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Implications of clean energy, oil and emissions pricing for the GCC energy sector stock

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ABSTRACT

In this study, we analyse the implications of clean energy, oil and emission prices for the energy sector stock in the GCC region. In so doing, we estimate one-day-ahead value at risk (VaR) and the expected shortfall (ES) for Saudi, Abu Dhabi and Kuwaiti energy stock prices over short and long trading positions using three different long memory Autoregressive conditional heteroskedasticity (ARCH)/ Generalized(G)- ARCH models: fractionally integrated asymmetric power ARCH (FIAPARCH), fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) and fractionally integrated hyperbolic generalized autoregressive conditional heteroskedasticity (HYGARCH). In the GARCH model, we employ the three global energy indexes: clean energy production, crude oil and CO_2 emission prices as exogenous regressors to consider their impacts on the GCC energy volatilities. Our findings indicate the presence of asymmetry, fat-tails and long memory in the GCC energy price volatilities, and that the three exogenous regressors do not play a significant role in the GCC daily returns volatility. The FIAPARCH produces the most accurate VaR and the expected shortfall for Saudi and Kuwait energy sectors, while HYGARCH performs better for the Abu Dhabi energy index. Our study has profound implications for the clean energy policy, emission pricing and investment strategies entailing energy stock.

1. Introduction

Since the mid-1990s when J.P. Morgan developed the first risk standardised approach to forecast future risks of financial markets, such an approach has become an ultimate framework for investors, financial managers, regulators as well as researchers and academics. Existing evidence and prevailing wisdom have been that the most effective risk quantifying techniques are value-at-risk (VaR) and the expected shortfall (ES) (see e.g., Aloui and Hamida, 2014; Su, 2015; Mabrouk, 2017; Mensi et al., 2017; Liu et al., 2018; Nguyen and Huynh, 2019; Molino and Sala, 2020; Yang and Xu, 2021). Whilst the VaR computes the maximum loss of value for a firm, sector, portfolio, etc. given specific prevailing market conditions over a limited time forecast and given a confidence interval, ES acts as a complementary tool to the VaR in order to quantify the losses that are not covered by the VaR under its confidence level (Gong and Weng, 2016; Mensi et al., 2017; Liu et al., 2018).

Predicting the risks of highly volatile markets commonly involves using the historical time-series of the same markets (e.g., Chen and Chen, 2013; Aloui and Hamida, 2014; Su, 2015; Gong and Weng, 2016; Mabrouk, 2017; Mensi et al., 2017; Liu et al., 2018; Chen et al., 2020; Yang and Xu, 2021). Some authors have developed VaRs models while taking into account spillover effects between the markets (Aloui and Mabrouk, 2010; Degiannakis and Kiohos, 2014; Du and He, 2015; Zolfaghari and Sahabi, 2017; Li and Wei, 2018; Wen et al., 2019; Tiwari et al., 2020; Yang et al., 2021). However, the literature remains more or less silent regarding the estimation of VaR and ES for conventional energy stock prices, especially for heavy oil-exporting countries like those in the GCC region. For instance, Hung et al. (2008), Marimoutou et al. (2009) and Marimoutou et al. (2009) only focused on oil or a few energy commodities and did not account for the long-memory frameworks[2]. Although, Youssef et al. (2015) did use a long-memory GARCH-EVT model but focused only on gasoline and crude oil. These are the caveats and research gaps in the existing body of knowledge that the subject study is intended to address.

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[1] Alkathery graduated from Leeds University Business School in 2021.
[2] There are also other studies that only focused on the oil market using different framework (e.g. see Liu and Lee, 2021).

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In terms of focus on the GCC region, it is crucial to acknowledge that the GCC is a very important political and economic block[3]. The developments in the region have implications for the global economy and particularly for the global energy markets (See, Nasir et al., 2019 for a detailed discussion of GCC economies and energy shocks). Due to the extreme dependence of GCC economies on energy exports, the energy prices, as well as the emissions pricing can have potential effects on the GGC region and its financial markets. Clean energy is vital for economic growth (Wang and Lee, 2022). The global drive to clean energy also makes this region a direct stakeholder in tackling environmental challenges (Luomi, 2014). Nevertheless, the GCC economies are among the most vulnerable economies in the face of climate change where climate change can lead to a loss of about 1% of GDP per anum (Livermore, 2021). In this context, it is vital to comprehend the importance of oil shocks as well as clean energy and instruments such as emission pricing for the GCC economies.

There exists also a research gap in our knowledge to understand the crucial role of the statistical properties of highly volatile markets' VaRs (e.g., excessive volatility, leverage effects, fat-tails, asymmetry and long memory) especially in the context of GCC countries. On this aspect, according to Cabedo and Moya (2003), returns for energy commodities prices mostly display a large skewness, kurtosis or follow a long memory process. A phenomenon the subject study is exploring and hence contributing to the existing body of knowledge. As it stands, climate change is one of the most crucial and existential issues faced by human civilisation. In this regard, the importance of clean energy and pricing emissions is profoundly important for economic and ecological stability and meeting the environmental challenges (e.g., Doğan et al., 2020; Shahbaz et al., 2020, 2020b; Nasir et al., 2021; Nguyen et al., 2021). Furthermore, the oil price fluctuations do have significant implications for the economies and financial markets (Nasir et al., 2018, 2019; Lee et al., 2021b). However, existing evidence and thus our understanding of how these factors affect the financial markets and particularly the energy sector stock in the oil-exporting economies like GCC is very limited and merits further exploration. Concomitantly, in this paper, we analyse the implications of clean energy, oil and emission prices for the energy sector stock in the GCC region. Specifically, we focus on quantifying one-step ahead VaR and the ES for the three energy stock prices indices of Saudi and the UAE and Kuwait using three long memory autoregressive conditional heteroskedastic (ARCH/GARCH) models, namely fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH), fractionally integrated asymmetric power ARCH (FIAPARCH) and fractionally integrated hyperbolic generalized autoregressive conditional heteroskedasticity (HYGARCH). To the best of our knowledge, this is the first contribution to the existing literature on this subject. We use these models to capture potential leverage effects, fat-tails, asymmetry and long memory effects of our variables.[4] As the second contribution to the existing evidence, we also include the three global energy markets: clean energy production index, crude oil and CO_2 emission prices as regressors to explore their role in investigating statistical long memory effects on the GCC energy equities. Our key findings confirm the presence of asymmetry, fat-tails and long memory in the GCC energy price volatilities, and that the three exogenous regressors do not play a significant role in the GCC daily returns volatility. The FIAPARCH produces the most accurate VaR and the expected shortfall for Saudi and Kuwait energy sectors, while HYGARCH performs better for the Abu Dhabi energy index. These findings have profound implications for the clean energy policy, emission pricing and energy stock investment strategies.

