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Research article

Nexus between crude oil prices, clean energy investments, technology companies and energy democracy

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Abstract: In this study, we examine the nexus between crude oil prices, clean energy investments, technology companies, and energy democracy. Our dataset incorporates four variables which are S&P Global Clean Energy Index (SPClean), Brent crude oil futures (Brent), CBOE Volatility Index (VIX), and NASDAQ 100 Technology Sector (DXNT) daily prices between 2009 and 2021. The novelty of our study is that we included technology development and market fear as important factors and assess their impact on clean energy investments. DCC-GARCH models are utilized to analyze the spillover impact of market fear, oil prices, and technology company stock returns to clean energy investments. According to our findings when oil prices decrease, the volatility index usually responds by increasing which means that the market is afraid of oil price surges. Renewable investments also tend to decrease in that period following the oil price trend. Moreover, a positive relationship between technology stocks and renewable energy stock returns also exists.

Keywords: dynamic spillover; renewable energy companies; fossil-fuel price; energy democracy

JEL Codes: G1, G10, C32, Q4

1. Introduction

As the two major prosumers of the world, the US and China will inevitably have significant roles in the decarbonization act of the planet to reverse climate change. Since oil and gas heavyweights gave great support to Trump in his election campaign, during his presidency Trump did not apply Paris Agreement requirements and did not do much meaningfully address the climate crisis. However, Joe

Biden put clean energy in the center of his election strategy with a 2 trillion dollars plan to revive the US economy. In October 2020 when Biden's chance to win the election significantly increased the world's largest solar and wind power generators' stock market value surpassed major oil and gas companies such as ExxonMobil, the great supporter of Trump. Meanwhile, President Xi Jinping also stated that China will be carbon neutral by 2060. After the election completed President Joe Biden also declared that he wants fossil-fuel emissions from power generation to end by 2035 and the economy to be carbon neutral by 2050.

Yet on the 19th of February 2021, the US re-joined the Paris agreement by committing to more ambitious pledges to cut emissions. However, the US is in a less competitive position compared to China, the dominant producer of solar panels and batteries. The storage technology of renewable energy is the current battle area in the clean energy market. In this context, another comparative advantage of China is its minerals (rare earth) for battery production which also has a significant impact on financial markets (Ozdurak and Ulusoy, 2020).

In recent decades, renewable energy has become the primary issue of energy instruments with the increasing environmental pollution problems. Although promoting renewable energy became a priority of energy agents, the pressure of fossil energy always creates a bottleneck for the expansion of renewable investments and production percentages. However, according to BP[1] plc Energy 2020 Outlook report, the contribution of electricity markets to renewable energy return changes will also increase since the importance of electricity consumption is expected to increase significantly compared to fossil-fuel consumption for the next 30 years. Tough carbon emission targets are not adopted by the environmental experts especially after the recent[2] storm, flood, and all-time high-temperature experiences. According to the latest data from World Methodological Organisation (WMO), it is 1.1–1.3℃ warmer that it was before the steam engine invention. Even this fact itself confirms that Paris targets remain both incredibly ambitious and optimistic.

In this context, renewable energy is the key factor in this important climate change phase and energy democracy. Since renewables and nuclear power helps to improve carbon emissions by playing an important role for sectors such as passenger transport, electricity will have a greater impact on overall energy consumption. Coherently, according to International Energy Agency (IEA) and World Energy Outlook 2020 report, renewables grow rapidly and in all our scenarios and increase to 80% of the growth in global electricity demand till 2030 based on solar at the center of this new constellation of electricity generation technologies. Renewable energy investment costs significantly decreased with technological development in recent years which positioned clean energy as a strong alternative to fossil-fuel resources. Before that since the deployment of clean energy projects was not cost-effective any drop in oil prices resulted in a shift from renewable investment back to fossil fuel energy.

Consequently, the market doctrine which is firms should manage their business to maximize shareholder values, poor market incentives, and profit targets are the main reason of climate emergency. According to the energy democracy approach, replacing fossil-fuel resources with clean energy is a social restructuring act as well as a technological improvement via the deployment of renewable in a market where eight out of ten largest oil producer countries are not managed with democracy. Democratic countries try to improve environmental quality since it enables people to put pressure on the government

[1]BP studies on three different scenarios, rapid, net zero and business as usual, for changing the nature of global energy system.

[2]Storms at Belgium, Germany, the Netherlands, and Switzerland; floods and China-Henan; record temperature of 49.1℃ Turkey-Cizre.

via protest mechanisms to request environmental protection which is crucial for carbon emission limits (Barrett and Graddy, 2000; Farzin and Bond, 2006). Also, democracy increases the income level and income distribution equality which also increases the level of environmental degradation Roberts and Parks, 2007; Alhassan and Alade, 2017). The fossil fuel energy system depends on huge profits and multinational energy corporations which promotes capitalism and income inequality while renewable transformation can be a good alternative to empower local areas and redistribute this profit to prosumers. As a result, renewable energy improves the environmental quality, boosts rural development, and distributes energy generation profits from utilities to independent producers.

