Climate change mitigation policies, energy transitions, oil prices and the stock market: evidence from the GCC stock market

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Intellectual Property Statement

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Abstract

In this thesis, we utilise the stock prices of three Gulf Cooperation Council (GCC) countries namely Saudi, United Arab Emirates (UAE) and Kuwait in four different empirical frameworks. First, we build on Killian's (2009) approach and use structural vector autoregression (SVAR) to estimate the response of the three GCC stock prices to oil price changes (shocks). In the same multivariate system, we consider the impact of the US stock prices, wherein the foreign ownership limits are supposed as an exogenous factor. Second, we employ three multivariate generalised autoregressive conditional heteroskedasticity (GARCH) models to estimate volatility spillover effects and co-movement among global clean energy production, crude oil price, CO_2 emission price and conventional energy equities in the same countries. Next, we develop a dependence structure using a multiscale approach of wavelets to investigate the response of each GCC conventional energy stock price to changes in global clean energy production, crude oil price and CO_2 emission price. Finally, one step ahead value-at-risk (VaR) and the expected shortfall (ES) for the three GCC energy stock prices have been quantified using three long memory ARCH/GARCH models: FIGARCH, FIAPARCH and HYGARCH. Where the three global energy indexes: global clean energy production, crude oil and CO_2 emission prices are used as regressors.

The first study confirms the significant impact of oil price shocks on the three GCC stock markets, but the impact differs based on the structural characteristics of each of the three GCC stock markets. The US stock market has negatively and symmetrically affected the GCC stock markets as a result of the monetary begging policies between the three countries and the US. The second research proves that the current volatilities in the three GCC energy stock markets are highly persistent and largely driven by past

endogenous shocks of the same market and partially by shocks of other markets. The third study postulates that the three global energy markets: global clean energy production, oil prices and CO_2 emission weakly and positively influence the GCC energy stock prices at lower frequencies (higher scales). Finally, the VaR and ES of the three GCC energy stock price indexes have been statistically quantified. This thesis helps policymakers, portfolio managers as well as scholars to understand the response of traditional energy sectors in oil-exporting countries to transformations in the global energy markets.

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List of Abbreviations

ADF	Augmented Dickey-Fuller
AGDCC	Asymmetric Generalised DCC
AIC	Akaike's information criterion
ARDL	Autoregressive distributed lag
BIC	Bayesian information criterion
CPI	Consumer Price Index
CMA	Capital Market Authority in Saudi Arabia
DCC	Dynamic conditional correlation
DF-GLS	The modified Dickey-Fuller test
DFM	Dubai Financial Market
EIA	Energy Information Agency
ES	The expected shortfall
EU ETS	European Union Emissions Trading System
EU	European Union
EUAs	European Union Allowances
FIAPARCH	Fractional integrated asymmetric power ARCH
FIGARCH	Fractional integrated GARCH
GARCH	Generalized autoregressive conditional heteroskedasticity
GCC	Gulf Cooperation Council Countries
GDP	Gross Domestic Product
GWP	Gross world product
HYGARCH	Hyperbolic GARCH

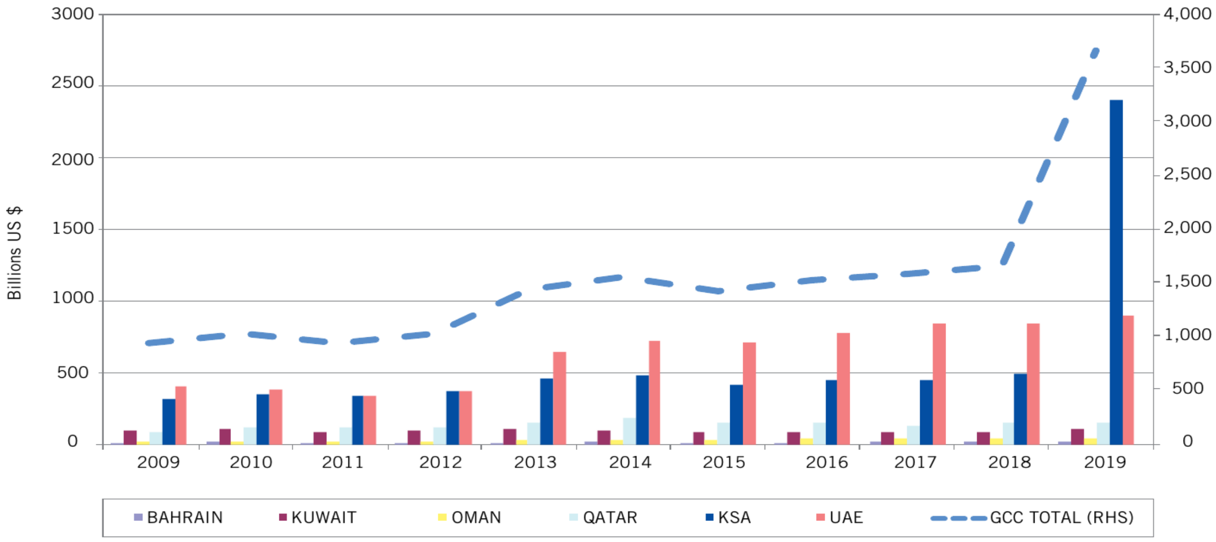
IMF	International Monetary Fund
IRF	Impulse Response Functions
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
MAE	Mean absolute error
MODWT	Maximal overlap discrete wavelet transforms
OECD	Organisation for Economic Co-operation and Development
OPEC	Organization of Petroleum Exporting Countries
PP	Phillips–Perron test
REN21	The Renewable Energy Policy Network for the 21st Century
RMSE	Root mean square error
SD	Standard Deviation
SVAR	Structural Vector Autoregressive Model
UK	United Kingdom
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
VaR	Value-at-risk
VAR	Vector Autoregressive Model
VECM	Vector error correction model
WC	Wavelet correlation
WCC	Wavelet cross-correlation

Chapter 1: Introduction

In the past decade, the Gulf Cooperation Council (GCC) countries: Saudi Arabia, United Arab Emirates (UAE), Qatar, Kuwait, Oman and Bahrain have achieved a boom in their stock market capitalisation.[1] Their capitalisation rates have increased by 8.2%, in the same decade, ranking these markets among the fastest-growing equity markets in the world (Marlene, 2021). The value of stock market capitalisation of the GCC countries in 2019 reached the highest level of $2327 billion for Saudi Arabia followed by the UAE, Qatar, Kuwait, Bahrain and Oman of values $923, $165, $109, $91, $24 and $16 billion respectively as shown in Figure 1.1. According to Abdullah (2020), the dramatic rise in the GCC market capitalisation was attributable to the high revenues of crude oil exports and government expenditure over the same period. Moreover, the GCC financial institutions have recently adopted new strategies for foreign investors' ownership. For example, the Saudi Arabian Capital Market Authority (CMA) has opened Saudi listed shares for foreign investors by 49% in 2018. Where the Dubai Financial Market (DFM) is committed to liberating most shares up to 100% from 2018 (PwC, 2021). The recent rapid developments in these markets led Morgan Stanley Capital International (MSCI) to upgrade the Qatar and UAE stock markets from the frontier to emerging markets in 2014; where the Saudi and Kuwait equities were elevated in 2019 and 2020 respectively.

1 The Gulf Cooperation Council (GCC) formed in 1981 and its headquarters is in Riyadh. The aim of the corporative council is to promote political, economic and scientific cooperation.

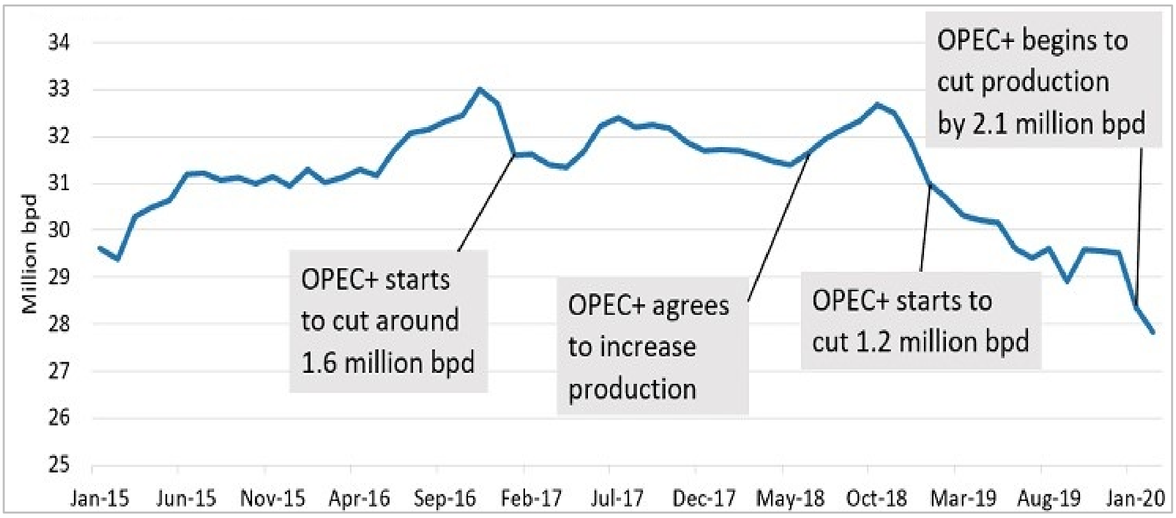
Figure 1.1: Stock market capitalisation of the GCC countries. 2009-2019



***Source**:* GCC Economic Statistics, 19th Edition, 2020 from Gulf Investment Corporation. **Note**: the values of the stock market capitalisation of each country calculated by US dollar as these countries use different currencies.

However, much of the literature since the mid-2000s emphasised that the stock markets in the Arabian Gulf still face serious challenges. Several prior studies reported that the response of the GCC stock markets to oil price collapse is strongly negative (e.g., Malik and Hammoudeh, 2007; Nusair and Al-Khasawneh, 2018; Alqahtani et al., 2019). During the 2008 global financial crisis, for example, when oil prices sharply dropped from $140 per barrel to $34.93, the GCC equities lost around 45% of its market capitalisation. These markets also dramatically fell in 2014 when oil prices plunged from $105 to $26.19 per barrel (Woertz, 2008). This is attributable to about three-fourths of the annual GCC countries' budgets that still rely on oil-exporting revenues. Giving the sensitivity of GCC economies, especially for those who are members of OPEC, to oil price collapse they often cut their oil production to prop up oil prices when it crashes. Figure 1.2 shows the OPEC oil-cut decisions that were announced over the past five years as responses to the recent oil price decreases.

Figure 1.2: OPEC crude oil supply reductions. 2015-2020

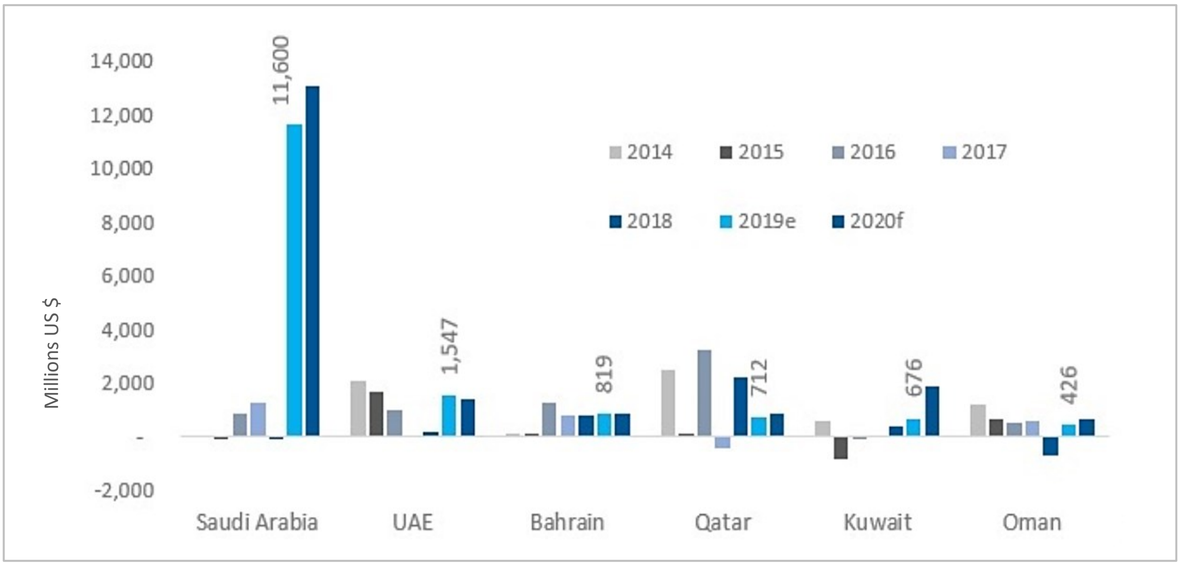


Source: The Organisation of the Petroleum Exporting Countries (OPEC**). Note:** bpd means barrels per day.

Some scholars stated that the six GCC equity markets still need more liberalisation for overseas investments (e.g., Sabri, 2018; Badawi et al., 2019). Although the GCC financial institutions recently lifted some of their foreign ownership restrictions, there is still wide room for further openness. Moreover, some of the GCC financial authorities impose further special restrictions. For example, Boursa Kuwait limits direct foreign investment rates in the banking and insurance sectors to 49%. Further, opening and liquating foreign investment portfolios in some countries require prior acceptance (Alharoun, 2021). Figure 1.3 displays the value of foreign institutional investments across the six equity markets. The total value of foreign investments into the markets were only around $10 million in 2014; where most of the investments were spread in Qatar and the UAE markets. However, from 2019 to 2020, the Saudi stock market was able to attract almost $12 million of foreign investments. This happened when the Saudi financial regulators partly opened the market for direct foreign investors by 49%

in 2018. In general, foreign investments rates in these markets are still relatively low compared to other emerging markets.

Figure 1.3: Net foreign institutional investments in the GCC stock markets. 2014-2020



Source: The Institute of International Finance (IIF). **Note:** the values of the net foreign institutional investments in each country calculated by US dollar as these countries use different currencies.