The remaining parts of this paper are divided into four parts. 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 provided in Section 4, whereas Section 5 concludes this study.

2. Literature review

Since the emergence of the basic VaR analysis by J.P. Morgan to estimate the potential financial market losses, two strands of literature have emerged and existed hitherto. The first strand has concentrated on the stock market volatility phenomenon to predict its possible risk (e.g., Chen and Chen, 2013; Aloui and Hamida, 2014; Su, 2015; Gong and Weng, 2016; Mabrouk, 2017; Mensi et al., 2017; Liu et al., 2018; Carvalho and Sáfadi, 2022; Chen et al., 2020; Yang and Xu, 2021). The second strand of literature has intended to evaluate the potential risk of stock prices taking into account its spillover or dependency effects in international financial markets such as crude oil, gas and interest rate (Aloui and Mabrouk, 2010; Degiannakis and Kiohos, 2014; Du and He, 2015; Zolfaghari and Sahabi, 2017; Li and Wei, 2018; Wen et al., 2019; Tiwari et al., 2020; Huynh et al., 2020; Yang et al., 2021).

The first strand of the literature has mostly applied the ARCH/GARCH class of models, in particular, long memory volatility GARCH (Chin et al., 2009; Aloui and Hamida, 2014; Balibey and Turkyilmaz, 2014; Su, 2015; Günay, 2017; Mabrouk, 2017; BenSaïda et al., 2018; Yang and Xu, 2021). Results of these studies displayed significant values of VaR and expected shortfall at 95% confidence level and higher. Moreover, they argued that the most accurate risk forecasts can be produced from the GARCHs that are modelled under student-*t* distribution due to fat-tail probability (Aloui and Mabrouk, 2010). Critical stock market losses have also been computed using more advanced techniques (Chen and Chen, 2013; Gong and Weng, 2016; Mensi et al., 2017; Liu et al., 2018; Carvalho and Sáfadi, 2022; Chen et al., 2020). For example, Mensi et al. (2017) estimated their analysis of selected stock markets using a wavelet-based VaR estimation. Liu et al. (2018) employed a heterogeneous autoregressive quantity (HARQ) model to forecast the VaR of the Chinese stock market. They also compared the VaR estimation accuracy of in-sample with out-of-sample data. In the same vein, Chen et al. (2020) applied regime-switching and mean-reverting volatility frameworks to compute the VaR of the Taiwan stock market. They argued that using regime-switching techniques for the most volatile equities produces the best performance of VaR.

Few studies have also considered estimating the VaR for international commodity prices such as (Cabedo and Moya, 2003; So and Yu, 2006; Tabak and Cajueiro, 2007; Bali and Theodossiou, 2007; Youssef et al., 2015; Yang and Hamori, 2020). Cabedo and Moya (2003) and Tabak and Cajueiro (2007) computed a VaR for crude oil markets using an ARMA and the Hurst exponent methods respectively. While So and Yu (2006), Bali and Theodossiou (2007) and Youssef et al. (2015) employed long-memory GARCH models for VaR estimation of various energy commodities. Recently, Yang and Hamori (2020) forecasted the VaR and expected shortfall in crude oil prices. They obtained contrasting results based on the GARCH and rolling-window approaches.

Aloui and Mabrouk (2010) have considered international financial markets spillovers while evaluating a VaR and expected shortfall analysis. They computed the VaR of crude oil prices considering its spillover on gas prices. Similarly, Du and He (2015); Li and Wei (2018) and Wen et al. (2019) defined the role of spillover and dependence effects between oil and stock markets for the VaR investigation. Unlike Wen et al. (2019) who used a vector autoregressive (VAR) model to capture oil spillover impacts for VaR of the US stock market, Degiannakis and Kiohos (2014) exploited a multivariate modelling method to forecast VaR given a direct correlation between real estate and stock prices for seven developed countries. Du and He (2015) and Li and Wei (2018) estimated the dependence structure among crude oil and China stock market to obtain more accurate VaR.

The above-mentioned studies thus clearly highlight the absence of the VaR and expected shortfall analysis for the conventional energy

[3] See Lee et al. (2021a) for geopolitical risks and energy markets.

[4] This comes in line with several works that indicated that financial time series are often not normally distributed (e.g., Bali and Theodossiou, 2007; Youssef et al., 2015; Yang and Hamori, 2020).

sectors, particularly for the largest oil exporters such as those in the GCC region. Furthermore, the analysis involving the spillover and dependence effects between markets is also absent in the context of the GCC countries. It is cogent to expect that the clean energy, oil and emission pricing that are crucial areas of debate under current global initiatives of tackling climate change, the same crucial factors can resultantly have implications for the energy sector stock in the oil-exporting countries like GCC.

3. Methodology and data

3.1. Methodology

We apply three long memory GARCH models: fractional integrated GARCH (FIGARCH), fractional integrated asymmetric power ARCH (FIAPARCH) and hyperbolic GARCH (HYGARCH) to compute one-day-ahead VaR and the expected shortfall of the three GCC energy sectors for both long and short trading positions. We include the global clean energy production, CO_2 emission and crude oil prices were used as explanatory variables to examine the spillover and interdependence effects.[5]

The three long memory time-varying volatility models have been used for two reasons: first, VaR alone is incapable to account for volatility clustering in stock market fluctuations. This limitation could confound loss predicting, especially during crises, as a result of ignoring serial dependence over time (Danielsson, 2011; Nguyen et al., 2019). Second, long memory volatility allows capturing the slow decay of the autocorrelation function in conditional variance. In other words, long memory volatility modelling enables the classification of conditional variance into short and infinite long memory (Alexander, 2008). This feature cannot be achieved by using the standard GARCH models. Therefore, the choice of three long memory time-varying volatility models is appropriate and overcomes these limitations.

3.1.1. The fractional integrated GARCH (FIGARCH) model

Baillie et al. (1996) have expanded the standard GARCH to the fractionally integrated GARCH model. They provide the FIGARCH model to analyse short and long memory in the conditional variance. The process of the FIGARCH(p,d,q) model can be given as:

$$\left[\varphi\left(L\right)(1-L)^{d}\right]\varepsilon_t^2=\omega+X_t+[1-\beta(L)](\varepsilon_t^2-\sigma_t^2) \tag{1}$$

Or

$$\sigma_t^2=\omega+X_t+\beta(L)\sigma_t^2+[1-\beta(L)]\varepsilon_t^2-\varphi(L)(1-L)^d\varepsilon_t^2 \tag{2}$$

$$=\omega[1-L]^{-1}+X_t+\lambda(L)\varepsilon_t^2$$

where ε_t is the error term at time t and $\sigma_t^2$is the conditional variance, (L) denotes the lag-operator and X_t is the set of exogenous variables. $(1-L)^d$ is the fractional differencing factor which ranges from zero to one; a short memory process can be captured when d = 0 and it shows a unit root process when d = 1. $\lambda(L)$ is an infinite summation that should be truncated.