Finally, we focus on the recent studies which show supportive evidence to the relationship between oil prices and renewable energy stock returns. An important outcome of these studies is that with different and complicated models, researchers find similar results about the roles of oil prices to clean energy investment. Academicians and practitioners question whether oil prices are a major driver of the financial performance of clean energy companies which may not be exactly the right question. However, in our opinion, this question should be supported with various approaches. As the world recovers from the pandemic will banks and investors finance a green global recovery or is economic growth and the will of heavyweight oil suppliers are incompatible with clean energy investments? In such an environment how quickly will fossil-fuelled economies achieve net-zero? These questions are the essence of this our research. The novelty of our study is that we included technology development and market fear as important factors and assess their impact on clean energy investments. DCC-GARCH models are utilized to analyze the spillover impact of market fear, oil prices, and technology company stock returns to clean energy investments.

2. Literature

As mentioned in the introduction part, renewable investment is not only an alternative energy source, but it is a catalyst for democracy and an application area for technological developments. Many empirical studies showing that renewable energy promotes economic growth and, income equality and improves environmental conditions. One of the major motivations of our study is to highlight the impact of democratization and understand whether there is any direct or indirect role in improving financial stability in renewable investments. Torras and Boyce (1998) Barret and Graddy (2000) argue about the impact of democratization on environmental protection via better informed and better-organized citizens who have the power to make political entrepreneurs more responsive. Burke and Stephens (2018) show that renewable energy promotes democratic energy development while Szulecki and Ovareland (2018), Becker and Kunze (2014) present evidence and show how energy democracy enables energy transformation. Lv (2017) claim that democracy reduces CO_2 emissions but only if the country has reached a certain level of income level. Moreover, decarbonization is a very complex problem dealing with various socio-economic indicators such as the level of population income (Nguyen et al., 2019), the institutional quality (Nguyen et al., 2018), the shadow economy (Nguyen et al., 2019), and agricultural development (Nguyen et al., 2019). Adams and Acheampong (2019) examine the impact of democracy and renewable energy on carbon emission for 46 sub-Saharan African countries concluding that democracy and renewable energy reduce carbon emission. Alola et al. (2019) studies the equilibrium relationship between ecological footprint, real gross domestic product, trade openness, fertility rate, renewable, and non-renewable energy consumption. Usman et al. (2020) investigated the effects of democracy, globalization, and energy consumption on degradation in South Africa based on the Kuznets curve concluding that the presence of cointegration exists between selected variables. Yet again, Usman et al. (2020) investigated the role of democracy, ecological footprint, and economic growth for Brazil.

Existing studies focus on the impact of oil prices on the returns of renewable energy stocks and there are a large number of recent papers concluding that renewables and oil prices co-move in the same direction. The oil price has a strategic role as a proxy to fossil energy prices. Although all the results of the existing literature are not consistent, recent studies tend to prove that oil-renewable energy stock prices have a significant relationship. Reboredo (2015) utilized copula models to model systemic dependence between renewable energy stock prices and crude oil prices. Inchauspe et al. (2015) also showed time-varying the relationship between alternative energy company returns and oil prices. Dutta (2017) studied the relationship uncertainty in the crude oil market by including volatility index and find that its impact on clean energy returns is significant in the long run. Ferrer et al. (2018) included VIX and TVIX in their study and in this aspect their study has the most-alike understanding with our study with their approach of capturing the response of market fear to oil price changes and their impact on renewable investments. However, their focus is to offer a better solution to investors and a better portfolio diversification based on the relationship between oil prices, renewables, treasury bonds, technology stocks, etc. while our main intention is to question a more carbon-free sustainable financial market environment. In their recent paper, Corbet et al. (2021) find out the existence of volatility spillover and co-movement between oil prices and renewable firms during the Covid-19 outbreak. Contradicting with existing literature and our findings as well, incorporating the spillover index of Diebold and Yılmaz (2012) they conclude that there is positive and economically meaningful spillover from falling oil prices to renewable energy markets. These findings encourage us to think that during extreme periods such as pandemics such relationships can change and evolve in a different direction.

