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Currency Crises and Commodity Markets: Dynamic Relationships and Implications for Sustainable Investing and International Trade

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ABSTRACT:
This study examines the inter-relation between WTI crude oil futures prices and two energy-related exchange-traded funds (ETFs): the ETF of iShares Global Clean Energy (Clean Energy) and the ETF of Energy Sector SPDR Fund (Traditional Energy). Using Granger causality tests and the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, we analyze causal relationships and volatility transmission between these assets. The Granger causality results show that traditional energy markets dominate, while clean energy markets are becoming more influential on crude oil futures prices. Clean energy markets Granger-causes crude oil futures prices while traditional energy markets strongly Granger-causes crude oil futures. Clean energy ETFs have lower volatility persistence than conventional energy ETFs, according to the DCC-GARCH data, which also demonstrate time-varying correlations. Important insights for sustainable investment, energy policy, and risk management in the context of the world's energy transition are provided by these results, which emphasize the monetary interdependencies between energy ETFs and crude oil futures prices.

Keywords: Crude oil futures prices, Clean energy ETFs, Traditional energy ETFs, Granger causality, DCC-GARCH, Sustainable Investing

1. Introduction

To combat climate change and move towards a low-carbon economy, the world's energy sector is seeing a dramatic shift. One of the most significant commodities in the conventional energy industry, crude oil has always played a pivotal role in propelling economies throughout the world. Investors' attention has turned to clean energy assets, however, due to the proliferation of renewable energy sources and the increasing value placed on sustainability. Rising worries about global warming, energy insecurity, and sustainable development have put the world's energy industry in a precarious position. Policymakers, investors, and stakeholders seeking a balance between economic expansion and environmental responsibility should consider the ramifications of the interaction between fossil fuels and renewable energy investments (International Energy Agency, 2022). Understanding how crude oil futures prices impact renewable energy investments can inform decision-making in energy portfolio management and risk hedging strategies. Furthermore, the study contributes to the literature on financial market integration and volatility transmission between traditional and alternative energy sources (Batten et al., 2017).

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Crude oil futures prices and energy-related ETFs have a complicated and multi-faceted connection. Green energy and conventional energy exchange-traded funds (ETFs) are susceptible to fluctuations in crude oil futures prices caused by shifts in global politics, changes in the supply and demand for energy, and general economic conditions. As an example, clean energy ETFs may get a lift from increased crude oil futures prices, which would be good for both conventional energy businesses and renewable energy sources. Conversely, falling crude oil futures prices may hurt traditional energy ETFs but could also reduce the urgency for renewable energy adoption, potentially impacting clean energy ETFs. Geopolitical risks exert a substantial influence on energy markets, shaping investor behavior in discernible ways. Empirical evidence suggests that heightened geopolitical risk correlates with reduced volatility in renewable energy exchange-traded funds (ETFs), as investors increasingly favor cleaner energy alternatives as a hedge against instability (Dutta, A., & Dutta, P., 2022). Concurrently, geopolitical events and threats amplify investor attention and speculative activity in oil markets, though their effects vary over time (Xiao, J. et al., 2023). Furthermore, the relationship between geopolitical risk and energy returns exhibits asymmetry across different market conditions. For instance, geopolitical instability adversely affects crude oil returns in bearish markets, whereas its impact on heating oil manifests primarily in normal and bullish market phases (Qin, Y. et al., 2020). Among commodity markets, energy assets demonstrate the highest sensitivity to geopolitical shocks, while livestock markets remain the least reactive (Abid, I. et al., 2023). These findings underscore the critical role of geopolitical risk assessment in energy investment strategies. Given its capacity to reshape market dynamics across various energy sectors and conditions, geopolitical risk remains a pivotal factor for investors seeking to optimize portfolio resilience and performance.