3.1.2. The fractional integrated asymmetric power ARCH (FIAPARCH) model

Since the FIGARCH (p,d,q) model does not capture asymmetry and long memory features in the conditional variance, Tse (1998) has developed the FIAPARCH (p, d, q) to include the function $(|\varepsilon_t|-\gamma\varepsilon_t)^\delta$ of the asymmetric power autoregressive conditional heteroscedasticity (APARCH) mode. The FIAPARCH (p, d, q) has been introduced as below:

$$\sigma_t^\delta=\omega[1-\beta(L)]^{-1}+X_t+\left\{1-[1-\beta(L)]^{-1}\rho(L)(1-L)^d\right\}(|\varepsilon_t|-\gamma\varepsilon_t)^\delta \tag{3}$$

where δ, γ *and* λ are the model parameters and d is the long memory term, Tse (1998) gives some underlying concepts under the FIAPARCH process; (i) when $0<d<1$, it can be decided that the conditional variance includes long memory factor. It implies that impact of a shock, whether it is bad or good news, on the conditional variance decays at a hyperbolic rate; (ii) if the asymmetry term $\gamma>0$, negative shocks affect volatility asset's prices more than positive shocks and conversely; (iii) whereas $\gamma=0$ *and* $\delta=2$, the process of the FIAPARCH reduces to the FIGARCH (p, d, q) mode. Accordingly, it can be noticed that the FIAPARCH process surpasses the FIGARCH as it captures both asymmetry and long memory in the conditional variance.

3.1.3. The hyperbolic GARCH (HYGARCH) model

Davidson (2004) has discovered the HYGARCH model as an extension of FIGARCH. He argues that HYGARCH gives more veritable long-memory property as it takes into account the hyperbolical decaying weights on the squared past shocks. Aloui and Mabrouk (2010) stated that this model is efficient in presence of volatility clustering, long memory feature and leptokurtosis, but it discounts asymmetry in the return distribution. The HYGARCH model can be defined as:

$$\sigma_t^\delta=\omega[1-\beta(L)]^{-1}+X_t+\left\{1-\left[1-\beta(L)\right]^{-1}\rho(L)\left[1+\alpha\left\{(1-L)^d\right\}\right]\right\}\varepsilon_t^2 \tag{4}$$

where ε_t^2 is the squared error term at time t with mean 0 and variance 1, $\alpha\geq 0$ and denotes weight parameters in the process.

3.1.4. Computing one step ahead VaR and expected shortfall

To forecast the maximum potential losses of the three GCC energy markets over a certain horizon (h) and according to a confidence level (1- α), we compute VaR and expected shortfall using FIGARCH, FIAPARCH and HYGARCH under student t- innovation distribution.[6] Given this framework, one can define the long and short trading positions as follows:

$$VaR_{long,t}=\widehat{\mu}_t+skst_\alpha(v,k)\widehat{\sigma}_t \tag{5}$$

$$VaR_{short,t}=\widehat{\mu}_t+skst_{1-\alpha}(v,k)\widehat{\sigma}_t \tag{6}$$

where $skst_\alpha(v,k)$ denotes the left quantile at the α% of the Student-*t* distribution, $skst_{1-\alpha}(v,k)$ is the right quantile. The conditional mean and conditional variance symbolised by $\widehat{\mu}_t$ and $\widehat{\sigma}_t$ respectively. Artzner et al. (1999) developed an expected shortfall to forecast the losses that might exceed the value of the VaR computed based on its confidence level, defined as:

$$ES_\alpha(X)=E\{X|X\geq VaR_\alpha(X)\} \tag{7}$$

3.1.5. Back-testing VaR

The VaR values accuracy has been statistically tested using the Kupiec (1995)'s test (also known as the unconditional coverage test). It relies on a likelihood ratio test (LR_{UC}). Consider a sample size of T observations and a number of exceptions of $N=\sum_{t=1}^{T}H_t$. Thus, the aim of the test is to discover whether $\widehat{P}\equiv N/T$ is statistically equal to τ*:

$$H_0:p=E(H_t)=\tau^* \ (5.8)$$

Following a binomial distribution, the null hypothesis of an accurate

[5] The heterogeneous effects of energy commodities prices on stock market are discussed in several contributions (e.g., Johnson and Soenen, 2009; Cevik et al., 2020; Muritala et al., 2020).

[6] Many studies such as Aloui and Mabrouk (2010) and Mabrouk (2017) point out that data for equity returns mostly point out fat-tail probability and Student-t return's innovation distribution is more appropriate to consider its statistical features.

VaR can be rejected if the actual fraction of VaR exceptions is statistically different than τ^*.

3.2. Data and preliminary statistics

We used daily log-differenced data from January 02, 2013, to March 20, 2019. The time horizon of the study is based on the availability of the data at the time of analysis. 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.[7] 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) which 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 log returns of the six variables.

We observe that CO_2 emission price to be the most volatile which indicates the price instability of the carbon market and the challenges associated with carbon pricing. Clean energy production, CO_2 emission price and Saudi petrochemical index are negatively skewed and oil price, Abu Dhabi energy index and Kuwait energy index are positively skewed. Further, fat tails are present in all six series, as evidenced by the statistically significant excess kurtosis values. To confirm the possibility that the presence of skewness and fat tails might point towards volatility in the market, we (i) use Engle's (1982) ARCH-LM test to analyse potential volatility clustering and (ii) employ the Ljung and Box, 1978 test on the squared standardised residuals to test for possible autocorrelation. The LM ARCH test indicates that the null hypothesis of volatility clustering is rejected for all the series up to lag 10, showing conclusive evidence of volatility clustering across all the series. Similarly, the Ljung-Box test result confirms the presence of autocorrelation in all the series. Following Kang and Yoon (2013), we also test the long memory property of the unconditional returns and unconditional volatility as shown in Table 2 using Lo(1991)'s modified R/S statistic, and two semiparametric estimates of Hurst coefficient, i.e., Long periodogram (GPH) estimate of Gewke-Poter-Hudak(1983) and Gaussian semiparametric (GSP) estimate of Robinson and Henry(1999).

From the results, we see that the presence of long memory in the unconditional return series is refuted for SPI, AEI and KEI for almost all the rests except for SPI (GSP estimate), where we find evidence of long memory. However, we find conclusive evidence of long memory for all three series in the absolute return series. We find that the long memory parameter is significant at 1% for all the series across all the three statistics estimated. Similarly, we find the conclusive presence of long memory in the squared returns as well. From these results, we can confirm the presence of long memory in unconditional volatility.