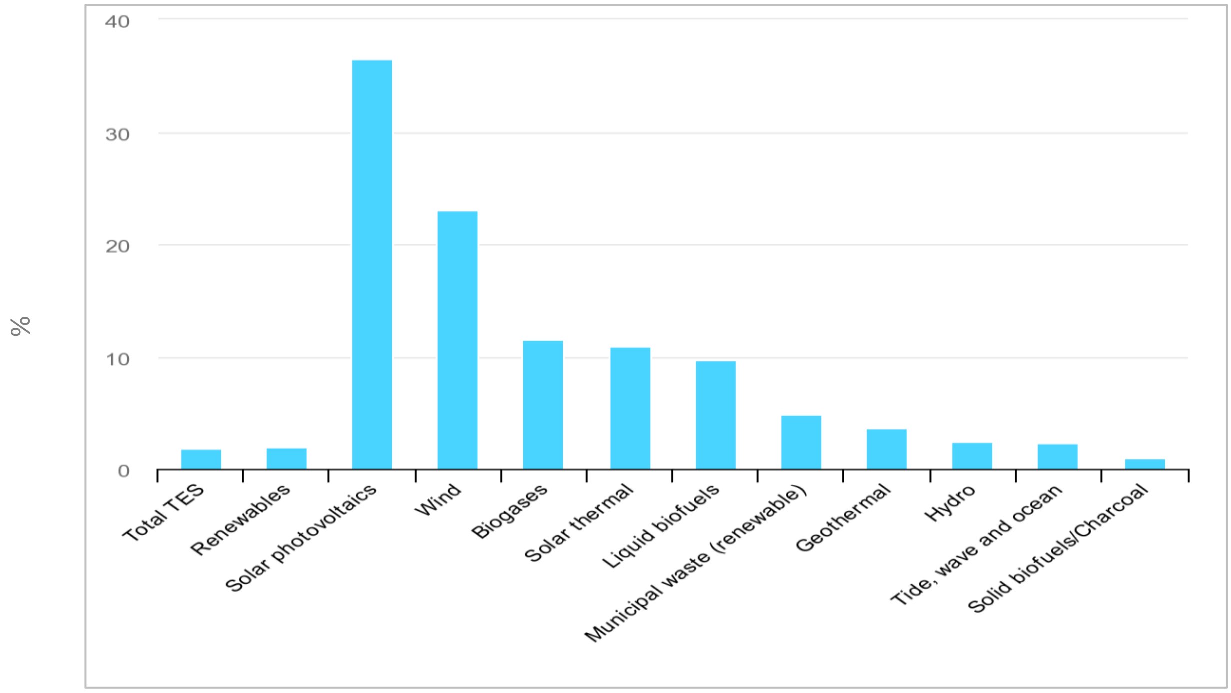
Some authors argued that GCC stock prices are increasingly sensitive to US stock market shocks (Malik and Hammoudeh, 2007; Balli et al., 2013; Alotaibi and Mishra, 2015). The influence of US stock market movements on the GCC equities markets is sound, given the pegged GCC-US exchange rate regimes and the crucial impacts of US equities on the global stock markets, in particular, after the global financial crisis in 2008 (Arouri et al., 2011; Kim and Hammoudeh, 2013; Sbia et al., 2016).[2] For instance,

[2] The Kuwaiti Dinar (KWD) is pegged to a basket of global key currencies, but the US dollar occupies the largest share.

as the US Federal Reserve increases interest rates, across the ocean and forthwith, the central banks of the GCC countries appreciate local interest rate, thus leading to a decline in the propensity of the GCC companies to borrow; hence higher cost of carrying on businesses as well as losses in profit margins.

Some reports drew attention to the potential impact of the recent rapid expansion in global renewable energy production on traditional energy sectors (Omri et al., 2015; Reboredo, 2015; Khan et al., 2017). Renewable energy production has undergone rapid developments in oil-importing countries. According to the Energy Information Administration (EIA) (2018), the US use of renewable energy has increased by 7% in 2017 and is expected to reach 37% by 2040. Furthermore, the Renewable Energy Policy Network for the 21st Century (REN21) (2018) reported that renewable energy sources contributed 18.1% to global energy consumption in 2017. The Energy Information Administration (EIA) (2019) announced that clean energy sources covered about 24% in China and expected to achieve nearly 40% in 2025. Regarding the GCC stock markets, the recent increases in clean energy production worldwide could carry serious implications on oil prices; leading to severe a decline in market returns and government revenues. Figure 1.4 illustrates the average yearly global growth of various clean energy types over the last ten years.

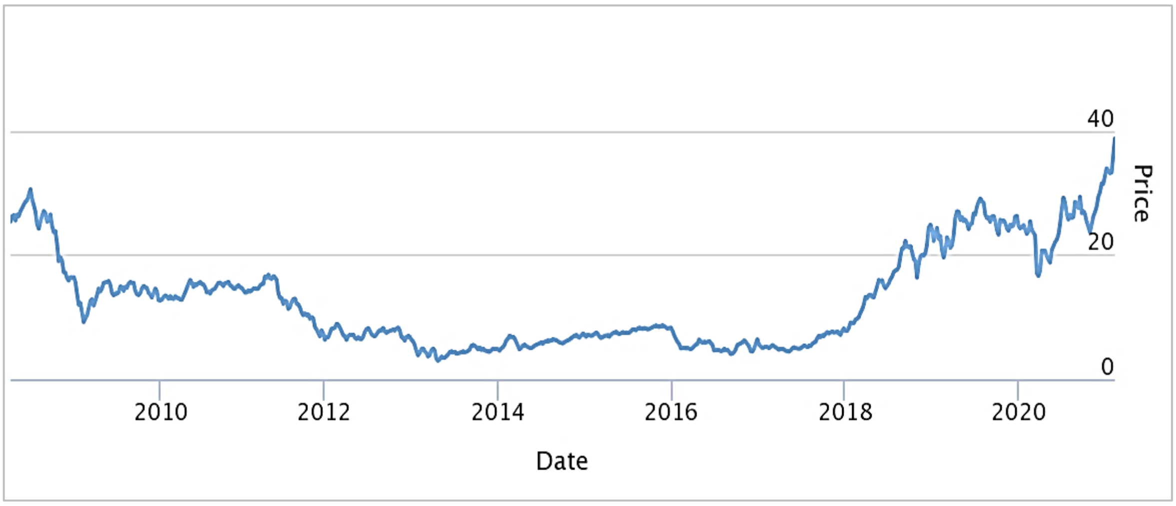
Figure 1.4: Average annual growth of global renewable energy sources. 2010-2020



***Source**:* The Energy Information Administration (EIA).

Booming in the clean energy industry is likely associated with the new implications of the emissions trading systems (ETS); which were recently imposed on the major industrial countries based on the Kyoto Protocol and the Paris agreement to combat climate change (Bauer et al. 2015). The strategic goal of setting up the ETS schemes is to encourage energy-intensive industries to use environmental-friendly energy sources (European Communities, 2008). The EU emissions trading system (EU ETS) is the world's first and largest greenhouse gas cap scheme which was established in 2005. It caps more than 11000 European energy-intensive installations and around 40% of the EU's carbon emissions (Galdi et al., 2021). It works based on the 'cap and trade rule'. Based on an annual cap of the total amount of emissions, EU companies are supposed to rationalise their CO_2 emissions accordingly. If the cap is outpaced, financial penalties will be enforced. Where if a factory consumes less than its annual limit, it can save the CO_2 allowances for future need or sell them to other factories which consume more than their limits. Thus, the EU ETS has created a market system so companies can buy/sell allowances (Eikeland and Skjærseth, 2019). Figure 1.5 shows the development of the emission price over the last ten years.

Figure 1.5: EU Emission allowances prices. 2010-2020



Source: The Markets Insider (2021).

1.1. Research questions posed in this thesis

In this thesis and over four chapters, we study the dynamic interactions between the GCC stock markets and global energy financial markets by posing and developing answers to four research questions.

In chapter 2, we examine the impact of oil price shocks, the US stock market and foreign investment regulations on the GCC stock market performance. This leads to our first research question:

Research Question 1: what is the impact of the structural oil price shocks and the US stock market on the stock markets of the largest GCC oil producers namely, Saudi Arabi, UAE and Kuwait while considering the various foreign ownership shares of these markets?

We attempt to answer this research question by utilising a structural vector autoregressive (SVAR) model based on monthly data from June 2002 to June 2019 for the 3 GCC countries. This analysis could provide more solid results for three main reasons. First, the impact of oil price movements on the GCC stock markets is estimated based on the alternative approach of Killian (2009); which analyse the underlying causes of oil price fluctuations by conducting a structural decomposition of the real price of crude oil. We also take into account the growing influence of the US stock market on GCC stock markets, especially after the 2008 global financial crisis (Arouri et al., 2011; Kim and Hammoudeh, 2013). Finally, while structuring our empirical models we consider the heterogeneous nature of the stock market regulations across the GCC countries.

The aim of chapter 3 is 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 GCC countries. The research question posed in Chapter 3, aimed at exploring these dynamics, is as follows:

Research Question 2: is the current volatility in the conventional energy stock prices of the three countries influenced by the past shocks of global clean energy production, oil and CO_2 emission prices? If yes, does the evidenced volatility exists over the short or the long term; and which country is the most sensitive to the three variables?

We attempt to answer this research question by using daily data over the period from January 02, 2013, to March 20, 2019, to run three multivariate GARCH frameworks: diagonal BEKK GARCH (1,1), asymmetric DCC GARCH (1,1) and copula DCC GARCH

(1,1) models for each country. This study could provide empirical evidence on the co-movements between the global clean energy production, the European Union Allowance (EUA) prices and the traditional energy sectors in the GCC countries. In addition, we could find that the impact of the EU Emissions Trading System also affects non-European countries such as those in the GCC region.

Chapter 4 analyses the response of each GCC energy stock price to changes in the three global energy indexes: global clean energy production, crude oil and CO_2 emission prices. The research question posed in Chapter 4 is this:

Research Question 3: do global clean energy production, CO_2 emission and oil price fluctuations influence the energy stock prices of Saudi, the UAE and Kuwait? To answer this research question we rely on the same dataset for chapter 3 developing a dependence structure of the multiscale approach of wavelet correlation (WC) and wavelet cross-correlation (WCC) for each of the GCC markets. We assume that the rapid surge in renewable energy sources, as well as emission trading schemes, could negatively affect oil price; thereby the GCC stock market performance.

In the last empirical chapter, we quantify one step ahead of value-at-risk (VaR) and the expected shortfall (ES) for the three GCC energy stock prices indexes. The research question posed in Chapter 5, aimed at exploring these financial risks, is as follows:

Research Question 4: what are the maximum financial risks that can hit the GCC stock markets; while considering the external impact of the clean energy production index, crude oil and CO_2 emission prices?

We attempt to answer this research question by running three long memory GARCH models: FIGARCH, FIAPARCH and 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 use the same dataset for the two previous chapters. We argue that modelling some statistical properties of energy markets (e.g., excessive volatility, leverage effects, fat-tails, asymmetry and long memory) taking into account the impact of the three mentioned regressors, could give the best VaR and expected shortfall (ES) for the GCC stock prices.

Chapter 2: Impact of Oil Price Fluctuations on Stock Markets: New Evidence from the Gulf Cooperation Council (GCC) Countries

2.1. Introduction

Interdisciplinary linkages between oil and stock prices, particularly, in major oil-exporting countries, have long been established within the literature.[3] However, no consensus has been established concerning the magnitude and directionality of this relationship. Some studies, for example, have found that hikes in oil prices positively impact GCC stock markets (e.g., Hammoudeh and Al-Gudhea, 2006; Mohanty et al., 2011; Jouini, 2013; Louis and Balli, 2014; Demirer et al., 2015; Mohanty et al., 2017; Menacer and Nurein, 2018). Other studies, such as those by Hammoudeh and Choi (2006), Nandha and Faff (2008) and Alhayki (2014), have suggested otherwise; that is, hikes in oil prices harm stock markets. Recent studies have also shown an ambiguous relationship between oil price and GCC stock market behaviour (e.g., Arouri et al., 2012; Waheed et al., 2018).

This study suggests three likely reasons for the abovementioned controversial findings regarding the interrelation between oil prices and stock market behaviour. First, prior researchers have estimated changes in oil price based on the nominal oil price (e.g., Kling, 1985; Jones and Kaul, 1996; Sadorsky, 1999; Hamilton, 2003; Miller and Ratti, 2009). Such an approach has been criticised by Kilian (2009) who argued that to better

[3] "The Gulf Cooperation Council (GCC) region is a political and economic alliance of six countries in the Arabian Peninsula: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and the United Arab Emirates" (Secretariat General of the Gulf Cooperation Council, 2018).

understand oil price movements, the underlying factors that influence oil price swings must first be understood. To do so, Kilian (2009) suggests three oil price shocks: oil supply shock driven by an actual shortfall in global oil production, often caused by political disruptions, global aggregate demand shock driven by changes in the global demand for all commodities caused by a growth/decline in the global economic activity and oil-specific demand shocks driven by changes in the precautionary demand for oil inventories.

Second, GCC stock markets are treated in the literature as a group of homogeneous markets (e.g., Hammoudeh and Choi, 2007; Malik and Hammoudeh, 2007; Arouri et al., 2011; Fayyad and Daly, 2011; Awartani and Maghyereh, 2013; Alhayki, 2014; Jouini and Harrathi, 2014; Bouri and Demirer, 2016; Balcılar et al., 2017). Ramady (2012) argues that this approach is not suitable since each of the GCC markets has different regulations, which likely impacts the dynamic relationship between oil price movements and GCC stock market swings.

Finally, despite applying Kilian's (2009) approach in several countries, findings on the relationship between oil price and stock market behaviour are still provocative (e.g., Lin et al., 2011; Abhyankar et al., 2013; Gupta and Modise, 2013; Lin et al., 2014). One possible reason is that these works have overlooked the influence of US stock markets on global stock price fluctuations (Hammoudeh and Choi, 2006).

The present study fills these gaps by following Killian's historical price decomposition approach to estimate the impact of the underlying sources of oil price fluctuations on the GCC stock markets of Saudi Arabia, UAE and Kuwait; while considering the impact of the US stock market movements and the foreign investment restrictions. We utilise a structural vector autoregressive (SVAR) model based on monthly data from June 2002 to June 2019 for the 3 GCC countries.[4]

The results show that the impact of oil price shocks differs based on the structural characteristics of the GCC stock markets. An oil supply shock has a stronger negative impact on Dubai relative to the Saudi stock markets, wherein the effect is reversed for the Kuwait stock market. A global aggregate demand shock leads to an interim reduction in the Saudi stock market and a rise in stock prices of Dubai and Kuwait. An oil market-specific demand shock leads to a decline in the three GCC stock market prices; however, Dubai and the Kuwait stock market exhibit a quicker recovery within the first two months relative to the Saudi market. A shock to the US stock markets levies a negative and symmetrical impact on the three GCC markets as a consequence of the tight linkages of the monetary policies between the US and the three countries.

This chapter has three contributions: first, to the best of our knowledge, no prior study has discussed the influence of the underlying causes of oil price fluctuations on the GCC stock prices. Second, in contrast to some studies (e.g., Abhyankar et al., 2013, Degiannakis et al., 2014 and Fang and You, 2014) that have followed Kilian (2009)'s approach, we take into account the influence of the US stock market as a significant leader for global stock markets (Hammoudeh and Choi, 2006). Finally, our study

[4] The three countries are selected first because of being the largest GCC countries in terms of their volume of oil exports and, second, as they are members of the Organization of Petroleum-Exporting Countries (OPEC).

considers the heterogonous stock market regulations of the GCC countries, unlike other studies which treated these countries as homogenous markets (Ramady, 2012).

