtered residuals, first on VAR filtered residuals, second on TVECM filtered residuals, third on MEAN plus DCC-GARCH filtered residuals, and finally on TVECM-DCC-GARCH filtered residuals. In the event of rejecting the null of no causal relationship between $\Delta lnBRENT$ and $\Delta lnCEI$ residuals at any stage, we could infer that the residual has not become white noise and the model applied has not been able to capture embedded information in the underlying variables completely. Table 7 shows the results. For the subperiod, 'Pre&at&post-crisis-pre-COVID,' no causal relationship between $\Delta lnBRENT$ and $\Delta lnCEI$ is rejected for the first three cases in both regimes. The causality from $\Delta lnCEI$ to $\Delta lnBRENT$ shows a strong rejection as opposed to $\Delta lnBRENT$ to $\Delta lnCEI$. But we fail to reject the null of no causality at the 5% level for the residuals of TVECM-DCC-GARCH. A similar finding is observed for the other subperiods as well. The outcomes support the statistical prudence of using a TVECM-DCC-GARCH. The results further support the finding that CEI plays a major role in driving the BRENT because the null of no causality is rejected from *ΔlnCEI* to *ΔlnBRENT* and not the opposite direction in the post-crisis period.

Table 7: D&P causality

	Regime I				Regime II			
Subperiods	*VAR-Filtered Residual Series*	*TVECM-Filtered Residual Series*	*MEAN-DCC-GARCH-Filtered Residual Series*	*TVECM-DCC-GARCH-Filtered Residual Series*	*VAR-Filtered Residual Series*	*TVECM-Filtered Residual Series*	*MEAN-DCC-GARCH-Filtered Residual Series*	*TVECM-DCC-GARCH-Filtered Residual Series*
				$\Delta lnBRENT \nRightarrow \Delta lnCEI$				
Post-crisis-pre-COVID	NS				NS			
Pre&at&Post-crisis-Pre-COVID	*	*	NS	NS	***	***	***	NS
				$\Delta lnCEI \nRightarrow \Delta lnBRENT$				
Post-crisis-pre-COVID	NS				**	*	**	NS
Pre&at&post-crisis-pre-COVID	***	**	***	NS	****	***	***	*

Notes: This table presents the results of D&P causality between *ΔlnBRENT* and *ΔlnCEI* for the subperiods where ARCH effect is present. Δ represents the first-difference. *, **, and *** show 10%, 5%, and 1% significance level. NS implies no statistical significance. Embedding dimension is m=2.

5.3.2. Hill's rolling causality test

We examine Hill's rolling window causality between crude oil and clean energy stock prices for three subperiods to understand how the dynamics of crude oil and clean energy prices change in the absence of regime. Table 8 shows the empirical results. In the pre-crisis period, the null of no causality from *ΔlnBRENT* to *ΔlnCEI* is rejected for more than 80% of the cases whereas the instance of rejecting the null from *ΔlnCEI* to *ΔlnBRENT* is zero. In the post crisis days, the causal link from *ΔlnCEI* to *ΔlnBRENT* has been rejected in a greater number of cases. The results again validate the prominence of CEI over BRENT in the post-crisis period.

Table 8: Hill's rolling window causality

	Pre-crisis		Post-crisis-pre-COVID		Pre&at&post-crisis-pre-COVID	
Causal Directions	*FW=180*	*FW=180*	*FW=180*	*FW=180*	*FW=180*	*FW> 180*
$\Delta lnBRENT \not\Rightarrow \Delta lnCEI$	85% (3)	15% (4)	57% (6)	57% (6)	85% (3)	81% (3)
$\Delta lnCEI \not\Rightarrow \Delta lnBRENT$	0%	44% (4)	56% (5)	56% (5)	0%	0%

Notes: The table presents the percentage of rejection of the null hypothesis of causality from *ΔlnBRENT* to *ΔlnCEI* and vice versa. Figures in parenthesis represent lag order of the VAR model based on the Akaike criterion in Hill (2007) model. .Δ is the first differenced operator and FW= Fixed window.

