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Co-Movement between Oil Price, CO_2 Emission, Renewable Energy and Energy Equities: evidence from GCC countries

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Abstract

Using the data from GCC countries, this paper analyses the co-movement between oil price, C02 emission allowable price, global clean energy index and equity index from three GCC counties, namely, Kuwait, Saudi Arabia and the United Arab Emirates. Almost no previous research has investigated the dynamic interrelations in the conventional energy markets, like those of the GCC countries, against the dramatic growth in clean energy production and the new emissions trading schemes. Employing three different multivariate GARCH models, we document the existence of volatility spillover effects and co-movement among global clean energy production, crude oil price, CO_2 emission allowable price and each of the three GCC energy stock markets. Furthermore, we found that the conditional variances of all return series are influenced by the shocks coming from the markets themselves. Volatilities in all the markets under consideration are highly persistent, and the long-run persistent volatilities are more pronounced especially for oil and CO_2 emission prices. The forecasting exercise demonstrates the superior performance of the multivariate diagonal-BEKK GARCH models.

Keywords: Multivariate GARCH models, GCC, Renewable Energy, Forecasting

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1. Introduction

Several past researches have investigated the impact of the establishment of the Kyoto Protocol and the European Union Emissions Trading System (EU-ETS) on mitigating greenhouse emissions and on global economies. The EU-ETS had been set up with the goal of using cleaner sources of energy (European Communities, 2008) and since then, renewable energy production has surged rapidly especially in developed countries. The U.S. Energy Information Administration (EIA) (2021) reports that the use of renewable energy sources in the US has increased by 12% in 2020; while in the same year, the world added about 50% of renewable energy capacity compared to 2019 (International Renewable Energy Agency (IRENA)(2021).

The transition of energy use was analysed in different ways by past researchers. For example, Marques and Fuinhas (2011); Payne (2012) Apergis and Payne (2014) Bloch et al. (2015); Waziri et al. (2018); and Sun et al. (2019) have examined the impact of growing clean energy consumption on oil prices whereas Oh et al. (2010); Diebold and Yilmaz (2012); Liu and Chen (2013); Andersson and Karpestam (2013); Hammoudeh et al. (2015); Chevallier et al. (2019); Mensah et al. (2019); Ullah et al. (2020) and Zheng et al. (2021) have demonstrated the two-way relation between crude oil prices and carbon dioxide emissions. The mechanism of energy transformations between oil prices, CO_2 emission along with its financial effects on stock prices of energy sectors have also been investigated by Oberndorfer (2009); Sadorsky (2012); Weigt et al. (2013); Madaleno and Pereira (2015); Zhang and Du

(2017); Lin and Chen (2019) and Sun et al. (2019); Maghyereh and Abdoh (2021) and Wang and Zhao (2021).

Existing literature, however, while examining the link between oil prices and renewable energy developments on one hand; or CO_2 emissions, oil prices and stock prices of clean energy firms, on the other hand, have mainly concentrated on oil-importing countries. To the best of our knowledge, almost no previous research has investigated the dynamic interrelations in the conventional energy markets, like those of the GCC countries, against the dramatic growth in clean energy production and the new emissions trading schemes. This is our first contribution to the existing literature.

Second, the prior studies have mainly used annual data and region-wise data instead of data on a single country. Given the dynamic nature of the relationship between oil price and renewable energy consumption, the usage of annual data could potentially be problematic. For instance, Kim et al. (2005) stated that a long horizon of data is not able to capture the short-lived effects of volatility spillover. Instead of annual data, we use daily data over the period from January 02, 2013, to March 20, 2019, to determine potential volatility spillover effects and co-movement among global clean energy production, crude oil price, CO_2 emission price and each energy stock market in the largest GCC oil producers namely, Saudi Arab, UAE and Kuwait. This is our second contribution to the existing literature.

Next, we compute the growth in renewable energy production using a global measure instead of a country or region-level. We employ weighted daily data for global clean energy production. We believe that this is our third contribution to the existing literature.

Finally, in terms of methodology, we use both univariate and different multivariate GARCH models. Rationale behind usage of Univariate GARCH models comes into play to depict volatility clustering in an univariate series, for example crude oil price. On the other hand, one needs to model the relationship between volatilities and covolatilies of global clean energy production, crude oil price, CO_2 emission price and each energy stock market in the largest GCC oil producers. A related issue is whether the correlations between returns in these markets are time-varying or not. These issues can be examined directly if one uses a multivariate GARCH model, and the specification of the dynamics of covariances or correlations can play a crucial rule in this connection.

Our results show that the present volatilities in the three GCC energy stock markets are influenced by past shocks from other markets. However, the most powerful influence is coming from the past shocks of the GCC markets themselves (the endogenous shocks). Abu Dhabi's energy price in the UAE is largely driven by its past shocks followed by Kuwait and Saudi energy markets. Although the volatilities are highly persistent; the GCC energy stock markets are more stable compared to other markets. The steadiest GCC energy index is Kuwait energy stock price followed by UAE and Saudi energy indexes. We demonstrate the presence of both short and long-term persistence in the conditional variance, but the long-run persistent volatilities are more pronounced, especially for oil and CO_2 emission prices. Forecasting evaluation shows the superior performance of the Diagonal BEKK model.

The rest of the paper is organised as follows; Section 2 provides a survey of the relevant literature. Section 3 offers a description of the methods and data used in this study. The empirical results are shown in Section 4, followed by a discussion of these results in Section 5. Finally, Section 6 concludes.

2. Literature review

We divide the existing literature into three sub-sections: sub-section 1 addresses the nexus between crude oil price and renewable energy, in sub-section 2, we survey the link between crude oil, emission allowances prices and stock prices of renewable energy sectors, finally, the relationship among crude oil price and carbon dioxide emissions is reviewed in sub-section 3.

2.1 Crude oil price and alternative energy growth

Existing research can be divided into two strands: i) investigation of direct relationship between changes in oil price and alternative energy developments (e.g. Stern, 1993; Stern, 2000; Oh and Lee, 2004; Payne, 2012; Chevallier, 2012; Tan and Wang, 2017; Ji et al., 2018; Corbet et al.2020; Chen et al., 2020; Asl et al., 2021 and Niu, 2021) and ii) using CO_2 emission as an influential channel between the prices of non-renewable and renewable energy sources (e.g. Sadorsky, 2009; Marques and Fuinhas, 2011; Payne, 2012; Apergis and Payne, 2014; Dogan and Seker, 2016a; Dogan and Seker, 2016b; Troster et al., 2018; Sharif et al., 2019).

Given the initial work by Stern (1993), recent studies such as Stern (2000) and Oh and Lee (2004) discussed the annual demand and supply of clean energy consumption sources considering the impact of economic activities. The results confirmed the presence of causal relationships among aggregate clean energy consumption, oil prices and economic activities. Bloch et al. (2015) using annual data of renewable energy consumption and autoregressive distributed lag (ARDL) and vector error correction model (VECM) have investigated the linkage between coal, oil and renewable energy consumption in China. The results indicate that economic activity growth and oil prices hike lead to increases in clean energy production. This view is also supported by Burkhardt (2019) using annual data for renewable energy consumption obtained from the U.S. Energy Information Administration. Recent studies such as Corbet et al. (2020), Asl et al. (2021) Niu (2021) also found a positive link between oil price and renewable energy markets, especially during the outbreak of the COVID-19 pandemic. Conversely, Waziri et al. (2018) found that renewable energy growth in Nigeria exerts a negative impact on oil and gas exports.

