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Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar)

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ABSTRACT

There is increased interest in the dynamic relationships between the stock prices of clean energy and technology firms and oil prices in the literature. Existing works suggest a time-dependent link between them, but there is a gap of knowledge regarding the drivers of this time-dependent relationship. To contribute to this literature, we first identify dynamic conditional correlations (DCCs) between the prices of clean energy and technology stocks and oil prices to investigate the nature of these dynamic correlations. Our findings suggest the existence of significant asymmetric effects in the DCCs. Using the autoregressive distributed lag (ARDL) model, we then investigate the impact of reserve currency (US dollar) value changes on the DCCs while also controlling for business cycles, monetary conditions, and financial stress. Our results highlight the dominant role of US dollar appreciations in driving the DCCs. This role intensifies when asymmetric impacts are taken into account. The implications of this study are important for clean energy investments and for optimal risk management strategies in the energy and financial markets.

1. Introduction

Oil price risk leads to negative effects on household consumption and aggregate output due to reduced household income-levels and increased production costs (hence reduced cash flows and reduced earnings), respectively, giving rise to reduced stock returns (Edelstein and Kilian, 2009; Brown and Yucel, 1999; Jones and Kaul, 1996). This mechanism also results in inflationary pressures (Darby, 1982; Fama, 1981; Hamilton, 1996) and ultimately decreases stock prices. However, the existing studies present mixed results on the impact of oil prices on aggregate stock markets. It may be argued that the reason behind the mixed results is due to the different characteristics of firms in the stock markets in terms of oil dependence (Smyth and Narayan, 2018). Previous studies argue that the impact of oil price risk on renewable energy stock prices could differ in the presence of the effects of substitution motives on investor reactions (e.g. Henriques and Sadorsky, 2008; Kumar et al., 2012). These motives also intensify due to depletable fossil fuels, environmental concerns, and geopolitical uncertainties (hence political risks), which are frequently observed in areas where fossil fuel reserves are located (Henriques and Sadorsky, 2008). There have been large increases in renewable energy investments after 2004 (New Energy Finance, 2010; Eyraud et al., 2011). The International Energy Agency's (IEA) Medium-Term Renewable Market Report (2016) predicts even higher growth in these investments in the following years compared to recent years. Among renewable energy sources, clean energy sources are the premier contributors to a low-carbon society.

Investing in clean energy requires well-developed funding mechanisms. One way of financing clean energy investments is through the stock markets. The allocation of clean energy stocks in an optimal portfolio depends on the dynamic relationships between these stocks and some other related assets. Rising oil prices might lead to better opportunities for clean energy investments due to substitution motives (Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013). The necessity of using high technology for clean energy investments creates similar investor perceptions on the stocks of technology and clean energy firms. (Sadorsky, 2012; Kumar et al., 2012). Based on these arguments, a line of research has investigated dynamic relationships between the stock prices of clean energy and technology firms and oil prices. The strong causality links and volatility spillovers

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between clean energy stocks, oil prices, and technology stocks are revealed in the related literature (Henriques and Sadorsky, 2008; Sadorsky, 2012; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo, 2015; Inchauspe et al., 2015; Bondia et al., 2016; Ahmad et al., 2018 and Ahmad, 2017).

More specifically, some studies focus on the hedging capacity of clean energy stocks considering their dynamic conditional correlations with technology stocks and oil prices (Sadorsky, 2012; Ahmad, 2017; Ahmad et al., 2018). The existing literature documents that time-varying relationships between oil and stock markets change depending on financial shocks (Smyth and Narayan, 2018; Martín-Barragán et al., 2015; Zhang, 2017). Therefore, a better understanding of the source of the effect of common macroeconomic shocks on clean energy and technology stocks and oil markets is of utmost importance in determining the hedging potential of clean energy stocks. However, there is a gap of knowledge on macroeconomic factors influencing the dynamic conditional correlations (DCCs) between the prices of clean energy and technology stocks and oil prices. Among these factors, previous research reveals that information on reserve and invoicing currency (US dollar) value changes is highly effective in altering the dynamics of global markets including stock and oil markets (Ridler and Yandle, 1972; Haughton, 1989; Zhang et al., 2008; Akram, 2009; Goldberg and Tille, 2009; Steiner, 2014; Maggiori, 2017). Hence, this information is important to understand the hedging potential of clean energy stocks and the related assets (i.e. oil) against macroeconomic risks for investment strategies. To fill this information gap, the main purpose of this study is to examine the impact of US dollar value changes on the dynamic (DCCs) and asymmetric dynamic conditional correlations (ADCCs) between the prices of clean energy and technology stocks and oil prices controlling for business cycles, monetary conditions, and financial stress.

Learning how to hedge volatility exposure in oil and stock markets is vital for market players. The US dollar is the invoicing currency which is widely used for global crude oil trade (Zhang et al., 2008). The law of one price argues that the US dollar appreciations (depreciations) would be expected to drive up (down) global crude oil prices in dollar currency compared to lower (higher) foreign prices of oil in other local currencies. This mechanism consequently leads to reduced (increased) foreign demand for oil and a lower (higher) dollar price of oil (Ridler and Yandle, 1972; Haughton, 1989; Akram, 2009).

The role of the US dollar as the major global reserve currency increases the sensitivity of global markets to U.S. monetary policy and creates global imbalances (Goldberg and Tille, 2009; Steiner, 2014). Also, recent experiences indicate that increased risks and uncertainties across global markets lead investors to perceive the US dollar as a safe haven. In times of high volatility, worsening funding conditions in interbank markets diminish the risk-bearing capacity of financial intermediaries, especially for the US intermediaries due to their risky positions taken in good times (Brunnermeier and Pedersen, 2009; Maggiori, 2017). This capacity reduction results in increased stock market volatility due to enhanced risk-avoiding behaviors. During these periods, the US financial intermediaries are not willing to provide dollar funds to foreign intermediaries, and thereby the US dollar comes to the forefront as the best hedging instrument in global markets leading to the US dollar appreciation (Maggiori, 2017). This appreciation, in turn, results in increased investments in the strong US dollar and encourages investors to avoid risky and speculative assets in stock markets, such as clean energy and technology stocks. The above transmission channels are expected to lead to increased (reduced) clean energy and technology stock volatilities (prices).

Under good business conditions, the positive impact of increasing oil prices on stock returns may be due to a booming economy (Kollias et al., 2013). In a period of global economic expansion, a rise in aggregate demand for industrial commodities (hence an increase in oil prices) is associated with improving investment climate conditions (hence an increase in stock prices) (Kilian and Park, 2009). These conditions positively influence clean energy and technology stock prices because clean energy and technology investments are perceived as input for enhancing economic growth. Also, substituting clean energy for fossil fuels, due to increased oil prices, may increase the magnitude of this effect. On the other hand, based on this transmission mechanism, it could be argued that a reduction in oil prices associated with a US dollar appreciation, resulting from reduced aggregate demand for oil (Ridler and Yandle, 1972; Haughton, 1989; Akram, 2009), implies low economic activity, which has a negative impact on clean energy and technology stock prices, particularly during market downturn periods. This impact may be also amplified through the hedging activity since the reserve currency (US dollar) serves as the best hedging instrument in global markets in bad times (Maggiori, 2017). In light of this information, one might argue that the US dollar fluctuations are the source of the effects of common macroeconomic shocks on clean energy and technology stocks and oil markets. Based on the above-mentioned economic mechanisms and arguments, we hypothesize that an increase in the US dollar value increases the dynamic conditional correlations between the prices of clean energy and technology stocks and oil prices due to simultaneously increased volatilities (decreasing prices) of these assets. Furthermore, we expect that this increase is observed more in an economic downturn.

The theoretical assertions and empirical evidence summarized above lead to the argument that the US dollar fluctuations alter speculation and investment opportunities for investors interested in clean energy and technology stocks and oil markets. To test this argument and our hypothesis, we aim to investigate how the US dollar fluctuations affect dynamic conditional correlations (DCCs) between oil prices and the stock prices of clean energy and technology firms. We do that by controlling for financial stress, monetary conditions, and business cycle variables which have potential impacts on oil prices and stock markets dynamics. This investigation makes an important contribution to the relevant literature by showing the main drivers of the DCCs between oil prices and clean energy and technology stock prices. A detailed understanding of the drivers of the DCCs enables market players to consider the hedging performance of clean energy and technology stocks and oil investments and ultimately helps determine sound hedging strategies and optimal portfolio allocation.