5.3.3. Wavelet-based portfolio weights and hedge ratios

In order to capture hedging dynamics from the perspective of investor trading behavior, we examine the hedge effectiveness short- to the long-run process by utilizing a multiscale decomposition process. This approach captures the heterogeneous behaviour and market trading mechanics among the investigated assets. The application of this process has some comparative advantages in comparison with the standard approach of hedging effectiveness. First, it captures the spectral process or second-order moments, which is very important for financial assets, (2) it captures market participants, who may have diverse (short-term vs. long-term) trading objectives, where short-run market fluctuations (i.e., several days or weeks), and long-run oscillations (i.e., months or quarters). Table 9 provides the summary statistics of the wavelet-based measure of portfolio weights and hedge for the three subsamples. For the pre-crisis period, the optimal portfolio weights (ω_t^{so}) does not significantly vary over the short-run horizon (S1-S2).[12] However, we observe a significant divergence in portfolio weights (ω_t^{so}) over the medium-run horizon (S3-S4) with an increased inclination towards the investment in the clean energy market. This is in accordance with the increased investment in renewables and clean technology. The portfolio

[12] These scales represent the decomposition scales of Maximal Overlap Discrete Wavelet Transform (MODWT). S1 corresponds to variations in series over two to four days, S2 shows variations over 4 to 8 days, S3 exhibits variations between 8 to 16 days, and so forth, S7 represents variations between 128 and 256 days.

weights over the medium- to the long-run horizon (scale 5 and 6) are more inclined towards investment in crude oil. One plausible explanation for such behavior is the fact that clean energy and clean technology have not been fully matured, with increased room for improvement over the medium-run. Over the long-run horizon, we observe a higher investment in optimum portfolio weight in the clean energy market. The values of hedge ratios indicate that hedging the $1 long position in crude oil may become expensive from medium- to the long-run horizon. In terms of HE, we observe an increase in the effectiveness of a hedging strategy, which has increased over the long-run horizon.

Table 9. Robustness check

	ω_t^{so}	β_t^{so}	Hedging Effectiveness	Standard deviation		Skewness		Kurtosis	
				Hedged	Unhedged	Hedged	Unhedged	Hedged	Unhedged
Panel A: Pre-crisis period									
Original	0.518	0.100	0.463	0.027	0.040	-0.427	-0.470	3.019	3.329
S1	0.580	0.037	0.560	0.017	0.027	-0.287	-0.118	3.677	3.199
S2	0.518	0.075	0.465	0.013	0.018	-0.065	-0.290	2.761	3.292
S3	0.335	0.015	0.419	0.010	0.013	0.263	0.039	2.394	2.303
S4	0.317	0.621	0.260	0.007	0.010	-0.200	-0.255	2.211	2.688
S5	0.604	0.249	0.444	0.004	0.006	-0.112	0.303	2.090	2.345
S6	0.791	0.188	0.705	0.002	0.006	-0.850	-0.073	3.272	1.622
S7	0.474	0.409	0.566	0.000	0.003	-1.294	-0.462	4.959	1.933
Panel B: Post-crisis-pre-COVID									
Original	0.551	0.215	0.446	0.027	0.038	-0.507	-0.481	4.975	4.153
S1	0.654	0.072	0.596	0.016	0.027	0.065	-0.141	4.012	4.055
S2	0.499	0.332	0.357	0.016	0.020	-0.194	-0.074	4.158	3.708
S3	0.547	0.385	0.437	0.010	0.016	-0.288	-0.017	4.924	3.650
S4	0.415	0.489	0.376	0.006	0.010	-0.092	-0.086	2.993	4.307
S5	0.293	0.950	0.194	0.004	0.006	0.133	0.000	3.487	3.914
S6	0.361	0.626	0.349	0.002	0.004	-0.059	0.186	3.473	3.528
S7	0.508	0.594	0.442	0.001	0.005	-0.284	-0.405	2.294	2.580
Panel C: Pre&at&post-crisis-pre-COVID									
Original	0.553	0.187	0.456	0.029	0.045	-0.776	-0.594	6.382	7.106
S1	0.639	0.065	0.589	0.018	0.031	0.196	0.107	6.816	8.071
S2	0.521	0.263	0.399	0.016	0.023	-0.090	-0.098	4.708	6.071
S3	0.501	0.270	0.452	0.010	0.016	-0.116	0.042	4.295	3.521
S4	0.378	0.479	0.349	0.007	0.011	-0.288	-0.178	3.318	5.490
S5	0.293	0.838	0.236	0.005	0.008	0.103	0.075	5.591	4.242
S6	0.411	0.558	0.410	0.002	0.006	-0.546	-0.501	7.428	5.051
S7	0.525	0.478	0.413	0.001	0.005	-0.410	-0.184	2.976	2.476

Notes: This table reports the wavelet-based estimates of portfolio weights, hedge ratios, and hedging effectiveness.