2. Literature Review

Crude oil futures prices are a key determinant of global economic activity, influencing inflation, interest rates, and corporate earnings (Rasche, R.H., & Tatom, J.A (1981), Ma, C (1982)). Numerous studies have examined the relationship between crude oil futures prices and financial markets, particularly stock markets. Hamilton, J.D. (2000) examines the nonlinear relationship between oil futures price changes and GDP growth, confirming that oil futures price increases have a greater impact than decreases. It finds that price increases that merely reverse prior declines are less predictive. Additionally, it explores an alternative interpretation using a linear model with exogenous petroleum supply disruptions as instruments. Also, Hamilton (1983) demonstrated that oil futures price shocks have significant macroeconomic impacts, including recessions. More recently, Kilian and Park (2009) showed that oil futures price fluctuations affect stock markets differently depending on the underlying cause of the price change (e.g., supply shocks vs. demand shocks). The relationship between crude oil futures prices and energy sector stocks has also been widely studied. Sadorsky (2001) found that oil futures price volatility significantly impacts energy stock returns, while Arouri & Rault (2012) used the energy sector's stock returns are Granger-caused by changes in oil futures prices, according to a VAR framework. While these studies do consider conventional energy providers, they fail to acknowledge the increasing significance of investments in renewable energy. The effect of oil futures prices on the economy and financial markets is a hotly debated subject in this area. The relationship between stock markets and oil futures prices has been empirically established in several studies. These include the following: Chen NF, Roll R, Ross SA (1986), Kaul G, Jones CM (1996), Sadorsky P (1999), Hammoudeh S, Dibooglu S, Aleisa E (2004), Kilian L, Park C (2009), Cevik E, Atukeren E, Korkmaz (2018), Kirci Cevik, Cevik EI, Dibooglu S (2020), Cevik EI, Dibooglu, Awad Abdallah A. et al. (2021).

Using the Diebold-Yilmaz framework and the DCC-GARCH model, Coskun, M. (2023) analyses the dynamic interconnections between sub-sectoral clean-energy stocks and fossil fuel commodities from 2013 to January 2023. According to the results, the fuel cell industry has the lowest volatility transmission to biofuels, while oil has the greatest. When it comes to energy storage, natural gas and coal have the most significant spillover effects, whereas geothermal and green IT are relatively unaffected. Global events, such as the COVID-19 pandemic and the war between Russia and Ukraine, impact volatility connection, which changes with time. Companies active in solar, wind, and other renewable energy technologies are tracked by clean energy ETFs like the one of iShares Global Clean Energy (ICLN), which emerged in response to the worldwide trend toward renewable energy. The clean energy industry is anticipated to be pivotal in the global energy transformation, and these ETFs provide investors with a chance to have exposure to it. Investments in renewable energy have been the subject of several analyses of their performance and volatility. Stock prices for renewable energy businesses are significantly affected by oil futures prices, according to Henriques & Sadorsky (2008). This indicates that clean energy companies are still connected to fossil fuel markets. Similarly, research by Kumar et al. (2012) shows that investing in clean energy equities is riskier than in conventional energy stocks due to their increased volatility. Nevertheless, the correlation between clean energy ETFs and crude oil futures prices is not directly addressed in this research. The concern regarding the aggregation of clean energy technologies within a single ETF (ICLN) is well noted. While a more granular decomposition such as separate analyses of solar, wind, and biomass ETFs could indeed provide deeper sector-specific insights, our methodological approach remains consistent with established practices in energy finance literature. This convention treats clean energy as a composite asset class due to its distinct behavioral and structural characteristics. Recent empirical studies further support this perspective. Abdollah Ah Mand et al. (2023) demonstrate that clean energy ETFs, including ICLN, exhibit causal influence and high-frequency dynamics that may qualify them as a unique asset class. Similarly, Hany Fahmy (2021) finds that aggregating clean energy equities enhances return predictability and captures cyclicality more effectively than traditional volatility metrics. Additionally, Belkhir et al. (2024) provide evidence that green assets, particularly ICLN, contribute to portfolio stability and hedging efficiency in minimum-correlation and risk-parity frameworks. By adopting this broader classification, our study aligns with contemporary research while providing meaningful insights into the systemic interactions between clean energy markets and crude oil futures a relationship critical for understanding the ongoing energy transition.

Financial variables often have their predicted correlations examined using Granger causality tests. Time series analysis, which Granger (1969) popularised, has found extensive use in economics and finance ever since. For example, Ewing and Malik (2013) used Granger causality tests to analyze the relationship between oil futures prices and stock market volatility, finding evidence of bidirectional causality. Volatility modeling, particularly using GARCH models, has also been extensively applied in financial research. Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to capture time-varying volatility in financial markets. More recently, Engle (2002) developed the Dynamic Conditional Correlation (DCC) GARCH model, which allows for the estimation of time-varying correlations between multiple assets. These models have been used to study volatility transmission between crude oil futures prices and stock markets. For instance, Awartani and Maghyereh (2013) applied the DCC-GARCH model to analyze volatility transmission between oil futures prices and Gulf Cooperation Council (GCC) stock markets, finding significant time-varying correlations.