Our analysis is split into two main steps. In the first step, as adopted by similar studies (e.g. Sadorsky, 2012; Ahmad et al., 2018; Ahmad, 2017), we use the dynamic conditional correlation model introduced by Engle (2002) and the asymmetric dynamic conditional correlation model developed by Cappiello et al. (2006) to derive the time-varying dynamic correlations (dynamic conditional correlations (DCCs) and asymmetric dynamic conditional correlations (ADCCs)) between the variables of interest. These models consider heteroscedasticity in asset returns and therefore enable us to avoid heteroscedasticity bias, which could lead to making wrong inferences about the presence of financial contagion between asset markets (Forbes and Rigobon, 2002). Thus, the adjustment of correlations between assets is made by accounting for time-varying volatility (Celik, 2012; Chiang et al., 2007). These considerations help to better capture dynamic herding behavior in the presence of financial contagion in response to fluctuations in macroeconomic conditions (Corsetti et al., 2005; Chiang et al., 2007; Boyer et al., 2006; Celik, 2012; Syllignakis and Kouretas, 2011).

In the second step, the autoregressive distributed lag (ARDL) model introduced by Pesaran and Shin (1998) and Pesaran et al. (2001) is utilized to examine the primary drivers of the derived DCCs and ADCCs. The second step of our analysis distinguishes our paper from the existing literature. The ARDL model helps examine the drivers of the DCCs and ADCCs irrespective of the integration order of the variables (I (1) or I (0)). Thereby, we obtain unbiased parameter estimates. Besides that, correcting for residual correlation diminishes the endogeneity problem in the model and ultimately leads us to make sound interpretations based on reliable statistical analyses.

The findings from our analysis confirm our hypothesis. The baseline results suggest that the US dollar appreciation is the dominant source of the dynamic correlations between the prices of clean energy and technology stocks and oil prices. This mechanism is stronger for the asymmetric DCCs. The increased US dollar value limits diversification opportunities across clean energy and technology stocks and oil markets by increasing the level of the DCCs and ADCCs. It appears that currency market conditions alter the asset allocation decisions of investors for hedging purposes, especially during times of economic downturns.

The rest of the article proceeds as follows. In the next section, we present studies related to the focal point of this paper. In Section 3, we identify the data and provide the results of preliminary analyses on the dynamic conditional correlations (DCCs and ADCCs) between the prices of clean energy and technology stocks and oil prices. Section 4 first mentions potential economic fundamentals which could affect the DCCs. Then, we outline the empirical framework and report test results. In Section 5, we discuss primary findings and conclude with the main remarks and further research suggestions.

2. Literature review

The dynamic interactions between the prices of clean energy and technology stocks and oil prices have been investigated by various studies employing a different set of econometric techniques. A stream of literature concentrates on the co-integration, causality, linear and non-linear relationships between the variables. Henriques and Sadorsky (2008) show the explanatory power of technology stocks and oil price changes on clean energy stock prices by conducting the Granger causality tests. In addition, this study reports a stronger shock transmission from technology stock prices to clean energy stock prices than the one from oil prices to clean energy stock prices. Kumar et al. (2012) provide supportive evidence for the study of Henriques and Sadorsky (2008). Taking into account the time-dependent dynamics, Managi and Okimoto (2013) utilize the Markov-switching VAR (vector autoregressive) approach and demonstrate a positive effect of oil prices on clean energy stock prices. Bondia et al. (2016) criticize the methodological procedure adopted by Managi and Okimoto (2013) and, alternatively, make use of threshold co-integration methods introduced by Gregory and Hansen (1996) and Hatemi-j (2008) and vector error correction model (VECM) representation. Their findings suggest that oil and technology stock prices have significant impacts on the clean energy stock prices in the short-run, but not in the long-run. Inchauspe et al. (2015) propose a state space multifactor model and show that the impact of oil prices on renewable energy stock returns has increased since 2007. They also find evidence of a stronger effect of technology stocks on clean energy stocks compared to the effect of oil prices. Reboredo (2015) employs copulas and concludes that the change in oil prices is a significant contributor to the upside and downside risk of renewable energy firms. Dutta (2017) documents the significant effect of oil price uncertainty on clean energy stock volatility. Using the nonlinear auto-regressive distributed lag (NARDL) model, Kocaarslan and Soytas (2019) indicate that the impacts of positive and negative changes in the oil prices on clean energy stock prices significantly vary across the short- and long-run.

Another stream of research focused on the hedging opportunities for global investors taking into account the dynamic correlations between the prices of clean energy and technology stocks and oil prices. Sadorsky (2012) finds that a portfolio consisting of both clean energy stocks and oil provides more hedging opportunities than the portfolio including clean energy and technology stocks. Ahmad (2017) confirms the findings of Sadorsky (2012). In another empirical investigation, Ahmad et al. (2018) document that crude oil and oil volatility index (OVX) are important assets for hedging clean energy stocks following the S&P 500 volatility index (VIX). Reboredo et al. (2017) examine the co-movements between renewable energy stocks and oil prices utilizing a wavelet approach. Their analysis suggests that the hedging opportunities for investors interested in renewable energy and oil markets differ in the short- and long-run.

There seems to be a consensus on the time-varying nature of the link between oil prices and technology and clean energy stock prices.

Table 1
Summary statistics of the returns of clean energy and technology stocks and oil futures.

	DLECO	DLPSE	DLOILF
Mean	−0.0003	0.0004	0.0002
Median	0.0010	0.0010	0.0008
Maximum	0.1452	0.1010	0.1641
Minimum	−0.1447	−0.0812	−0.1307
Std. Dev.	0.0203	0.0120	0.0236
Skewness	−0.3630	−0.2192	0.1086
Kurtosis	8.1454	8.6686	7.1906
Jarque-Bera	3958.0470	4738.3860	2581.1160
Probability	0.0000	0.0000	0.0000

Note: Table 1 reports summary statistics of the returns of clean energy and technology stocks and oil futures. D and L refer to the first difference and log operators, respectively. DLECO, DLPSE, and DLOILF represent the daily returns of the clean energy and technology stocks and oil futures, respectively.

However, previous studies have not investigated economic fundamentals which may drive the time-varying correlations between the prices of clean energy and technology stocks and oil prices. The purpose of this paper is to contribute to filling this gap by examining the role of reserve and invoicing currency (US dollar) in driving the DCCs between these assets. For robust analysis, we do that by controlling for other main macroeconomic risk factors, namely monetary conditions, business cycles, and financial stress. The results of this investigation will provide valuable information on the hedging potential of clean energy and technology stocks and oil investments in an optimal portfolio. Hence, results are of interest to market players including investors and speculators, as well as policy makers.

3. Data and preliminary analyses

3.1. Data

As they are widely used in the literature, we measure the performance of clean energy and technology stocks via the WilderHill Clean Energy Index (ECO) and the Arca Tech 100 index (PSE), respectively. The ECO index comprises of firms engaged in investments in clean energy or in contributions to developing or advancing clean energy.[1] The PSE index consists of major technology-related companies from various industries, such as computer hardware, software, electronics, aerospace and defense, telecommunications, semiconductors, and biotechnology and healthcare equipment. The ECO and PSE indexes data are collected from Bloomberg. The crude oil futures prices of the West Texas Intermediate (WTI) are commonly considered as proxies for fluctuations in global oil prices. Therefore, we use the futures prices for empirical tests.[2] The WTI futures prices refer to the closing prices of the nearest contract to maturity on the WTI crude oil futures contract and the data on the futures prices is sourced from Energy Information Administration (EIA). Our concentration is on the period following 2004, as in recent studies on clean energy (Ahmad, 2017; Lundgren et al., 2018). The selected time period includes the global financial crisis (2008–2009) period. We also note that clean energy investments seem to have increased significantly since 2004. (New Energy Finance, 2010; Eyraud et al., 2011). We use daily data ranging from 5/1/2004 to 1/18/2018.