The remainder of this paper is organised as follows; Section 2 provides a survey of the relevant literature on oil prices and stock market behaviour. Section 3 offers a description of the methods and data used in this study. The empirical results are provided in Section 4, followed by a discussion of these results in Section 5. Finally, Section 6 concludes this chapter.

2.2. Literature review

Several scholars since the mid-1970s have examined the dynamic relationship between oil price fluctuations and stock prices, mainly using two different analyses. Classical studies have dealt with the global price of oil as an exogenous factor and the impact of nominal (or real) oil price fluctuations on stock prices without knowing the reasons for oil price changes. Recent researchers have developed an alternative approach that decomposes the relationship based on the underlying causes of oil price spikes (oil supply shocks, aggregate demand shocks and specific demand shocks).

For further discussions about the two previous literature patterns, we have divided the literature review into two key sections: section 1 addresses the conventional approach in examining the relationship between oil prices and stock prices and in section 2, we survey the alternative approach using the structural decomposition of the real price of crude oil.

2.2.1. Conventional approach

To analyse the bilateral relationship between oil price fluctuations and stock prices, several studies have used the conventional approach that directly links stock prices with the global price of oil (West Texas Intermediate [WTI] or Brent crude) (Kilian and Park, 2009; Kilian, 2014; Kilian and Vigfusson, 2017). Furthermore, these studies have dealt with oil price changes as an exogenous factor without knowing the underlying reasons for oil price changes (Kilian, 2009). Here, the impacts of oil prices on stock prices often arose from the supply side of crude oil (Kilian, 2008, 2009; Kilian and Park, 2009; Bastianin and Manera, 2018). According to Effiong (2014) and Bastianin and Manera (2018), this trend of studies was influenced by the oil supply shocks caused by political events in the Middle East in 1979, 1983, 1991 and 2003. Hamilton (1983), Gisser and Goodwin (1986) and Hamilton (2009) added that most of these works concluded that increases in oil prices negatively affected developed economies due to increasing production costs and positively affected exporting countries due to the transmission of wealth (e.g., Kaul and Seyhun, 1990; Faff and Brailsford, 1999; Barsky and Kilian, 2004; Hammoudeh et al., 2004; Jones et al., 2004; Miller and Ratti, 2009; Silvapulle et al., 2017).

The next three subsections include descriptions of the existing studies that have used the conventional approach and provided mixed evidence by applying it to different economies worldwide.

2.2.1.1. The US and other developed economies

The US and other developed stock markets have received the bulk of attention from most researchers while examining the relationship between the price of crude oil and stock prices. A large number of researchers have argued that a negative relationship exists between oil and stock prices (e.g., Kling, 1985; Jones and Kaul, 1996; Sadorsky, 1999; Hamilton, 2003; Miller and Ratti, 2009; Diaz et al., 2016; Silvapulle et al., 2017). For example, Kling (1985) examined the relationship between oil prices and stock market activity through the Standard & Poor's 500 indexes during the 1973–1982 period and concluded that a purely negative nexus exists, particularly in energy-intensive sectors. Similarly, Jones and Kaul (1996) found that the oil price surge after the second Gulf War led to a drop in stock market price in the United States, Canada, Japan and the UK. Using a standard cash-flow and dividend-valuation model, the conclusions specifically indicated that the stock market contagion in the United States and Canada was more significant. The same finding was complemented by Hamilton

(2003) and confirmed that the oil price surge after World War II had caused nine of the ten US recessions since the end of the war. Sadorsky (1999) used a VAR model with monthly data from 1947 to 1996 and concluded that the rise in oil prices led to a decline in US stock returns.

Miller and Ratti (2009) investigated the long-term relationship between the price of crude oil and 35 different stock price indices of countries belonging to the Organisation for Economic Co-operation and Development (OECD) during 1971–2008. The findings detected abundant evidence of negative indices for breaks during the 1971–1980 and 1988–1999 periods. Diaz et al. (2016) analysed the oil price/stock-return relationship within G7 economies (Canada, France, Germany, Italy, Japan, the UK and the US) by collecting monthly data for the 1970–2014 period. The study employed a VAR model to estimate several factors, such as stock market returns, interest rates, oil price fluctuations and economic activity, using the adjusted Industrial Production Index of each country. The results showed that a negative nexus exists between stock market volatility and oil price fluctuations. More recently, Silvapulle et al. (2017) used a nonparametric panel data model to examine the link between oil price indexes and stock market prices in China, France, Italy, India, Japan, Germany, Singapore, South Korea, Spain and the United States. The results indicated that oil prices play a negative role in only three stock markets.

Few authors have argued that changes in crude oil prices positively affect developed stock markets (e.g., Sadorsky, 2001; El-Sharif et al., 2005; Park and Ratti, 2008; Narayan and Sharma, 2011; Tsai, 2015). A pivotal study was carried out by El-Sharif et al. (2005), finding a positive link between oil price fluctuations and the oil and gas sectors in the UK's stock markets. Likewise, Sadorsky (2001) analysed the response of

Canadian’s stock market returns to oil price fluctuations and some primary commodities prices. The outcomes indicated that increases in oil prices were accompanied by increases in stock market returns for oil and gas firms. Park and Ratti (2008) reported that surges in oil prices produced an increase in real stock returns in the Standard & Poor's 500 and other stock markets in 13 European countries; however, the interactions between US stock markets and oil prices were lower compared to the others from European exporters of crude oil, such as Norway. Both Narayan and Sharma (2011) and Tsai (2015) supported Park and Ratti's (2008) view after collecting daily data on US firms to examine how stock returns respond to oil price shocks. Narayan and Sharma (2011) found that the effect on stock returns differs based on firm size. Tsai (2015) provided clear evidence of the existence of a positive relationship between oil price shocks and US firms’ stock returns during the 2008–2009 recession.

A small body of extant literature found ambiguous or no effects from oil price changes on stock market prices (e.g., Chen et al., 1986; Apergis and Miller, 2009; Mollick and Assefa, 2013). Chen et al. (1986) and Mollick and Assefa (2013) tested whether some macroeconomic variables and international oil prices impact US stock returns. The findings showed that the relationship between oil prices and stock returns is subject to other macroeconomic factors, for example, interest rates and inflation. Apergis and Miller (2009) compared the effects of oil price shocks on stock market returns in Australia, Canada, France, Germany, Italy, Japan, the UK and the United States. The authors employed a VAR model to decompose the stock price swings into oil price shocks. The findings indicated that stock prices in most of these economies do not effectively respond to oil-market shocks. Finally, Miller and Ratti (2009) found a negative relation between OECD stock indexes and global oil prices during the 1971–

1980 and 1988–1999 periods in the long term and concluded that there has been no significant relation since 1999.

2.2.1.2. Emerging economies

In the case of emerging markets, no unequivocal relationship exists between oil and stock prices. Fewer studies have reported a negative relationship between them (e.g., Basher and Sadorsky, 2006; Nandha and Faff, 2008; Boubaker and Raza, 2017; Tchatoka et al., 2018) compared to those on developed markets. Basher and Sadorsky (2006) applied an international multi-factor model with daily data for the 1992–2005 period to examine stock markets' reactions to oil price fluctuations in 21 emerging economies. The conclusions mentioned that surges in oil prices led to declines in stock market indexes. However, the impact of oil prices on stock returns was positive in some countries, such as Brazil, Colombia and South Africa. Nandha and Faff (2008) analysed 35 DataStream global indices for the 1983–2005 period and concluded that increases in oil prices led to decreases in stock returns. In the same context, Nandha and Faff's (2008) work resembles a study by Boubaker and Raza (2017) examining the spillover effects between oil and stock prices in Brazil, Russia, India, China and South Africa (i.e., BRICS markets). Using the ARMA-GARCH model with daily data from the 2000–2016 period, they found a negative relationship. The results also confirmed that news and movements of stocks affected the BRICS markets. Supporting this view, Tchatoka et al. (2018) reviewed the relationship between oil price shocks and stock market returns using the quantile-on-quantile (QQ) model for US stock markets and 15 oil-importing countries. They find that oil price increases might decrease stock returns, particularly for stock markets that are net importers of crude oil, such as South Korea and Singapore.

Some studies have documented the positive linkage between oil prices and stock returns in emerging economies (e.g., Boyer and Filion, 2007; Miller and Ratti, 2009; Li et al., 2012; Phan et al., 2015). For example, Li et al. (2012) examined the relationship between crude oil prices and the Chinese stock market across different sectors. Using monthly data and panel co-integration, they documented that increases in oil prices led to increases in sectoral stock prices, for example, manufacturing, technology and mining. Gupta (2016) examined the interaction between stock returns in 70 countries with oil price fluctuations using comprehensive firm-level data. The findings discovered that most firm-level stock returns in emerging economies (e.g., Brazil, China, India, Indonesia, Malaysia and Turkey) are positively associated with oil prices.

Some studies (e.g., Maghyereh, 2004; Le and Chang, 2011; Asteriou and Bashmakova, 2013; Reboredo and Ugolini, 2016) have found an ambiguous effect or no effect on oil price changes on stock markets in the case of emerging countries. Maghyereh (2004) used a VAR model based on daily data from 1998 to 2004 to examine the relationship between oil prices and stock markets in 22 emerging economies. In contrast with most of the developed economies, the findings revealed that oil price shocks do not play a vital role in stock market volatility. This view was supported by Le and Chang (2011), who investigated interactions between oil price changes and stock market prices in Japan, Malaysia, Singapore and South Korea. Using impulse responses and VDC functions during the 1986–2011 period, they concluded that the influence of oil prices on the stock market is inconspicuous, particularly in small stock markets (e.g., Singapore). Le and Chang's (2011) work on the nexus between oil price fluctuations and stock prices was complemented by Reboredo and Ugolini (2016), who measured the influence of quantile and interquartile oil price shifts on various stock market return quantiles. Using the marginal models for stock returns and copula, the results show that oil price changes did not influence stock return quantiles in most of these countries. Asteriou and Bashmakova (2013) analysed the interaction between oil price risk and stock market returns for emerging capital markets in central and eastern European countries (CEECs) during the 1999–2007 period. The results statistically clarified that oil prices are a crucial factor in determining stock returns. However, the authors found no significant nonlinear dependency between stock returns and market risks.

2.2.1.3. Gulf cooperation council countries (GCC)

Several empirical studies have been conducted to understand the dynamic relationship between oil price movements and GCC nations' stock markets. However, conflicting evidence about the nature of the relationship between these two components has been collected. For a further description, prior researchers have examined the dramatic impact of global oil prices on GCC stock markets in three major strands: studies concentrated on the sector-level analysis or the country-level analysis, or recent studies that used nonlinear analyses to obtain further evidence.

The first group of research focuses on the influence of oil price fluctuations on stock prices based on sector-level analyses (e.g., Hammoudeh and Al-Gudhea, 2006; Mohanty et al., 2011; Arouri et al., 2012; Jouini, 2013; Louis and Balli, 2014; Demirer et al., 2015; Mohanty et al., 2017). Several of these empirical studies have achieved dissimilar conclusions. For example, Mohanty et al. (2011) assessed the effect of crude oil prices on equity returns in GCC countries, finding a positive relation for 12 out of 20 sectors. In contrast, Mohanty et al. (2017) found a very limited positive effect from oil price swings on firms' returns. Hammoudeh and Al-gudhea (2006) conducted an empirical study on six of the largest Saudi equity sectors, finding a robust positive impact from oil price fluctuations on those sectors' stock markets. Arouri et al. (2012) provided empirical proof of spillover effects between the price of crude oil and GCC stock markets, except in the Saudi stock market. However, when Jouini (2013) used the VAR-GARCH model on 2007–2011 data, the findings confirmed a unidirectional impact from oil prices on critical sectors of the Saudi stock market. Louis and Balli (2014) and Demirer et al. (2015) discovered a significant positive relationship between oil price fluctuations and GCC stock returns. Menacer and Nurein (2018) used a panel data approach to capture the relationship between macroeconomic variables, including oil prices and bank stock returns, among GCC countries. The study also found a positive nexus between macroeconomic variables and Islamic banking sectors.

The second strand of literature, which evaluated the impact of oil price swings on GCC stock markets, focused on country-level analyses (e.g., Hammoudeh and Choi, 2007; Malik and Hammoudeh, 2007; Arouri et al., 2011; Fayyad and Daly, 2011; Awartani and Maghyereh, 2013; Alhayki, 2014; Jouini and Harrathi, 2014; Bouri and Demirer, 2016; Balcılar et al., 2017). Most of these studies have determined a positive relationship between oil price fluctuations and stock prices, particularly during the global financial crisis of 2008. For example, Fayyad and Daly (2011), Awartani and Maghyereh (2013) and Bouri and Demirer (2016) argued that the interaction between oil price activity and GCC stocks became more pronounced during and after the global financial crisis. Bouri and Demirer (2016) added that the relationship between oil price movements and most GCC stock markets during and after the global financial crisis is unidirectional. Finally, unlike Hammoudeh and Choi (2007), who claimed that Saudi Arabia's and Oman's stock markets are less sensitive to oil price fluctuations, Alhayki

(2014) reported that Bahrain, Saudi Arabia and the United Arab Emirates' stock markets have a negative relationship with oil price fluctuations.

To resolve the mixed evidence among the aforementioned studies, nonlinear dynamic models have been employed by several studies (e.g., Maghyereh and Al-Kandari, 2007; Alharbi, 2009; Onour, 2009; Jouini, 2013b; Naifar and Al Dohaiman, 2013; Ajmi et al., 2014; Guesmi, 2014; Mensi et al., 2016). Both Onour (2009) and Jouini (2013b) exploited a nonparametric test to examine the nonlinearity within the long-term relationship between oil prices and GCC stock markets. The findings indicated a robust nonlinear co-integration across GCC stock markets. Naifar and Al Dohaiman (2013) examined the nonlinear relationship between GCC stocks (except Oman's stock market) and three macroeconomic variables: oil prices, interest rates and inflation rates. The study concluded that the macroeconomic variables react with low volatility to oil price swings. Naifar and Al Dohaiman (2013) also claimed that employing Markov-regime-switching models achieved more reliable results. In the same vein, Ajmi et al. (2014) examined a short-run nonlinear causal relationship between the price of crude oil and Middle East stock markets, including those in GCC countries. The findings showed a significant nonlinear relationship between GCC stock markets' performance and oil prices. Mensi et al. (2016) fully supported this argument, also claiming that the financial risk (FR) rating has a significant positive effect on the performance of GCC stock markets. Guesmi (2014) undertook one key study about the influence of oil price movements on GCC stock returns based on the conventional view of oil price shocks: the supply-and-demand side of oil price shocks. The findings indicated that the impact on stocks from the demand side of oil price shocks was stronger than the supply side.