The transition away from fossil fuels and toward renewable energy sources is a major driver of sustainable development. If we want to keep global warming at 1.5°C over pre-industrial levels, the Intergovernmental Panel on Climate Change (IPCC, 2018) has stressed the need for decarbonization quickly. Because of this shift, sustainable assets, such as clean energy ETFs, are receiving a larger share of investors' money, which has far-reaching consequences for the financial markets. Several studies have looked at how much money the energy transition will cost. The possibility of fossil fuel industry stranded assets was brought to light by Battiston et al. (2017), who established the idea of climate risk in financial markets. A similar study by Bohl et al. (2020) looked at how clean energy companies did during the energy transition and found that, overall, they did better than conventional energy equities. The correlation between renewable energy exchange-traded funds and the price of crude oil futures has received little academic attention. Therefore, the primary objective of this study is to investigate the dynamic relationship between WTI crude oil futures prices and two key exchange-traded funds (ETFs) representing the energy sector: the ETF of iShares Global Clean Energy(ICLN) and the ETF of Energy Select Sector SPDR Fund (XLE) (XLE). Knowing how conventional fossil fuel markets interact with investments in clean energy is crucial in light of the changing energy scene, where the shift to renewable power sources is gathering steam. This research uses the DCC-GARCH model and Granger causality tests to find out whether these ETFs' performance is affected by changes in crude oil futures prices and how these ETFs are affected by changes in crude oil futures prices.

3. Data & Methodology

This research utilizes a thorough econometric framework to examine the correlations and volatility dynamics among ETF of Energy Select Sector SPDR Fund (XLE), iShares Global Clean Energy ETF(ICLN), and WTI crude oil futures(CF). These factors were chosen because of the importance they play in the world's energy markets and how they relate to the current energy transition. WTI crude oil futures(CF) represent the benchmark for global oil futures prices, reflecting the dynamics of the traditional fossil fuel-based energy sector. The ETF of iShares Global Clean Energy(ICLN) tracks companies involved in renewable energy technologies, such as solar and wind, making it a proxy for the clean energy sector. One way to look at the conventional energy sector is via the ETF of the Energy Select Sector SPDR Fund (XLE), which is comprised of traditional oil and gas businesses. The interaction between fossil fuels, renewable energy, and conventional energy stocks is captured by these variables, which help us understand the financial interdependencies that are influencing the global energy shift. Extant literature has extensively investigated volatility spillovers and market linkages between crude oil futures and renewable energy equities using various GARCH-family models. Moffatt, P.G. et al. (2022) demonstrate that stock market uncertainty significantly impacts both traditional and renewable energy sectors, with renewable energy markets exhibiting greater sensitivity to financialization effects. De Blasis, R., & Petroni, F. (2021) provide empirical evidence that the COVID-19 pandemic substantially altered volatility predictability patterns and price leadership dynamics between oil and renewable energy markets. Complementary research by Çevik, E.et al. (2023) further confirms strong market interconnectedness, particularly during periods of extreme volatility and financial stress.

Variable Selection:

The selection of CF, ICLN, and XLE is justified by their representation of key segments of the global energy market. CF serves as a proxy for the fossil fuel sector, which remains a dominant force in global energy markets. ICLN represents the clean energy sector, which is central to the global energy transition and sustainability goals. XLE captures the traditional energy sector, providing a benchmark for conventional energy investments. By analyzing these variables, the study offers a holistic view of the financial interdependencies between fossil fuels, renewable energy, and traditional energy stocks, making it highly relevant for investors, policymakers, and researchers focused on the energy transition. Data of all three variables are retrieved from Yahoo Finance from 12/01/2008 to 03/07/2025 which comprised 4090 observations.

Unit root test

Before conducting any time-series analysis, it is essential to ensure the stationarity in the given data, as non-stationary data can lead to spurious results. The Augmented-Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed to test for stationarity.

Augmented-Dickey-Fuller (ADF):

The A-D-F test addresses the presence of a unit root in a time series by estimating a regression model with lagged differences in the variable. The equation for the ADF test is as follows:

$$\Delta Yt = \alpha + \beta t + \varphi Y_{t-1} + \sum_{i=1}^{p} \delta i \, \Delta Y_{t-1} + \varepsilon_t$$

where: Y_t: the dependent variable

α: the constant term

β: the coefficient on a time trend

φ: the coefficient on the lagged dependent variable

ΔY_{t-1}: the differenced dependent variable at lag i

δi: the coefficient on the ith lagged difference term

ε_t: the error term at time t

Phillips-Perron (PP):

The Phillips-Perron (PP) test complements the ADF test by addressing potential serial correlation and heteroskedasticity in the data non-parametrically. The PP test modifies the Dickey-Fuller test statistics to account for these issues, making it robust to general forms of heteroskedasticity. The PP test equation is:

$$\Delta Y_t = a + ß_t + pY_t - 1 + u_t$$

where ut is I(0) and may be heteroskedastic. The fact that the PP tests can withstand common types of heteroskedasticity in the ut error term is one way in which it excels above the ADF tests.