We employ the first differences of logarithmic prices of the related stock indexes and oil futures as the returns on the stocks and oil futures. Table 1 presents summary statistics of stock and oil returns data. All stock and oil returns exhibit excess kurtosis (fat tail). The standard deviation of technology stocks returns is slightly lower, indicating lower risk than clean energy stocks and oil futures returns. Fig. 1 illustrates the evolution of clean energy stocks, technology stocks, and oil futures

[1] For a detailed exposition of the ECO index, see https://wildershares.com/about.php.

[2] For robustness, we also employ the crude oil spot prices of the West Texas Intermediate (WTI) for analyses throughout the paper and observe very similar findings. The results are provided upon request.

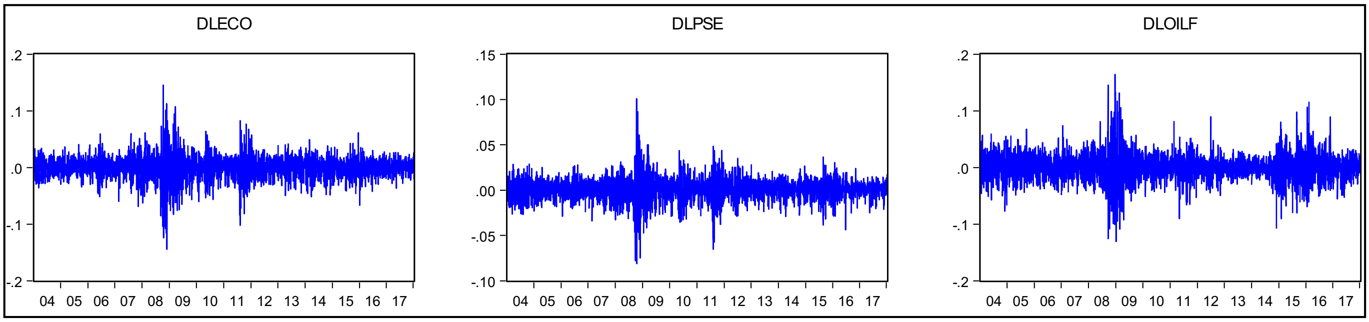

Fig. 1. Evolution of related asset returns during the sample period. Note: D and L refer to the first difference and log operators, respectively. DLECO, DLPSE, and DLOILF are the daily returns of the clean energy and technology stocks and oil futures, respectively.

returns for the sample period. The illustration clearly indicates the existence of volatility clustering and hence encourages us to utilize the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models to investigate dynamic conditional correlations between the prices of clean energy and technology stocks, and oil prices.

3.2. Dynamic conditional correlations

In this subsection, we derive the dynamic correlations utilizing the dynamic conditional correlations (DCC) (Engle, 2002) and asymmetric DCC (Cappiello et al., 2006) models.[3] Multivariate DCC-GARCH (1,1)[4] models are estimated for a better understanding of information transmission across asset markets (Martens and Poon, 2001). The asymmetric DCC model enables us to diminish the omitted variable bias and to take into consideration increased dynamic correlations in times of high financial stress. A vector autoregressive (VAR) model is estimated to consider serial correlations in asset returns and linear interactions between asset markets in the mean equations (Forbes and Rigobon, 2002). The mean equation is indicated below;

$$Y_t = \varphi_0 + \sum_{i=1}^{n} \varphi_i Y_{t-i} + \varepsilon_t \tag{1}$$

Y_t refers to a 3-variable vector, which includes the returns of clean energy and technology stocks and oil futures returns and ε_t are residuals. Previous literature provides strong evidence of causality and volatility spillovers between the prices of clean energy and technology stocks and oil prices (Henriques and Sadorsky, 2008; Sadorsky, 2012; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo, 2015; Inchauspe et al., 2015; Bondia et al., 2016; Ahmad et al., 2018 and Ahmad, 2017). Therefore, we first consider linear effects between these variables in the mean equations using a VAR model. We choose the VAR (1) specification using the Schwarz Information Criterion (SIC). The exponential generalized autoregressive conditional heteroskedasticity (EGARCH (1,1)) model introduced by Nelson (1991) is used for the variance equation since this model accounts for the leverage effects and does not require positivity constraints on parameters due to the logarithmic transformation of conditional variance.[5] The variance equation in the EGARCH (1,1) model is as follows:

Table 2
Mean equation results.

Independent variables	Dependent variables		
	DLECO	DLPSE	DLOILF
Constant	0.000246	0.000697***	0.000229
DLECO(-1)	0.057481**	−0.010266	0.012045
DLPSE(-1)	0.008949	−0.023345	0.004868
DLOILF(-1)	0.011799	−0.004595	−0.041179**

Note: Table 2 provides the estimated coefficients in the mean equations for the returns series. DLECO, DLPSE, and DLOILF are the daily returns of the clean energy and technology stocks and oil futures, respectively. Dependent variables refer to the DLECO, DLPSE, and DLOILF. Explanatory variables are the lagged returns.
** Significant at the 5% level.
*** Significant at the 1% level.

$$\ln(h_t) = \beta_0 + X\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + +\gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_h \ \ln(h_{t-1}) \tag{2}$$

γ represents the asymmetry parameter while β_h and X are the GARCH and ARCH parameters, respectively.

Table 2 reports the mean equation results. The clean energy stocks and oil futures returns are influenced by their own lags but the lagged returns do not have an impact on the technology stock returns. The variance equation findings are presented in Table 3. The significant statistical parameters support the presence of conditional heteroscedasticity for each of the variables. We observe smaller short-run ARCH parameters than GARCH parameters implying long-run volatility. The estimated asymmetry parameters (γ_s) indicate significant leverage effects for all assets.[6]

Cappiello et al. (2006) point out a limitation of the DCC-GARCH method introduced by Engle (2002) in understanding the nature of global market returns over time. Despite the fact that the effect of previous shocks on the following market dynamics is taken into account by the DCC-GARCH model, this model does not consider the differentiated impact of positive and negative shocks. The evolution of dynamic correlations in the DCC-GARCH model is represented as follows;

$$Q_t = (1-a-b).\overline{\gamma} + a\left(\epsilon_{t-1}\acute{\epsilon}_{t-1}\right) + b(Q_{t-1}) \tag{3}$$

$$\gamma_t = {Q^*}_t^{-1}.Q_t.{Q^*}_t^{-1} \tag{4}$$

where $\overline{\gamma} = E[\epsilon_t \epsilon_t']$ and a and b symbolize scalars then $a + b < 1$. ${Q^*}_t = [{q^*}_{iit}] = [\sqrt{q_{iit}}]$ means a diagonal matrix with the square root of ith diagonal component of Q_t on its ith diagonal position. If Q_t is positive definite, ${Q^*}_t$ represents a matrix which guarantees that $\gamma_t = Q_t^{*-1}.Q_t$.

[3] The estimations are made using Student's t-distribution based on Schwarz Information Criterion (SIC), Akaike Information Criterion (AIC) and log-likelihood values. It may be due to fact that the asset returns show fat tails.

[4] GARCH (1,1) is used due to numerical difficulties in the estimation procedure of the multivariate model parameters (Silvennoinen and Terasvirta, 2008).

[5] We also use the GJR-GARCH (1,1) model developed by Glosten et al. (1993) and traditional GARCH (1,1) model (Bollerslev, 1986). GJR-GARCH (1,1) model suffers from non-negativity constraints on parameters. We observe that the EGARCH (1,1) model is the best fitted model based on log-likelihood values, Akaike information criterion and Schwarz information criterion. The findings are available upon request.

[6] We do not find any significant problem conducting some diagnostic tests. The findings are provided upon request.