Moreover, various studies that focus on the relationship between technology stocks and renewable energy stock returns. Sadorsky (2012), and Bondia (2016) find stock prices of renewable energy stocks have a long-term cointegrating relationship with alternative energy and technology stock prices. Kumar et al. (2012), Omri et al. (2015), Maji (2015) mainly argue that the rise in crude oil prices also has an increasing effect on clean energy stocks which also increases the technology stocks. Ferrer et al. (2018) find that there is significant pairwise connectedness between clean energy and technology stock prices in the short run. Symitsi and Chalvatzis (2018) analyze spillover effects between Bitcoin, energy, and technology companies indicating significant return spillover from energy and technology companies to bitcoin. Eventually, most of the studies conclude that renewable energy company stock performance is strongly correlated with high technology firms.

3. Methods

Firstly, we used GARCH instruments to model the volatility behavior of oil prices. The major advantage of the model is that, instead of considering heteroskedasticity as a problem to be corrected, ARCH and GARCH models treat it as a variance to be modeled. Usually, financial data suggests that some time periods are riskier than others; that is, the expected value of the magnitude of error terms at sometimes is greater than at others. The goal of such models is to provide a volatility measure, like a standard deviation, which then can be used in financial decisions related to risk analysis, portfolio selection, and derivative pricing (Engle, 1982; Engle and Victor, 1993).

ARCH model assumes that the variance of t u_t in period t, σ_t^2 depends on the square of the error term in t−1 period, u_{t-1}

In this context, ARCH(q) and GARCH(q) models are as follows.

$\alpha_0 > 0$, $\alpha_i > 0$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}{}^2 + \alpha_2 \varepsilon_{t-2}{}^2 + \ldots + \alpha_q \varepsilon_{t-q}{}^2 + \nu_t \tag{1}$$

GARCH models which express the generalized form of ARCH models were developed by Engle (1982) and Bollerslev (1986) to provide reliable estimations and predictions. GARCH models consist of conditional variance, in Equation (2) in addition to conditional mean in Equation (1).

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i r^2{}_{t-i} + \sum_{i=!}^{p} \beta_j h_{t-j} \tag{2}$$

In this context, restrictions of variance model are as follows.

for $\alpha_i \geq 0$ and $\beta_i \geq 0$, $\alpha_i + \beta_i < 1$

If $\alpha_i + \beta_i \geq 1$ it is termed as non-stationary in variance. For non-stationarity in variance, the conditional variance forecasts will not converge on their unconditional value as the horizon increases (Brooks, 2008). In this context ARCH and GARCH models have become very popular as they enable the econometrician to estimate the variance of a series at a particular point in time. Clearly asset pricing models indicate that the risk premium will depend on the expected return and the variance of that return (Enders, 2004). The coefficient α_i refers to the ARCH process in the residuals from asset i which depicts the fluctuations of the assets reflecting the impact of external shocks on fluctuations. The ARCH effects measure short-term persistence while the GARCH effect measure long-term persistence which is represented by β_i.

3.1. DCC-GARCH Model in a Nutshell

The Dynamic Conditional Correlation (DCC- GARCH belongs to the class Models of conditional variances and correlations. It was introduced by f and Sheppard in 2001. The idea of the models in this class is that the covariance matrix, H_t, can be decomposed into conditional standard deviations, Dt, and a correlation matrix, R_t. In the DCC-GARCH model both D_t and R_t are designed to be time-varying.

Suppose we have returns, at, from n assets with expected value 0 and covariance matrix H_t. Then the Dynamic Conditional Correlation (DCC-) GARCH model is defined as:

$$r_t = \mu_t + \alpha_t$$

$$\alpha_t = H_t^{1/2} z_t \tag{3}$$

$$H_t = D_t R_t D_t$$

r_t: n × 1 vector of log returns of n assets at time t.,

α_t: $E[\alpha_t] = 0$ and $Cov[\alpha_t] = H_t$ n × 1 vector of mean-corrected returns of n assets at time t, i.e.,

μ_t: n × 1 vector of the expected value of the conditional r_t

H_t: n × n matrix of conditional variances of α_t at time t.

$H_t^{1/2}$: Any n × n matrix at time t such that H_t is the conditional variance matrix of at. $H_t^{1/2}$ may be obtained by a Cholesky factorization of H_t.
D_t: n × n, diagonal matrix of conditional standard deviations of α_t at time t
R_t: n × n conditional correlation matrix of α_t at time t
Z_t: n × 1 vector of iid errors such that $E[Z_t] = 0$ and $E[Z^T{}_t]$

In addition, Q_0, the starting value of Q_t, has to be positive definite to guarantee H_t to be positive definite. The correlation structure can be extended to the general DCC (M, N)-GARCH model:

$$R_t = \varrho_t^{*1} \varrho_t \varrho_t^{*1} \tag{4}$$

$$\varrho_t = (1 - \varrho_1 - \varrho_2)\bar{\varrho} + \varrho_1 \varepsilon_{t-1} \varepsilon_{t-1}^T + \varrho_2 \varrho_{t-1}$$