3.2.1. Unit root test

Table 3 shows the results of the augmented Dickey-Fuller GLS test (Elliott et al. (1996)) and Phillips-Perron unit root tests applied to the log of the six-time series. The unit-roots tests clearly show that all the six-time series are stationary at the first difference.

3.2.2. Fat-tailed distribution

Following Daniel and Wood (1980), we apply various diagnostic tests. In Fig. 1, we analyse the quantile-quantile (Q-Q) plots to examine the distributional property of the six series. It can be noticed that all the Q-Q plots diverge from the straight line at both ends implying that our time series follows a fat-tailed distribution. This comes in line with several works that indicated that financial time series are often not normally distributed (e.g., Bali and Theodossiou, 2007; Youssef et al., 2015; Yang and Hamori, 2020).

Fig. 2 shows the normal probability plots of all the daily returns. The actual distributions of the six series greatly differ from their hypothesised normal distribution. In other words, we have clear evidence of positive Kurtosis and all the series are found to be Leptokurtic. This finding justifies our use of the three GARCH models under the assumption of Student-t innovation's distributions.

4. Results

4.1. The three GARCH-type models results

The results of the FIAPARCH, FIGARCH and HYGARCH models for the three GCC energy sectors are displayed in Tables 4, 5 and 6. As it shows, the long-range memory, ARCH, GARCH, asymmetry and asymmetric response phenomena are statistically significant whereas the exogenous regressors (global clean energy production, crude oil and CO_2 emission prices) are statistically insignificant. Estimation results of the FIAPARCH model for the three GCC energy markets are presented in Table 4. The long memory parameter (d) of the Saudi petrochemical index rejects the GARCH null hypothesis at a 1% significance level, implying long memory in conditional volatility implying high volatility episodes would be followed by high volatility episodes and vice versa. The long memory parameter value of the Abu Dhabi energy index is >0.5, but significant, implying anti-persistence this shows a period of high volatility would be followed by a period of low volatility and vice versa. However, the long memory parameter of the Kuwait energy index is insignificant, implying the absence of long memory in conditional volatility. The ARCH (α) and GARCH (β) effects are found to be statistically significant at a 1% level for all the indexes.[8] The asymmetric response of volatility to news (γ) is positive and statistically significant at a 1% level for the Saudi and Abu Dhabi energy indexes. It signifies that unexpected bad news causes higher volatility in these two stocks compared to the good news, whereas the asymmetric parameter for the Kuwait model is found negative indicating the leverage effect. The power parameters (δ) are significant for the three models, implying that the functional form of the GARCH equations is not quadratic. The goodness of fit test of the Ljung-Box with 10 lags rejects the null hypothesis and this indicates the absence of serial correlation in the estimated residuals within the variables. Thus, it can be concluded that the estimated models can capture the volatility dynamics.

Estimation results of the FIGARCH (1,1) models for the three GCC markets are shown in Table 5. The long memory parameters (d) are found to be more persistent compared to the FIAPARCH models. This implies the persistence of long memory in conditional volatilities of the three energy indexes. In simple words, it indicates that a high volatility period will be followed by a high volatility period and vice versa. Both ARCH (α) and GARCH (β) effects are statistically significant, but the ARCH effects are more persistent compared to the FIAPARCH models. The three models are able to capture the volatility dynamics as per the post estimation diagnostic test results.

The results of the HYGARCH models for the three GCC energy sectors are presented in Table 6. Manifestation of long memory in volatility and anti-persistent behaviour in conditional volatility is explicit in the three markets as shown by the p-values of (d) parameters. ARCH (α) effects are insignificant for the Abu Dubai and Kuwait markets, but the GARCH (β) effects are found to be highly significant for all markets. The hyperbolic coefficients Log ($\hat{\alpha}$) HY are not statistically significant for all markets

[7] It comprises a diverse mix of companies that use environment-friendly processes to produce clean energy.

[8] Except the ARCH effects of Abu Dhabi energy markets analysis which was statistically found significant at a 1% level.

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 $Var(yt|H_{t-1}) = Var(\varepsilon t|H_{t-1}) = E(\varepsilon_t^2|H_{t-1}) = \sigma_t^2$ where the Ljung-Box test is defined as $Q = n(n+2)\sum_{k=1}^{h}\frac{\rho_k^2}{n-k}$. Numbers in parenthesis denote the p-value associated with each of the reported statistics.

Table 2
Long memory in the unconditional returns and unconditional volatility.

Returns	Statistic	SPI	AEI	KEI
	Lo's R/S statistic	1.53507	1.27157	1.37049
	GPH	0.0270681	−0.0195204	−0.0263519
	GSP	0.0365713**	−0.00793387	−0.0307581
Absolute Returns	Lo's R/S statistic	4.74906***	3.89316***	2.87233***
	GPH	0.267917***	0.236043***	0.201311***
	GSP	0.279124***	0.245078***	0.2293***
Squared Returns	Lo's R/S statistic	3.42547***	3.34533***	2.85075***
	GPH	0.10784	0.0999626**	0.148808
	GSP	0.270854***	0.187***	0.188777***

*** significance at 1% level, ** significance at 5% level. The critical values Lo's R/S statistics test are 90%: [0.861, 1.747], 95%: [0.809, 1.862] and 99%: [0.721, 2.098].

indicating that the GARCH elements are covariance stationary. The post estimation diagnostic test shows that the models capture the volatility dynamics.

4.2. Performance assessment of the three GARCH-type models

To choose the best models for the value at risk (VaR) analysis, we use three key forecast measures namely Root Mean Square Error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). These measures are conducted over an in-sample window of length 5. The three criteria are defined as:

$$RMSE = \sqrt{\frac{\Sigma_{t=1}^{t=N}(X - X_F)^2}{N}}; MAE = \frac{\Sigma_{t=1}^{t=N}|X_F - X|}{N} \ and\ MAPE = \frac{100}{N}\Sigma_{t=1}^{t=N}|\frac{X - X_F}{X}|$$

where N is the total number of observations; X is the actual value and X_F the forecasted value. The results are shown in Table 7.

Table 3
Unit root tests.

Variables	DF-GLS test		PP test	
	Level	First dif.	Level	First dif.
CE	−0.417910	−2.858014***	−2.640044*	−32.14744***
OP	−0.111376	−10.08350***	−1.645372	−42.90586***
EP	0.403696	−3.186813***	0.646400	−48.26537***
SPI	−0.998246	−6.033719***	−1.264757	−36.05854***
AEI	−1.718527	−41.29152***	−1.706390	−41.27211***
KEI	−1.108942	−40.19248***	−1.307199	−41.45450***

Note: The null hypothesis for the DF-GLS and PP tests is the existence of a unit root. *, ** and *** denote the significant level at 1%, 5% and 10% levels, respectively.