Q_t^{*-1} indicating a correlation matrix with ones on the diagonal and every other element ≤1 in absolute value. Asymmetric impacts are not taken into consideration in this model. Cappiello et al. (2006) extended the DCC-GARCH model incorporating the asymmetric effects into the DCC estimation procedure. The extended Eq. (3) is represented as follows;

$$Q_t = (\overline{\gamma} - A'\overline{\gamma}A - B'\overline{\gamma}B - G'\overline{N}G) + A'(\epsilon_{t-1}\epsilon_{t-1}')A + G'(n_{t-1}n_{t-1}')G + B'(Q_{t-1})B \quad (5)$$

where G, A, and B indicate $k*k$ (diagonal) parameter matrices, $n_t = (I[\epsilon_t{<}0]o\epsilon_t)$ ($I[.]$ is k*1 function meaning an indicator which takes value 0 if the argument is not true or 1 otherwise as "o" is a Hadamard product) and $\overline{N} = E[n_t n_t']$. Eq. (5) represents an asymmetric DCC model. In this paper, the standard scalar DCC and asymmetric scalar DCC models are estimated to derive the DCCs and ADCCs between assets. A, and B are diagonal matrices with the same value on each diagonal element in the standard scalar DCC model ($A = [a_{ij}] = [\sqrt{a}]$, $B = [b_{ij}] = [\sqrt{b}]$, $G = [0]$). The asymmetric one takes into account asymmetric interactions($A = [a_{ij}] = [\sqrt{a}]$, $B = [b_{ij}] = [\sqrt{b}]$, $G = [g_{ij}] = [\sqrt{g}]$). G, A, and B each contains a single unique element.

The asymmetric DCC model including an asymmetric term is indicated below;

$$Q_t = \left(\overline{\gamma} - a^2\overline{\gamma} - b^2\overline{\gamma} - g^2\overline{N}\right) + a^2\epsilon_{t-1}\epsilon_{t-1}' + g^2\eta_{t-1}\eta_{t-1}' + b^2Q_{t-1} \quad (6)$$

A sufficient and necessary requirement is fulfilled if $a^2 + b^2 + \delta g^2 < 1$, where δ refers to the maximum eigenvalue $[\overline{\gamma}^{-1/2}\overline{N}\,\overline{\gamma}^{-1/2}]$.

The estimates of the DCC models are presented in Table 4. The effects of previous standardized shocks and lagged dynamics on current dynamics are measured by the a_i^2 and b_i^2 parameters, respectively. The g_i^2 parameter, which is used to consider market downturn periods, refers to the asymmetric term. We find statistically significant parameters. The sum of a_i^2 and b_i^2 parameters is smaller than one, which shows that the stability condition of our model is satisfied. Based on these findings, the estimation results are satisfactory for sound interpretations of the DCCs and ADCCs. The higher log-likelihood value implies that the asymmetric DCC model is a better fit model. The findings point out the positive impact of negative market momentum on the conditional correlations between the assets leading to the increased DCCs in bad times.

The graphs of the DCCs and ADCCs between asset classes are illustrated in Figs. 2 and 3. All the DCCs and asymmetric DCCs display similar trends. Also, the patterns of dynamic correlations of clean energy and technology stocks with oil futures are very similar. Table 5 provides the summary statistics for the obtained DCCs and ADCCs. The dynamic correlations between clean energy and technology stocks appear to be stronger than the correlations between clean energy stocks and oil futures. This finding is consistent with the studies of Sadorsky (2012) and Ahmad (2017). The standard deviation statistics suggest that the conditional correlations of clean energy and technology stocks with oil futures have higher volatility than the correlations between clean energy and technology stocks.

Table 4
Estimates of DCC and ADCC models.

Model	a_i^2	b_i^2	g_i^2	Log-likelihood
ADCC-EGARCH(1,1)	0.024074	0.960641	0.003413	31,130.32
P value	0.000	0.000	0.000	
DCC-EGARCH(1,1)	0.029381	0.958303		31,121.28
P value	0.000	0.000		

Note: Table 4 reports the estimated coefficients of the DCC and ADCC models. a_i^2 shows the impact of previous standardized shocks on the current dynamics, b_i^2 shows the impact of lagged dynamics on the current dynamics, and g_i^2 refers to the asymmetric term showing the presence of asymmetric effects.

4. Determinants of dynamic conditional correlations

4.1. Economic fundamentals and global crisis

Business cycle fluctuations are strongly associated with oil and stock prices dynamics (Fama and French, 1989; Mork, 1994). As in the study of Fama and French (1989), we consider the default spread (DEF hereafter) and the term spread (TERM hereafter) as business cycle variables since they reflect the changes in long- and short-term business conditions, respectively. During bad times, the term and default spreads are expected to be higher compared to in good times. The relevant literature suggests the significant impact of interest rates on stock market valuations and oil prices (Chen et al., 1986; Hotelling, 1931; Working, 1949; Sadorsky, 1999; Akram, 2009). To take into account interest rate impacts, we use the federal funds rate (FF hereafter) as the influential interest rate, which considerably affects monetary conditions (Hamilton and Jorda, 2002; Spindt and Hoffmeister, 1988). Funding liquidity conditions in interbank markets have negative impacts on global market liquidity conditions through the changes in speculative investments (Brunnermeier and Pedersen, 2009). Therefore, we also employ the TED spread (TED hereafter) (the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill), which is widely used in the finance literature, to consider financial stress in interbank markets. As explained in the introduction part, our focus is on the impact of reserve currency (US dollar) value changes on the DCCs and ADCCs. Trade-weighted U.S. dollar index is used to explain the US dollar (USD) impacts on the dynamic correlations as this index is a weighted average of the exchange value of the US dollar relative to the currencies of the main US trading partners. In sum, based on the discussion above, we employ the DEF, TERM, FF, and TED as the control variables to better capture the effect of the US dollar value changes on the DCCs and ADCCs.

We also take into consideration the significance of pre-crisis and post-crisis differences by employing a dummy variable for the Global Financial Crisis (2008) (GFC) in the model. This

Table 3
Variance equation results.

Asset returns	Model chosen	β_0	χ	Υ	β_h
DLECO	EGARCH(1,1)	−0.279711***	0.160132***	−0.047566***	0.981089***
DLPSE	EGARCH(1,1)	−0.266165***	0.106586***	−0.123473***	0.980372***
DLOILF	EGARCH(1,1)	−0.114007***	0.089486***	−0.054830***	0.994441***

Note: Table 3 presents the estimated coefficients in the variance equations for the EGARCH (1,1) model. *** Significant at the 1% level. DLECO, DLPSE, and DLOILF are the daily returns of the clean energy and technology stocks and oil futures, respectively. χ, β_h, and Υ, refer to ARCH, GARCH, and leverage parameters, respectively.

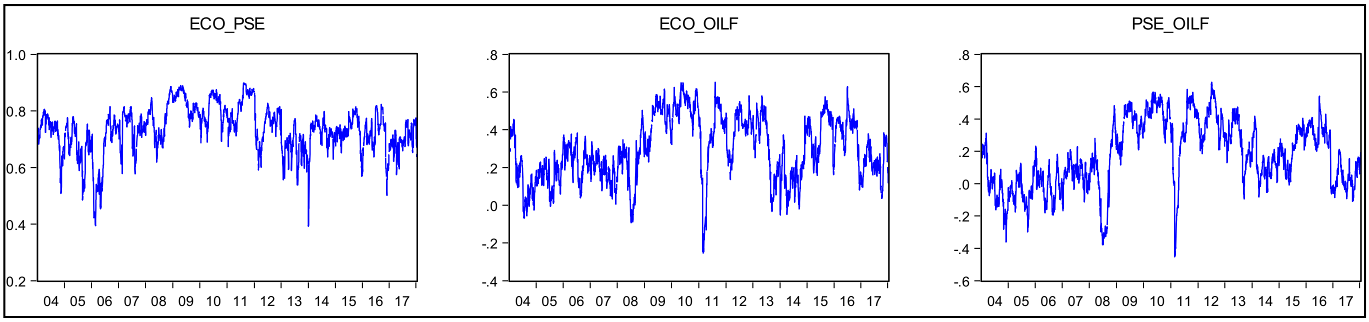

Fig. 2. Dynamic conditional correlation series (DCCs) graphs. Note: This figure illustrates the dynamic conditional correlation series obtained from the DCC model. ECO_PSE is the correlation series between clean energy and technology stocks. ECO_OILF is the correlation series between clean energy stocks and oil futures. PSE_OILF is the correlation series between technology stocks and oil futures.