In this context ϱ_t can be estimated as mentioned below:

$$\varrho_t = \frac{1}{T} \sum_{t=1}^{T} \varepsilon_t \varepsilon_t^T \tag{5}$$

There are imposed some conditions on the parameters ϱ_1 and ϱ_2 to guarantee H_t to be positive definite. In addition to the conditions for the univariate GARCH model to ensure positive unconditional variances, the scalars a and b must satisfy:$\varrho_1 \geq 0$, $\varrho_2 \geq 0$ ve $\varrho_1 + \varrho_2 < 1$

5. Data

The data of this paper incorporates four variables which are S&P Global Clean Energy Index[3] (SPClean), Brent crude oil futures (Brent), CBOE Volatility Index[4] (VIX), and NASDAQ 100 Technology Sector (DXNT). We prepared our models for two different periods such as 2009-2021 (long period), 2016–2021.

Next, the return of each market is calculated as follows:

$$ln(P_t) - ln(P_{t-1}) \tag{6}$$

where RSPClean, RBrent, RVIX, and RDXNT refers to the return series of related variables.

In Figure 1, we can see when Brent decreases, VIX usually responds by increasing which means that the market is afraid of oil price surges. Contradicting with that gold prices and clean energy investment index responds to VIX surges in the same way and follows the volatility trend. This relationship set is the essence of our study which is when the clean energy investment trend increases and brent prices decrease volatility also increase in the financial markets.

Moreover, Table 1 exhibits the descriptive statistics for the returns for two separate periods. However, the results are pretty much the same. The mean values are close to zero for all the returns. The statistics of each return differ from each other, but in common the skewness of each return is not equal to zero and neither is the kurtosis, indicating that each return has typical characteristics of leptokurtosis and fat-tail. It

[3]The S&P Global Clean Energy Index is designed to measure the performance of companies in global clean energy-related businesses from both developed and emerging markets, with a target constituent count of 100.

[4]The Cboe Volatility Index (VIX) is a real-time index that represents the market's expectations for the relative strength of near-term price changes of the S&P 500 index (SPX). Because it is derived from the prices of SPX index options with near-term expiration dates, it generates a 30-day forward projection of volatility.

is well known that leptokurtosis and fat-tail are the typical characteristics of financial time series. The J-B statistic of each return is significant from zero, which means none of the returns obey the normal distribution. Further, the stationarity of the variables has been examined using the Augmented Dickey-Fuller (ADF) unit root test. The null hypothesis of the unit root is rejected for all return series.

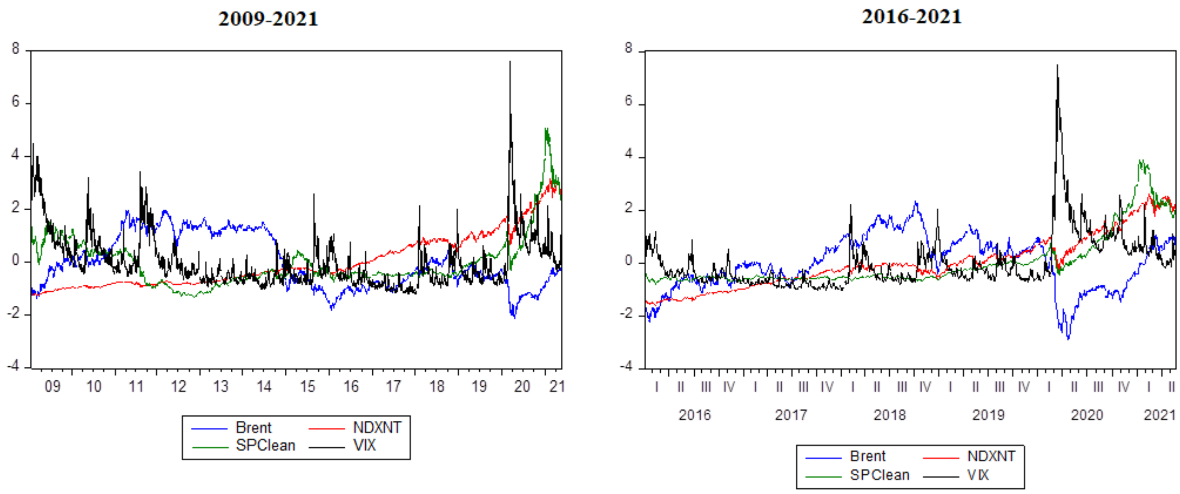

Figure 1. Normalized values of S&P Clean, Brent, VIX and and DXNT.

Table 1. Descriptive statistics.