On the other hand, Sadorsky (2009) and Marques and Fuinhas (2011) examined the indirect linkage between oil prices and alternative energy consumption. They found that CO_2 emissions have a positive relationship with oil prices and renewable energy consumption using annual data from a panel of European countries. Dogan and Seker (2016) have documented the presence of bidirectional causality between CO_2 emissions and renewable energy; and unidirectional causality from CO_2 emissions to traditional energy. Similar results were found by Troster et al. (2018) in each quantile of the distribution of oil prices and renewable energy consumption. Nguyen and Kakinaka (2019) demonstrated that the relationship differs across low-income and high-income countries: renewable energy consumption in low-income countries is positively associated with CO_2 emissions; while for the high-income countries, the relationship is negative. The same has been corroborated by Furlan and Mortarino (2018) and Amri (2019) regarding the relationship between oil price and renewable energy consumption. In sum, it seems that evidence on the link between alternative energy growth and oil price is mixed in nature.

2.2 Crude oil, emission allowance price and clean energy stock market

The impact of crude oil and carbon emission prices on stock prices of renewable energy have been addressed by several empirical studies (e.g. Henriques and Sadorsky, 2008; Oberndorfer, 2009; Weigt et al., 2013; Koch, 2014; Reboredo, 2015; Madaleno and Pereira, 2015; Bondia et al., 2016; Moreno and Pereira da Silva, 2016; Reboredo et al., 2017; Hodson et al., 2018; Sun et al., 2019; Zhang and Du, 2017; Lin and Chen, 2019; Sun et al., 2019). Oberndorfer (2009), has argued that oil price surges positively and symmetrically impact electricity stock returns. Reboredo (2015) has pointed out that an increase in oil price contributes to around 30% of clean energy profits. This view has also been supported by Bondia et al. (2016), who argue that oil and clean energy stock prices are cointegrated with two structural breaks. Reboredo et al. (2017) investigated the co-movement and dependence between oil prices and the clean energy stock market using continuous wavelets and cross-wavelet analyses. It turns out that the causal relationship, in the long run, is stronger compared to the short-run. Similarly, Dutta (2017) revealed the significant relationship between oil price changes and renewable energy stock returns using several stochastic volatility models. In the same vein, Narayan and Sharma (2011), Sun et al. (2019) and Lin and Chen (2019) have investigated the effect of oil and coal prices on the Chinese clean energy stock market. The findings indicate that increases in oil or coal prices positively impact on new energy stock market. Lastly, Hodson et al. (2018) argued that natural gas price boosts also led to a surge in the U.S. clean energy prices.

Most recent studies concentrated on the direct relationship between oil price changes and clean energy stock indices (Yu-Ling Hsiao et al., 2019; Dominioni et al., 2019; Fuentes and Herrera, 2020; Lv et al., 2021; Di Febo et al., 2021; Dawar et al., 2021; Ghabri et al., 2021). Most of these works found a significant oil price spillover effect on clean energy stock prices. This impact was observed during the COVID-19 pandemic when crude oil collapse led to a significant surge in clean energy stocks (Ghabri et al., 2021). Other scholars have analysed clean energy market responses according to oil price shocks (Naeem et al., 2020; Zhang et al., 2020; Zhao, 2020; Maghyereh and Abdoh, 2021). Despite investigating different renewable energy markets, the authors found that oil supply shocks and aggregate demand shock positively impact clean energy markets in both the short and long term. Moreover, Maghyereh and Abdoh (2021) argue that the influence of aggregate demand shocks is more significant in comparison with oil supply shocks. Zhang et al. (2020) and Zhao (2020) use Kilian (2009)'s approach of oil price decomposition to explore its impact on clean energy markets. In contrast to Zhang et al. (2020), Zhao (2020) states that oil specific demand shocks create a negative impact, especially in the long term.

Another group of scholars have augmented the argument that alternative energy stock prices are also indirectly influenced by technology stock price swings (e.g. Henriques and Sadorsky, 2008; Kumar et al., 2012; Zhang and Du, 2017; Ahmad, 2017; Maghyereh et al., 2019; Niu, 2021). Both Henriques and Sadorsky (2008) and Kumar et al. (2012) utilised a vector autoregressive (VAR) model to examine the endogeneity of renewable energy stocks, crude oil and technology stock prices. The results confirm the proposed positive nexus. This view was also supported by Zhang and Du (2017) using Chinese data. Lastly, Sadorsky (2012), Ahmad (2017), Maghyereh et al. (2019) and Niu (2021) applied wavelet and multivariate-GARCH techniques and presented evidence of the co-movements and correlation among clean energy firms stock prices, oil prices and technology companies stock prices.

Few empirical works have also investigated the link between oil prices, new energy stock prices and some macroeconomic factors (e.g. Shah et al., 2018; Lin and Jia, 2019; Abbasi et al., 2020). Shah et al. (2018) employed a VAR model to capture the linear interdependencies between alternative energy investment, oil prices, GDP and the interest rate in three developed countries. A significant relationship between oil prices and clean energy stock performance for the U.S. and Norway cases is confirmed. Likewise, Lin and Jia (2019) constructed five counter-measured scenarios to examine the impact of China's Emissions Trading Scheme (ETS) on GDP and renewable energy stock prices. The results reveal that establishing the emissions trading system led to a decrease in GDP by 1.44%; however, clean energy firms gained higher annual revenue. Lastly, Abbasi et al. (2020) argue that renewable energy prices and terrorism have a significant positive long-term impact on economic growth in Pakistan.

2.3 Crude oil price and carbon dioxide emissions

Two different methods exist in the literature regarding investigating the causal link between oil prices and CO_2 emissions. On one hand, empirical studies have examined the linkage of oil prices with the actual volume of carbon dioxide in a particular country measured in tonnes (e.g. Fisher-Vanden et al., 2004; Oh et al., 2010; Andersson and Karpestam, 2013; Alshehry and Belloumi, 2015; Li et al., 2018; Mensah et al., 2019;

Wang et al., 2019; Agbanike et al., 2019; Malik et al., 2020; Ullah et al., 2020) and on the other hand, studies have investigated the relationship of oil prices with CO_2 emission allowances prices (e.g. Koljonen and Savolainen, 2005; Diebold and Yilmaz, 2009; Liu and Chen, 2013; Koch, 2014; Hammoudeh et al., 2014; Boersen and Scholtens, 2014; Hammoudeh et al., 2015; Tan and Wang, 2017; Zeng et al., 2017; Wang and Guo, 2018; Ji et al., 2018; Chevallier et al., 2019; Chang et al., 2020; Lee and Yoon, 2020; Wang and Zhao, 2021; Zheng et al., 2021).