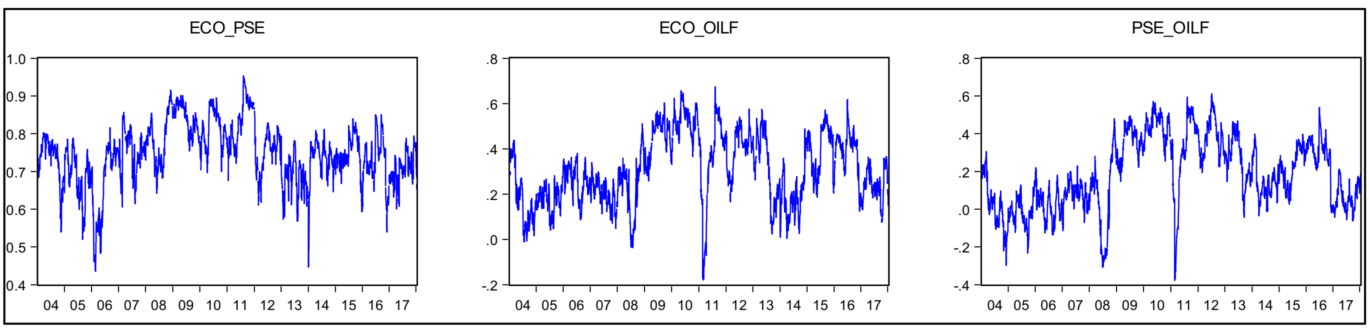

Fig. 3. Asymmetric dynamic conditional correlation series (DCCs) graphs. Note: This figure illustrates the asymmetric dynamic conditional correlation series obtained from the ADCC model. ECO_PSE is the correlation series between clean energy and technology stocks. ECO_OILF is the correlation series between clean energy stocks and oil futures. PSE_OILF is the correlation series between technology stocks and oil futures.

corresponds to the collapse of Lehman Brothers in September 2008.[7] We consider the beginning of September 2008 to be a structural breakpoint in our sample period.[8] The value of the dummy variable is one if it is in the post-crisis period (after September 2008) and zero otherwise.[9]

Daily data on the federal funds rate, 3-month Treasury bill, and 10-year Treasury bond yields are collected from the H.15 database of the Federal Reserve Board as daily data on the BAA-rated and AAA-rated corporate bond yields are obtained from the Federal Reserve Bank of St. Louis. The term spread represents the difference between the yields on the 10-year Treasury bond and the 3-month Treasury bill while the default spread refers to the difference between the yields on the BAA-rated and AAA-rated corporate bonds. The trade-weighted U.S. dollar index and TED spread data are sourced from the Federal Reserve Bank of St. Louis. The higher values of the trade-weighted U.S. dollar index and TED spread show stronger reserve currency (U.S. dollar) in global markets and worsening funding liquidity conditions in interbank markets, respectively.

4.2. Methodology

To investigate the long-run predictors of the DCCs and ADCCs, the autoregressive distributed lag (ARDL) approach introduced by Pesaran and Shin (1998) and Pesaran et al. (2001) is utilized. In employing this approach, consistent and unbiased long-run coefficient estimates are obtained in the presence of cointegrating relationships regardless of the integration order of variables (I(1) or I(0)). By using the ordinary least square method (OLS) and choosing appropriate lag orders for the regressors, Pesaran and Shin (1999) conclude that the use of the ARDL model reduces the endogeneity problem and the residual correlations. Based on these advantages, the ARDL approach helps provide more robust results on the long-run predictors of the DCCs. The first step of the ARDL procedure is an estimation of the following error-correction model.

$$\Delta DEP_t = \phi_0 + \alpha_0 DEP_{t-1} + \sum_{j=1}^{k} \alpha_j INDEP_{j,t-1} + \sum_{i=1}^{p} \theta_{0i} \Delta DEP_{t-i} + \sum_{i=0}^{q} \sum_{j=1}^{k} \theta_{ji} \Delta INDEP_{j,t-i} + \varepsilon_t \quad (7)$$

The k represents the number of independent variables[10] and the p and q refer to the lagged levels of variables. We select the lag orders of p and q using the Akaike Information Criterion (AIC). The α_s and θ_s represent the long- and short-run parameters, respectively. Where DEP_t is the DCCs/ADCCs between the stock prices of clean energy and

[7] The standard Chow (1960) test for structural break and some unit root tests allowing for a structural break point (Zivot and Andrews (1992) and the ADF structural break (Kim and Perron, 2009) tests) provide a supportive evidence for this structural break point. The results are provided upon request.

[8] We also include the interaction terms of the USD with the dummy variable in the model. Our main results are not changed. The results are provided upon request.

[9] Some studies use different dummy specifications (e.g. dummy is coded as one for the September 2008–August 2009 period, as one for the August 2007–August 2009 period and as one for the September 2008–March 2010 period) to control for the effect of the GFC (e.g. Chor and Manova, 2012; Büyükşahin and Robe, 2014). For robustness, we also use these specifications and do not find significant dummy variables. Robustness analyses do not change our main findings. The results are available from authors.

[10] We determine the maximum number of lags for the independent and dependent variables to be 12.

Table 5
Summary statistics for DCCs and ADCCs.

	Panel A. The DCCs series statistics			Panel B. The asymmetric DCCs series statistics		
	ECO-PSE	ECO-OILF	PSE-OILF	ECO-PSE	ECO-OILF	PSE-OILF
Mean	0.733569	0.294656	0.17372	0.746388	0.307513	0.186862
Median	0.739125	0.281792	0.165538	0.749231	0.294576	0.173993
Maximum	0.898504	0.651723	0.627175	0.953653	0.673653	0.611521
Minimum	0.392641	−0.252721	−0.453226	0.434755	−0.178381	−0.377018
Std. Dev.	0.082062	0.168634	0.210994	0.080377	0.153906	0.191608
Skewness	−0.70955	−0.138007	−0.142968	−0.462897	−0.068728	−0.094987
Kurtosis	4.239282	2.366045	2.326685	3.84974	2.332052	2.325438
Jarque-Bera	520.1712	70.05912	78.41631	231.4119	68.14902	71.97016
Probability	0	0	0	0	0	0

Note: Table 5 presents the summary statistics of dynamic (DCCs) and asymmetric dynamic conditional correlations (ADCCs) obtained from DCC-EGARCH (1,1) and ADCC-EGARCH (1,1) models in Panel A and B, respectively. ECO-PSE, ECO-OILF, and PSE-OILF refer to pairwise correlations between two related assets. ECO-PSE is the correlation series between clean energy and technology stocks. ECO-OILF is the correlation series between clean energy stocks and oil futures. PSE-OILF is the correlation series between technology stocks and oil futures.

technology firms and oil prices and $INDEP_t$ is a vector of the determinants of the DCCs and ADCCs. The Δ represents the first difference of the variables. By following the Bounds-testing procedure proposed by Pesaran et al. (2001), we conduct a joint significance test (H_0: $\alpha_0 = \alpha_1 = \ldots\ldots = \alpha_k = 0$) using an F-statistic. To examine long-run cointegration relationships, we use the two asymptotic critical values for upper and lower bounds assuming that the independent variables are either I(1) or I(0), respectively. If the F-statistic is less than the lower bound the null hypothesis of no cointegration cannot be rejected. But, if the F-statistic is greater than the upper bound no cointegration null can be rejected. The F-statistics being between the lower and upper bounds is interpreted as an inconclusive finding.

Table 6
Unit root test results.

Panel A. The test results for the levels.

		PP Statistics		PP Statistics
DCCs series				
ECO-PSE	Intercept	−5.715756***	Intercept and trend	−5.714269***
ECO-OILF		−4.795988***		−4.932526***
PSE-OILF		−3.970451***		−4.206626***
ADCCs series				
ECO-PSE	Intercept	−5.638671***	Intercept and trend	−5.637051***
ECO-OILF		−4.636510***		−4.762864***
PSE-OILF		−3.871858***		−4.110647***
Macroeconomic factors				
△USD	Intercept	−57.64595***	Intercept and trend	−57.65068***
DEF		−2.177179		−2.220479
TERM		−1.976265		−2.02864
FF		−1.059023		−1.471202
TED		−3.774603***		−3.941939**

Panel B. The test results for the first differences.