	RBRENT	RDXNT	RSPCLEAN	RVIX		RBRENT	RDXNT	RSPCLEAN	RVIX
Describtive Statistics (2016–2021)					Describtive Statistics (2009–2021)				
Mean	0.0004	0.0009	0.0006	0.0001	Mean	0.0001	0.0008	0.0001	−0.0002
Median	0.0020	0.0015	0.0009	−0.0074	Median	0.0007	0.0014	0.0006	−0.0067
Maximum	0.1908	0.0971	0.1069	0.7682	Maximum	0.1908	0.0971	0.1165	0.7682
Minimum	−0.2798	−0.1421	−0.1207	−0.2998	Minimum	−0.2798	−0.1421	−0.1207	−0.3506
Std. Dev.	0.0272	0.0163	0.0154	0.0838	Std. Dev.	0.0235	0.0151	0.0159	0.0777
Skewness	−1.2197	−0.7265	−0.8240	1.5001	Skewness	−0.8303	−0.4393	−0.3316	1.1504
Kurtosis	23.4073	12.1440	14.0767	11.7494	Kurtosis	20.4177	9.5632	9.6481	9.6619
Jarque-Bera	23795.7	4829.1	7064.7	4819.5	Jarque-Bera	39401.9	5643.5	5745.1	6393.5
Probability	0.0000	0.0000	0.0000	0.0000	Probability	0.0000	0.0000	0.0000	0.0000
ADF Test Level	−36.2	−14.19	−36.15	−40.65	ADF Test Level	−56.4	−21.52	−35.88	−60.34
	[0.0000]	[0.0000]	[0.0000]	[0.0000]		[0.0000]	[0.0000]	[0.0000]	[0.0000]
Between parenthesis: p-values. The number of observations is 1352.					Between parenthesis: p-values. The number of observations is 3089.				

Notes: ADF Tests refer to Augemented Dickey Fuller test for the presence of unit root for long differences (returns).

Figure 2 shows the time series of the daily returns of the markets where the time-varying and volatility clustering characteristics can be observed. Recently in March 2020, oil prices plunged to multi-year as the conflict between Russia and Saudi Arabia sparked fears about a price war. First Saudi Arabia cut the price of oil it provided to Europe, the US, and Asia which triggered a downfall in oil prices. Although Saudi Arabia decided to increase its production level later, Russia responded by increasing its own production and supply as well. As a result, markets faced serious supply excess and price surge because of the sharp fall in demand due to the Covid-19 pandemic. Just the opposite of this scenario also has a high occurrence possibility resulting in a price hike and demand excess which creates a burden for most of the economies since it will trigger high inflation rates. At this point energy democracy and reducing the impact of oil wars between dominant suppliers becomes crucial.