The first seminal study that employed average atmospheric carbon dioxide was by Fisher-Vanden et al. (2004). By using panel data analysis, the findings confirmed that oil price changes are the key factors behind China's new energy system of reducing CO_2 emissions. This view is supported by Andersson and Karpestam (2013) and Mensah et al. (2019). Mensah et al. (2019) determined a unilateral cause from oil prices to carbon emissions both in the long and short run. Similarly, Malik et al. (2020) and Ullah et al. (2020) investigate the same relationship in different countries, but they explored that the link is positive in the short run. Alshehry and Belloumi (2015) and Agbanike et al. (2019) have considered that the low price levels of oil increase carbon emission through a rise in energy consumption. Oh et al. (2010) and Li et al. (2018) have analysed determinants of changes in carbon emissions magnitude in several economies. The outcomes indicate that economic development, energy investment, energy intensity, energy prices and energy consumption are highly driven by CO_2 emissions levels. Wang et al. (2019) have differentiated between the actual and current oil prices that are subsidised by governments. The results indicate that removing oil price distortions has reduced greenhouse gas emissions in China.

A large stream of the literature used CO_2 emission allowances prices to test its volatility spillover and/or dependence structure with prices of fossil fuel. Koljonen and Savolainen (2005) have found that changes in fuel and emissions prices are correlated. Hammoudeh et al. (2014a), Zeng et al. (2017) and Ji et al. (2018) have modelled the dependence structure between emission allowances and energy prices using vector autoregressive (VAR) models. The results generally revealed that energy price shocks, including oil, persistently affect the CO_2 allowance prices, practically in the short run. Hammoudeh et al. (2014b) and Tan and Wang (2017) have analysed the casual relationship using the quantile regression approach and the results showed that the oil price surge makes a considerable drop in the carbon allowances prices. In the same vein, nonlinear autoregressive distributed lag (NARDL) was applied by Hammoudeh et al. (2015) and Zheng et al. (2021) where Chevallier et al. (2019) used copula frameworks. The negative impact between crude oil and the European Union allowances prices is mostly observed in the long run. Similar results were found by Wang and Zhao (2021) who employ the Bayesian Network and build a structural equation framework.

Further research focused on volatility spillover impacts and dynamic correlation utilising diverse multivariate GARCH models. Boersen and Scholtens (2014), Koch (2014), Chang et al. (2019), Chen et al. (2019) and Lee and Yoon (2020) have demonstrated the existence of a positive correlation and significant co-movements between emissions and oil prices. However, Chang et al. (2019), has pointed out the presence of weaker correlation and spillover between emissions and oil prices compared with coal and natural gas using an asymmetric BEKK model. In contrast to Chen et al. (2019), Wang and Guo (2018) used a novel measure of volatilities suggested by Diebold and Yilmaz (2012) and argued that the WTI oil market is highly correlated with CO_2 emission allowance prices. Finally, while Chang et al. (2020) discuss a dependence structure between the Chinese emission allowances and oil price and find significant heterogeneity, Chevallier (2012) and Liu and Chen (2013) addressed both volatility spillover and dependence structure methods. The results reveal the presence of the long memory causality effects and time-varying correlations in the nexus of oil and CO_2 emissions prices.

3. Methodology and data

3.1 Data and Descriptive Statistics

We use daily log-differenced data from January 02, 2013, to March 20, 2019. The S&P Global Clean Energy Index (CE) is obtained from the S&P Dow Jones Indices. It is a weighted index that measures the performance of the biggest listed 30 clean energy companies around the world. It comprises a diverse mix of companies that use environment-friendly processes to produce clean energy. The CO_2 emissions allowance price (EP) is obtained from the European Energy Exchange (EEX). It represents the spot price of the European Union CO_2 emissions allowances. The prices of the EU CO_2 emissions allowances have been converted from euros to U.S. dollars utilising the WM/Refinitiv FX rates of the U.S. dollar-euro exchange rate. The rest of the data is obtained from Invisting.com such as Brent crude oil price (OP) that is measured in US dollars per barrel. Saudi petrochemical index (SPI), Abu Dhabi energy index (AEI) in the UAE and Kuwait Oil & Gas index (KEI) are the stock price energy indices under consideration.

Table 1 shows basic statistics and pre-estimation diagnostics of the six variables. The volatile nature of the variables gets reflected in standard deviation; CO_2 emission price (EP) and Saudi petrochemical index (SPI) are negatively skewed and oil price (OP), Abu Dhabi energy index (AEI) and Kuwait energy index (KEI) are positively skewed. Fat tails are present in all six series as shown in terms of excess kurtosis and Jarque-Bera statistics. We use Engle's (1982) ARCH-LM test to analyse potential volatility clustering and the results indicate that the null hypothesis of no volatility clustering is rejected for all the series up to lag 10, showing evidence of volatility clustering. The Ljung-Box test on the squared standardised residuals to test for possible autocorrelation confirms the presence of autocorrelation in our dataset. Although not reported, we have also conducted the unit root test (Augmented Dickey-Fuller and Phillips-Perron unit root) in all the variables. Results indicate that they series are stationary at the first difference.

Table 1: Summary statistics

	CE	OP	EP	SPI	AEI	KEI
Obs.	1614	1614	1614	1614	1614	1614
Min	-0.02156	-0.03847	-0.1888	-0.0411	-0.04519	-0.02796
Mean	0.000118	-0.00013	0.000332	-8.09E-05	4.40E-05	6.02E-05
Max	0.019796	0.045237	0.17567	0.04031	0.05848	0.038385
Std. Dev	0.004612	0.008627	0.022646	0.006364	0.009682	0.005381
Skewness	-0.197 (0.001)	0.128 (0.000)	-0.010 (0.876)	-0.3502 (0.000)	0.4736 (0.000)	0.1540 (0.011)
Excess Kurtosis	1.861 (0.000)	3.047 (0.000)	11.110 (0.000)	7.246 (0.000)	4.276 (0.000)	3.985 (0.000)
Jarque-Bera	243.79 (0.000)	629.21 (0.000)	8305.4 (0.000)	3567.1 (0.000)	1291.1 (0.000)	1075.2 (0.000)
$Q^2(10)$	176.524 (0.000)	910.673 (0.000)	264.985 (0.000)	414.778 (0.000)	253.611 (0.000)	146.664 (0.000)
ARCH (1)	10.432 (0.000)	28.05 (0.000)	19.476 (0.000)	25.687 (0.000)	15.376 (0.000)	10.737 (0.000)

Note: The formula of the Engle's (1982) ARCH-LM test can be identified as $Var(y_t|H_{t-1}) = Var(\varepsilon_t|H_{t-1}) = E(\varepsilon_t^2|H_{t-1}) = \sigma_t^2$ where the Ljung-Box test is $Q = n(n+2)\sum_{k=1}^{h}\frac{\rho_k^2}{n-k}$. Numbers in parenthesis denote p-values.

3.2 Methodology

We employ a set of multivariate GARCH models: diagonal BEKK GARCH (1,1), asymmetric DCC GARCH (1,1) and copula DCC GARCH (1,1) models for each GCC country. Let r_t be the vector of the N multivariate return series which can be written as:

$$A(L)r_t|F_{t-1} = \mu_t + \epsilon_t \qquad (1)$$

where ϵ_t is the vector containing the return shocks; F_{t-1} the information set at t-1 and $A(L)$ is the lag-polynomial. In the multivariate GARCH models, ϵ_t is related to the vector of z_t through the following equation:

$$\epsilon_t = H_t^{\frac{1}{2}} z_t \qquad (2)$$

where H_t is the conditional volatilities (variance) estimated in the univariate models. We assume $E(z_t) = 0$ and $Var(Z_t) = I_N$, where I_N is the identity matrix of order N. The multivariate GARCH models differ by the way they define the structure of the conditional variance matrix.