The robustness check for the Post-crisis-pre-COVID subsample is reported in Panel B of Table 9. We observe significant variations in portfolio weights over pre-and post-crisis periods across different scales. The medium-term portfolio weights are more inclined towards a higher proportion of investment in the clean energy market. In terms of hedge ratios, we observe an expensive hedge over the post-crisis-pre-COVID period. However, in terms of HE, we report an increase in the effectiveness of the optimal portfolio towards the long-run horizon. The subsample of Pre&at&post-crisis-pre-COVID in Panel C of Table 9 closely follows the same trend as that of the post-crisis-pre-COVID subsample. This may be attributable to a significantly larger number of observations over this sample period comparative to the pre-crisis period. Overall, these findings are in accordance with the summary statistics of regime-based portfolio weights and hedge ratios.

6. Conclusion

We examine the price dynamics between two nonstationary series, namely clean energy index and crude oil price, by applying a two regime TVECM and then integrating DCC-GARCH to the residuals of TVECM to model the volatility spillover. The integrated model is then used to develop a dynamic regime-dependent hedging strategy supplemented by wavelet-based hedging. The empirical outcomes are validated with other variants of oil price and its futures along with a set of control variables like carbon price, policy uncertainty, and volatility index. Additionally, to validate the information value of a TVECM-DCC-GARCH model, we apply D&P causal tests sequentially on the filtered residuals of VAR, TVECM, MEAN-DCC-GARCH, and TVECM-DCC-GARCH. Our study covers the period from 2nd April 2004 to 10th July 2020, which is further subdivided into seven different subperiods that incorporate the effects of the 2008 financial crisis and the ongoing COVID pandemic period. The study advances the literature by examining the long-and short-term dynamics of these assets in their levels where the information of the first moment of these assets is preserved, which generally disappears or becomes a random walk process in the return series.

Our research establishes that the two nonstationary series, crude oil price, and clean energy stock price, share a two-regime nonlinear cointegrating relationship with a threshold effect. Our findings indicate a weak cointegration link before the financial crisis of 2008, which becomes stronger over the post-crisis subsample. The threshold cointegration link, however, breaks when the data period encompasses the COVID pandemic period. Similar evidence is also uncovered when the threshold cointegration is examined for financial crisis days. The broken link between clean energy and crude oil price in a disruptive external environment indicates that the two nonstationary assets have wandered substantially from the common link. This phenomenon was temporary for the 2008 financial crisis days as the nexus between these assets has reemerged as a cointegrated link in the post-crisis periods. The first half of the COVID pandemic period may have impacted the relationship in a similar fashion. The causal dynamics from the TVECM indicates the dominance of crude oil over the clean energy stock price in the pre-crisis period. The dynamics reverse over the post-crisis period, where the clean energy stock emerges as a strong driver of crude oil price in a normal regime.

The study further establishes that policy uncertainty and the S&P volatility index share a threshold cointegration with BRENT crude oil and clean energy stock price for the entire sample. In the post-financial crisis days, policy uncertainty exhibits a threshold cointegration link with BRENT, WTI, and clean energy stock price. This suggests the importance of policy uncertainty in the linkage between clean energy and crude oil price over S&P volatility. The presence of policy uncertainty corroborates the findings that the clean energy stock price is the key driver for the crude oil price. The volatility spillover analysis indicates that the link between crude oil and clean energy is more dynamic in the post-crisis days. The dynamic conditional correlation of volatilities has stayed at a low level suggesting an effective hedging possibility between clean energy and crude oil price. The hedging effectiveness statistics have further confirmed that hedging can be considered useful in oil and clean energy stock markets.