In the case of the Abu Dhabi Energy Index (AEI), the HYGARCH is the best-fitted model according to all three criteria. Similarly, for the Kuwait energy sector (KEI), the FIAPARCH outperforms the other two models. Conflicting evidence was obtained for the Saudi petrochemical sector (SPI): the FIGARCH outperforms other models based on RMSE criteria while FIAPARCH is the best as per the MAE and the MAPE criteria.

4.2.1. Forecasting one-day-ahead VaR and the expected shortfalls

Table 8 exhibits the VaRs and the expected shortfalls for the FIAPARCH models of the three GCC energy sectors. The null hypothesis of a correct specification is rejected when the p-values of the Kupiec's (1995) back-testing VaR lie between 95% and 99% confidence levels. The Kupiec test is employed to see whether the number of observed violations is significantly different from the number of expected violations for the sample under study. The test statistic follows a χ^2 distribution with 1 degree of freedom.

Table 9 shows that the estimated VaRs for the FIGARCH models are less robust relative to other models because the null is rejected in five positions across the different GCC stocks. For the short trading position, the null hypothesis of the correct specification at 99.5% and 99.8% failure rate is rejected for the Saudi and Kuwait models respectively. For the long trading position, the null hypothesis of the correct specification is rejected at two quantiles in the case of Saudi and one for Abu Dhabi energy indexes. The null of the correct specification is not rejected for any other quantiles. Therefore, it can be decided that the VaRs and the expected shortfalls are mostly computed and the FIGARCHs are valid in predicting the critical losses in the GCC energy indices.

Empirical findings of the VaRs and expected shortfalls for the HYGARCH models are reported in Table 10. It can be noticed that the null hypothesis of correct specification in all quantiles of the three indexes for both short and long positions is not rejected, excluding the

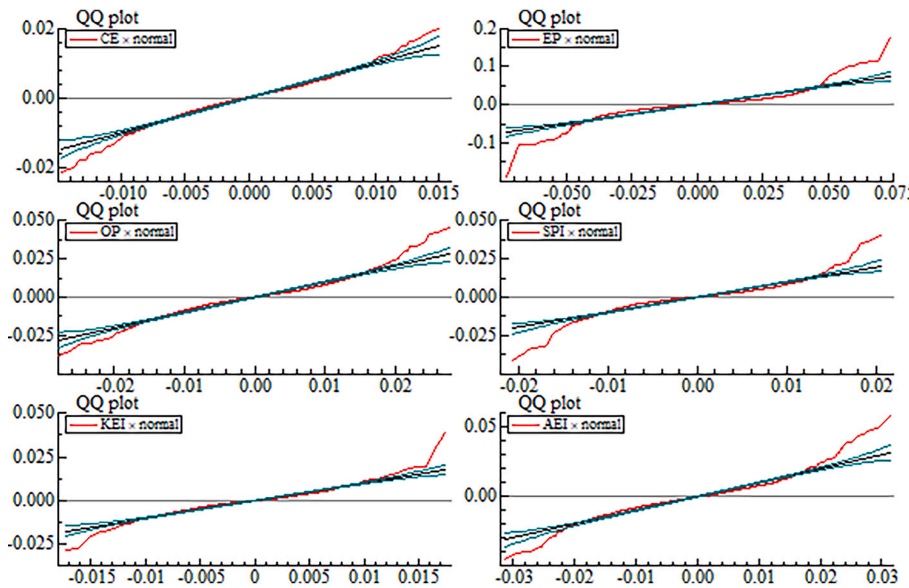

Fig. 1. Normal Q-Q plots for the time series daily returns.

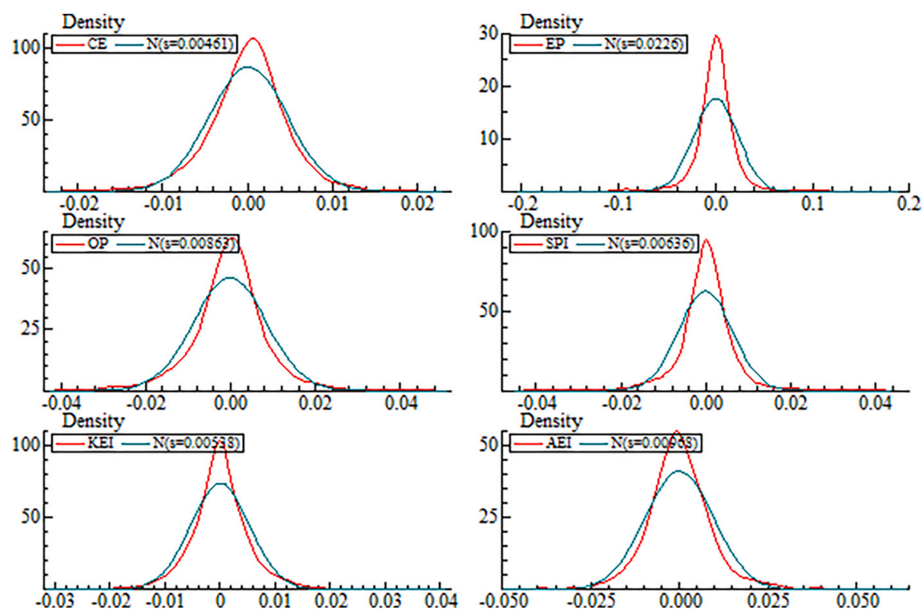

Fig. 2. Normal probability plots.

99% and 99.5% short trading position quantiles of Saudi and Kuwait indexes respectively. Therefore, the HYGARCH models are able to estimate the critical losses for the GCC energy indexes in different trading positions.

The Kupiec test statistic shows that the number of observed violations are not significantly different from the expected violations for both the Abu Dhabi energy index and Kuwait index for both long and short positions for the FIAPARCH model. For the Saudi petrochemical index, the number of observed violations are significantly different from the expected violations for the short position at 99%. For the FIGARCH model, we find that the number of observed violations are significantly different from the expected violations for the Saudi petrochemical index for both short and long positions. For the Kuwait index, we find that the number of observed violations is significantly different from the expected violations for the shot positions at 99.5%. Similarly, for the long positions, we find a significant difference of 2.5% for the Saudi index and 0.5% for the Abu Dhabi energy index. For the HYGARCH model, the number of observed violations is significantly different from the expected violations for the short position at 99% for SPI and 99.5% for Kuwait Oil & Gas index. For the long positions, the HYGARCH model correctly predicts the expected number of violations.

Overall, we can conclude that the HYGARCH model is the best VaR predictor across all quantiles for the Abu Dubai energy index, wherein the null hypothesis is not rejected at any quantile for both short and long positions. Whilst the VaR based on FIAPARCH is the best for Kuwait and Saudi energy sectors. This conclusion comes in compliance with the results of the RMSE and MAE criteria displayed in Table 7.