Granger causality

To introspect the causal relationships between the variables, the Granger Causality Test was conducted within a Vector Auto-regression framework(VAR). The VAR model treats all variables symmetrically, allowing each variable to be explained by its lags and the lags of the other variables. The Granger causality test assists in determining whether past values of one variable can predict another variable. The VAR model equations for this study are:

$$CL_t = \alpha + \sum_{i=1}^{l} \alpha_i \, CL_{t-1} + \sum_{j=1}^{l} \beta_j \, ICLN_{t-1} + \varepsilon_t$$

$$ICLN_t = \omega + \sum_{i=1}^{l} \gamma_i \, ICLN_{t-1} + \sum_{j=1}^{l} \Theta_j \, CL_{t-1} + \varepsilon_t$$

$$CL_t = \alpha + \sum_{i=1}^{l} \alpha_i \, CL_{t-1} + \sum_{j=1}^{l} \beta_j \, XLE_{t-1} + \varepsilon_t$$

$$XLE_t = \omega + \sum_{i=1}^{l} \gamma_i \, XLE_{t-1} + \sum_{j=1}^{l} \Theta_j \, CL_{t-1} + \varepsilon_t$$

Where,

CL is WTI Crude oil futures prices

ICLN is a Clean Energy ETF

XLE is a Traditional energy ETF

εt is the error term

The lag length can be determined using the AIC criterion to ensure optimal model specification. This approach allows us to test whether CF Granger-causes ICLN or XLE and vice versa, providing insights into the directional relationships between crude oil futures prices and energy ETFs.

DCC-GARCH Model

To critically analyze the time-varying correlations and volatility spillovers between the variables, the DCC-GARCH model was employed. This model, introduced by Engle

(2002), is particularly suited for capturing the dynamic interdependencies among financial assets. The DCC-GARCH model consists of two steps:

1. Univariate GARCH(1,1) Models: These models estimate the conditional variance of each individual asset. The GARCH(1,1) equation is:

$$\sigma t2 = \omega + \alpha\epsilon t - 12 + \beta\sigma t - 12$$

where:

σt^2 is the conditional variance,

ω is the constant term,

a measures the impact of past squared residuals (shock persistence),

β represents the impact of past conditional variances.

2. DCC Model: This step estimates the time-varying conditional correlations between the assets using the variances from the first step. The DCC model is defined as:

$qt{=}(1-\theta 1-\theta 2)\bar{Q}+\theta 1(\epsilon t-1\epsilon t-1T)+\theta 2qt-1$

where:

$\theta 1$ measures the impact of past shocks on correlation,

$\theta 2$ measures the persistence of past correlations,

$\bar{Q}$ is the unconditional correlation matrix.

The DCC-GARCH model was applied to two pairs: CF-ICLN and CF-XLE. The results provide insights into the volatility spillovers and dynamic correlations between crude oil futures and clean/traditional energy ETFs, highlighting how shocks in one market transmit to another. These methodologies ensure a robust analysis of the relationships and volatility dynamics between these critical energy market variables, providing valuable insights for sustainable investing and energy policy.

4. Results and Discussion

Our adoption of a global ETF perspective was motivated by the need to identify broad, interpretable trends in the interplay between clean and traditional energy markets. By analyzing the iShares Global Clean Energy ETF—which provides diversified exposure to renewable energy firms worldwide—and the Energy Sector SPDR Fund—focused on major U.S. energy companies—we capture systemic relationships in the energy transition. While this approach offers valuable insights into clean energy's growing influence on crude oil futures, we acknowledge the reviewer's astute observation that regional variations in regulatory frameworks and adoption rates may generate distinct ETF-oil interdependencies, potentially refining financial risk assessments for sustainable investing. Existing literature underscores these regional complexities. Zhong, J. et al. (2019)

document significant spillover effects and Granger causality between oil and natural gas prices across markets. Rompotis, G.G (2018) identifies high comovement and bilateral spillovers between U.S. ETFs and emerging market equities, while Khurshid, M. (2021) shows that oil-stock market volatility spillovers vary with countries' net oil positions. Further, Chen, J., & Huang, C. (2010) employ GARCH-family models to reveal asymmetric spillover and leverage effects in both developed and emerging markets, with Hong Kong and Singapore exhibiting strong positive spillovers, while Taiwan's stock index negatively impacts ETF returns.