The outcomes of the study have significant implications for the investors and policymakers. Traditionally, the crude oil price has been the main driver of the energy market representing the state of the world economy, primarily due to the main energy supply source and one of the largest traded commodities in the world. However, unlike the majority of earlier studies, this paper strongly advocates that clean energy stocks have become the new leading indicator of the energy market. This indicates that market participants would rely more on the clean energy stocks' movements to allocate and diversify portfolios in most cases, and oil may not be the appropriate safe haven for the clean energy index. Our outcomes are in accordance with the focus of global investors who have now shifted towards non-fossil fuel because the investment in fossil fuel companies is becoming risky as global action on emissions gets tougher, which may create stranded assets in the oil sector (Henriques and Sadorsky, 2018). The fossil fuel divestment movement seems to have accelerated post the COVID pandemic.

This study further benefits the investors by allowing them to adjust their portfolio basis a regime dependent mean and variance return of the stocks. One of the important practical implications of our research is that it encourages the investors' and traders' communities to develop trading strategies based on the proposed model. The policymakers, on the other hand, need to ensure that the investment in the sector remains uninterrupted and sustainable to prevent a major downfall of the global economy. Moreover, investing in green businesses has ecological and social impacts that assure a certain degree of sustainability. Therefore, it is crucial for socially responsible investors to have proper knowledge of how to hedge their portfolio risk. We believe that the results of this paper would have valuable information for those investors who intend to identify every possible trait associated with clean energy stocks. In particular, our investigation offers stylized facts about ethical investments which investors might consider when swapping dirty assets for green stocks to maintain a low-carbon portfolio. Given that eco-friendly investors not only focus on the environmental performances of a firm but also consider its financial performances, the findings of this research will be useful for such stakeholders.

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Appendix

A.1 Rolling Window Causality Test

Following Hill (2007), we utilize recursive subsampling to evaluate non-causality among the assets. Let $W_t = (X_t, Y_t)$ be a bivariate series then we may define h-step-ahead VAR as:

$$W_{t+h} = \sum_{j=1}^{\infty} \pi_j^{(h)} W_{t+1-j} + \vartheta_{t+h} \qquad \text{A1}$$

where ϑ_t represent the white noise and $\pi_j^{(h)}$ represent the coefficients characterized as:

$$\pi_j^{(h)} = \begin{bmatrix} \pi_{XX.j}^{(h)} & \pi_{XY.j}^{(h)} \\ \pi_{YX.j}^{(h)} & \pi_{YY.j}^{(h)} \end{bmatrix} \qquad \text{A2}$$

The following condition must be satisfied to demonstrate no h-step-ahead flow of linear causality from X to Y, $\Leftrightarrow \pi_{XY.j}^{(h)} = 0 \; \forall \geq 1$. If there is no 1-step-ahead causality from Y to X, then there is no h-step-ahead causality from Y to X (Theorem 2.1, Hill, 2007). Alternatively, there would be causal flow across all horizons from Y to X if there is causality at $h = 1$.

A.2. Nonparametric Causality Test:

Diks and Panchenko's (2006) (D&P) causality test is an extension of the nonparametric nonlinear causality test of Hiemstra and Jones (1994) (H&J). D&P has contributed to the literature by reducing the potential bias of over rejection non-causality null-hypothesis of two variables of the H&J test. Let X_t and Y_t represent two variables *lnBRENT* and *lnCEI.* The null hypothesis for D&P can be re-written as follows:

$$q = E\left[\left(f_{X,Y}(X,Y).\,f_Y(Y) - f_X(X).\,f_Y(Y)\right)\right] = 0 \tag{A3}$$

where $f_{X,Y}(X,Y)$ is the joint probability density function of *X* and *Y*. $f_X(X)$ and $f_Y(Y)$ are the marginal density functions of *X* and *Y,* respectively.