Tables 11, 12 and 13 show the Dynamic Quantile Test of Engle and Manganelli (DQ). The DQ is employed to test the performance of the VaR models by estimating their failure rate, i.e. the number of times the return on a specific day exceeds the forecasted VaR. Here, we estimate the VaR for both the short positions (90%,95%,99%,99.5% and 99.75%) and for the long positions (5%,2.5%,1%, 0.5% and 0.25%). For the FIGARCH models, we see that the DQ test rejects the model for Abu

Table 4
FIAPARCH (1,1) results.

	Saudi petrochemical index		Abu Dhabi energy index		Kuwait Oil & Gas index	
Parameters	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Cst (M)	0.000131	0.206	−0.00026	0.091	0.000005	0.961
CE (M)	0.002126	0.921	0.039179	0.269	0.044471	0.057
OP (M)	0.017685	0.228	−0.0226	0.304	0.008813	0.439
EP (M)	−0.00208	0.503	−0.002	0.747	−0.00171	0.698
AR (1)	0.083778	0.002	−0.10365	0.000	−0.03357	0.205
Cst (V)	6.932519	0.523	140.2714	0.467	26.70621	0.673
d-fiaparch	0.417008	0.000	0.677077	0.000	0.13722	0.139
ARCH (α)	0.393229	0.001	0.194737	0.032	0.042112	0.000
GARCH (β)	0.627057	0.000	0.678309	0.000	0.899913	0.000
APARCH (γ)	0.375109	0.001	0.249576	0.002	−0.13648	0.297
APARCH (δ)	1.666201	0.000	1.364884	0.000	1.409255	0.005
Student (*df*)	4.191607	0.000	4.529636	0.000	3.918731	0.000
Q (10)	1.62068	0.995	8.11879	0.421	7.9013	0.443

Note: Q (10) is the Box-Pierce Q- statistics with 10 lags.

Dhabi stock for the short positions at 97.5% and 99.5%, while fails to reject it for the long positions. For the FIAPARCH models, the DQ test rejects the model for the short position at 99% for the Saudi petrochemical index and rejects the model for the short position at 97.5%, 99% and 99.5% for the Abu Dhabi index. For the long positions, the FIAPARCH model also is found to be adequate. For the HYGARCH models, we see that the model is not rejected except for the Saudi market at 99.5% for the short positions, and the model adequately explains the long positions for all three markets.

From the results, we see that all the three models for the three markets are adequate in forecasting VaR for the long positions. However, for the short positions, both the FIGARCH and FIAPARCH are found to be inadequate for Saudi and Abu Dhabi indexes to predict value at risk for extreme fluctuations. In this regard, we find HYGARCH to be marginally better to provide better VaR forecasts.

5. Conclusion

One of the most important and pressing issues of the contemporary world is tackling climate change. The environmental challenges are

Table 7
Forecasting comparison of the estimated models.

Variables (Energy Index)	FIAPARCH		
	RMSE	MAE	MAPE
SPI	2.318e-005	2.056e-005	0.651
AEI	5.305e-005	4.734e-005	1.644
KEI	2.192e-005	2.185e-005	0.984
	FIGARCH		
	RMSE	MAE	MAPE
SPI	2.308e-005	2.067e-005	0.672
AEI	4.643e-005	3.846e-005	1.431
KEI	2.516e-005	2.49e-005	0.985
	HYGARCH		
	RMSE	MAE	MAPE
SPI	2.869e-005	2.652e-005	0.689
AEI	4.327e-005	3.495e-005	1.337
KEI	2.335e-005	2.321e-005	0.984

Table 5
FIGARCH (1,1) results.

	Saudi petrochemical index		Abu Dhabi energy index		Kuwait Oil & Gas index	
Parameters	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Cst (M)	0.000203	0.048	−0.00015	0.3245	−1.6E-05	0.869
CE (M)	0.004923	0.821	0.040013	0.2725	0.038699	0.091
OP (M)	0.01841	0.209	−0.02062	0.3588	0.008017	0.478
EP (M)	−0.00229	0.492	−0.00132	0.852	−0.00096	0.821
AR (1)	0.084015	0.002	−0.10868	0.000	−0.03548	0.171
Cst (V)	12.74064	0.001	6.456213	0.0109	162.5567	0.000
d-figarch	0.323217	0.000	0.547671	0.0168	0.433906	0.000
ARCH (α)	0.426922	0.000	0.233132	0.0424	0.083866	0.000
GARCH (β)	0.587193	0.000	0.558649	0.0026	0.807037	0.000
Student (*df*)	4.514395	0.000	4.148904	0.000	3.286868	0.000
Q (10)	0.772683	0.995	5.84207	0.664	8.94996	0.338

Note: Q (10) is the Box-Pierce Q- statistics with 10 lags.

Table 6
HYGARCH (1,1) results.

	Saudi petrochemical Index		Abu Dhabi energy index		Kuwait Oil & Gas index	
Parameters	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Cst (M)	0.000202	0.044	−0.00015	0.315	−1.5E-05	0.884
CE (M)	0.004889	0.819	0.039318	0.280	0.040063	0.077
OP (M)	0.017991	0.213	−0.02032	0.368	0.008316	0.469
EP (M)	−0.00228	0.468	−0.00149	0.832	−0.00175	0.696
AR (1)	0.082042	0.001	−0.10856	0.000	−0.03246	0.221
Cst (V)	0.341424	0.638	7.876892	0.007	6.32502	0.051
d-hygarch	0.421396	0.002	0.701595	0.001	0.469111	0.173
ARCH (α)	0.390738	0.001	0.176118	0.149	0.329644	0.117
GARCH (β)	0.622428	0.000	0.632138	0.000	0.487041	0.014
Student (*df*)	3.78255	0.000	4.374508	0.000	3.901158	0.000
Log ($\hat{\alpha}$)HY	0.081825	0.378	−0.07031	0.194	−0.26592	0.146
Q (10)	1.10976	0.921	5.65773	0.660	8.47149	0.388

Note: Q (10) is the Box-Pierce Q- statistics with 10 lags.

Table 8
VaR results of FIAPARCH.