2.2.2. Alternative approach

The aforementioned studies that discussed the relationship between oil price fluctuations and stock prices based on the conventional approach have elicited mixed results. Besides, Kilian (2009) criticised the results of conventional studies which have not provided a careful analysis explaining the underlying causes of oil price swings. Through a theoretical and empirical study, Kilian (2009) designed 'a structural decomposition of the real price of crude oil' using a developed structural VAR model during the 1975–2007 period. Kilian (2009, 2014) examined the primary sources of shocks (or origins) to clarify how an oil price increase might not only be attributed to supply variations (exporters), but also demand changes (importers). Hence, Kilian (2009) divided oil price shocks into three categories: crude-oil supply shocks that are driven by distribution cases in exporting countries, aggregate demand shocks that are driven by a sustained increase (or decrease) in real growth in the global economy and oil-specific demand shocks that are driven by the precautionary increase in the global demand for crude oil caused by concerned cases for supporting oil reserves.

Kilian and Park (2009) employed a structural VAR model to interpret the reason why the oil price hikes after 2003 were not followed by a massive recession in the US financial markets. They found that the adverse economic effects of higher oil price usually stems from oil specific demand shocks, a.k.a. the rise in precautionary demand for crude oil. Crude oil supply shocks driven by oil production disruptions do not exert a significant impact on stock market returns in the United States. However, Kilian and Park (2009) found that crude oil demand shocks driven by an increase in the global aggregate demand for commodities exert a positive and sustained impact on US stock returns within the first year.

A few authors have recently simulated Kilian and Park's (2009) study to decompose oil price shocks and analyse their impact on stock markets (e.g., Lin et al., 2011; Abhyankar et al., 2013; Gupta and Modise, 2013; Lin et al., 2014; Degiannakis et al., 2014; Broadstock and Filis, 2014; Fang and You, 2014; Effiong, 2014; Kang et al., 2015; Bastianin et al., 2016; Andrea Bastianin and Manera, 2018). Most of these empirical studies have been applied to developed economies. For example, both Kang et al. (2015) and Bastianin and Manera (2018) used a structural VAR model to examine the influence of oil price shocks on US stock market volatility. Unlike Kilian and Park (2009), these two studies collected delayed data on returns and volatility in the stock market. The findings clarified that oil price shocks driven by aggregate demand and oil-specific demand are significantly associated with stock market volatility, but the impact from supply shocks is insignificant. Contrary to previously published studies, Degiannakis et al. (2014) found that oil-specific demand shocks and oil supply shocks do not react to stock market volatility based on European data. Furthermore, aggregate demand shocks negatively influenced European stock markets. Abhyankar et al. (2013) and Bastianin et al. (2016), like Kilian and Park (2009), achieved the same results by employing the decomposition of oil price shocks on the Japanese and other G7 stock markets.

Fewer studies have been carried out on stock markets in emerging economies, for instance, Gupta and Modise (2013) employed the decomposed-oil-price-shocks on the South African stock market. The findings illustrated that aggregate demand crude oil shocks positively impact stock returns, unlike supply and specific demand shocks. Contrary to the results from the US studies, Lin et al. (2011) discovered that all three oil price shocks exerted a positive influence on Hong Kong's stocks. Fang and You

(2014) and Lin et al. (2014) indicated that aggregate demand shocks often lead to a decline in Chinese stock prices. Broadstock and Filis (2014) obtained a similar result when using the BEKK model to examine the relationship between the decomposition of oil price shocks and stock market returns in China. Finally, Effiong (2014) applied the structural decomposition of oil price shocks developed by Kilian (2009) on Nigeria's stock market. The results showed that oil supply shocks negatively and insignificantly impacted the stock market. However, oil-specific and aggregate demand shocks for crude oil have significantly raised oil prices.

2.3. Methodology and data

2.3.1. The theoretical model

2.3.1.1. Oil price shocks

The basic theory of oil price shocks formulated by Hamilton (1983) argues that oil price surge leads to an increase in inflation rates, as oil is a major input into global industrial commodities.[5] Hence, the purchasing power of consumers is eroded, leading to a fall in aggregate demand and, subsequently, recession (see Hamilton, 1983; Kling, 1985; Hamilton, 2003; Barsky and Kilian, 2004). However, the oil price surge also leads to an increase in oil revenues in oil-exporting countries, stimulating macroeconomic indicators and wealth (Bjørnland, 2009).[6]

2.3.1.2. Oil prices and stock markets

According to Huang et al. (1996), the influence mechanisms of oil price shocks on stock prices systematically arise from the two key channels. The first channel is expected cash flows, as oil is considered the main production input for global commodities, so an increase in oil prices will have a direct inflationary impact on the production costs, hence, the firms' profits decline, causing a decrease in the expected cash flow that can be invested into stocks. A parallel inflationary impact affects consumers' real income

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[5] Hamilton (1983) concentrates on the classical supply-side model in which oil price is treated as an exogenous component, suggesting that oil price shocks often produce a decline in macroeconomic growth.

[6] The fundamental theory of oil price shocks examines the expansion of the exporting countries revenues during high oil price periods. It postulates that oil price surge leads to an increase in oil revenues in these countries.

and purchasing power.[7] Second, the discount rate is also substantially affected by the expectations of oil prices. The balance of payments suffers from oil price increases due to the loss of foreign exchange and inflation.

2.3.2. Methodology

The methodology in this study relies on the SVAR model over two phases. Following Kilian (2009), a historical decomposition of the real price of crude oil is conducted in Phase I to distinguish the three underlying shocks: oil supply shock, aggregate demand shock and oil-specific demand shock. Following this, in Phase II, the decomposed real oil price is used along with other relevant variables to examine the response of the three GCC stock markets.

Phase I: creating a historical decomposition of real oil price

The first SVAR estimates the three variables: global oil production, global real economic activity and real price of crude oil to distinguish the three underlying causes of oil price fluctuations (oil market shocks). The vector time series y_t assumes the endogeneity of the real oil price to the other two variables considering some proposed restrictions (for details, see Kilian, 2009).

[7] In the case of oil exporting countries, oil price surge increases oil revenues that directly stimulate macroeconomic indicators such as gross incomes and exporters' wealth. Hence, this allows policymakers to boost government expenditures that feed into higher household's income, investment spending and stock market returns.

Phase II: estimating combined impacts on the three GCC stock markets

This part of the methodology develops three SVAR models to examine the impact of oil price shocks, based on the historical decomposition of real oil price obtained in Phase I, along with two additional variables: US stock markets and domestic stock market regulations on the three GCC stock markets. The SVAR framework for each stock market can be written as follows:

$$A_0 Z_t = \alpha + \sum_{i=1}^{p} A_i Z_{t-i} + \beta X_{t-i} + \varepsilon_t \quad \dots\dots\dots\dots\dots\dots (2.1)$$

where ε_t serially and mutually indicates the vector of dynamic structural innovations and Z_t denotes the vector of endogenous variables, including global oil production, the global real economic activity index, the real price of crude oil, the US stock markets' index and a stock price index for each country. βX_{t-i} represents the exogenous variable in our model (stock market regulations for each institution), while e_t is the reduced innovations of VAR, such that $e_t = A_0^{-1}\varepsilon_t$ by imposing exclusion assumptions on A_0^{-1}, creating structural innovations.

The model assumes the following identifying restrictions of the SVAR model:

$$e_t \equiv \begin{pmatrix} e_{1t}^{\text{Global oil production}} \\ e_{2t}^{\text{Global economic activity}} \\ e_{3t}^{\text{Real oil price}} \\ e_{4t}^{\text{US stocks}} \\ e_{5t}^{\text{Each GCC stock}} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{\text{Oil supply shock}} \\ \varepsilon_{2t}^{\text{Aggregate demand shock}} \\ \varepsilon_{3t}^{\text{Oil specific−demand shock}} \\ \varepsilon_{4t}^{\text{The US stock market shock}} \\ \varepsilon_{5t}^{\text{Other shocks to stock prices}} \end{pmatrix} \dots\dots (2.2)$$

Equation (2.2) explains the SVAR restrictions of error decomposition arranged into two blocks: global crude oil block and stock markets block. The assumptions of the first block, as identified by Kilian (2008a; 2008b; 2009) are as follow (i) Global oil production will not react to the two oil demand shocks during a month. This is because oil-producing countries are not able to immediately respond to sudden demand shocks; since increasing crude oil supply is costly and needs considerable time.[8] (ii) Global real economic activity will not be affected by an increase in the real oil price driven by oil-specific demand shock within a month, given that the reaction of global economic activity to oil price changes is sluggish (Kilian and Park, 2009).[9] (iii) Oil-specific demand shock captures the innovations to the real oil price, which are not captured by oil supply shock or aggregate demand shock.[10]

Stock markets block identifies structural assumptions for US stock markets and their linkages with the GCC stock markets. US stock market shock captures an immediate impact caused by changes in oil prices; this is driven by changes in global oil production, global real economic activity and the real price of oil. The justification of this assumption is given by the two key channels discussed in the theoretical model Section 2.3.1.

Each of the three GCC stock markets will likely respond to all of the previous shocks. Oil market shocks may influence the three stock market behaviour, as oil price surges improve the macroeconomic indicators in oil-exporting countries (Bjørnland, 2009). The three GCC stocks might also be affected by fluctuations in the US stock market,

[8] Oil exporting countries set their production plans based on the predicted growth trend instead of the higher unforeseen oil demand (Malik and Hammoudeh, 2007).

[9] Aggregate demand shock does not capture the total demand for all global goods and services. It is an average estimate of the OECD countries' dry cargoes of oil inventories (Kilian, 2009).

[10] See Kilian (2009) to identify the five key reasons which justify why oil specific-demand shocks are counted by innovations that cannot be captured by oil supply or aggregate demand shocks.

which as a leading major player, impacts stock markets' movements worldwide (Hammoudeh and Choi, 2006). Finally, the GCC stock markets are potentially affected by other related shocks to stock prices, such as changes in US interest and exchange rates (Bjørnland, 2009 and Basher et al., 2012).

2.3.3. Data

In Phase, I, we use monthly data from May 2000 to June 2018.[11] Global oil production measured in thousands of barrels per day is obtained from the US Energy Information Agency database. The real crude oil price of West Texas Intermediate [WTI] is measured in US dollars per barrel and deflated by the US consumer price index (CPI). These data are obtained from the US Department of Energy. Third, real global economic activity is used as a proxy for global aggregate demand for industrial commodities. The index of real global economic activity has been constructed and updated by Kilian (2009) based on the average monthly rates of dry cargo single-voyage ocean freight, including various global commodities, such as coal, fertiliser, grain, iron ore, scrap metal and oilseed.[12]

In Phase II, we use monthly data from June 2002 to June 2019. US stock market impact was proxied by the Wilshire 5000 Total Market Index (the Wilshire 5000) from the

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[11] The first stage data starts from May 2000 because the oil price decomposition requires 24 lags (see Kilian, 2009), while the starting date of the second stage data is based on the availability of the monthly stock price indices of the three GCC stock markets.

[12] According to Kilian (2009), this index does not compute all global goods and services as it is an average estimate of the OECD countries' dry cargoes of oil inventories.

Investing database.[13] It measures the performance levels of the key US stock markets in the United States, comprising all publicly traded stocks (ETF, 2003). The main variables of interest are the three stock price indexes: the Saudi Stock Exchange (Tadawul), Boursa Kuwait (Premier Market) and the Dubai Financial Market (DFM). These data are sourced from the Investing database. Figure 2.1 illustrates the raw data for the oil price decomposition variables, the US stock market and the three GCC stock markets.

The maximum share of foreign investments allowed in the three stock markets is used as a proxy to appraise the impact of stock market regulations. Table 2.1 shows that the Dubai Financial Market began with a maximum foreign share of 35%, increasing in value to 49% in June of 2005 before eliminating all ownership restrictions in 2018. Boursa Kuwait has had no limit on foreign investment since the study period began. The Saudi Stock Exchange only permitted foreign investment in January of 2018 with a value of 49%.

[13] The Wilshire 5000 Total Market Index was introduced in 1974 to serve economists, legislators, academicians and practitioners. It is the major barometer of US equity investment performance, capturing a number of US stock market indexes, such as S&P 500, NASDAQ and Dow Jones (ETF, 2003).

Table 2.1: Chronology of institutional changes in the direct foreign investment rates in the stock markets

Stock market	At the start of the research sample (2002)	Changes	
Saudi	No DFI rates	49% from January, 2018	
Dubai	35%	Up to 49% from June, 2005	Up to 100% from May, 2018
Kuwait	Up to 100% from the start of the research period		

**Sources*: Saudi Capital Market Authority, Securities and Commodities Authority in the UAE and the Kuwait Capital Markets Authority.

Notes: The stock market authorities in the three countries impose further special restrictions on the banking and insurance sectors. The direct foreign investment rates in the two sectors cannot exceed 49%. Moreover, foreign investment rates in Kuwait are inhibited by other non-financial regulations. For instance, opening or liquating foreign investment portfolios in some sectors requires prior acceptance from the Kuwaiti financial authorities.

2.4. Empirical work

2.4.1. Preliminary statistics

To reduce the potential influences of outlying observations and various measurement units, the natural logarithm of the variables was used.[14] Table 2.2 reports the descriptive statistics for the study variables.

[14] Except the data for real economic activity index (see Table 2.2 for details).