Under the null, the test statistic can be written as:

$$T_n(\tau_n) = \frac{n-1}{n(n-2)} \sum_i \left(\hat{f}_{X,Y}(X_i, Y_i)\hat{f}_Y(Y_i) - \hat{f}_X(X_i), \hat{f}_Y(Y_i)\right) \tag{A4}$$

For $\tau_n = Cn^{-\beta}\left(c > 0, \frac{1}{4} < \beta < \frac{1}{3}\right)$; $T_n(\tau_n)$ the test statistic follows standard normal distribution as:

$$\sqrt{n}\frac{(T_n(\tau_n) - q)}{S_n} \xrightarrow{D} N(0,1); \tag{A5}$$

S_n is the standard error of asymptotic variance of $T_n(.)$. The null hypothesis is rejected if, for a given n, the L.H.S of equation 9 is too large.

Table A1: Threshold cointegration summary

Variables and Sample Subperiods	Pre&at&post -crisis	Pre&at&post-crisis-pre-COVID	At&post-crisis	At&post-crisis-pre-COVID	Post-crisis	Post-crisis-pre-COVID	At crisis (Daily data)	Pre-crisis
lnBRENT & *lnCEI*		**		**		**		*
lnWTI & *lnCEI*		**		**		**		*
lnS&POI & *lnCEI*								*
lnWTI_F1 & *lnCEI*		**				**	**	
lnWTI_F2 &*lnCEI*								
lnWTI_F3 &*lnCEI*	**	**						
lnWTI_F6 &*lnCEI*		**						
lnWTI_F9 & *lnCEI*								
lnWTI_F12&*lnCEI*								

Notes: The table presents the results of threshold cointegration (SupLM test) for different variants of crude oil price, its futures with clean energy index. *, ** indicate the statistical significance at 10% and 5% level. The variable descriptions are provided in Table A1.

Table A2: Seo (2006, 2011) TVECM-three-regime results

	lnBRENT (Y)Vs *lnCEI* (X)						*lnWTI* (Y)Vs *lnCEI* (X)					
	Regime I		Regime II		Regime III		Regime I		Regime II		Regime III	
	ΔY_t	ΔX_t	ΔY_t	ΔX_t	ΔY_t	ΔX_t	ΔY_t	ΔX_t	ΔY_t	ΔX_t	ΔY_t	ΔX_t
					Panel A: Pre&at&post-crisis-pre-COVID							
ECT	*			*					**	***		
Constant	*	*		**					*	**		
$Y_{(t-1)}$	***				***						***	
$X_{(t-1)}$			***	***	***				**	**	***	
%Obs	20%		11%		69%		31%		5%		64%	
					Panel B: At&post-crisis-pre-COVID							
ECT	***			*			*					
Constant	***			*			*					
$Y_{(t-1)}$		***			***						***	
$X_{(t-1)}$			*	***	***		**			***	***	
%Obs	5%		6%		89%		5%		6%		89%	

Note: The table shows the three regime TVECM estimation results. Regime 1 = ECT (η_{t-1}) <=λ_1 -0.7772; regime 2 λ_1 <=ECT(η_{t-1})<=λ_2 and regime 3 > λ_2. λ_1 and λ_2. are two threshold parameters ECT= η_{t-1} = Y_{t-1} – C X_{t-1}; C is the cointegrating parameter. In the case of BRENT and CEI for Pre&at&post-crisis-pre-COVID, th e threshold values are (-0.7772 -0.2347), and the cointegrating parameter is 0.9521. The values for other cases are not produced here to maintain brevity. The lag structure has been selected based on the lowest AIC and SC criteria.

Table A3: Causal dynamics of TVECM

	Pre&at&post-crisis		Pre&at&post-crisi-pre-COVID		At&post-crisis-pre-COVID		Post-crisis-pre-COVID		At crisis (Daily data)		Pre-crisis	
Y-variables	X-Variable: *ΔlnCEI*											
	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X
	Normal Regime											
ΔlnBRENT			**	**	*	**		**				
ΔlnWTI			**	**				**				
ΔlnS&POI											**	
ΔlnWTI_F1			**	*						**		
ΔlnWTI_F3	**											
ΔlnWTI_F6												
	Extreme Regime											
ΔlnBRENT				**		**	**				**	
ΔlnWTI				**		**	**					
ΔlnS&POI												**
ΔlnWTI_F1				**			**			**		
ΔlnWTI_F3			**									
ΔlnWTI_F6			**	**								

Note:
This table presents the results of two-regime TVECM estimates. The lag structure has been selected based on the lowest AIC and SC criteria. ***, ** and * indicate rejection of null hypothesis at the 1%, 5%, and 10% significance level. Y|X implies that variable X Granger-causes variable Y and X|Y implies that variable Y Granger-causes variable X. Y variables are in the columns, and X variable is in the row. Δ indicates the first difference in variables.