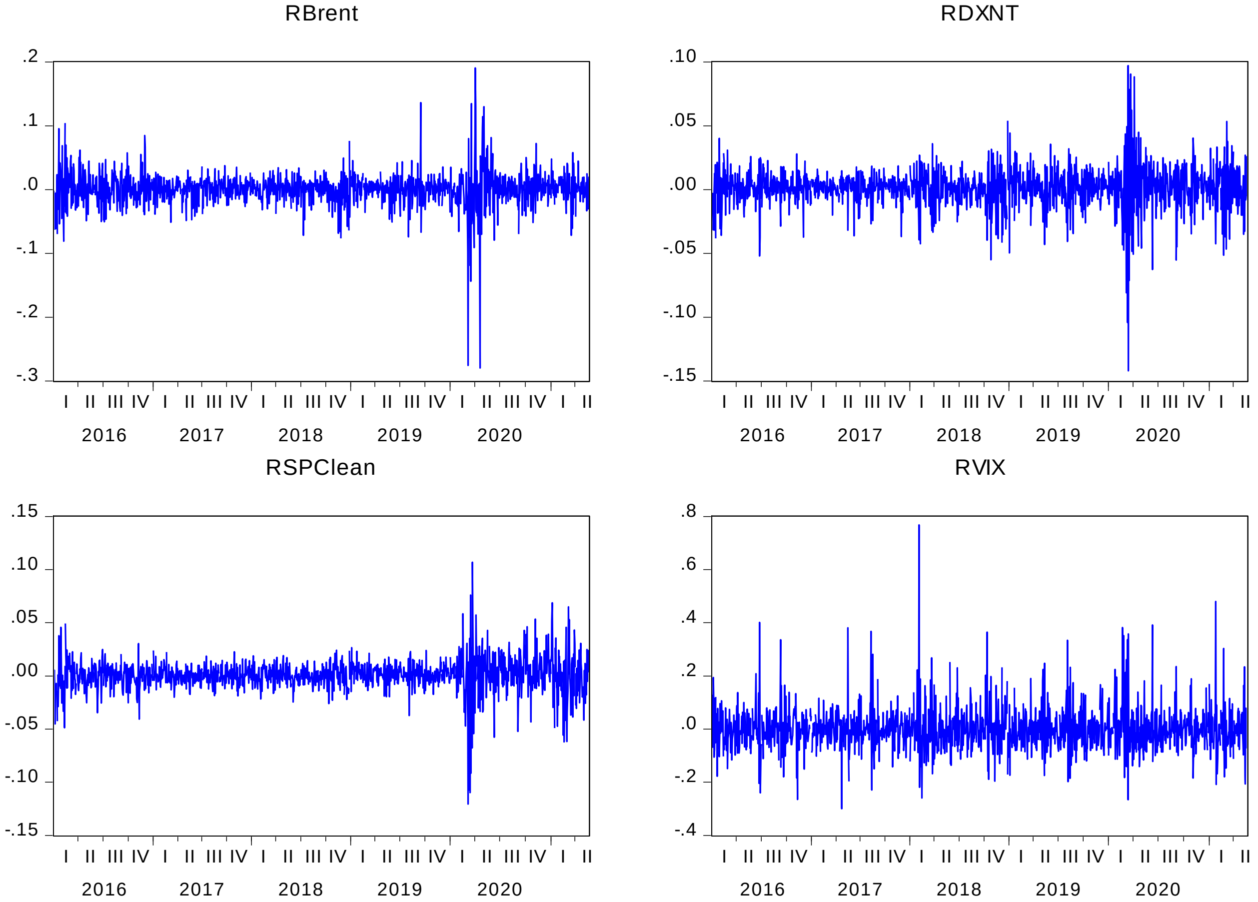

Figure 2. Daily Returns of S&P Clean, Brent, VIX and DXNT (2009–2021).

4. Empirical results

Empirical analysis with time series data supports the possibility of volatility spillover between crude oil prices, renewable energy investments, and market fear. In this context, the importance of price and volatility dynamics of oil price increase due to the climate change problems since the major dynamics of global energy depends on fossil fuels. The majority of the literature on the relationship between oil prices, renewable energy, other commodity markets, and stock markets utilize GARCH models. Since we use daily data for a relatively long time GARCH models and more specifically DCC-GARCH models. The main reasons for choosing the DCC-GARCH model is as follows; it easier to compute than many other complex MGARCH models, the number of parameters that are estimated in the correlation process are independent on the number of series that are to be estimated and conditional correlation graphs present the overall dynamic interactions in a nutshell.

Having performed unit root tests next step is to run different versions of GARCH models for S&P Global Clean Energy Index (SPClean), Brent crude oil futures (Brent), CBOE Volatility Index (VIX) and NASDAQ 100 Technology Sector (DXNT). In Table 2-Panel A, the results of GARCH models for a long period (2009-2021) indicate that coefficients of all variables are all significant at %1 significance level in both mean and variance equations. In Panel B the results of GARCH models for the Trump period (2016–2021) also indicate that coefficients of all variables are significant at a %1 significance level in both mean, and variance equations. Moreover, the sum of the coefficients of the lagged squared error and the lagged conditional variance is close to unity (0.99) for all models implying that shocks to conditional variance are highly persistent.

Table 2. GARCH Model Representations.

	Period: 2009–2021											
	Model 1: RSPClean				Model 2: RBrent				Model 3: RDXNT			
Panel A	Mean Equation		Variance Equation		Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
c	−2E−04	−1.05			2E−04	0.88			9E−04	6.59		
RBRENT	0.07	8.15							0.03	4.52		
RDXNT	0.44	24.42			0.23	−4.77						
RVIX	−0.02	−6.03			−0.02	6.68			−0.09	−48.17		
RSPCLEAN(-1)	0.14	9.83										
RBRENT(-1)					−0.04	7.88						
RSPCLEAN					0.15	−2.36			0.27	24.50		
RDXNT(-1)									−0.05	−4.27		
α_0			0.00	3.89			0.00	3.89			0.00	4.12
α_1			0.06	6.93			0.09	7.52			0.09	7.14
β_1			0.92	88.95			0.90	75.12			0.88	55.32
Observations	3088				3088				3088			
R^2	0.40				0.12				0.59			
DW	2.16				1.94				2.16			