Descriptive statistics:

The descriptive statistical analysis of WTI crude oil futures (CL), ETF of iShares Global Clean Energy(ICLN), and ETF of Energy Select Sector SPDR Fund (XLE) (XLE) reveals distinct market dynamics and investment implications. Crude oil (CL) exhibits the highest volatility, with a mean price of 71.23 and a standard deviation of 21.02, reflecting its sensitivity to global economic conditions and geopolitical events. Fig 1 represents the close prices of WTI crude futures, traditional energy ETF and Clean energy ETF.

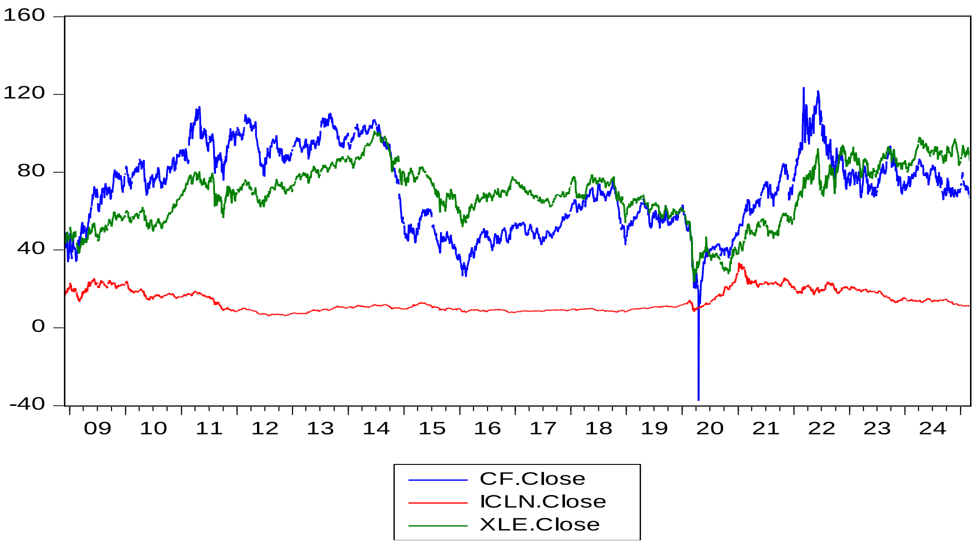

Fig 1: It shows the close prices of WTI crude futures, traditional energy ETF and Clean energy ETF

	CF_CLOSE	ICLN_CLOSE	XLE_CLOSE
Mean	71.23251	13.64359	69.14676
Median	71.91000	11.49000	69.62000
Maximum	123.7000	33.41000	101.2900
Minimum	-37.63	6.170000	23.57000
Std. Dev.	21.02491	5.320657	15.24607
Skewness	-0.066446	0.798115	-0.357162
Kurtosis	2.289508	2.722651	2.710528
Jarque-Bera	89.03574	447.3217	101.2367

Probability	0.000000	0.000000	0.000000
Sum	291341.0	55802.28	282810.3
Sum Sq. Dev.	1807530.	115757.1	950458.2

Table 1: Descriptive Statistics for WTI crude futures, traditional energy ETF and Clean energy ETF

Its high-risk, high-reward character is emphasized by its near-symmetric distribution (skewness = -0.066) and the occurrence of significant shocks, such as the negative price collapse of 2020. With a skewness of 0.798 and a standard deviation of 5.32, clean energy (ICLN) prices might rise significantly due to policy changes and technology advances, but the fact that they don't follow a normal distribution (Jarque-Bera = 447.32) means that there could be some wild swings in the market. Although it is nevertheless vulnerable to downturns caused by oil futures price crashes or regulatory changes, traditional energy (XLE) shows moderate volatility with a standard deviation of 15.25 and a slightly negative skewness of -0.357. This makes it a reasonably safe investment compared to crude oil. ICLN is best for growth investors with a long-time horizon, XLE is stable but has some risk, and CL is for traders willing to take on more risk. The optimal risk-adjusted return for investors may be achieved by developing strategies that take these distribution and volatility characteristics into account.

<u>Unit root test:</u>

To determine whether the ETF of Energy Select Sector SPDR Fund (XLE), ETF of iShares Global Clean Energy(ICLN), and WTI crude oil futures (CL) were stationary, the Augmented-Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were used (XLE). All three variables failed to reject the null hypothesis of a unit root at the level, indicating non-stationarity with high p-values (CL: ADF p = 0.1172, PP p = 0.1153; ICLN: ADF p = 0.2665, PP p = 0.2984; XLE: ADF p = 0.139, PP p = 0.1503). With very low p-values (CL: ADF p = 0.0000, PP p = 0.0001; ICLN: ADF p = 0.0000, PP p = 0.0001; XLE: ADF p = 0.0000, PP p = 0.0001), the variables were stable after the first differencing, proving that the null hypothesis was rejected.