		PP Statistics		PP Statistics
DCCs series				
ECO-PSE	Intercept	−59.69718***	Intercept and trend	−59.68894***
ECO-OILF		−59.63068***		−59.62226***
PSE-OILF		−60.06417***		−60.05522***
ADCCs series				
ECO-PSE	Intercept	−59.63041***	Intercept and trend	−59.62229***
ECO-OILF		−59.70181***		−59.69350***
PSE-OILF		−59.88222***		−59.87329***
Macroeconomic factors				
△USD	Intercept	−568.8274***	Intercept and trend	−568.7191***
DEF		−66.54410***		−66.51907***
TERM		−55.01120***		−54.99430***
FF		−65.81564***		−65.76947***
TED		−48.70144***		−48.69380***

Note: Table 6 reports the results of Phillips-Perron tests used in this study, for the levels and first differences in Panel A and B, respectively. DCCs and ADCCs series are the dynamic and asymmetric dynamic conditional correlation series between two related assets, respectively. ECO-PSE is the correlation series between clean energy and technology stocks. ECO-OILF is the correlation series between clean energy stocks and oil futures. PSE-OILF is the correlation series between technology stocks and oil futures. DEF and TERM represent the default spread and term spread, respectively. FF refers to the federal funds rate. TED represents the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. △USD is the percentage change of the trade-weighted U.S. dollar index.
*** Significant at the 1% level.
** Significant at the 5% level.

For the second step, based on the proposed optimal lag lengths, the estimates of long-run coefficients are made. These estimates allow us to assess the long-run effect of macroeconomic determinants on the DCCs and ADCCs based on cointegration relationships. We estimate the following model to determine the long-run predictors of the dynamic correlations.

$$DEP_t = \lambda C_t + \sum_{i=1}^{p} \tau_i DEP_{t-i} + \sum_{i=0}^{q} \beta_i INDEP_{t-i} + \varepsilon_t \tag{8}$$

where DEP is a t * 1 vector of the DCCs and ADCCs (dependent variable), $INDEP$ is a t * k vector of macroeconomic factors (independent variables), and C represents a t * n vector of deterministic variables such as dummy variables and an intercept. In vector notation, Eq. (8) can be written as follows;

$$\tau(L)DEP_t = \lambda C_t + \beta(L)INDEP_t + \varepsilon_t \tag{9}$$

where $\tau(L)$ represents the polynomial lag operator $1 - \tau_1 L - \tau_2 L^2 - \ldots - \tau_p L^p$; $\beta(L)$ refers to the polynomial lag operator $\beta_1 + \beta_1 L + \beta_2 L^2 + \ldots + \beta_q L^q$; L represents the usual lag operator ($L^r x_t = x_{t-r}$). To derive long-run coefficients, the ARDL model is first estimated by OLS and the estimated version of Eq. (8) is solved for the cointegrating relationships $DEP_t = \delta C_t + \psi INDEP_t + v_t$ via:

$$\hat{\psi} = \frac{\hat{\beta}_0 + \hat{\beta}_1 + \ldots + \hat{\beta}_q}{1 - \hat{\tau}_1 - \hat{\tau}_2 - \ldots - \hat{\tau}_p} \tag{10}$$

$$\hat{\delta} = \frac{\hat{\lambda}}{1 - \hat{\tau}_1 - \hat{\tau}_2 - \ldots - \hat{\tau}_p} \tag{11}$$

$\hat{\psi}$ and $\hat{\delta}$ show the long-run effect of independent and deterministic exogenous variables (e.g. intercept and dummy variables) on the dependent variable, respectively.

4.3. Unit root test results

To obtain a consistent measurement interval across our variables, we first consider matching dates of macroeconomic factors with the

DCCs and ADCCs for the ARDL analyses. Then, before examining the long-run predictors of the dynamic correlations, the order of integration of variables is tested using Phillips and Perron (1988) (PP) test.[11] Unit root test results are reported in Table 6. The results propose that some of the variables are integrated of order one (I(1)) while the rest of them are integrated of order zero (I(0)). According to the mixed test results, we can use the ARDL model, which requires that variables should be either I(1) or I(0), to provide unbiased estimates. In the next subsection, the empirical results provided by the ARDL model are presented.

4.4. Empirical findings

In this section, we first test the long-run cointegration relationships between the DCCs/ADCCs and macroeconomic factors using the ARDL model. As we mentioned before, the optimal lag length in the ARDL model is determined employing the Akaike information criterion (AIC).[12] We conduct several stability and diagnostic tests to check the robustness of our analyses.[13] The test results do not suggest any significant problem regarding standard assumptions except for heteroscedasticity. To avoid inefficient estimations stemming from heteroscedasticity, Newey and West (1987) standard errors with lags based on the AIC are used for the estimated coefficients in the ARDL model.

The F-statistics testing the cointegration relationships are presented in Table 7. In this table, Panel A (Panel B) reports the estimated F-statistics for the cointegration relationships between the DCCc (the ADCCs) and macroeconomic factors. The statistics are larger than the upper critical value at 1% significance level, which indicates significant cointegration relationships between the variables of interest. The cointegration relationships between the ADCCs and macroeconomic factors appear to be stronger than the relationships for the DCCs. This finding emphasizes the potential importance of significant asymmetric effects on the equilibrium relationship between the dynamic correlations and economic fundamentals. To this respect, it could be argued that the pattern of the dynamic correlations is influenced more by macroeconomic conditions during times of recessions than during tranquil periods. The overall assessment implies that the consideration of asymmetric impacts on the dynamic correlations may help us to better understand the real nature of relationships between the dynamic correlations and macroeconomic risks.

The long-run predictors of the DCCs and ADCCs are reported for the dynamic correlations between clean energy and technology stocks (ECO-PSE), between clean energy stocks and oil futures (ECO-OILF), and between technology stocks and oil futures (PSE-OILF) in Tables 8, 9, and 10, respectively. Panel A and B for each table present the long-run predictors of the relevant DCCs and ADCCs, respectively. Our findings suggest that compared to an increase in other macroeconomic risks (DEF, TERM, FF, and TED), reserve currency (US dollar) appreciations more strongly (and significantly) increase the level of the dynamic correlations. Compared to the DCCs, this increase is more pronounced for the ADCCs. Also, we observe a greater impact of US dollar appreciations on the PSE-OILF and the ECO-OILF than the impact on the ECO-PSE.[14]

We find a significant effect of the GFC (Global Financial Crisis (2008)) dummy variable on the dynamic correlations. As for the impact of business cycle variables and federal funds rate on the DCCs and ADCCs, an increase in the DEF and TERM significantly intensifies the level of the ECO-PSE for both the DCCs and ADCCs. This result points out that worsening business conditions represented by increased default and term spreads lead to increased clean energy and technology stocks volatilities and, hence increased dynamic correlations between each other. Similarly, it appears that an increase in the DEF leading to increased clean energy stocks and oil futures volatilities increases the level of ECO-OILF due to deteriorated long-term business conditions. In addition, an increase in the FF increases the level of the ECO-PSE for the ADCCs. This may be due to fact that an increased federal funds rate is an indicator of contractionary monetary policy, which slows down economic activities and therefore is a bad signal for stock market players during high volatility periods.

For robustness, we use a dummy specification to assess the impact of the political color of the presidency on the DCCs and ADCCs. The political dummy is coded as one for the November, 6 2008–November, 6 2016 period (under Democratic administration) and zero otherwise (under Republican administration). We also include the returns of the natural gas, corn and coal futures (the percentage change of the prices of the natural gas, corn and coal futures) as explanatory variables in the model since they are close substitutes of renewables.[15] These robustness checks do not change our main findings. Our results are robust to the effects of the political color of the presidency and the returns of the natural gas, corn and coal futures on the DCCs and ADCCs. Specifically, we observe the positive impact of the political color of the presidency on the DCCs and ADCCs while the impacts of the returns of the natural gas, corn, and coal futures are not significant. This impact could be due to increased lobbying activities of special interest groups on climate change under Democratic administration. The impact of an information event might result in simultaneously changing expectations in different markets, such as stock and oil markets, which causes strong volatility linkages between different asset classes (Fleming et al., 1998). In this respect, it could be argued that the increased lobbying activities on climate change lead to substantial changes in the speculative demands of traders and hence result in rebalancing their portfolio composition over time. This economic mechanism explains common movements in the volatility of different assets (e.g. clean energy and technology stocks and oil futures).