Table A4: Threshold cointegration adjusted for control variables

	Pre&at&post-crisis-pre-COVID	At&post-crisis-pre-COVID	Post-crisis-pre-COVID	Pre-crisis
lnBRENT&CO2		NTC		
lnBRENT&UNCERTAINTY	**	**	**	
lnBRENT&SPXVOL	**		**	
lnWTI&CO2		NTC		
lnWTI& UNCERTAINTY	**	**	**	NTC
lnWTI&SPXVOL	**	**	**	
lnCEI&CO2		NTC		
lnCEI&UNCERTAINTY	**	**	**	
lnCEI&SPXVOL	**		NTC	

Notes: The table represents the results of threshold cointegration of BRENT, WTI, and CEI residuals with control variables. ** shows the statistical significance of threshold cointegration at the 5% level. The blank cell implies threshold cointegration is statistically insignificant. NTC: No threshold cointegration exists.

Table A5: Causal dynamics after adjusting for control variables in TVECM-RESIDUALS-VAR

	Uncertainty adjusted for						SPX Volatility adjusted for					
	Pre&at&post-crisis-pre-COVID		At&post-crisis-pre-COVID		Post-crisis-pre-COVID		Pre&at&post-crisis-pre-COVID		At&post-crisis-pre-COVID		Post-crisis-pre-COVID	
	X-Variable: *ΔlnCEI*											
Y-variables	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X	X|Y	Y|X
	Normal Regime											
ΔlnBRENT	**			**		**		*			NA	
ΔlnWTI												
	Extreme Regime											
ΔlnBRENT		**		**				**			NA	
ΔlnWTI												

Notes: The table represents the causal dynamics of BRENT and WTI residuals with CEI residuals after adjusting for uncertainty and SPX volatility. NA: Not applicable, as the threshold cointegration does not hold true. *, ** indicate the statistical significance at 10% and 5% level, respectively.

Table A6: TVECM regime selection tests

Panel A: BBC-SETAR test				
Max Wald Test	Pre&at&post-crisis-pre-COVID	At&post-crisis-pre-COVID	Post-crisis-pre-COVID	Pre-crisis
lnBRENT	17.2524*	18.0047*	16.0206	5.036
lnCEI	14.4113	17.8647*	14.2243	12.1964
lnWTI	18.0452*	18.6707**	13.7713	
lnS&OPI				11.5428
lnWTI_F1	17.7415*		13.9022	
lnWTI_F3	18.4775**			
lnWTI_F6	16.6138*			

Panel B: KapShin test				
Avg(W) Test	Pre&at&post-crisis-pre-COVID	At&post-crisis-pre-COVID	Post-crisis-pre-COVID	Pre-crisis
lnBRENT	0.0679	0.0476	0.0333	0.202
lnCEI	0.029	0.0654	0.0165	0.0566
lnWTI	0.0563	0.0355	0.0168	0.2754
lnS&OPI				0.2748
lnWTI_F1	0.0502		0.0131	
lnWTI_F3	0.0534			
lnWTI_F6	0.0456			

Note: The null hypothesis of unit root proposed by Bec, Ben Salem and Carrasco (BBC) (Bec et al., 2004) is H_0: $\rho_L = \rho_H = \rho_M$ against H_1: $\rho_L < 1$, $\rho_H < 1$, $\rho_M \leq 1$; L, H and M stand for lower, upper and middle regimes respectively. It tests for unit root against a symmetric three regime Self Exciting Threshold Autoregressive (SETAR) model. The critical values for the BBC are 16.181, 18.4, and 23.01 for 10%, 5%, and 1%, respectively. 'm' represents lag orders. KapShinTest tests for the presence of unit root against a stationary three regime SETAR alternative with random walk in the inner regime.

Critical values for KapShin test is 0.90, 0.95, and 0.99, and the Avg(W) values are 6.01, 10.94, and 42.30, respectively.