Continued on next page

Panel B	Period: 2016−2021 Model 4: RSPClean				Model 5: RBrent				Model 6: RDXNT			
	Mean Equation		Variance Equation		Mean Equation		Variance Equation		Mean Equation		Variance Equation	
	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats	coefficient	z-stats
c	2E−04	0.68			1E−03	3.17			1E−03	4.97		
RBRENT	0.08	6.86			−0.02	−0.41			0.00	−0.02		
RDXNT	0.37	15.62			−0.04	−6.72						
RVIX	−0.01	−3.12							−0.09	−33.75		
RSPCLEAN(-1)	0.13	5.68			−0.03	−0.98						
RBRENT(-1)												
RSPCLEAN					0.24	5.74			0.33	18.64		
RDXNT(-1)									−0.07	−4.26		
α_0			0.00	2.54			0.00	3.09			0.00	2.90
α_1			0.06	4.79			0.11	4.70			0.11	4.99
β_1			0.93	61.60			0.87	35.68			0.86	31.37
Observations	1351				1351				1351			
R^2	0.41				0.10				0.60			
DW	2.12				1.89				2.25			

Note: *Since the data sets are not normally distributed, t-Distribution is applied to all four Models.

In all the models one own lagged variable of the dependent variable is included which shows that all variables have an autoregressive structure. According to Model 1, we see that VIX and SPClean have a negative relationship in terms of returns while DXNT and Brent have a positive relationship in terms of returns with SPClean. This relationship is coherent with what we observed in Figure 1 and validates that when Brent decreases, VIX usually responds by increasing which means that the market is afraid of oil price surges. Based on the literature review is also expected that technology stocks and clean energy investment move in the same direction since they are assessed in the same group by investors[5]. Model 4 also confirms the same results represented in Model 1 which means both in the long period and Trump presidency period the relationship exists in the same way. In this context, Model 3 and Model 6 states that DXNT reacts in the same way with SPClean to Brent and VIX meaning that when Brent decreases, VIX usually responds by increasing which means that the market is afraid of oil price surges and when

[5]There are various studies that focus on the relationship between technology stocks and renewable energy stock returns. For example, Sadorsky (2012) used MGARCH models and finds a stronger relationship between renewable energy company prices and technology stock prices compared to oil prices in terms of volatility.

VIX increases a decrease in DXNT returns is expected. Moreover, when SPClean increases an increase in DXNT returns is expected coherent with the literature practice. Regarding the coefficient magnitudes in Model 1, 3, 4, and 6 we can say that the impact of SPClean and DXNT returns to each other is more compared to other variables. So as a result, the market and VIX are influenced by Brent fluctuations while SPClean and DXNT react to financial market distress in the same way.

Table 3. DCC-GARCH Tables.

Model 1 and Model 2 DCC-GARCH rhos (2009–2021)					Model 1 and Model 3 DCC-GARCH rhos (2009–2021)				
	Coefficient	Z-statistics	Probability	AIC		Coefficient	Z-statistics	Probability	AIC
ϱ_1	0.0123	4.9272	0.0000	5.6628	ϱ_1	0.0174	4.4125	0.0000	5.5463
ϱ_2	0.9776	157.3142	0.0000		ϱ_2	0.9731	135.7832	0.0000	
Observations	3089				Observations	3089			
Model 4 and Model 5 DCC-GARCH rhos (2016–2021)					**Model 4 and Model 6 DCC-GARCH rhos (2016–2021)**				
	Coefficient	Z-statistics	Probability	AIC		Coefficient	Z-statistics	Probability	AIC
ϱ_1	0.0312	3.8920	0.0001	5.6458	ϱ_1	0.0268	2.9988	0.0027	5.5562
ϱ_2	0.9194	36.9228	0.0000		ϱ_2	0.9147	24.1823	0.0000	
Observations	1352				Observations	1350			

According to Francq and Zakoian (2010), there are two definitions regarding the GARCH process. The first one is called semi-strong, where there exists the coefficient of the constant, Arch and Garch (no need to be positive, but must significant). The second one is called a strong GARCH process, where the coefficient of arch and garch are nonnegative while the coefficient of the constant must be positive. In our case both ϱ_1 and ϱ_2 are positive and significant at 1%[6] level.

In Table 3 ϱ_1 and ϱ_2 dynamic conditional correlation coefficients are exhibited. A DCC model really should only be applied to a set of series which are relatively similar since the cross correlations are all governed by just two parameters. If ϱ_2 is very close to 1, then the process is closer to being a CC. The "dynamic" part comes from ϱ_1. However, in practice, a "large: value for DCC ϱ_1 is something like .1 to .2, with ϱ_2 being relatively close to 1-ϱ_2. If both ϱ_1 and ϱ_2 are small, it means that there appears to be no systematic correlation among the variables. In this context, we see that in Trump's presidency period ϱ_1 increases significantly (nearly doubles) compared to the long period suggesting that the dynamic correlation between brent-clean energy investments, and technology companies and clean energy investments increased. In Figure 3 we see the conditional variance between Brent, SPClean, and DNXT stock return models. In October 2009[7], July 2015[8] and March 2021[9] there are significant fluctuations in the conditional correlation coefficients.