In sum, as expected in our hypotheses, our findings demonstrate that a worsening business and financial environment reduces the hedging potential of clean energy and technology stocks and oil futures by intensifying the level of dynamic correlations between them. In the following section, we discuss the implications of our results regarding the primary role of US dollar appreciations in driving the dynamic correlations in detail and then conclude with highlights of our baseline results and future study suggestions.

[11] For robustness, Zivot and Andrews (1992) and the modified augmented Dickey-Fuller (MADF) (Kim and Perron, 2009) unit root tests are also applied to account for a structural break point. We find very similar results. For brevity, we do not report test results. The results are provided upon request.

[12] We also use the Schwarz information Criterion (SIC) to choose the optimum lag length and find very similar results about cointegration relationships and the long-run determinants of the DCCs and ADCCs. The results are provided upon request.

[13] The CUSUM (cumulative sum) and Ramsey RESET tests are applied to check the stability of our models. To test for heteroskedasticity and serial correlation, we employ the Breusch-Pagan-Godfrey heteroskedasticity and Breusch-Godfrey serial correlation LM tests. The findings are available from authors.

[14] For robust analysis, we employ the nonlinear ARDL (NARDL) approach developed by Shin et al. (2014) to control for asymmetric interactions between the US dollar value and the dynamic and asymmetric dynamic correlations (DCCs and ADCCs) between the prices of clean energy and technology stocks and oil prices. Our results indicate that the impacts of the negative and positive changes in the US-dollar value on the DCCs and ADCCs are very similar in terms of the magnitude and significance of the coefficients. Also, similar to the results in the paper, an increase in the US dollar value is the primary driver of the DCCs and the impact of this driving force is more pronounced for the asymmetric DCCs. Overall, we find that the nonlinear ARDL (NARDL) estimates are consistent with the linear ARDL estimates in this study. These findings suggest that our results are robust to the asymmetric effects of the negative and positive changes in the US-dollar value on the DCCs and ADCCs. The results are provided upon request.

[15] We thank an anonymous referee for these constructive suggestions. Results are available from the authors upon request.

Table 7
Bounds-testing procedure results.

Panel A. Results for the DCCs		Panel B. Results for the ADCCs	
Cointegration hypotheses	F Stat.	Cointegration hypotheses	F Stat.
F(ECO-PSE$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	8.302297***	F (ECO-PSE$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	13.06441***
F(ECO-OILF$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	8.335669***	F (ECO-OILF$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	10.06025***
F(PSE-OILF$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	9.616485***	F (PSE-OILF$_t$/△USD$_t$,DEF$_t$,TERM$_t$,FF$_t$,TED$_t$)	11.23401***

Note: Table 7 presents the bounds-testing procedure results. For the ARDL models, the critical values are 2.62–3.79 and 3.41–4.68 for 5%, and 1% significance levels, respectively. DCCs and ADCCs series are the dynamic and asymmetric dynamic conditional correlation series between two related assets, respectively. ECO-PSE is the correlation series between clean energy and technology stocks. ECO-OILF is the correlation series between clean energy stocks and oil futures. PSE-OILF is the correlation series between technology stocks and oil futures. DEF and TERM represent the default spread and term spread, respectively. FF refers to the federal funds rate. TED represents the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. △USD is the percentage change of the trade-weighted U.S. dollar index.
*** Significant at the 1% level.

5. Discussion and conclusions

5.1. Discussion

Some aspects of the analyses are worth mentioning to shed more light on our findings. In this study, we investigate the impact of reserve currency (US dollar) value fluctuations on the dynamic correlations between clean energy and technology stock prices and oil prices controlling for business cycles, monetary conditions, and financial stress. To do so, we first obtain dynamic conditional correlations (the DCCs and ADCCs) employing the DCC-EGARCH (1,1) and ADCC-EGARCH (1,1) models. Our findings suggest the existence of significant asymmetric effects in the dynamic correlations between clean energy and technology stocks and oil markets. The reason behind these asymmetric effects is due to the amplified volatility in global markets during economic downturns. We find stronger dynamic correlations between technology and clean energy stocks than the correlations between oil markets and clean energy stocks, which could be stemming from similar investor perceptions on the clean energy and technology companies based on the use of high technology in clean energy investments (Sadorsky, 2012; Kumar et al., 2012). The results imply that the portfolio including clean energy stocks and oil provides more diversification opportunities than the portfolio including technology and clean energy stocks. This finding supports previous evidence from the related literature.

As for the impact of US dollar value changes on the DCCs and ADCCs, compared to other economic indicators, the changes in the US dollar value have the highest importance in driving the dynamic correlations. This impact is even stronger for the PSE-OILF and ECO-OILF compared to that for the ECO-PSE. Also, the ADCCs are more influenced by the US dollar fluctuations than the DCCs. It could be due to the fact that an appreciated US dollar pushes investors, especially speculators (e.g. financial intermediaries), to close out risky positions in global oil and stock markets in recessionary periods. For example, as explained in the introduction part, increased US dollar value reduces oil demand and ultimately leads to decreasing oil prices (increasing oil price volatilities) according to the law of one price. This reduction is more in times of crisis (e.g. GFC (2008)) and hence signals worsening economic conditions in these times. Also, during market downturn periods, investments in the US dollar increase due to hedging motives and ultimately investors tend to avoid speculative investments in risky assets, particularly in global stock markets. These tendencies intensify the volatility of clean energy and technology stocks, which is stemming from low participation of investors (and thereby low liquidity) in the stock markets. In sum, an increase in the US dollar value is the driving force behind the increases in clean energy and technology stocks volatilities since the US dollar is considered as the safest haven to hedge risky stocks. This appears to be due to speculative trader behavior leading to enhanced herding behavior, low liquidity, and high volatility in the stock markets due to low stock market participation (Brunnermeier and Pedersen, 2009).

The above transmission mechanisms result in increased volatility (decreased prices) in the global oil and stock markets and consequently increased dynamic correlations between oil prices and clean energy and technology stock prices, especially in crisis periods. The results imply that an increase in the US dollar value due to hedging purposes and herding behavior in the global oil and stock markets considerably reduces diversification opportunities for investors interested in closely related assets in energy and financial markets, such as clean energy and technology stocks and oil, particularly in bad times. Substantial US dollar appreciations are strongly associated with worsening economic conditions in global markets (Maggiori, 2017). This increases investments in the US dollar and distorts demand-supply mechanism in the global stock and oil markets due to low market participation and hence due to low market liquidity. Therefore, during the periods of low economic activity, the hedging potential of the US dollar investments against risky positions in global markets increases since it is the safest instrument as the premier invoicing, reserve and funding currency for market

Table 8
Estimated long-run predictors of the ECO-PSE.

Panel A. Long-run predictors of the DCCs					Panel B. Long-run predictors of the ADCCs				
EV	Coefficient	Robust std. error	t-statistic	Prob.	EV	Coefficient	Robust std. error	t-statistic	Prob.
△USD	0.09205	0.036616	2.513937	0.0120	△USD	0.226834	0.067084	3.381355	0.0007
DEF	0.045172	0.02171	2.080666	0.0375	DEF	0.05677	0.021455	2.645932	0.0082
TERM	0.048119	0.017755	2.710174	0.0068	TERM	0.051865	0.017482	2.966702	0.0030
FF	0.033151	0.017741	1.86861	0.0618	FF	0.039002	0.016877	2.311011	0.0209
TED	0.02281	0.029238	0.780145	0.4354	TED	0.008047	0.029688	0.271071	0.7864
DUM^{GFC}	0.097228	0.045817	2.122084	0.0339	DUM^{GFC}	0.105029	0.042274	2.484494	0.0130
C	0.470361	0.079842	5.891137	0.0000	C	0.456825	0.077275	5.91164	0.0000

Note: Table 8 shows the long-run predictors of the ECO-PSE. EV refers to the explanatory variables. The Newey and West (1987) autocorrelation and heteroskedasticity robust standard errors and t-statistics are reported. DCCs and ADCCs series are the dynamic and asymmetric dynamic conditional correlation series between two related assets, respectively. ECO-PSE is the correlation series between clean energy and technology stocks. DEF and TERM represent the default spread and term spread, respectively. FF refers to the federal funds rate. TED represents the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. △USD is the percentage change of the trade-weighted U.S. dollar index. DUM^{GFC} is the global financial crisis dummy variable (equal one after September 2008).