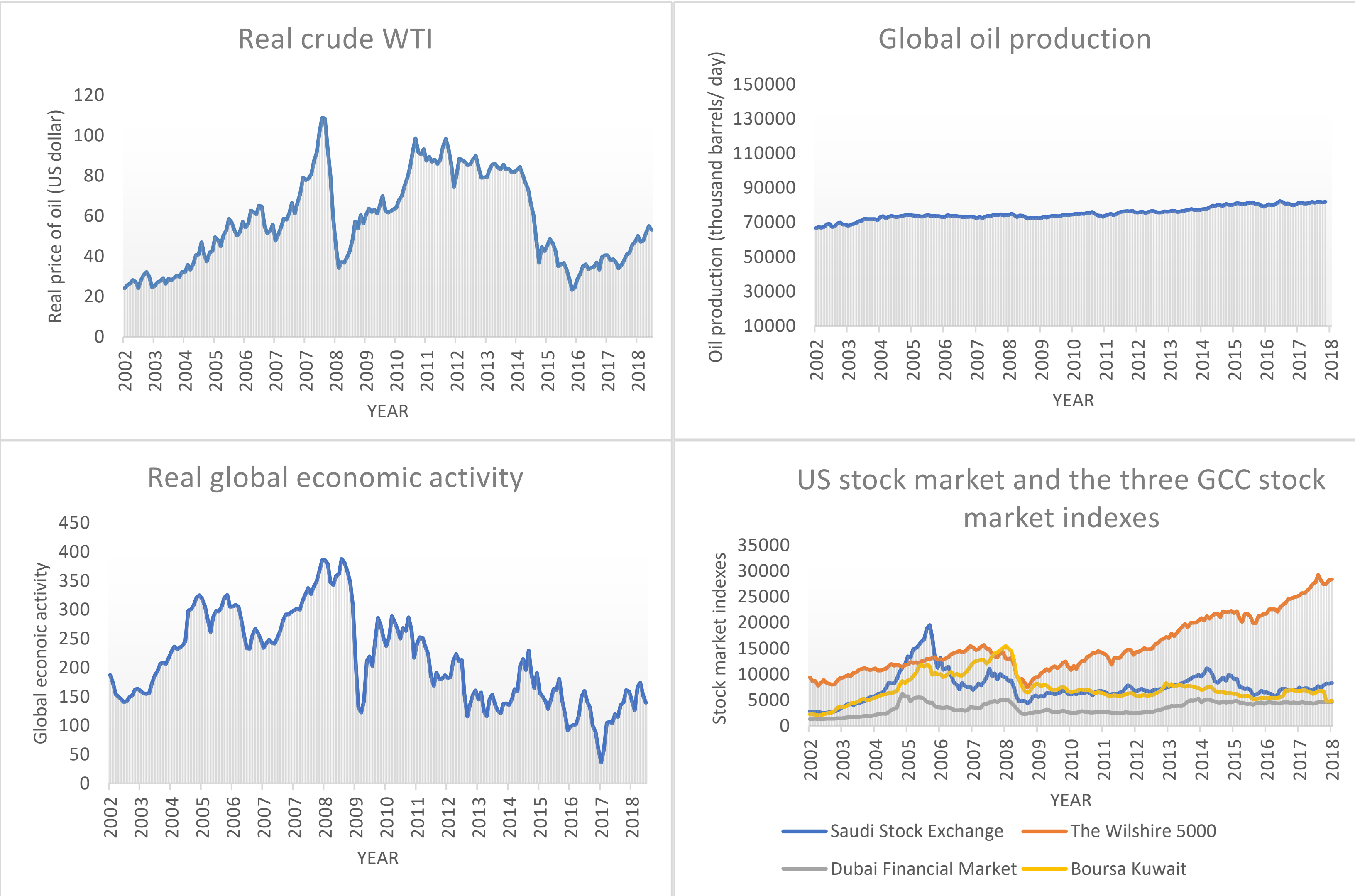
Table 2.2: Descriptive statistics for the variables

Global oil production					Global real economic activity					Real price of oil				
Obs.	Mean	Std. Dev.	Skw.	Kurt.	Obs.	Mean	Std. Dev.	Skw.	Kurt.	Obs.	Mean	Std. Dev	Skw	Kurt.
218	11.21	0.05	-0.10	-0.65	218	11.35	74.60	0.39	-0.53	218	-0.45	0.40	-0.14	-1.09

US stocks					Saudi stock					Dubai stock					Kuwait stock				
Obs.	Mean	Std. Dev.	Skw.	Kurt.	Obs.	Mean	Std. Dev.	Skw.	Kurt.	Obs.	Mean	Std. Dev.	Skw.	Kurt.	Obs.	Mean	Std. Dev.	Skw.	Kurt.
193	9.58	0.33	0.22	-0.84	193	8.86	0.38	-0.45	1.38	193	8.08	0.38	-0.67	-0.33	193	8.82	0.38	-0.64	1.62

Note: Real economic activity index is employed as raw data as it abundantly contains negative values.

Figure 2.1: Line charts of oil price shocks and stock markets variables



2.4.2. Unit root tests

The stationarity of the time series in the two models is examined by using the modified Dickey-Fuller (DF-GLS), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. Table 2.3 shows that most of the time series are non-stationary at the level. Hence, we rely on (DF-GLS) to determine that the natural logarithm of all the variables is stationary at I (1).[15]

Table 2.3: Unit root tests

Variables	DF-GLS test		PP test		KPSS test	
	Level	First dif.	Level	First dif.	Level	First dif.
Global oil production	0.410	-2.494**	2.020*	-27.53***	2.688	0.116***
Global economic activity	-1.605	-1.650*	-3.635***	-16.58***	0.169***	0.054***
Real price of oil	-2.805**	-15.54***	-0.934	-15.61***	0.476*	0.047***
US stocks	-2.061	-2.987**	-0.406	-12.169***	1.394	0.276***
Saudi stock	-1.859	-3.488***	-2.575	-11.380***	0.106***	0.101***
Dubai stock	-1.399	-4.466***	-2.353	-10.784***	0.588*	0.072***
Kuwait stock	-0.723	-7.402***	-2.770*	-9.230***	0.272***	0.236***

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

2.4.3. Lag length selection for the structural VAR models

To obtain the historical decomposition of real oil price in the first phase, we take $j = 24$, following Kilian (2009), whereas for investigating the responses of the GCC stock

[15] The data of oil price decomposition is stationary at I (0).

markets to the oil market and other shocks, we rely on Akaike's information criterion (AIC). The results indicate that the optimal length is a one-period lag.[16]

2.4.4. Results

2.4.4.1. The historical decomposition of real oil price

Figure 2.2 plots the responses of the real oil price to the three supply and demand shocks over a horizon of 16 months. The 95% confidence interval is illustrated by the grey area in these plots and the graphs clearly show the differential impact that the three shocks have on the real oil price. The oil supply shock, for example, immediately increases the real oil price in the first three months; this is followed by a gradual decline over time, whereas both demand shocks cause a steady increase in the real oil price, followed by a decrease during the term. These findings are in line with the work of Kilian (2009), in which oil price hikes were found to be mainly driven by aggregate and oil-specific demand shocks. The cumulative effects of the three shocks are shown in Figure 2.3.

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[16] The 24 lags assist to remove the possible serial correlation and to capture innovations of the business cycle in commodity markets, such as oil(Kilian, 2009; Gupta and Modise, 2013; Kang et al., 2015a). It is also important in structural models of the global oil market to account for the slow-moving relation between the real price of oil and global economic activity (Hamilton and Herrera, 2004; Ciner, 2013; Kang et al., 2015a).

Figure 2.2: **Responses of the real oil price to one standard deviation of structural shocks**

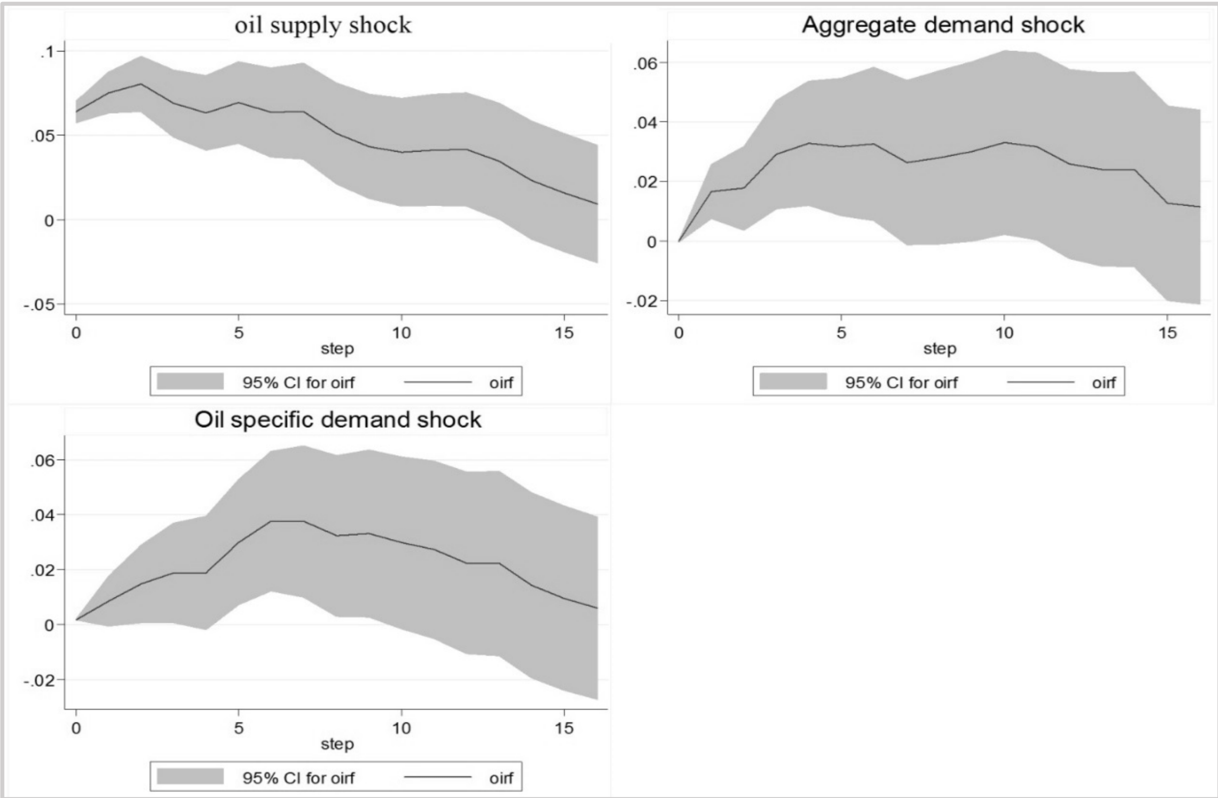
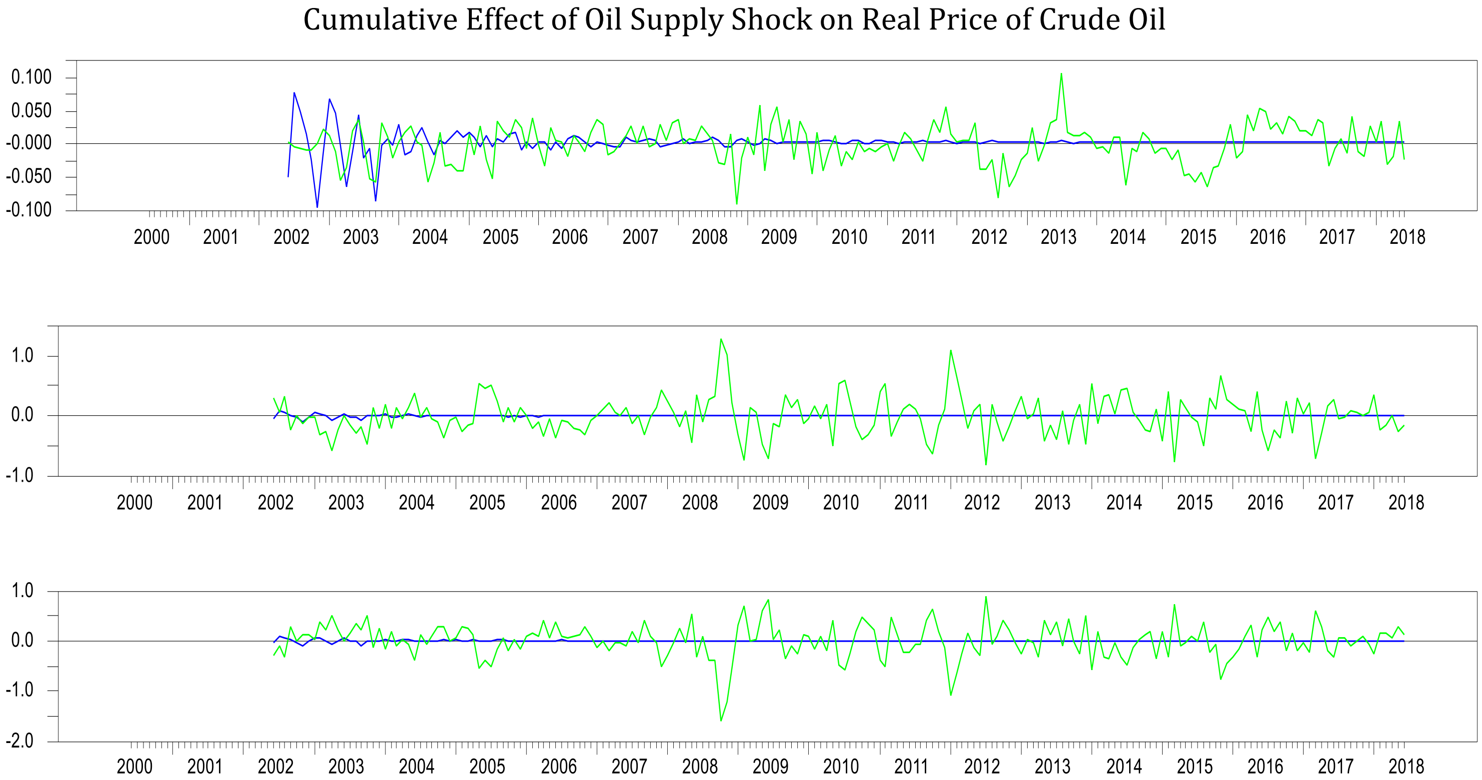


Figure 2.3: Historical decomposition of the real price of crude oil (05.2000–06.2018)



Note: The time span of the decomposition of the real price of crude oil is selected to correspond with monthly stock data availability of the GCC stock markets.

2.4.4.2. The response of the GCC stock markets to shocks

2.4.4.2.1. Saudi stock market

Figure 2.4 shows the impulse responses of Saudi stock market prices to the three-oil market shocks, along with the US stock market and other shocks related to the stock market. Oil supply shock reduces Saudi stock prices during the first two months; following this, prices revert until the impact fades away after the fifth month. However, the magnitude of the decline in the stock prices driven by the aggregate demand shock is larger. Oil-specific demand shock, at 95% confidence intervals, significantly reduces the stock market for six months until fading away. The US stock market and other stock market shocks also have significant and negative impacts during the first three months, showing a less-inclined decrease in the stock market prices until the fifth month, after which the impact fades away. Table 2.4 numerically shows the variance decomposition of the Saudi stock market.