Engle and Kroner (1995) have proposed the BEKK model. This model ensures the positive definiteness of H_t. The BEKK (1,1) model is defined as:

$$H_t = C'C + \sum_{i=1}^{p} A_i' \epsilon_{t-i}\, \epsilon'_{t-i} A_i + \sum_{j=1}^{q} B_i' H_{t-j}\, B_j \qquad (3)$$

where $C', A' and\ B'$ are matrices of dimension $N \times N\ and\ C$ is upper triangular. The BEKK model also has its diagonal form by assuming $A, and\ B$ are diagonal matrices. We follow the diagonal BEKK model for the sake of parsimony. In the BEKK model, A measures the degree of market shocks and B measures the persistence in conditional volatility between the markets.

The standard DCC model assumes that the conditional returns are normally distributed with zero mean and conditional covariance matrix $H_t = E[r_t r'|F_{t-1}]$, where I is an $N \times N$ identity matrix. The covariance matrix for the DCC-GARCH model can be expressed as:

$$H_t \equiv D_t R_t D_t \tag{4}$$

where $D_t = diag\{\sqrt{H_{it}}\}$ is a diagonal matrix of time-varying standard deviations from the estimation of univariate GARCH processes and R_t is the conditional correlation matrix of the normalised disturbances ε_t. In the DCC model, both D_t and $R_t$are time-varying. The matrix R_t is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

where Q_t is the positive definite matrix containing the conditional variance-covariance matrix of ε_t, Q_t^{*-1} is the inverted diagonal matrix with the square root of the diagonal elements of Q_t. The DCC model is thus:

$$Q_t = (1 - a - b)\bar{Q} + a\epsilon_{t-1}\epsilon'_{t-1} + bQ_{t-1} \tag{6}$$

where a and b are non-negative scalars, such that $a + b < 1$ in order to impose stationarity and positive semidefinite property. $\bar{Q}$ being is the unconditional covariance of the standardised disturbances ε_t. According to Engle (2002), the estimation of this model is done using a two-step maximum likelihood estimation method. The DCC model is being criticised as the estimation of scalar variables becomes difficult with an increase in the number of variables. To mitigate this, Cappiello et al. (2006) proposed the Asymmetric Generalised DCC (AGDCC) which can be expressed as:

$$Q_t = (Q - A'QA - B'\bar{Q}B - G'\bar{Q}^{-}G) + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'Q_{t-1}B + G'\epsilon_t\epsilon'^{-}_{t}G \tag{7}$$

where A, B and G are the $N \times N$ parameter matrices, ϵ'^{-}_{t} are the zero-threshold standardised errors which are equal to ϵ_t when less than zero or else zero, $\bar{Q}$ and $\bar{Q}^{-}$ are the unconditional matrices of ϵ_t and ϵ'^{-}_{t}. For G=0, $A = \sqrt{\mathrm{a}}$ and $\mathrm{B} = \sqrt{\mathrm{b}}$, the AGDCC model reduces to asymmetric DCC model, that we use in our paper.

Sklar (1959) first proposed the Copula based DCC-GARCH models which helps in identifying the interdependence between large number of assets. Copula functions are not only useful in obtaining the univariate marginal distribution function from the dependence structure from a set of random variables but also have an advantage while dealing with high-dimensional joint distributions. The time-varying conditional correlation using copulas is essentially an extension of the DCC model and a copula–GARCH model with joint distribution given by:

$$F\,(r_t|\mu_t, h_t) = C(F_1(\,r_{1t}|\mu_{1t}, h_{1t}) \ldots\ldots\ldots F_n\,(\,r_{nt}|\mu_{nt}, h_{nt}) \quad (8)$$

where F and C are the conditional distribution and the copula function, respectively. The conditional mean is assumed $to\ be$ a linear function of past one-lag with an ARMA(1,1) process and the conditional variance h_{it} follows a GARCH(1,1) process.

4. Results

4.1 Univariate GARCH model

In the first stage of a multivariate GARCH analysis, we estimate an AR(1)-GARCH (1,1) model. The results are shown in Table 2.

Table 2: Univariate GARCH results

Parameters	CE	OP	EP	SPI	AEI	KEI
ω_0	0.000168 (0.1918)	-2.8E-05 (0.852)	0.00086 (0.005)	0.000172 (0.198)	-2.6E-05 (0.885)	0.000036 (0.777)
AR (1)	0.190294 (0.000)	-0.04721 (0.071)	-0.19002 (0.000)	0.10239 (0.000)	-0.07016 (0.015)	-0.03785 (0.210)
$\alpha_0 * 10^6$	0.651881 (0.226)	0.500059 (0.035)	0.016019 (0.234)	0.797941 (0.242)	4.337447 (0.001)	1.9269 (0.242)
α_1	0.073598 (0.032)	0.073977 (0.000)	0.05453 (0.006)	0.093315 (0.001)	0.160916 (0.000)	0.081019 (0.017)
β_1	0.895228 (0.000)	0.92134 (0.000)	0.943756 (0.000)	0.891855 (0.000)	0.802576 (0.000)	0.851917 (0.000)

Note: Where $\varepsilon_t = z_t\sigma_t \text{ and } z_t$ is white noise, the univariate GARCH equation can be written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

The results reveal that all the series have significant conditional volatility and both ARCH (α_1) and GARCH (β_1) components are statistically significant. The sum of the values of the lagged squared error coefficient (ARCH effects) and the lagged conditional variance coefficient (GARCH effects) is close to one. This implies that the current volatility is influenced by its past highly persistent shocks. In sum, the results of the univariate GARCH model demonstrate the existence of time-varying conditional volatility as well as the persistence of volatility shocks in the returns.

4.2 Multivariate GARCH models

4.2.1 Diagonal BEKK-GARCH model

Table 3 reports the results of the time-varying variance-covariance obtained from the diagonal BEKK-GARCH(1,1) models for each country. The AR(1) coefficients denote the autoregressive coefficients; the C_{ij}coefficients of the variance equation explain how the lagged returns of the i^{th}markets influence the current return of the j^{th} markets, (C_{ii}) reflect the influence of a particular market's lagged return on its present value. Our focus is on the diagonal lagged squared errors $A(\alpha_{ii})$ (ARCH effects) and conditional variance $B(\beta_{ii})$ (GARCH effects). The values of α_{ii}represent shocks (innovations) in each market and estimate the impact of the own past shocks on the future volatility of the market and that of β_{ii} explain the persistence of shocks (the piecemeal decline of the influence of news). The stabilisation of the variance is being assessed using the sum of the parameters $A(\alpha_{ii})$ and $B(\beta_{ii})$. The sum of A and B values is close to one indicates the effects of long memory in the time series.

Our results show that the coefficients (C_{ii}) for the three models are significant, except for the element of (C_{11}) for the Saudi model. This indicates that the current values of all the series are influenced by its own lagged returns. The coefficients (C_{ij}) were found statistically insignificant for the three models; except the parameter (C_{34}) of the Saudi model which was found significant at 5% level. The negative value of (C_{34}) by (-0.0005) signifies that the previous increases in CO_2 emission returns will lead to a slight decrease in the current price of the Saudi petrochemical index (or vice versa).