	Short trading position					Long trading position				
	Quantile	Failure rate	Kupiec LRT	p-value	ESF	Quantile	Failure rate	Kupiec LRT	p-value	ESF
Saudi petrochemical index	0.9500	0.9509	0.0296	0.8634	0.0126	0.0500	0.0571	1.6565	0.1981	−0.0135
	0.9750	0.9795	1.4257	0.2325	0.0150	0.0250	0.0280	0.5541	0.4566	−0.0171
	0.9900	0.9950	5.0510	0.0246	0.0193	0.0100	0.0124	0.8861	0.3465	−0.0206
	0.9950	0.9963	0.5757	0.4480	0.0209	0.0050	0.0081	2.5765	0.1085	−0.0234
	0.9975	0.9975	0.0002	0.9900	0.0234	0.0025	0.0031	0.2197	0.6393	−0.0279
Abu Dhabi energy index	0.9500	0.9398	3.3507	0.0672	0.0117	0.0500	0.0559	1.1386	0.2860	−0.0115
	0.9750	0.9733	0.1886	0.6641	0.0138	0.0250	0.0242	0.0402	0.8410	−0.0137
	0.9900	0.9907	0.0777	0.7805	0.0172	0.0100	0.0068	1.8360	0.1754	−0.0192
	0.9950	0.9975	2.5152	0.1128	0.0225	0.0050	0.0031	1.3435	0.2464	−0.0232
	0.9975	0.9988	1.2550	0.2626	0.0284	0.0025	0.0012	1.2550	0.2626	−0.0234
Kuwait Oil & Gas index	0.9500	0.9398	3.3507	0.0672	0.0117	0.0500	0.0559	1.1386	0.2860	−0.0115
	0.9750	0.9733	0.1886	0.6641	0.0138	0.0250	0.0242	0.0402	0.8410	−0.0137
	0.9900	0.9907	0.0777	0.7805	0.0172	0.0100	0.0068	1.8360	0.1754	−0.0192
	0.9950	0.9975	2.5152	0.1128	0.0225	0.0050	0.0031	1.3435	0.2464	−0.0232
	0.9975	0.9988	1.2550	0.2626	0.0284	0.0025	0.0012	1.2550	0.2626	−0.0234

Note: Kupiec LRT denotes the Kupiec's (1995) Back-testing VaR and ESF are the expected shortfall values.

Table 9
VaR results of FIGARCH.

	Short trading position					Long trading position				
	Quantile	Failure rate	Kupiec LRT	p-value	ESF	Quantile	Failure rate	Kupiec LRT	p-value	ESF
Saudi petrochemical index	0.9500	0.9522	0.1624	0.6869	0.0125	0.0500	0.0602	3.3507	0.0672	−0.0137
	0.9750	0.9776	0.4769	0.4898	0.0154	0.0250	0.0342	4.9836	0.0256	−0.0166
	0.9900	0.9957	6.5911	0.0102	0.0195	0.0100	0.0149	3.4025	0.0651	−0.0211
	0.9950	0.9969	1.3435	0.2464	0.0229	0.0050	0.0081	2.5765	0.1085	−0.0240
	0.9975	0.9969	0.2197	0.6393	0.0229	0.0025	0.0068	8.1985	0.0042	−0.0252
Abu Dhabi energy index	0.9500	0.9503	0.0033	0.9544	0.0224	0.0500	0.0497	0.0033	0.9544	−0.0198
	0.9750	0.9727	0.3480	0.5553	0.0268	0.0250	0.0230	0.2765	0.5990	−0.0247
	0.9900	0.9913	0.2894	0.5906	0.0331	0.0100	0.0068	1.8360	0.1754	−0.0304
	0.9950	0.9932	0.9744	0.3236	0.0362	0.0050	0.0019	4.1935	0.0406	−0.0350
	0.9975	0.9981	0.2872	0.5920	0.0451	0.0025	0.0006	3.2706	0.0705	−0.0281
Kuwait Oil & Gas index	0.9500	0.9491	0.0293	0.8642	0.0118	0.0500	0.0559	1.1386	0.2860	−0.0112
	0.9750	0.9776	0.4769	0.4898	0.0141	0.0250	0.0211	1.0499	0.3055	−0.0143
	0.9900	0.9932	1.8360	0.1754	0.0173	0.0100	0.0068	1.8360	0.1754	−0.0183
	0.9950	0.9988	6.5527	0.0105	0.0284	0.0050	0.0025	2.5152	0.1128	−0.0221
	0.9975	0.9994	3.2706	0.0705	0.0384	0.0025	0.0006	3.2706	0.0705	−0.0190

Note: Kupiec LRT denotes the Kupiec's (1995) Back-testing VaR and ESF are the expected shortfall values.

Table 10
VaR results of HYGARCH.

	Short trading position					Long trading position				
	Quantile	Failure rate	Kupiec LRT	p-value	ESF	Quantile	Failure rate	Kupiec LRT	p-value	ESF
Saudi petrochemical index	0.9500	0.9565	1.5052	0.2199	0.0128	0.0500	0.0540	0.5389	0.4629	−0.0141
	0.9750	0.9814	2.9320	0.0868	0.0160	0.0250	0.0286	0.8060	0.3693	−0.0171
	0.9900	0.9957	6.5911	0.0102	0.0195	0.0100	0.0118	0.4988	0.4800	−0.0216
	0.9950	0.9969	1.3435	0.2464	0.0229	0.0050	0.0075	1.6914	0.1934	−0.0244
	0.9975	0.9975	0.0002	0.9900	0.0234	0.0025	0.0031	0.2197	0.6393	−0.0318
Abu Dhabi energy index	0.9500	0.9497	0.0033	0.9545	0.0223	0.0500	0.0497	0.0033	0.9544	−0.0198
	0.9750	0.9721	0.5541	0.4566	0.0267	0.0250	0.0248	0.0016	0.9681	−0.0241
	0.9900	0.9901	0.0006	0.9800	0.0323	0.0100	0.0099	0.0006	0.9800	−0.0290
	0.9950	0.9926	1.6914	0.1934	0.0354	0.0050	0.0043	0.1440	0.7043	−0.0358
	0.9975	0.9969	0.2197	0.6393	0.0402	0.0025	0.0006	3.2706	0.0705	−0.0281
Kuwait Oil & Gas index	0.9500	0.9391	3.7562	0.0526	0.0116	0.0500	0.0584	2.2666	0.1322	−0.0114
	0.9750	0.9739	0.0770	0.7815	0.0138	0.0250	0.0224	0.4769	0.4898	−0.0141
	0.9900	0.9919	0.6454	0.4218	0.0177	0.0100	0.0062	2.6986	0.1004	−0.0196
	0.9950	0.9981	4.1935	0.0406	0.0247	0.0050	0.0031	1.3435	0.2464	−0.0232
	0.9975	0.9988	1.2550	0.2626	0.0284	0.0025	0.0006	3.2706	0.0705	−0.0190

Note: Kupiec LRT denotes the Kupiec's (1995) Back-testing VaR and ESF are the expected shortfall values.

multifaced and complex, entailing trad-offs and the necessity to strike the right balance between economic, financial and environmental sustainability. While clean energy usage and putting the price on emissions are some of the most crucial policy instruments on hand, there are various unintended consequences of these instruments and policies for economies across the world. The volatile oil prices also add to the uncertainty with their implications for both oil-importing and exporting economies and their financial sectors. GCC countries with their fossil fuel-based economies, in particular, are the biggest stakeholders of the global move to clean energy usage, oil price dynamics and pricing of

Table 11
Dynamic Quantile Test of FIGARCH models.