Figure 2.4: The impulse response functions of the Saudi stock market

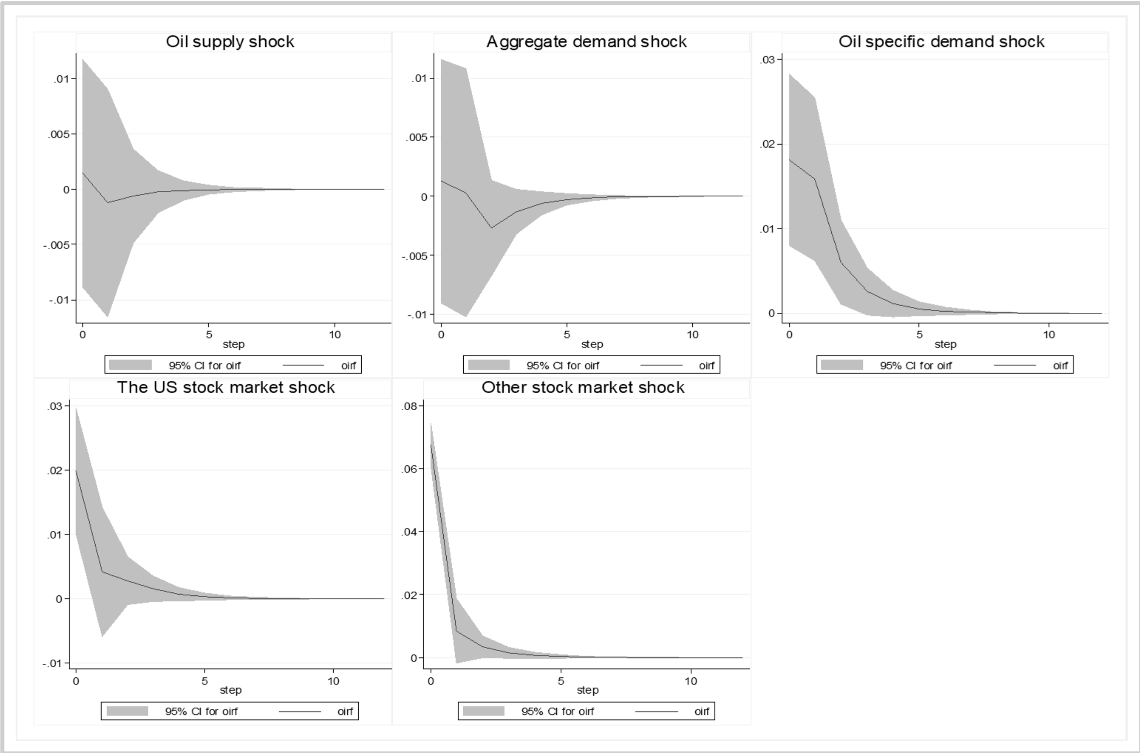


Table 2.4: Variance decomposition of the Saudi stock market

	Oil supply shock	Aggregate demand shock	Oil specific-demand shock	The US stock market shock	Other stock market shock
1	0.000397	0.000306	0.062042	0.074292	0.862964
2	0.000642	0.000302	0.102853	0.072866	0.823337
3	0.000698	0.001588	0.108079	0.073442	0.816192
4	0.000707	0.001885	0.108986	0.073699	0.814722
5	0.000708	0.001946	0.10917	0.073752	0.814423
6	0.000708	0.001958	0.109208	0.073763	0.814362
7	0.000708	0.00196	0.109216	0.073766	0.81435
8	0.000708	0.001961	0.109217	0.073766	0.814347
9	0.000708	0.001961	0.109218	0.073766	0.814347
10	0.000708	0.001961	0.109218	0.073766	0.814347
11	0.000708	0.001961	0.109218	0.073766	0.814346
12	0.000708	0.001961	0.109218	0.073766	0.814346

2.4.4.2.2. Dubai stock market

Figure 2.5 shows that the influence of the five shocks on the Dubai stock market is similar to the impact of the estimated shocks on the Saudi stock market, except for the influence of aggregate demand and oil-specific demand shocks. An aggregate demand shock boosts Dubai stock prices with a powerful effect, starting from the second month until the fifth month. An oil-specific demand shock temporarily increases the stock market prices in the first two months, followed by a gradual decrease until the seventh month. The effectiveness of the shocks on Dubai stock market prices is numerically shown through the variance decomposition in Table 2.5.

Figure 2.5: The impulse response functions of the Dubai stock market

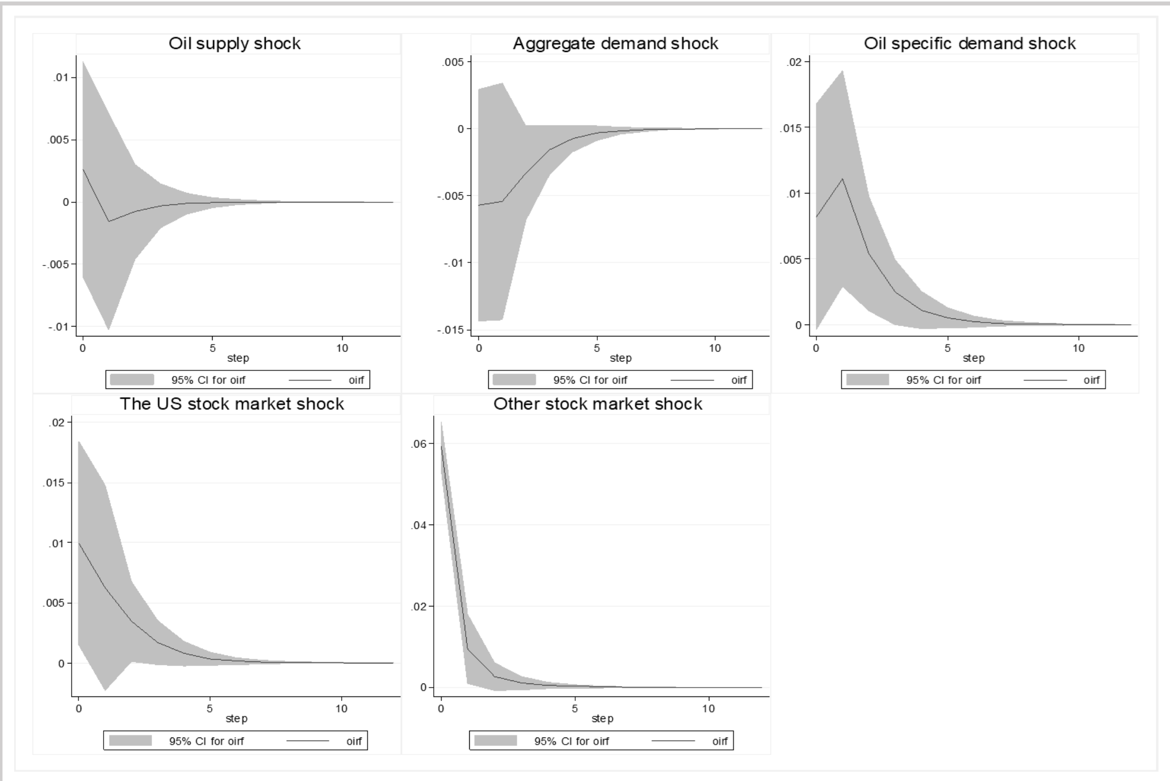


Table 2.5: Variance decomposition of the Dubai stock market

	Oil supply shock	Aggregate demand shock	Oil specific-demand shock	The US stock market shock	Other stock market shock
1	0.001847	0.008782	0.018026	0.026669	0.944676
2	0.002344	0.015546	0.047542	0.034559	0.90001
3	0.002468	0.018026	0.054019	0.037007	0.88848
4	0.002486	0.018604	0.05533	0.037602	0.885978
5	0.002489	0.018727	0.055598	0.037731	0.885455
6	0.002489	0.018753	0.055653	0.037758	0.885346
7	0.00249	0.018758	0.055664	0.037764	0.885324
8	0.00249	0.018759	0.055667	0.037765	0.885319
9	0.00249	0.01876	0.055667	0.037765	0.885318
10	0.00249	0.01876	0.055667	0.037765	0.885318
11	0.00249	0.01876	0.055667	0.037765	0.885318
12	0.00249	0.01876	0.055667	0.037765	0.885318

2.4.4.2.3. Kuwait stock market

Figure 2.6 shows that an oil supply shock leads to an immediate increase in the Kuwaiti stock prices in the first two months and then a gradual decrease until the fifth month. The impact of a global aggregate demand shock, in contrast, increases during the first month and then slowly reverts in the second month. Following this, a gradual upward trend is once more visible until the fifth month. An oil-specific demand shock, which statistically is significant within a 95% confidence interval, increases the Kuwaiti stock prices in the first two months, reverting gradually back until the sixth month. Finally, the impact of the US stock market and other shocks on Kuwait stocks is similar to the previous analyses. The average variation of Kuwait stock prices is quantified in Table 2.6.

Figure 2.6: The impulse response functions of the Kuwait stock market

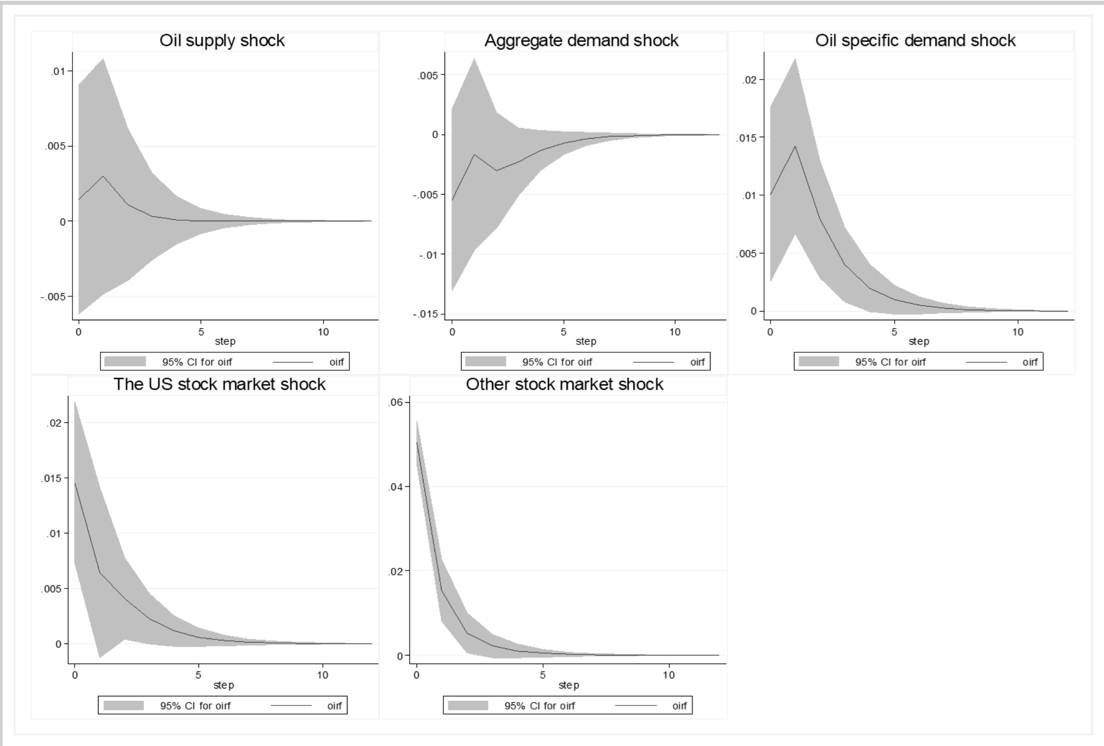


Table 2.6: Variance decomposition of Kuwait stock market

	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	The US stock market shock	Other stock market shock
1	0.000732	0.010379	0.034855	0.073145	0.880888
2	0.003255	0.00967	0.089794	0.074698	0.822582
3	0.003484	0.011908	0.104578	0.077014	0.803016
4	0.003481	0.013246	0.108139	0.077757	0.797377
5	0.003474	0.013706	0.109001	0.077958	0.795861
6	0.003472	0.013836	0.109215	0.078009	0.795468
7	0.003472	0.01387	0.109268	0.078021	0.795368
8	0.003472	0.013879	0.109282	0.078024	0.795343
9	0.003472	0.013881	0.109285	0.078025	0.795337
10	0.003472	0.013882	0.109286	0.078025	0.795335
11	0.003472	0.013882	0.109286	0.078026	0.795335
12	0.003472	0.013882	0.109286	0.078026	0.795334

2.5. Discussion of results

Three key findings are discussed in this section: first, the results show that crude oil supply shock has a stronger negative impact on Dubai relative to the Saudi stock market and contrasting with the response of the Kuwait stock market. These results could be in part due to the Dubai stock market structure, consisting of a considerable number of transportation and service companies that increasingly use fuel. (Balcılar et al., 2017). Moreover, the UAE has a small proven reserve of crude oil (OPEC, 2018).[17] In contrast, the Kuwait stock market temporarily benefits from oil supply shock, as Kuwait exports a high percentage of its production unlike the other two countries (Awartani and Maghyereh, 2013).[18]

Second, a global aggregate demand shock leads to an interim reduction in the Saudi stock market and a rise in stocks in Dubai and Kuwait. One possible justification is that the Saudi stock market heavily contains energy and petrochemical companies, which their activity associated with the global business cycle condition.[19] This is in comparison to Dubai and Kuwait stocks, which have more diversified business

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[17] UAE's proven reserve of crude oil amounts to 97,800 (million barrels), while Saudi Arabia and Kuwait have 266, 26 and 110, 50, respectively (OPEC, 2018).

[18] The percentage of crude oil exports out of produced oil in Kuwait is 76.2%, while the levels are 69.9% and 64.7%, respectively, in Saudi Arabia and the UAE (OPEC, 2018).

[19] For example, Saudi stock market growth mainly relies on the revenues of the Saudi Basic Industries Corporation (SABIC), which is a global leading company in the diversified chemicals industry.

activities, such as real estate, tourism and financial services. These findings are consistent with Arouri et al. (2011), who also reported that Kuwait and Dubai's stock markets are highly dominated by banking and service companies and thus are less dependent on oil revenues. The results also reveal that the two stock markets potentially profit from the large share of foreign investment portfolios (Ajmi et al. 2014 and Young 2015).

An oil-market-specific demand shock that is driven by a rise in precautionary demand leads to a decline in the three GCC stocks. However, Dubai and the Kuwait stock market indexes quickly revert after the first two months. The negative responses of the three stock markets are anticipated, as the stocks are susceptible to the political events in the Middle East, which are often the primary source of the precautionary demand of crude oil (Kim and Hammoudeh, 2013; Balcilar et al., 2017). Also, the GCC governments usually hold non-sustained financial surpluses driven by the political concerns in the region (Nusair and Al-Khasawneh, 2018).[20]

The US stock market and other stock market shocks symmetrically and negatively affect the three stock markets. The responses of the three stocks to US stock market movements are reasonable, given its crucial impacts on the global stock markets, in particular, after the global financial crisis in 2008 (Arouri et al., 2011; Kim and

[20] The GCC policymakers build annual spending plans based on consistent prices of crude oil (Kim and Hammoudeh, 2013).

Hammoudeh, 2013). Other stock market shock is related to the monetary policy elements and generates the most decisive influence on the three stocks. The expected reason is that GCC's interest and exchange rates are not fully flexible, as they are shackled by the US monetary policy goals (Sbia et al., 2016).[21]

The importance of our findings stems from first, GCC countries are the largest suppliers of crude oil; thus, the stock prices are likely to be receptive to shifts in oil prices.[22] Second, GCC markets differ from those in developed as well as other emerging countries; as such, stocks are adjacent to the political events taking place within the Middle East, which are directly relevant to oil supply and oil-specific demand shocks. Finally, GCC stocks might be promising for international portfolio diversification, especially given the recent ambitious economic plans launched by the GCC governments.