Table 9
Estimated long-run predictors of the ECO-OILF.

Panel A. Long-run predictors of the DCCs					Panel B. Long-run predictors of the ADCCs				
EV	Coefficient	Robust std. error	t-statistic	Prob.	EV	Coefficient	Robust std. error	t-statistic	Prob.
△USD	0.346129	0.115679	2.992152	0.0028	△USD	0.449809	0.123676	3.637004	0.0003
DEF	0.146819	0.057411	2.557344	0.0106	DEF	0.131557	0.052942	2.484928	0.0130
TERM	0.023606	0.052284	0.451501	0.6517	TERM	0.026394	0.048872	0.540078	0.5892
FF	0.056781	0.045344	1.25224	0.2106	FF	0.05644	0.041944	1.345592	0.1785
TED	−0.105284	0.054309	−1.93861	0.0526	TED	−0.093356	0.049733	−1.877123	0.0606
DUM^{GFC}	0.280884	0.115831	2.424934	0.0154	DUM^{GFC}	0.268892	0.105861	2.540052	0.0111
C	−0.127276	0.200562	−0.6346	0.5257	C	−0.100451	0.186432	−0.53881	0.5901

Note: Table 9 shows the long-run predictors of the ECO-OILF. EV refers to the explanatory variables. The Newey and West (1987) autocorrelation and heteroskedasticity robust standard errors and t-statistics are reported. DCCs and ADCCs series are the dynamic and asymmetric dynamic conditional correlation series between two related assets, respectively. ECO-OILF is the correlation series between clean energy stocks and oil futures. DEF and TERM represent the default spread and term spread, respectively. FF refers to the federal funds rate. TED represents the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. △USD is the percentage change of the trade-weighted U.S. dollar index. DUM^{GFC} is the global financial crisis dummy variable (equal one after September 2008).

players. When taking into account the superior characteristics of the US dollar (the invoicing currency for oil trading and the premier funding and reserve currency for global banks) for the global economic activities, the aforementioned transmission channels explain the reason why the US dollar appreciations strongly intensify the level of the dynamic and asymmetric dynamic correlations between the stock prices of clean energy and technology firms and oil prices.

5.2. Conclusions

To be able to determine proper energy policies and optimal investment strategies, investors and policy makers should concentrate not only on the dynamic and asymmetric dynamic conditional correlations (DCCs and ADCCs) between energy and financial markets but also on the drivers of these correlations. The investment potential of clean energy attracts the attention of market players and policy makers recently. The previous literature examines the dynamic correlations between clean energy and technology stocks and oil markets, with a focus on the hedging potential of these assets. However, there is a lack of information on the driving forces behind these correlation dynamics. The level of the DCCs and ADCCs is expected to change depending on the different episodes of economic activity due to the differentiated reactions of market participants. The US dollar plays a key role in determining transmission channels between energy and financial markets because it is the invoicing currency for global crude oil trading and the primary funding and reserve currency in global markets. In light of this information, we take into consideration various economic fundamentals to make a correct economic analysis on the macroeconomic determinants of the DCCs and ADCCs by concentrating our focus on the effect of reserve currency (US dollar) value changes on the DCCs and ADCCs in this study.

Our baseline findings suggest that the US dollar appreciation is the main driver of the dynamic and asymmetric dynamic conditional correlations (the DCCs and ADCCs) between the stock prices of clean energy and technology firms and oil prices. Also, we observe that the magnitude and significance of the impact of reserve currency value changes on the ADCCs are greater than on the DCCs. This finding implies that worsening economic circumstances lead global investors to invest more in the US dollar and less in clean energy and technology stocks and oil due to increased hedging demands in low economic activity. Identifying the main drivers of the dynamic correlations between clean energy and technology stocks and oil markets is important in understanding the information transmission between global markets. In this regard, our findings are valuable for the formation of hedging and diversification strategies in the financial and energy markets as well as for designing incentives for clean energy investments.

Our results emphasize that clean energy stocks, technology stocks, and oil exhibit high sensitivity to the US dollar appreciations giving common information on the behavior of these assets, particularly during market downturn periods. It appears that the reduced oil demand, along with an increase in the US dollar value against major foreign currencies during these periods, does not encourage investors to make investments in clean energy stocks. In this respect, it could be argued that the reduced oil demand provides a bad signal about risky investments in global stock markets (e.g. clean energy and technology stocks) because it indicates lower global economic activity. This leads to information transmission between oil and stock markets. Hence, despite the reduced oil demand in global markets, simultaneously increased volatility transmission between oil and stock markets limits the hedging potential of clean energy stocks, especially during a period of recession. Therefore, global investors are inclined to invest in different assets to hedge clean energy stock price risks. To be able to increase the hedging capacity of clean energy stocks and consequently to motivate investors to invest in these stocks, it is necessary to diminish the vulnerability of clean energy stocks to the negative impacts of the US dollar appreciations. To do that, it may be useful for policy makers to inform the investors that clean energy investments are less risky investments financed by government subsidy rather than by dollar

Table 10
Estimated long-run predictors of the PSE-OILF.

Panel A. Long-run predictors of the DCCs					Panel B. Long-run predictors of the ADCCs				
EV	Coefficient	Robust std. error	t-statistic	Prob.	EV	Coefficient	Robust std. error	t-statistic	Prob.
△USD	0.490023	0.153175	3.199114	0.0014	△USD	0.575374	0.164681	3.493874	0.0005
DEF	0.15726	0.08021	1.960609	0.0500	DEF	0.15159	0.07747	1.956758	0.0505
TERM	0.057388	0.057049	1.005932	0.3145	TERM	0.055333	0.056368	0.981653	0.3263
FF	0.090648	0.052548	1.725069	0.0846	FF	0.086974	0.050665	1.716627	0.0861
TED	−0.069649	0.064323	−1.082801	0.2790	TED	−0.063805	0.069498	−0.918093	0.3586
DUM^{GFC}	0.480962	0.140849	3.414727	0.0006	DUM^{GFC}	0.448842	0.136549	3.287045	0.0010
C	−0.519057	0.226833	−2.288279	0.0222	C	−0.473253	0.219829	−2.152824	0.0314

Note: Table 10 shows the long-run predictors of the PSE-OILF. EV refers to the explanatory variables. The Newey and West (1987) autocorrelation and heteroskedasticity robust standard errors and t-statistics are reported. DCCs and ADCCs series are the dynamic and asymmetric dynamic conditional correlation series between two related assets, respectively. PSE-OILF is the correlation series between technology stocks and oil futures. DEF and TERM represent the default spread and term spread, respectively. FF refers to the federal funds rate. TED represents the difference between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill. △USD is the percentage change of the trade-weighted U.S. dollar index. DUM^{GFC} is the global financial crisis dummy variable (equal one after September 2008).

credits. The information provision by the government could reduce uncertainty in clean energy investments and thereby lead to less vulnerability of these investments to the adverse impacts of the US dollar increases.

For further studies, rather than clean energy stocks, researchers might concentrate their effort on other renewable energy stocks to investigate their dynamic correlations with related assets and the main drivers of these dynamics. In addition, future research may focus on country-specific studies to examine the sensitivity of alternative energy investments to macroeconomic risks and their hedging potential in different developed and emerging countries. It is also suggested that future studies might investigate the determinants of dynamic conditional correlations between sector-level (country-level) stock prices and oil prices by considering the underlying characteristics of sectors (countries).

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.104502.

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