The coefficients of ARCH $A(\alpha_{ii})$ and GARCH effects $B(\beta_{ii})$ are highly statistically significant for the three countries, except the coefficient (α_{11}) for the UAE model. All the ARCH parameters $(\alpha_{11}, \alpha_{22}, \alpha_{33} and \alpha_{44})$ enters with positive and statistically significant coefficients implying that the shocks coming from the markets themselves fundamentally cause their future volatility. The highest own-past shock spillovers

(ARCH effects) among the three models were found for the GCC energy stock market parameters (α_{44}). Specifically, we found that the present volatility of the Abu Dhabi energy price is the most related to its past shocks followed by Kuwait and Saudi energy markets as evidenced by the values (0.3830), (0.3372) and (0.2767) respectively. The estimated coefficients of the ARCHs show that the future volatilities of the three GCC energy stock markets are highly sensitive to their past shocks compared to the other markets. Therefore, the investors who deal with the three GCC energy equities should pay greater attention to the shocks coming from the markets themselves compared to those who deal with the clean energy production index, CO_2 emission and oil prices.

The values of the GARCH coefficients ($\beta_{11},\ \beta_{22},\ \beta_{33}\ and\ \beta_{44}$) across the three models are mostly higher than 0.8 indicating strong volatility persistence (the impact of the past shocks on the current prices of the markets). However, the impact of the past shocks of the GCC energy stock markets is less persistent compare to clean energy production, CO_2 emission and oil prices. In other words, the GCC energy volatilities are more stable compared to the other markets. This is because the values of the parameters (β_{44}) are lower than the values of ($\beta_{11},\ \beta_{22}\ and\ \beta_{33}$). Finally, the stabilisation of the conditional variance has been confirmed as the sum of the parameters $A\ and\ B$ among the three models is less than one, however long memory behaviour is detected as the sum of these parameters for each model is almost equal to one.

4.2.2 Dynamic conditional correlation Models

In Table 4, we present the results of the asymmetric DCC-GARCH (1,1) and the copula DCC-GARCH (1,1) models for the three countries. The lagged squared error coefficients of (α_i) denote the ARCH effects. The ARCH parameters of the GCC energy sectors and clean energy production are statistically significant for the two DCC-types GARCH models. This indicates short term persistence in the individual conditional variances. All the individual GARCH coefficients (β_i) are highly statistically significant and its values are large (around 90%) for the two DCC-types GARCH models. This is clear evidence of the presence of long-run persistence in all the individual return series of the three countries. Overall, the GARCH effects seem to be more powerful compared to the ARCH effects, pointing towards highly long run persistent volatility in all the individual series. The highly long run persistent volatilities in oil and CO_2 emission prices are greater than the volatilities in the GCC energy stock and clean energy production indexes.

The DCC_α terms symbolise the joint ARCH effects and found to be statistically insignificant for the three countries/the two DCC-types GARCH models. This implies that the joint conditional variance is absent in the short-term. The DCC_β parameters are highly statistically significant, indicating the presence of time-varying conditional correlation across the markets. The high value of DCC_β coefficients indicate that volatility of a market can be largely attributed to the endogenous shocks more than spillover across the markets. The sum of the $DCC_\alpha \ and \ DCC_\beta$ parameters are close to unity. Thus, it can be understood that the conditional correlations will return to their unconditional levels in the long term (mean-reverting process). The asymmetry parameter DCC_γ estimated by the asymmetric DCC GARCH model is found to be statistically insignificant. This means that the volatility spillover effects are not symmetric.

Table 3: Estimation results of the diagonal BEKK-GARCH(1,1) models

	Saudi		**UAE**		**Kuwait**	
	CE, OP, EP, SPI		CE, OP, EP, AEI		CE, OP, EP, KEI	
	Coeff	p-value	Coeff	p-value	Coeff	p-value
$mean_1$	0.00016	0.264	0.00012	0.403	0.00017	0.175
$mean_2$	-0.00004	0.751	-4.3E-05	0.776	-3.9E-05	0.795
$mean_3$	0.00072	0.024	0.00077	0.016	0.00082	0.012
$mean_4$	0.00012	0.360	-7.8E-05	0.665	0.000003	0.984
AR_{11}	0.19952	0.000	0.21884	0.000	0.195761	0.000
AR_{12}	-0.0601	0.035	-0.0529	0.056	-0.04886	0.087
AR_{13}	-0.1867	0.000	-0.1919	0.000	-0.19214	0.000
AR_{14}	0.10004	0.002	-0.0659	0.031	-0.02399	0.446
C_{11}	0.0000	1.000	0.00225	0.000	0.000302	0.040
C_{12}	0.0004	0.776	0.00000	0.888	0.00002	0.818
C_{13}	-0.0007	0.784	-9.1E-05	0.494	-3.5E-05	0.854
C_{14}	-0.0003	0.869	0.00009	0.345	0.00043	0.391
C_{22}	0.0004	0.831	0.00058	0.005	0.00064	0.005
C_{23}	0.0006	0.824	-0.0001	0.619	-0.0001	0.513
C_{24}	0.0005	0.709	0.00009	0.758	0.00032	0.380
C_{33}	0.0010	0.068	0.00135	0.006	0.00142	0.008
C_{34}	-0.0005	0.038	0.00030	0.414	-2E-06	0.996
C_{44}	0.0002	0.022	0.00257	0.000	0.00298	0.000
α_{11}	0.1073	0.000	0.00000	1.000	0.11541	0.000
α_{22}	0.2202	0.000	0.21256	0.000	0.22346	0.000
α_{33}	0.1936	0.000	0.19372	0.000	0.20725	0.000
α_{44}	0.2767	0.000	0.38303	0.000	0.33725	0.000
β_{11}	0.9942	0.000	0.86608	0.000	0.99105	0.000
β_{22}	0.9734	0.000	0.97554	0.000	0.97279	0.000
β_{33}	0.9788	0.000	0.97918	0.000	0.97650	0.000
β_{44}	0.9529	0.000	0.88795	0.000	0.74943	0.000

Note: the numbers 1, 2 and 3 simplify the variables CE, OP and EP respectively, whereas 4 indicates each GCC energy stock index.

Table 4: Estimation results of asymmetric multivariate GARCH (1,1) and copula DCC(1,1) models