[21] The Kuwaiti Dinar (KWD) is pegged to a basket of global key currencies, but the US dollar occupies the largest share.

[22] The GCC region produces more than 21% of the global demand for crude oil and has 47% of the global verified reserves (Arouri and Rault, 2012; Malik and Hammoudeh, 2007).

2.6. Conclusion

Using structural VAR models and data from June 2002 to June 2019, we follow Kilian (2009) and estimate the impact of oil price shocks, US stock prices and foreign investment restrictions on Saudi, Dubai and Kuwait stock markets. The findings confirm the significant impact of oil price shocks on the three GCC stock markets, but the impact differs based on the structural characteristics of each of the GCC stock markets. An oil supply shock has a stronger negative impact on Dubai relative to the Saudi stock markets, contrasting with the response of the Kuwait stock market. While a global aggregate demand shock leads to an interim reduction in the Saudi stock market and a rise in stocks in Dubai and Kuwait. An oil market-specific demand shock leads to a decline in the three GCC stocks. However, the Dubai and Kuwait stock market indexes quickly improve after the first two months. The impact of the US stock market on the GCC stock markets is negative and symmetrical as a consequence of common features of monetary policies between the GCC central banks and the US Federal Reserve.

The study, in general, inspects the primary causes of GCC stock market fluctuations and how much they are attributed to oil price shocks. Our findings can help GCC policymakers and investors to mark the stagnant response of stock markets to some periods of oil price increases. This study also shows the importance of stock market liberalisation and the diversification of economic activities to reduce the sensitivity of GCC economics to oil price shocks. Our results confirm that pegging the GCC's interest and exchange rates with the US adversely impact the GCC economies. Future researchers could further investigate other sources of oil price fluctuations and how they impact GCC economics.

Chapter 3: Spillover Effects and Co-Movement between Oil Price, CO_2 Emission, Renewable Energy Production and the GCC Energy Equities

3.1. Introduction

Following the Kyoto Protocol and the establishment of the European Union Emissions Trading System (EU ETS) in 2005, several studies have been conducted to investigate their impact on mitigating greenhouse emissions and global economies. The strategic goal of setting up the EU ETS is to prompt energy-intensive industries to use cleaner sources of energy (European Communities, 2008). Accordingly and since then, renewable energy production has witnessed a rapid surge, especially in developed countries. According to the Energy Information Administration (EIA) (2018), the use of renewable energy sources in the US has increased by 7% in 2017 and is panned to reach 37% by 2040. Furthermore, the Renewable Energy Policy Network for the 21st Century (REN21) (2018) reported that renewable energy sources contributed 18.1% to global energy consumption in 2017. Moreover, the Energy Information Administration (EIA) (2019) announced the fastest global growth in renewables by 34%, whilst China alone achieved around 40%.

Most research in the energy use transitions field was discussed in several different ways. Scholars have analysed the impact of growing clean energy consumption on oil prices (e.g. Marques and Fuinhas, 2011; Payne, 2012; Apergis and Payne, 2014; Bloch et al., 2015; Waziri et al., 2018; and Sun et al., 2019). Some authors have demonstrated the two-way relation between crude oil prices and carbon dioxide emissions (e.g. 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). Other scholars have debated an underlying mechanism of energy transformations between oil prices, CO_2 emission along with its financial effects on stock prices of renamable energy sectors (e.g. Oberndorfer, 2009; Sadorsky, 2012; Weigt et al., 2013; Madaleno and Pereira, 2015; Zhang and Du, 2017; Lin and Chen, 2019; C. Sun et al., 2019).

The 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. In other words, there is 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. Also, the prior studies have used annual data depending on the availability of data for renewable energy consumption in particular by applying to regions instead of single countries. 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 spillovers.

The present study aims 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 Arabi, UAE and Kuwait. Specifically, we address the following research questions: is the current volatility in the conventional energy stock prices in the three countries influenced by the past shocks of global clean energy production, oil and CO_2 emission prices? If yes, does the evidenced volatility exist over the short or the long term and which country is the most sensitive to the three variables? We use daily data over the period from January 02, 2013, to March 20, 2019, to run three multivariate GARCH frameworks: diagonal BEKK GARCH (1,1), asymmetric DCC GARCH (1,1) and copula DCC GARCH (1,1) models for each country.

The findings 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. We also found that volatilities in all the returns under consideration are highly persistent; though the GCC energy stock markets are more stable compared to other markets. The steadiest GCC energy index is Kuwait energy stock price followed by Abu Dhabi and Saudi energy indexes. Both short and long-term persistence in the conditional variance of all the time series are confirmed, but the long-run persistent volatilities are more pronounced, especially for oil and CO_2 emission prices.

The key contribution of this study is providing empirical evidence about the impact of the changes in global clean energy production and the new carbon allowances prices on traditional energy sectors. We prove that the UE ETS, which established in the European countries, can also affect the traditional energy sectors in oil-exporting countries such those in the GCC region. In addition, we compute the growth in renewable energy production using a global measure instead of a country or region-level. The last contraption comes from employing weighted daily data for global clean energy production. This statistically enables us to run several volatility spillovers and dynamic correlations frameworks that correspond to energy markets behaviour.

The rest of this chapter is constructed 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 this chapter.

3.2. Literature review

We divide the existing literature into three sub-sections: sub-section 1 addresses the nexus between crude oil price and renewable energy growth impact, in sub-section 2, we survey the link of 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 section 3.

3.2.1. Crude oil price and alternative energy growth

In recent years, several studies have looked into the nexus between crude oil and renewable energy sources. However, mixed results based on annual data of clean energy consumption are reported. (e.g. Stern, 2000; Sadorsky, 2009; Marques and Fuinhas, 2011; Payne, 2012; Apergis and Payne, 2014; Bloch et al., 2015; Dogan and Seker, 2016; Dutta et al., 2018; Waziri et al., 2018; Troster et al., 2018; Chevallier et al., 2019; Sun et al., 2019; Burkhardt, 2019; Sharif et al., 2019). One strand of the literature directly researched the overlapping impacts of new energy growth and oil price swings (e.g. Stern, 1993; Stern, 2000; Oh and Lee, 2004; Payne, 2012; Chevallier, 2012; Tan and Wang, 2017; Ji et al., 2018). Another strand used 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).

The initial research on the direct relationship between changes in oil price and alternative energy developments was conducted by Stern (1993). More 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 existing of casual relationships among aggregate clean energy consumption, oil prices and economic activities. Some empirical studies adopted multivariate models in various countries while using annual data of renewable energy consumption. For instance, Bloch et al. (2015) have used autoregressive distributed lag (ARDL) and vector error correction model (VECM) to investigate the link of coal, oil and renewable energy consumption in China using yearly data over the period 1977 to 2011. The results indicate that economic activity growth and oil prices hike lead to increases in clean energy production. This view is supported by Burkhardt (2019), who also used the annual data for renewable energy consumption obtained from the U.S. Energy Information Administration. In contrast to Bloch et al. (2015) and Burkhardt (2019), 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. Moreover, the results revealed that CO_2 emissions are found to be a key driver behind renewable energy consumption. Dogan and Seker (2016a) and Sharif et al. (2019) have criticised the works of Sadorsky (2009) and Marques and Fuinhas (2011) stating that these works ignored cross-section data analysis. Thus, both panel and cross-section data was used for several European nations by Dogan and Seker (2016b) who explored the bidirectional causal relationship between CO_2 emissions and renewable energy on one hand; and unidirectional causal relationship running from CO_2 emissions to traditional energy on the other hand. Similar results were found by Troster et al. (2018) using a Granger-causality analysis in each quantile of the distribution of oil prices and renewable energy consumption.

To better understand the transmission mechanisms between oil prices, alternative energy consumption and CO_2 emissions, Nguyen and Kakinaka, (2019) distinguished between low- and high-income countries. The findings indicate that renewable energy consumption in low-income countries is positively associated with CO_2 emissions; while for the high-income countries, the relationship is negative. In the same way, Furlan and Mortarino (2018) and Amri (2019) confirmed the adverse interrelation between oil price and renewable energy consumption using annual data and applying a global sample. Furlan and Mortarino (2018) used annual data for renewable energy consumption in the U.S., EU, China and India over the period 1965 to 2014, while Amri (2019) covered a larger number of developed and developing countries from 1990 to 2012. Considering the above studies, it seems that evidence on the link between alternative energy growth and oil price shifts is still unclear.

3.2.2. Crude oil, emission allowances prices and clean energy stock market

The overlapping impacts of crude oil and carbon emission prices on stock prices of renewable energy firms have been addressed by several empirical studies (e.g. Henriques and Sadorsky, 2008; Oberndorfer, 2009; Weigt et al., 2013; Reboredo, 2015; Madaleno and Pereira, 2015; Bondia et al., 2016; Moreno and Pereira da Silva, 2016;

Zhang and Du, 2017; Lin and Chen, 2019; C. Sun et al., 2019). The significant stream of literature has focused on the influence of oil prices on clean energy stock returns (e.g. Koch, 2014; Reboredo, 2015; Bondia et al., 2016; Dutta, 2017; Reboredo et al., 2017; Hodson et al., 2018; C. Sun et al., 2019). An increase in oil or emission allowances prices promote investment in alternative energy firms, thereby its returns. 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 correlated with two structural breaks.

More recent empirical research has been carried out employing advanced techniques of volatility modelling. For instance, 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 than in 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) 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.

Another group of scholars researched 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). 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 supported by Zhang and Du (2017), who stated that technology stock prices are highly correlated with clean energy stock prices in China. Lastly, Sadorsky (2012), Ahmad (2017) and Maghyereh et al. (2019) applied wavelet and multivariate-GARCH analyses presenting evidence of the co-movements and correlation among clean energy firms stock prices, oil prices and technology companies stock prices.

Few empirical works have investigated the link between oil prices, new energy stock prices and some macroeconomic factors (e.g. Shah et al., 2018; Lin and Jia, 2019). 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 research 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.

Further, there is a broad consensus among economists about the positive influence of the European Union Allowance (EUA) prices on renewable energy stock prices (e.g. Oberndorfer, 2009; Weigt et al., 2013; Madaleno and Pereira, 2015; Moreno and Pereira da Silva, 2016; Dutta et al., 2018). Dutta et al. (2018) investigated return and volatility linkages between the EUA prices and renewable energy stock returns using a bivariate VAR-GARCH analysis. The positive impact of the EUA prices on stock returns of clean energy has been documented, although the correlation is found to be statistically insignificant. Both Weigt et al. (2013) and Madaleno and Pereira (2015) provided evidence on the positive effect of the EUA prices on the German renewable energy firms' stock prices, although Weigt et al. (2013) estimated the reaction of renewable energy stock prices with and without carbon emissions regulations. In contrast to the last views, Madaleno and Pereira (2015) reported a statistically significant and negative effect of Phase III of the EUA on Spanish stock market performance.

Overall, the evidence presented in this section suggests that the new emissions trading systems and oil price surges contribute towards promoting investments in the clean energy stock market. There is still uncertainty, however, whether the new global emissions schemes could also impact petroleum energy stock prices in oil-exporting countries.

3.2.3. 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) 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).

The first seminal study that employed average atmospheric carbon dioxide was published 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 recently supported by Andersson and Karpestam (2013) and Mensah et al. (2019). However, Mensah et al. (2019) determined a unilateral cause from oil prices to carbon emissions both in the long and 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) estimated the casual relationship using the quantile regression approach. The outcomes clearly showed that the oil price surge makes a considerable drop in the carbon allowances prices. Nonlinear autoregressive distributed lag (NARDL) and copula frameworks were applied by Hammoudeh et al. (2015) and Chevallier et al. (2019), respectively. The negative impact between crude oil and CO_2emission allowance prices is mostly observed in the long run.

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) and Chen et al. (2019) 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, 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.

3.3. Methodology and data

3.3.1. The theoretical model

The possible links between variables under consideration are hypothesised based on an original economic theory called 'top-down analysis of energy demand'. Schwarz et al. (2017) discussed the theory and its five foundations that are used to understand energy market spillovers (or dependency). First, the theoretical link between population growth (PG_t) and the aggregate demand for energy (D_t) as formulated by:

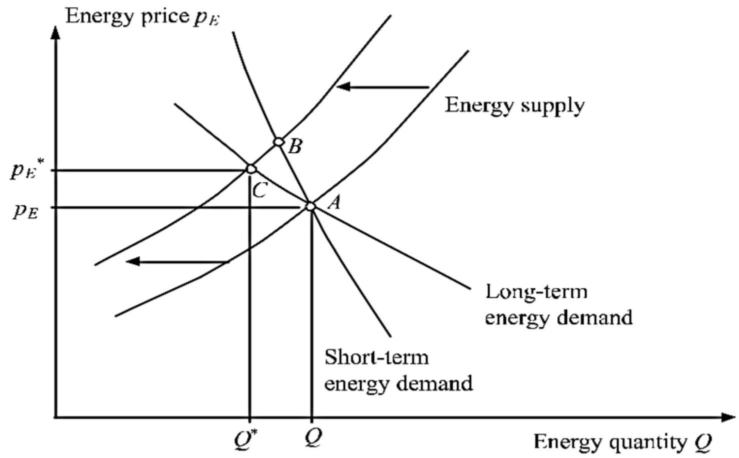
$$\frac{\Delta D_t}{D_t} \approx \frac{\Delta PG_t}{PG_t} + \frac{\Delta(D_t/PG_t)}{(D_t/PG_t)} \qquad (3.1)$$

Second, changes in the gross world product (GWP) is argued as a key factor behind changes in aggregate energy demand D_t. Where PCI_t denote per capita income, the process can be reformed as follows:

$$\frac{\Delta D_t}{D_t} \approx \frac{\Delta PG_t}{PG_t} + \frac{\Delta PCI_t}{PCI_t} + \frac{\Delta(D_t/GWP_t)}{(D_t/GWP_t)} \qquad (3.2)$$

Next, the global aggregate demand for energy commodities is inelastic. It implies that decreasing the quantity supplied of an energy commodity, caused by an increase in the demand side, the price of the commodity proportionally rises more than the reduction of the quantity supplied. This is due to producers cannot boost the quantity supplied immediately for technical and financial issues. Therefore, the equilibrium price in the market will first shift towards a short-term equilibrium point before reaching the long-term equilibrium point (the new equilibrium place). This situation is displayed in Figure 3.1.

Figure 3.1: Short and long-run impacts of a fall in energy supply



Fourth, using less energy-intensive techniques of production could yield a higher level of production. This is due to the substitution relationship between less and more energy-intensive energy sources. Finally, the rapid technological changes over time play a critical role in energy use. Technological developments enable manufactories to produce the same level of outputs (or more) using smaller quantities of energy. This is formally given by the following function:

$$Q = f(C, L, D, M) = r[s_C(t)C, s_L(t)L, s_D(t)D, s_M(t)M \qquad (3.3)$$

where output Q is a function of C, L, D, M which denote capital, labour, energy demand and non-energy materials respectively, $s_C(t)$, $s_L(t)$, $s_D(t)$ and $s_M(t)$ represent changes in technology.