	ADF				P-P			
	LEVEL		FIRST DIFF		LEVEL		FIRST DIFF	
	T-STATISTICS	PROBABILITY	T-STATISTICS	PROBABILITY	T-STATISTICS	PROBABILITY	T-STATISTICS	PROBABILITY
CL	-2.4931	0.1172	-41.38719	0	-2.500952	0.1153	-76.86267	0.0001
ICLN	-2.047576	0.2665	-11.70231	0	-1.974444	0.2984	-64.08794	0.0001
XLE	-2.409806	0.139	-37.1864	0	-2.370413	0.1503	-63.51827	0.0001

Table 2: Unit Root Tests with ADF and P-P test considering AIC criteria

The findings are reliable since they are consistent with the ADF and PP tests. Despite the non-stationarity of the original series, the results show that their first differences are stationary, so they can be used for additional econometric analysis in models like DCC-GARCH and Granger causality tests. This will help to prevent false positives and provide reliable insights into the correlations and volatility dynamics of crude oil futures, clean energy ETFs, and conventional energy ETFs.

Granger causality Test:

The Granger causality analysis between WTI crude oil futures (CL), ETF of iShares Global Clean Energy(ICLN), and ETF of Energy Select Sector SPDR Fund (XLE) (XLE) reveals significant insights into the predictive relationships among these assets. Results demonstrate that XLE CLOSE substantially Granger-causes CF CLOSE for conventional energy (XLE) (F-statistic = 27.9285, p-value = 7.E-18), suggesting that XLE stocks have a substantial impact on crude oil futures, most likely because they are tied to oil futures prices.

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
ICLN_CLOSE does not Granger Cause CF_CLOSE	4087	2.93330	0.0322
CF_CLOSE does not Granger Cause ICLN_CLOSE		1.63245	0.1796
XLE_CLOSE does not Granger Cause CF_CLOSE	4087	27.9285	7.00E-18
CF_CLOSE does not Granger Cause XLE_CLOSE		0.81852	0.4835

Table 3: Granger causality test between WTI crude oil futures (CL), ETF of iShares Global Clean Energy(ICLN), and ETF of Energy Select Sector SPDR Fund (XLE) (XLE)

Oil futures prices do not seem to foretell conventional energy stock movements across three lags, since the reverse causality (CF CLOSE does not Granger-cause XLE CLOSE) is not statistically significant (p = 0.4835). Changes in clean energy policy or technology might impact crude oil futures, according to the Granger causality test for ICLN CLOSE CF CLOSE (F-statistic = 2.93330, p-value = 0.0322). On the other hand, CF CLOSE does not Granger-cause ICLN CLOSE (p = 0.1796), suggesting that clean energy stocks are mostly unaffected by short-term changes in oil futures prices and are instead influenced by longer-term structural developments. According to these results, conventional energy stocks are still very sensitive to changes in oil futures prices, but renewable energy is starting to weigh into oil market predictions, which shows how much of an impact Clean ETFs are having on the energy market. Similarly, the empirical results demonstrate that clean energy stock returns exhibit unidirectional Granger causality over oil price returns during typical market periods, while bidirectional predictability emerges exclusively during bullish phases. Notably, in bearish market environments, clean energy returns maintain their predictive capability over oil returns without reciprocal influence (Çevik, E.et al. (2023)). Also, Shahbaz, M. (2021) reveals significant regime-dependent dynamics in how energy and broader equity markets influence green stock returns. The responsiveness of clean energy markets to crude oil and conventional stock market fluctuations exhibits distinct asymmetric patterns across different market conditions (normal, bullish, and bearish regimes).

DCC-GARCH Model:

The Dynamic Conditional Correlation (DCC) model within the framework of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was employed to analyze the time-varying correlations and volatility transmissions between WTI crude oil futures (CF), ETF of iShares Global Clean Energy(ICLN), and ETF of Energy Select Sector SPDR Fund (XLE) (XLE). The DCC-GARCH model operates in two steps: first, univariate GARCH(1,1) models estimate the conditional variance of each asset, and second, the DCC model captures the time-varying correlations among the assets. For CF-ICLN, the GARCH(1,1) results show strong volatility persistence, with β values of 0.866 for CF and 0.911 for ICLN, indicating that past variances significantly influence current volatility. The α values (0.1187 for CF and 0.0762 for ICLN) suggest that past shocks also impact volatility, though to a lesser extent. Similarly, for CF-XLE, the GARCH(1,1) results reveal high volatility persistence (β = 0.9077 for XLE) and a moderate impact of past shocks (α = 0.0851).