	Asymmetric DCC						Copula DCC					
	Saudi		**UAE**		**Kuwait**		**Saudi**		**UAE**		**Kuwait**	
	CE, OP, EP, SPI		CE, OP, EP, AEI		CE, OP, EP, KEI		CE, OP, EP, SPI		CE, OP, EP, AEI		CE, OP, EP, KEI	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
$mean_1$	0.0002	0.102	0.0002	0.101	0.0002	0.101	0.00018	0.082	0.00018	0.082	0.00018	0.082
$mean_2$	0.0009	0.015	0.0009	0.015	0.0009	0.015	0.00091	0.015	0.00091	0.015	0.00091	0.015
$mean_3$	2.9e-05	0.875	2.9e-05	0.874	2.9e-05	0.875	2.9e-05	0.864	2.9e-05	0.864	2.9e-05	0.864
$mean_4$	0.0002	0.185	1.7e-05	0.925	4.0e-05	0.759	0.00016	0.189	1.7e-05	0.926	0.00004	0.751
C_1	1.0e-06	0.064	1.0e-06	0.064	1.0e-06	0.064	1.0e-06	0.096	1.0e-06	0.096	1.0e-06	0.096
C_2	2.0e-06	0.015	2.0e-06	0.015	2.0e-06	0.015	2.0e-06	0.744	2.0e-06	0.744	2.0e-06	0.744
C_3	1.0e-06	0.980	1.0e-06	0.980	1.0e-06	0.980	1.0e-06	0.975	1.0e-06	0.975	1.0e-06	0.975
C_4	1.0e-06	0.518	4.0e-06	0.229	2.0e-06	0.000	1.0e-06	0.535	4.0e-06	0.246	2.0e-06	0.254
α_1	0.1002	0.000	0.1002	0.000	0.1002	0.000	0.09992	0.000	0.09921	0.000	0.09921	0.000
α_2	0.0594	0.153	0.0594	0.156	0.0594	0.153	0.05929	0.153	0.05929	0.153	0.05929	0.153
α_3	0.0758	0.848	0.0758	0.849	0.0758	0.849	0.07643	0.813	0.07643	0.813	0.07643	0.813
α_4	0.0909	0.009	0.1611	0.000	0.0788	0.000	0.09032	0.011	0.16098	0.000	0.07481	0.000
β_1	0.8522	0.000	0.8522	0.000	0.8522	0.000	0.85547	0.000	0.85547	0.000	0.85547	0.000
β_2	0.9396	0.000	0.9396	0.000	0.9396	0.000	0.93970	0.000	0.93970	0.000	0.93970	0.000
β_3	0.9193	0.015	0.9193	0.016	0.9193	0.015	0.91890	0.002	0.91890	0.002	0.91890	0.002
β_4	0.8950	0.000	0.8011	0.000	0.8550	0.000	0.89618	0.000	0.80155	0.000	0.86657	0.000
DCC_α	0.0000	0.998	0.0000	0.999	0.0000	0.999	0.00078	0.886	0.000	0.050	0.000	0.964
DCC_β	0.7829	0.000	0.7615	0.000	0.7917	0.004	0.82883	0.000	0.91239	0.000	0.903	0.000
DCC_γ	0.0067	0.484	0.0078	0.839	0.0050	0.676	-	-	-	-	-	-

Note: the numbers 1, 2 and 3 simplify the variables CE, OP and EP respectively, whereas 4 indicates each GCC energy stock index.

4.2.3 Time-varying conditional correlations

Figures 1, 2 and 3 display the dynamic conditional correlations for the market pairs obtained from the three multivariate GARCH models illustrating some similarities of volatility clustering across the countries. For example, the pairwise conditional covariance between clean energy production index/oil price is found to be highly fluctuating between 2015-2017. Likewise, the conditional covariances between clean energy production index / CO_2 emission price indicates two spikes in 2013 and 2014; except the conditional covariances for the BEKK models which were constantly fluctuating over the entire period of analysis. A peak is found around 2016 for oil and CO_2 emission prices indicating a highly volatile period. The covariance among clean energy production index /Saudi petrochemical index is found to be stable, except for the two spikes during the end of 2014 and 2017. The same market pairs for UAE and Kuwait were turbulent throughout the analysis. The covariances of oil price with the three GCC energy indexes indicate a volatile period between 2015-2017, however, their pattern of volatiles is not observed among the conditional correlations of the GCC energy stock markets with CO_2 emission price.

Some political and economic events could explain the pairwise conditional covariance among the markets. For instance, the Yemen war, which has been waged in 2015 and an oil price drop at the beginning of 2016 likely led to extreme volatility in the GCC stock market. Also, the GCC governments have established strategic frameworks to mitigate their dependence on oil revenues and diversify their economies. Some governments levied taxes and cut domestic electricity, water and energy subsidies between 2015 and 2018. For example, Saudi and the UAE have imposed a value-added tax (VAT) by 5% on most goods and services starting from January 2018 (Kerr and Al Omran, 2018). Further, Saudi launched a 5-year plan to increase the prices of diesel, natural gas, electricity gasoline and water. Where in the UAE, the government release fuel prices to align with global energy prices (Morgan, 2016). Finally, the Kuwait cabinet had announced a plan to impose a 10% tax on companies' profits, to reduce the public budget deficit in 2016 (Arabian Business, 2016).