[6] ϱ_2 is even statistically significant at 1% level.

[7] Oil prices began to rise in 2009 from a low point of about $40 a barrel in January to over $70 a barrel.

[8] The sudden jump in crude prices came after a decline in the number of oil rigs in the U.S., which is an indication of the well-being of the country's oil industry.

[9] Oil prices surged with third Covid wave concerns and more-than-expected build in US crude inventories.

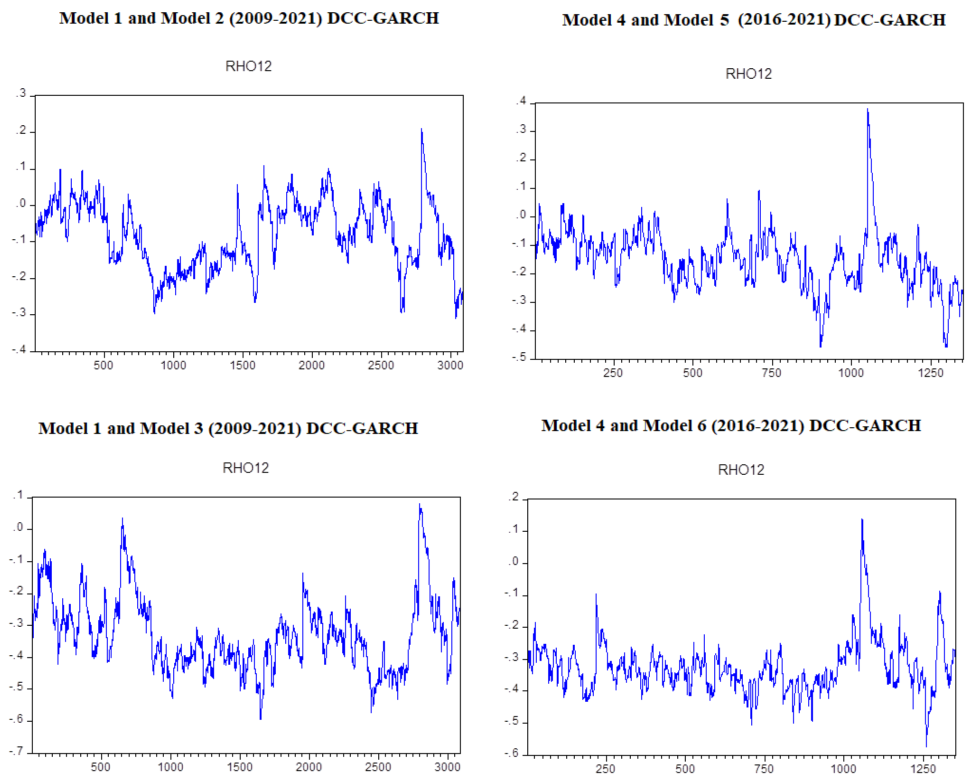

Figure 3. Conditional correlation graphs for GARCH models.

5. Conclusions

In our paper, we focus on technology development and market fear as important factors and analyze their impact on clean energy investments. DCC-GARCH models are utilized to analyze the spillover impact of market fear, oil prices, and technology company stock returns to clean energy investments. Although academicians and practitioners question whether oil prices are a major driver of the financial performance of clean energy companies which may not be exactly the right question. In our opinion, this question should be supported with various approaches. According to the energy democracy approach, replacing fossil-fuel resources with clean energy is a social restructuring act as well as a technological improvement via the deployment of renewable in a market where eight out of ten largest oil producer countries are not managed with democracy. The fossil fuel energy system depends on huge profits and multinational energy corporations which promotes capitalism and income inequality while renewable transformation can be a good alternative to empower local areas and redistribute this profit to prosumers. As a result, renewable energy improves the environmental quality, boosts rural development, and distributes energy generation profits from utilities to independent producers. According to our findings when oil prices decrease, the volatility index usually responds by increasing which means that the market is afraid of oil price surges. Renewable investments also tend to decrease in that period following the oil price trend. Moreover, a positive relationship between technology stocks and renewable energy stock returns also exists. In this context, energy democracy along with technological developments are the solely tools to flourish renewable energy deployment and reduce the energy giants' dominance in the energy markets. This act will gradually enable shifting profits from conglomerate utilities to individuals by empowering them to generate their own electricity which is not welcomed by heavy weights of politics and major oil supplier countries. However, the relationship between oil prices and renewables may be revisited during extreme periods since recent articles suggest that Covid-19 boosted renewables. Further research papers shall focus especially on this relationship in the pandemic.

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Conflicts of interest

The author declares no conflict of interest.

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