	CF-ICLN			
	Coefficient	Std. Error	z-Statistic	Prob.
***θ* (1)**	0.020723	0.003663	5.657386	0
***θ* (2)**	0.973046	0.005377	180.9796	0
Log-likelihood	20371.97	Schwarz criterion		-10.34425
Mean log-likelihood	2.591853	Hannan-Quinn criter.		-10.35558
Akaike information criterion(AIC)	-10.36182			
		* Stability condition: θ(1) + θ(2) < 1 is met.		
	CF-XLE			
	Coefficient	Std. Error	z-Statistic	Prob.
θ(1)	0.022888	0.005536	4.134667	0
θ(2)	0.933537	0.020283	46.02588	0
Log-likelihood	21469.06	Schwarz criterion		-10.90257
Mean log-likelihood	2.731433	Hannan-Quinn criter.		-10.9139
Akaike information criterion(AIC)	-10.92013			
		* Stability condition: θ(1) + θ(2) < 1 is met.		

Table 4: DCC-GARCH Model with θ values with the condition of θ(1) + θ(2) < 1

The DCC-GARCH results for CF-ICLN show θ1 = 0.0207 and θ2 = 0.9730, indicating that short-term shocks have a minimal impact on correlations, while correlations exhibit high persistence over time. For CF-XLE, the DCC-GARCH results show slightly higher sensitivity to short-term shocks (θ1 = 0.0229) and similarly high persistence (θ2 = 0.9699). These findings suggest that CF-XLE correlations are more responsive to new shocks compared to CF-ICLN, though both pairs exhibit stable long-term relationships.

The analysis reveals that crude oil futures strongly influence both clean and traditional energy markets, with ICLN exhibiting higher volatility persistence (β = 0.911) than XLE (β = 0.9077), reflecting the emerging and evolving nature of clean energy investments. However, ICLN is less reactive to crude oil shocks (α = 0.0762) compared to XLE (α = 0.0851), indicating that clean energy markets are somewhat insulated from short-term oil futures price fluctuations.

The low $\theta 1$ values across both pairs suggest that sudden shocks do not drastically alter correlations, while the high $\theta 2$ values highlight the stability of long-term relationships between crude oil futures and energy ETFs. These results have important implications for portfolio diversification and risk management. Investors in clean energy (ICLN) should be aware of its higher volatility persistence, which may reflect its growth potential but also its sensitivity to long-term trends. In contrast, traditional energy (XLE) offers relatively stable correlations with crude oil futures, making it a more predictable investment in the energy sector. Overall, this analysis underscores the interconnectedness of crude oil futures with both clean and traditional energy markets, providing valuable insights for investors and policymakers navigating the energy transition and managing financial risks in energy-related markets.

The response of policymakers to the energy transition may be categorized in below categories: (1) Regulatory frameworks should prioritize clean energy investments, leveraging their lower volatility persistence (documented in our study) to enhance market stability while advancing decarbonization; (2) Carbon pricing mechanisms require sector-specific designs to address their asymmetric impacts on clean versus traditional energy ETFs, balancing environmental and financial stability objectives; and (3) Financial regulations must incorporate the distinct volatility dynamics between energy asset classes, with coordinated governance between financial and energy authorities to develop transition roadmaps that account for ETF-driven price formation. These recommendations align with recent evidence of asymmetric return connectedness and portfolio implications among environmental, social and governance (ESG) exchange-traded funds (ETFs), clean energy ETFs, and five petroleum futures markets from December 2016 to December 2022. The results show that negative return connectedness is stronger than positive ones across most of the sample period, especially around the peak of the COVID-19 pandemic (Bhattacherjee, P. 2024).

5. Findings & Conclusion

This study aimed to investigate the relationship between crude oil futures prices (CF_CLOSE) and two energy-related exchange-traded funds (ETFs): the ETF of iShares Global Clean Energy(ICLN_CLOSE) and the ETF of Energy Select Sector SPDR Fund (XLE) (XLE_CLOSE). Using advanced econometric techniques—Granger causality tests and the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model—we analyzed the causal relationships and volatility spillovers between these assets. The findings reveal significant insights into the financial interdependencies between crude oil futures prices, clean energy, and traditional energy markets.