Figure 1: Conditional covariance: Diagonal BEKK GARCH(1,1) model

Saudi **UAE** **Kuwait**

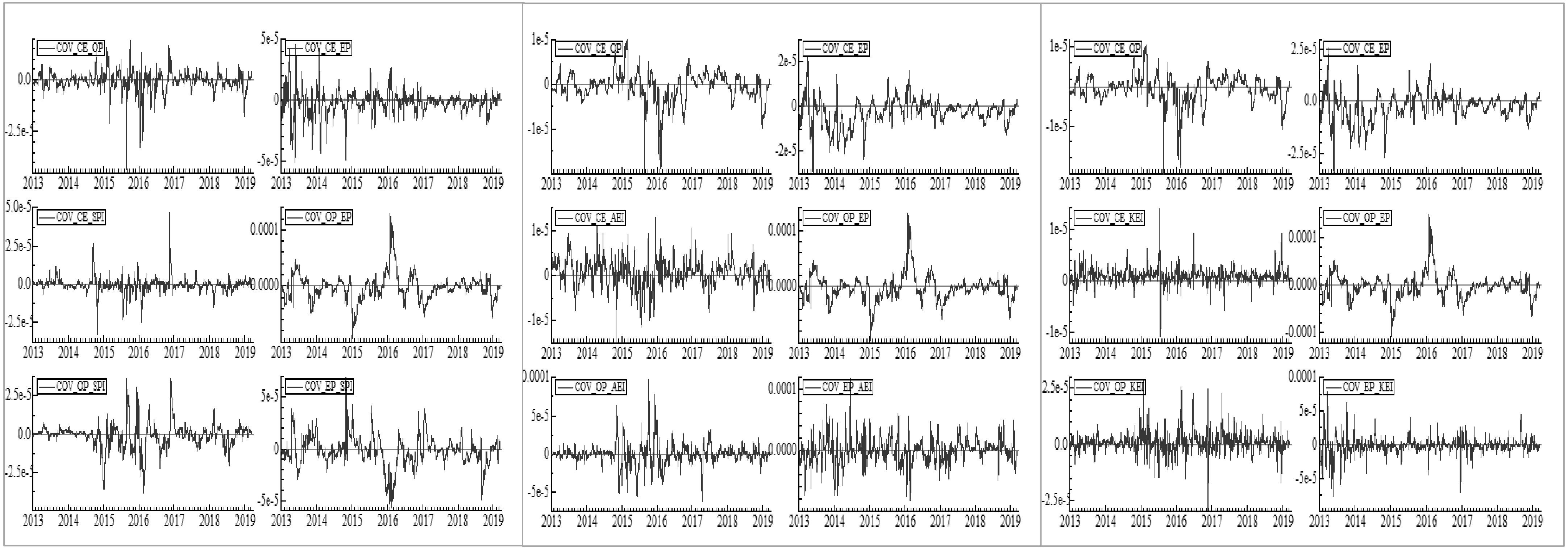


Figure 2: Conditional covariance: Asymmetric DCC GARCH(1,1) model

Saudi **UAE** **Kuwait**

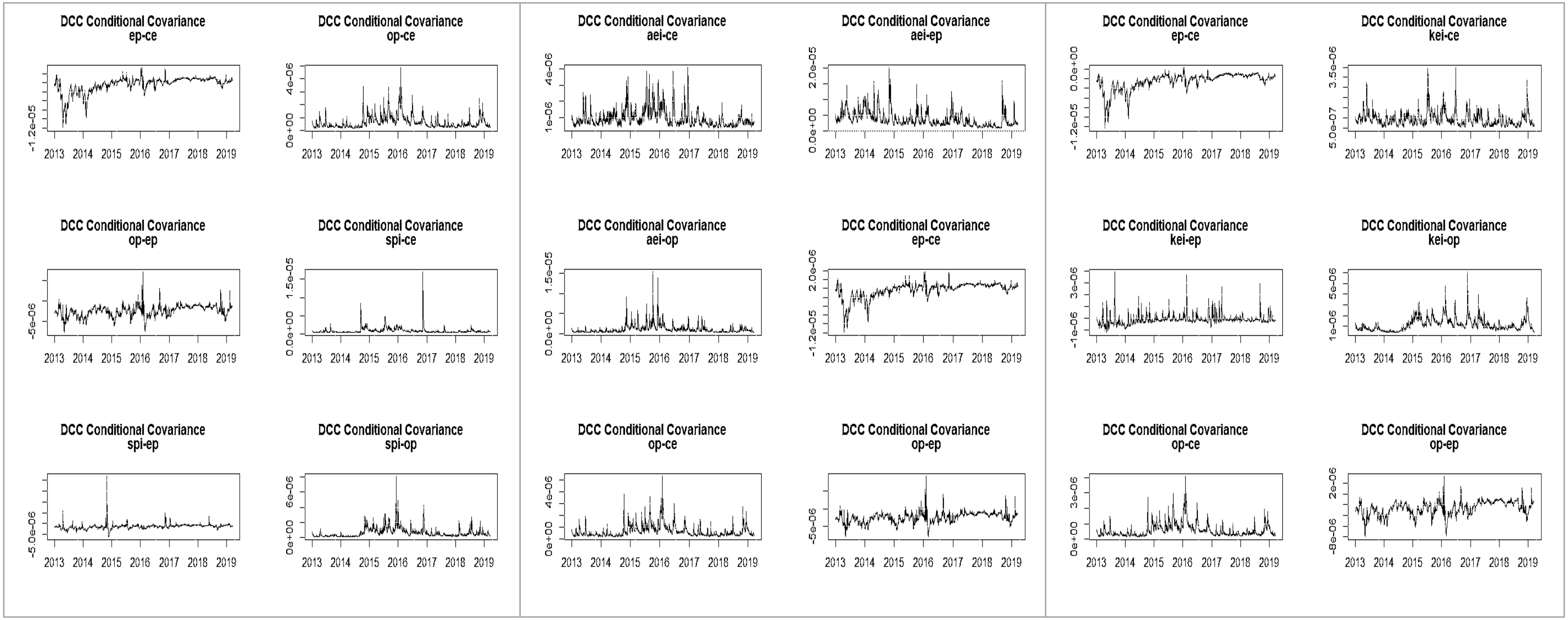
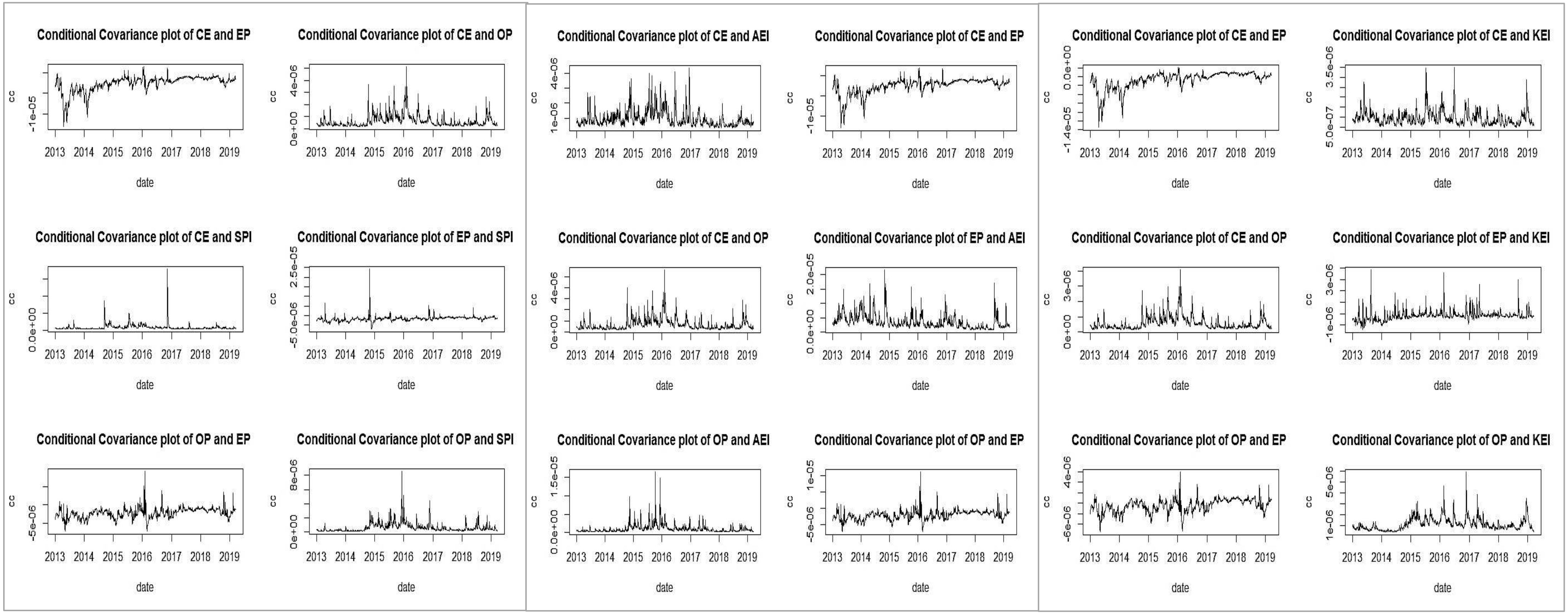


Figure 3: Conditional covariance: Copula DCC GARCH(1,1) model

Saudi **UAE** **Kuwait**



4.3 Diagnostics statistics and model comparison

In this sub-section, we present various diagnostic statistics along with model comparison. Table 6 displays the results of the modified multivariate portmanteau tests developed by Hosking (1980) and Li and McLeod (1981). The results of Hosking and Li and McLeod test statistics confirm that the diagonal BEKK models for the UAE and Kuwait markets can capture the spillover dynamics, but not so for the Saudi market. Asymmetric and copula DCC GARCH models were unable to explain the volatility spillover dynamics for all the three countries. Table 7 compares the