Saudi petrochemical index			Abu Dhabi energy index			Kuwait Oil & Gas index		
Short positions								
Quantile	Stat.	*P*-value	Quantile	Stat.	P-value	Quantile	Stat.	P-value
0.95	2.5451	0.86339	0.95	4.1232	0.66	0.95	7.295	0.29442
0.975	4.7482	0.57649	0.975	12.319	0.055227	0.975	2.3695	0.88278
0.99	5.2643	0.51038	0.99	6.2634	0.39434	0.99	8.4641	0.20603
0.995	1.2109	0.97634	0.995	17.161	0.008711	0.995	3.1946	0.78406
0.9975	0.33528	0.99931	0.9975	0.050473	1	0.9975	2.2799	0.89224
Long positions								
Quantile	Stat.	P-value	Quantile	Stat.	*P*-value	Quantile	Stat.	P-value
0.05	3.5177	0.74161	0.05	4.3944	0.62347	0.05	8.1006	0.23083
0.025	2.822	0.83083	0.025	8.3033	0.21671	0.025	3.4178	0.75487
0.01	8.2774	0.21847	0.01	1.0511	0.9836	0.01	9.7012	0.13781
0.005	2.6457	0.85182	0.005	2.0731	0.91285	0.005	1.2109	0.97634
0.0025	2.4762	0.87112	0.0025	2.2799	0.89224	0.0025	2.2799	0.89224

Table 12
Dynamic Quantile Test of FIAPARCH models.

Saudi petrochemical index			Abu Dhabi energy index			Kuwait Oil & Gas index		
Short positions								
SPI	Short Positions		AEI	Short Positions		KEI	Short positions	
Quantile	Stat.	P-value	Quantile	Stat.	P-value	Quantile	Stat.	P-value
0.95	6.7521	0.34439	0.95	8.2688	0.21906	0.95	7.1194	0.30994
0.975	3.9864	0.67851	0.975	23.076	0.000771	0.975	2.4548	0.87349
0.99	15.874	0.014446	0.99	49.182	6.86E-09	0.99	5.195	0.51906
0.995	0.61044	0.99622	0.995	16.39	0.011809	0.995	3.1946	0.78406
0.9975	0.050473	1	0.9975	56.438	2.37E-10	0.9975	1.0276	0.98454
Long positions								
Quantile	Stat.	P-value	Quantile	Stat.	P-value	Quantile	Stat.	P-value
0.05	2.1763	0.9028	0.05	1.7142	0.94402	0.05	4.2358	0.6448
0.025	2.9116	0.81986	0.025	7.2598	0.29749	0.025	3.4178	0.75487
0.01	5.0271	0.54035	0.01	0.76848	0.99289	0.01	7.16	0.3063
0.005	2.6457	0.85182	0.005	4.5729	0.59963	0.005	1.2109	0.97634
0.0025	0.33528	0.99931	0.0025	2.2799	0.89224	0.0025	1.0276	0.98454

Table 13
Dynamic Quantile Test of HYGARCH models.

Saudi petrochemical index			Abu Dhabi energy index			Kuwait Oil & Gas index		
Short positions								
Quantile	Stat.	P-value	Quantile	Stat.	P-value	Quantile	Stat.	P-value
0.95	2.8931	0.82214	0.95	4.3304	0.63206	0.95	7.4809	0.27865
0.975	4.7482	0.57649	0.975	12.319	0.055227	0.975	1.7192	0.94363
0.99	5.2643	0.51038	0.99	8.915	0.17841	0.99	7.3094	0.29318
0.995	1.2109	0.97634	0.995	16.39	0.011809	0.995	3.1946	0.78406
0.9975	0.050473	1	0.9975	65.173	3.98E-12	0.9975	1.0276	0.98454
Long positions								
Quantile	Stat.	P-value	Quantile	Stat.	P-value	Quantile	Stat.	P-value
0.05	4.5666	0.60047	0.05	4.3934	0.6236	0.05	8.1006	0.23083
0.025	3.1765	0.78639	0.025	10.834	0.093643	0.025	3.684	0.71936
0.01	5.0716	0.53467	0.01	0.84369	0.99085	0.01	11.391	0.077006
0.005	2.6457	0.85182	0.005	0.27418	0.99961	0.005	1.2109	0.97634
0.0025	0.33528	0.99931	0.0025	2.2799	0.89224	0.0025	2.2799	0.89224

emissions. In this regard, we explored the implications of clean energy, oil and emissions prices for the energy sector of these economies. For this purpose, we estimated one-day-ahead VaR and the expected shortfall for Saudi, Abu Dhabi and Kuwait energy stock prices over short and long trading positions using three different long memory ARCH/GARCH models: FIAPARCH, FIGARCH and HYGARCH. In the GARCH framework, we employed the three global energy indexes: clean energy production, crude oil and CO_2 emission prices as exogenous regressors to consider their impacts on the GCC energy sector volatilities.

Our key findings lead us to conclude on the presence of asymmetry, fat-tails and long memory in the GCC energy sector stock price volatilities. Furthermore, we also conclude that the three underlying factors of interest i.e., clean energy, emissions pricing and oil prices do not play a significant role in the GCC energy sector's daily returns volatility. This is a crucial finding as it would imply that clean energy or pricing of emissions are instruments that can be used for tackling climate challenges without causing turmoil in the energy sector returns in the GCC region. In terms of empirical choice, we also conclude that the FIAPARCH produces the most accurate VaR and the expected shortfall for Saudi and Kuwait energy sectors, while HYGARCH performs better for the Abu Dhabi energy index.

Our findings also carry three important policy implications and lessons for future research: first, it is recommended to forecast more than one-day-ahead or five-day-ahead VaR and the expected shortfall for the three GCC energy stocks. Second, since clean energy, oil prices and emission prices are poor predictors of the GCC energy daily fluctuations, it would be interesting to see how they impact other major traditional energy sectors in different regions.[9] The statistical insignificance implies that clean energy and emission pricing do not have adverse consequences for energy stock. Concomitantly, the move to clean energy and pricing of emissions do not pose huge costs to the energy sector stock on these markets. Finally, our work levy useful insights for risk managers, investors and financial institutions to manage the level of potential losses in their portfolios in the three markets that we have studied in this paper.

CRediT authorship contribution statement

Mohammed A. Alkathery: Conceptualization, Methodology, Software, Writing – original draft, Data curation. **Kausik Chaudhuri:** Conceptualization, Methodology, Software, Formal analysis. **Muhammad Ali Nasir:** Resources, Writing – review & editing, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106119.

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