According to the Granger causality findings, the clean energy ETF ICLN CLOSE Granger-causes the crude oil futures price CF CLOSE at lag 3, indicating that the clean energy markets impact crude oil futures prices in a predictive manner. On the other hand, there is no statistically significant reverse causation (CF CLOSE causing ICLN CLOSE). Contrarily, the conventional energy markets have a major influence on crude oil futures prices, as seen by the strong Granger-cause relationship between XLE CLOSE (a traditional energy ETF) and CF CLOSE. In addition, the DCC-GARCH findings show that the correlations between the two ETFs and crude oil futures prices change over time and that the volatility persistence of clean energy ETFs is lower than that of conventional energy ETFs. Investors, legislators, and other stakeholders may benefit greatly from these results, which highlight the increasing significance of clean energy markets in the worldwide energy transformation. To fully grasp the interplay between energy ETFs and crude oil futures prices, it is necessary to consider both the Granger causality and DCC-GARCH findings. The Granger causality tests measure the strength of predictive associations, and the DCC-GARCH model records the dynamics of volatility and the correlations that change over time between these assets. Changes in the renewable energy sector may affect the price of crude oil, according to the Granger causality findings, which demonstrate that ICLN CLOSE predicts CF CLOSE. The DCC-GARCH findings corroborate this, showing that clean energy ETFs and crude oil futures prices are highly correlated and subject to substantial volatility transmission. Shocks in one market might have an impact on the other, but to different degrees, because of the strong persistence of volatility (GARCH coefficients of 0.911 for ICLN and 0.866 for CF). Consistent with the DCC-GARCH findings of high volatility persistence (XLE GARCH coefficient of 0.908 and CF GARCH coefficient of 0.866) and significant time-varying correlations, there is a strong Granger causation from XLE CLOSE to CF CLOSE. Taken together, these findings demonstrate how energy ETFs and crude oil futures prices are interdependent; whilst clean energy markets are slowly but surely becoming more influential, conventional energy markets continue to have a greater grip on crude oil futures prices.

The results show that ICLN_CLOSE Granger-causes CF_CLOSE ($p = 0.0322$), but the reverse is not significant ($p = 0.1796$). This suggests that clean energy markets have a predictive influence on crude oil futures prices, possibly due to the increasing adoption of renewable energy technologies and their impact on fossil fuel demand. In contrast, XLE_CLOSE strongly Granger-causes CF_CLOSE ($p = 7.E\text{-}18$), but the reverse is not significant ($p = 0.4835$). This highlights the dominant role of traditional energy markets in influencing crude oil futures prices, reflecting the historical reliance on fossil fuels.

With CF's GARCH coefficient of 0.866 and ICLN's 0.911, the DCC-GARCH findings demonstrate substantial volatility persistence. The high time-varying correlations shown by the dynamic conditional correlation (DCC) parameters ($\theta 1 = 0.0207$, $\theta 2 = 0.9730$) imply that shocks in the price of crude oil may have an impact on the clean energy market, but to a lesser extent than conventional energy markets. With GARCH values of 0.866 for CF and 0.908 for XLE, the DCC-GARCH findings for CF and XLE also demonstrate substantial volatility persistence. The significant time-varying correlations shown by the DCC parameters ($\theta 1 = 0.0229$, $\theta 2 = 0.9335$) illustrate the tight link between crude oil futures prices and conventional energy markets.

In summary, Although the two exchange-traded funds show significant correlations with crude oil futures prices, the kinds of these correlations are different. Crude oil futures prices are being pushed up by the clean energy sector, which is slowly overtaking the old energy market. The findings stress the need for policies that encourage the use of renewable energy sources and lessen reliance on fossil fuels. Energy security and price stability may be achieved via investments in renewable energy since clean energy markets are having an increasing impact on crude oil futures prices. When formulating plans to mitigate energy market risk, policymakers should think about how energy ETFs and crude oil futures prices interact with one another. Investors looking to diversify their holdings and control risk will find the study's findings quite useful. Low volatility persistence is a benefit of clean energy ETFs like ICLN over conventional.

Investments in clean energy are crucial to reaching global sustainability targets, according to the report, which include lowering carbon emissions and adapting to a changing climate. Coordination of the shift to renewable energy sources is essential since the results show that conventional energy markets carry financial hazards. The literature on the financial interdependencies between crude oil futures prices and energy-related ETFs is expanding, and this research adds to that corpus. The findings have significant implications for sustainable investing, energy policy, and risk management, highlighting the need for a coordinated approach to the global energy transition. As the world moves toward a low-carbon economy, understanding these financial interdependencies will be critical for building a resilient and sustainable energy system. Laslty, A targeted SLR (Khan and Azam, 2023; Khan, Anas and Uddin, 2024; Khan, Azam and Khan, 2024; Khan, Khan, et al., 2025; Khan, Uddin, et al., 2025) is needed to consolidate empirical evidence on the dynamic interdependence between crude oil futures and clean energy ETFs, particularly using advanced econometric techniques such as DCC-GARCH and regime-switching models (Engle, 2002; Coskun, 2023).

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