Table 6: Diagnostic Statistics

	Diagonal BEKK			**Asymmetric DCC**			**Copula DCC**		
Lag	**Saudi**	**UAE**	**Kuwait**	**Saudi**	**UAE**	**Kuwait**	**Saudi**	**UAE**	**Kuwait**
Hosking (5)	121.08 (0.001)	122.43 (0.001)	110.272 (0.011)	1302.96 (0.000)	1140.599 (0.000)	1093.831 (0.000)	1300.038 (0.000)	1140.574 (0.000)	1093.789 (0.000)
Hosking (10)	194.164 (0.030)	191.608 (0.039)	189.078 (0.051)	1824.07 (0.000)	1602.788 (0.000)	1484.363 (0.000)	1818.665 (0.000)	1602.802 (0.000)	1484.363 (0.000)
Hosking (20)	374.379 (0.017)	361.175 (0.051)	343.017 (0.169)	2811.72 (0.000)	2539.609 (0.000)	2436.403 (0.000)	2804.813 (0.000)	2539.513 (0.000)	2436.322 (0.000)
Li-McLeod (5)	121.015 (0.001)	122.358 (0.001)	110.222 (0.011)	1301.22 (0.000)	1138.929 (0.000)	1092.29 (0.000)	121.015 (0.001)	1138.904 (0.000)	1092.246 (0.000)
Li-McLeod (10)	194.137 (0.030)	191.598 (0.039)	189.056 (0.051)	1820.17 (0.000)	1599.225 (0.000)	1481.31 (0.000)	194.137 (0.000)	1599.239 (0.000)	1481.31 (0.000)
Li-McLeod (20)	374.155 (0.018)	361.103 (0.052)	343.103 (0.169)	2799.96 (0.000)	2528.667 (0.000)	2425.69 (0.000)	374.155 (0.000)	2528.573 (0.000)	2425.61 (0.000)

Notes: 1) The null hypothesis of the two tests is that absence of autocorrelation. 2) Numbers in parenthesis denote the p-values.

performance of the three empirical models using the Bayesian information criterion (BIC) as well as Akaike information criteria (AIC). Both BIC and AIC confirm that the diagonal BEKK model performs the best for all the three countries.

Table 2: Estimated model comparison

	Diagonal BEKK GARCH		Asymmetric DCC		Copula DCC	
	BIC	AIC	BIC	AIC	BIC	AIC
Saudi	-27.781	-27.627	-27.791	-27.693	-27.803	-27.700
UAE	-26.377	-26.667	-26.387	-26.773	-26.379	-26.780
Kuwait	-27.682	-27.782	-27.687	-27.835	-27.685	-27.843

4.4 Forecasting performance

In this sub-section, we evaluate forecasting performance using two evaluation measures: mean absolute error (MAE) and root mean square error (RMSE) which are defined as: $MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$ and $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$ where y_j is the actual series and $\hat{y}_j$ is the forecasted series from the estimated model. Table 8 evaluates the forecasts based

Table 8: Forecast evaluation tests

	MAE			RMSE		
Stock indices	Diagonal BEKK	Asymmetric DCC	Copula DCC	Diagonal BEKK	Asymmetric DCC	Copula DCC
Saudi	0.049166	0.062736	0.049320	0.061741	0.061942	0.061786
UAE	0.054218	0.068014	0.054817	0.065024	0.066941	0.065744
Kuwait	0.045131	0.045133	0.045141	0.055391	0.056861	0.055764

on the conditional variance for the three-competing multivariate GARCH models. In terms of both criterion, we observe that diagonal-BEKK performs slightly better than the other two multivariate GARCH models. Combining the evidence based on both the diagnostics and forecasting tests, we confirm that the diagonal BEKK performance is better and therefore we compare the diagonal BEKK's forecasts with the univariate GARCH (1,1)'s forecasts based on the conditional mean and conditional forecast of the three energy indices using RMSE. The values of the RMSE shown in Table 9 are slightly lower for the diagonal-BEKK(1,1) model for all three energy stocks. Hence, we conclude that forecasts obtained from the diagonal BEKK model are better compared to those of the univariate GARCH (1,1) in terms of in-sample forecast comparison.

Table 9: Comparison between diagonal BEKK and the univariate GARCH models forecasts

	RMSE			
Stock indices	**Conditional mean forecast**		**Conditional variance forecast**	
	Univariate GARCH	Diagonal BEKK	Univariate GARCH	Diagonal BEKK
Saudi	0.006444	0.006439	0.0000398	0.0000395
UAE	0.002772	0.002768	0.0000297	0.0000294
Kuwait	0.000394	0.000391	0.0000188	0.0000186

5 Conclusion

Our study confirms the existence of volatility spillover effects and co-movement among global clean energy production, crude oil price, CO_2 emission price and each of the three GCC energy stock markets. Furthermore, we found that the conditional variances of all return series are influenced by the shocks coming from the markets themselves. One possible explanation for this might be that the GCC equities are classified as Islamic stock markets. It means that investors in these markets are committed to follow the Shari'ah guidelines, which prohibits some of the financial activities that are applied in conventional financial markets (e.g., short selling, leverage and financial derivatives).

Another possible explanation is that the GCC energy companies are partly owned by the GCC government funds. For example, over 70% of the Saudi Basic Industries Corporation (SABIC), the world's largest petrochemicals manufacturers, is held by the Public Investment Fund (PIF). For the UAE, the total government shareholding in Abu Dhabi Power Corporation (ADPC) is around 74.1% (Mubasher, 2021). Besides, the foreign investment restrictions in the GCC stock markets could impact our results. The Saudi Stock Exchange, for example, has permitted foreign investment in January of 2018 by 49%. While the Dubai Financial Market is not fully open for foreign investments, especially in banking and energy sector (Capital market authorities in Saudi and Dubai, 2020).

Our findings are consistent with Koljonen and Savolainen (2005), Hammoudeh et al. (2014a), Zeng et al. (2017) and Ji et al. (2018) who found a binary causal relationship between crude oil and CO_2 emission prices. Also in line with Sadorsky, (2009), Marques and Fuinhas, (2011), Dogan and Seker, (2016a), Dogan and Seker, (2016b) and Troster et al., (2018) who discovered the binary nexus between CO_2 emission prices and clean energy. However, our results reveal that the impact of emissions trading systems is not limited to stock returns of those countries that established ETS (e.g. Koch, 2014; Reboredo, 2015; Bondia et al., 2016; Dutta, 2017; Reboredo et al., 2017; Hodson et al., 2018; Sun et al., 2019). The possible explanation for the correlation among CO_2 emission allowances prices and the GCC energy stock prices are that carbon schemes boost global clean energy production/consumption, which in turn alter the levels of global conventional energy uses and oil prices.

This paper examines spillover effects and co-movements among global clean energy production, crude oil price, CO_2 emission price and each energy stock market in the largest GCC oil producers namely, Saudi Arab, the UAE and Kuwait. Using daily data over the period from January 02, 2013, to March 20, 2019, and applying three multivariate GARCH frameworks: diagonal BEKK GARCH (1,1), asymmetric DCC GARCH (1,1) and copula DCC GARCH (1,1) models for each country, we document that the past endogenous shocks turn out to be the most powerful driver of volatilities in the GCC markets. Volatilities in all the markets under consideration are highly persistent, and the long-run persistent volatilities are more pronounced especially for oil and CO_2 emission prices.

This study helps policymakers in oil-producing countries to design appropriate mechanisms to speed up revenue diversification policies. Investors and portfolio managers would benefit from the stabilisation of the GCC energy stock market that we have confirmed, and they would get a systematic assessment of the likelihood of alternative portfolios and hedge their strategies. However, investors should take into account the huge impact of internal shocks on the GCC markets. Finally, we provide evidence on the response of the largest oil-exporting economies, such as those in the GCC region, to global energy market transformations.

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Declaration of competing interest

We declare that we have no competing interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Statement

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