3.3.2. 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 under analysis. We define $B(L)$ as the lag polynomial, then:

$$B(L)r_t/\Omega_{t-1} = \mu_t + \varepsilon_t \qquad (3.4)$$

Where ε_t is the vector containing the error-term and Ω_{t-1} is the information up to the previous period.

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

where $H_t^{\frac{1}{2}}$ is a $N \times N$ positive definite matrix such that H_t is the conditional variance matrix of y_t. For the random vector z_t, it is assumed that:

$$E(z_t) = 0$$

$$Var(Z_t) = I_N$$

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.

3.3.2.1. The diagonal BEKK model

Baba, Engle, Kraft and Kroner (1990) proposed the BEKK model. This model ensures the positive definiteness of H_t. The BEKK (1,1) model is defined as:

$$H_t = C'C + \sum_{i=1}^{p} A_i' \epsilon_{t-i} \epsilon'_{t-i} A_i + \sum_{j=1}^{q} B_i' H_{t-j} B_j \qquad (3.5)$$

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.

3.3.2.2. The dynamic conditional correlation models

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

$$H_t \equiv D_t R_t D_t \qquad (3.6)$$

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

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (3.7)$$

where Q_t is the positive definite matrix containing the conditional variances-covariances 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 then given by:

$$Q_t = (1 - a - b)\bar{Q} + a\epsilon_{t-1}\epsilon'_{t-1} + bQ_{t-1} \qquad (3.8)$$

Here 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 likelihood function is given by:

$$\ln\big(L(\theta)\big) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\{n\ \ln(2\pi) + ln|D_t|^2 + \ln(|R_t|) + \varepsilon_t' D_t^{-2}\varepsilon_t \qquad (3.9)$$

However, one criticism placed against the DCC model was that the estimation of scalar variables becomes difficult as the number of variables increases. As a result, Cappiello et al. (2006) proposed the Asymmetric Generalised DCC (AGDCC) where the dynamics:

$$Q_t = (Q - A'QA - B'\bar{Q}B - G'\bar{Q}^{-}G) + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'Q_{t-1}B + G'\epsilon_t\epsilon'^{-}_{t}G \quad (3.10)$$

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, which we use in this analysis.

Copula DCC GARCH models were first proposed by Sklar (1959). He argues that Copula functions are useful in obtaining the univariate marginal distribution function from the dependence structure of a set of random variables. In addition, copulas have an advantage while dealing with high-dimensional joint distributions. For practical purposes, copula-based models help in identifying the interdependence between a large number of assets.

Sklar (1973) shows that for a set of n random variables, each multivariate distribution function $F\ (x_1, \dots, x_n)$ can be represented as its marginal distribution function by using a copula such as:

$$F\ (x_1, \dots, x_n) = C\{F_1(x_1), \dots, F_n(x_n)\}. \qquad (3.11)$$

Where an n-dimensional copula and C for distributions, F can be defined as:

$$C(u_1 \dots . u_n) = F\left(F_1^{-1}(u_1) \dots \dots . F_n^{-1}(u_n)\right) \text{ for } \forall u_i \ \in [0,1], i = 1,2 \dots \dots n \qquad (3.12)$$

Then the density functions of $F\ and\ C$ are given by:

$$f(x_1 \dots \dots \dots \dots . x_n) = c\left(F(x_1) \dots \dots F(x_n)\right) \prod_{i=1}^{n} f_i(x_i) \qquad (3.13)$$

$$c(u_1 \dots \dots . u_n) = \frac{f\left(F_1^{-1}(u_1) \dots\dots F_n^{-1}(u_n)\right)}{\prod_{i=1}^{n} f_i\left(F_i^{-1}(u_i)\right)} \qquad (3.14)$$

where $f_i$are the marginal densities and F_i^{-1} are the quantile function of the marginals. The time-varying conditional correlation using copulas is essentially an extension of the DCC model. Let $r_t = (r_{it} \dots \dots . . r_{nt})$ be a $n \times 1$ vector of asset returns and it follows a copula–GARCH model with joint distribution given by:

$$F\ (r_t|\mu_t, h_t) = C(F1(\ r_{1t}|\mu_{1t}, h_{1t}) \dots\dots\dots\ Fn\ (\ r_{nt}|\mu_{nt}, h_{nt}) \qquad (3.15)$$

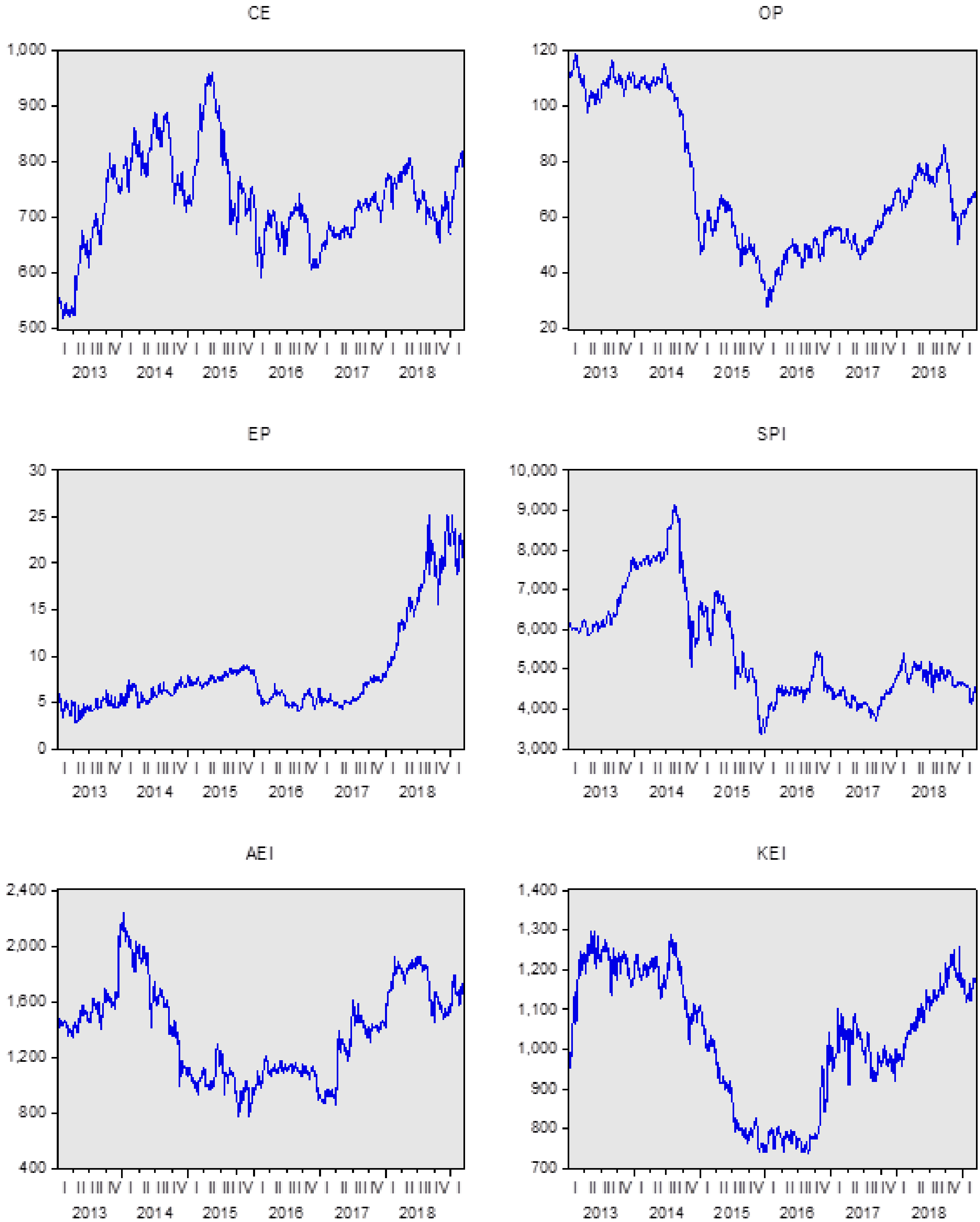
where F and C are the conditional distribution and the copula function, respectively. The conditional mean μ_{it} is a linear function of its one-lag past returns and it follows an ARMA (1,1) process. The conditional variance h_{it} follows a GARCH (1,1) process.

3.3.3. Data

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.[23] 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 indexes under consideration. Figure 3.2 plots the raw data of the all-time series.

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

Figure 3.2: The raw data of the time series of the study (2013-2019)



3.4. Empirical work

3.4.1. Preliminary statistics

Table 3.1 shows basic statistics and pre-estimation diagnostics of log-returns of the six variables.

Table 3.1: 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 $Q = n(n+2)\sum_{k=1}^{h}\frac{\rho_k^2}{n-k}$

The standard deviation values indicate that all-time series are fluctuating in nature and CO_2 emission price is found to be the most volatile. The variables of 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-Box 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 our dataset.

3.4.2. Unit root test

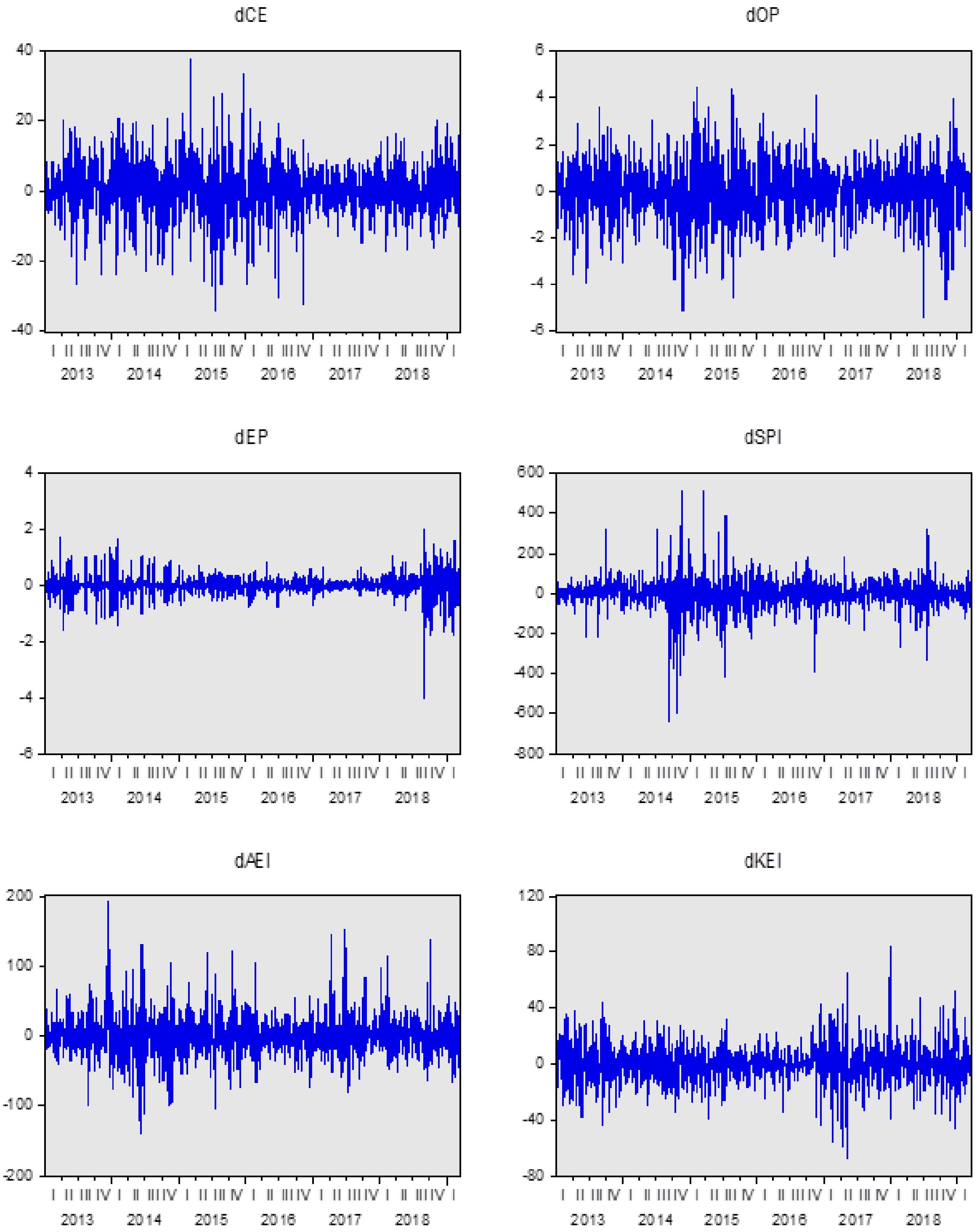
Table 3.2 shows the results of augmented Dickey-Fuller and Phillips-Perron unit root tests applied to the log of the six-time series. The unit-roots tests clearly show that all the six-time series are stationary at the first difference. Where Figure 3.3 illustrates the fluctuations of the log-returns of the variables.

Table 3.2: 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.

Figure 3.3: Log returns of the time series of the study (2013-2019)



3.4.3. Results

3.4.3.1. Univariate GARCH model

In the first stage of a multivariate GARCH analysis, an AR (1)-GARCH (1,1) model is estimated for all six series. The results are shown in Table 3.3.

Table 3.3: Univariate GARCH results

Parameters	**CE**	**OP**	**EP**	**SPI**	**AEI**	**KEI**
$\boldsymbol{\omega_0}$	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)
$\boldsymbol{\alpha_0 * 10^6}$	0.651881 (0.226)	0.500059 (0.035)	0.016019 (0.234)	0.797941 (0.242)	4.337447 (0.001)	1.9269 (0.242)
$\boldsymbol{\alpha_1}$	0.073598 (0.032)	0.073977 (0.000)	0.05453 (0.006)	0.093315 (0.001)	0.160916 (0.000)	0.081019 (0.017)
$\boldsymbol{\beta_1}$	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 $\varepsilon_t = z_t\sigma_t$ *and* z_t is white noise, the univariate GARCH equation can be written as:

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

The results reveal that all the series have significant conditional volatility and both ARCH (α_1) and GARCH (β_1) components are statistically significant. This confirms the presence of time-varying conditional volatility of the returns of time series. 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. To sum up, 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.

3.4.3.2. Multivariate GARCH models

The estimation results of the three multivariate GARCH models are interpreted through two main sections. We first show the results of time-varying variance-covariance estimated by the diagonal BEKK (1,1) model, followed by the results of the two dynamic conditional correlation (DCC) models.

3.4.3.2.1. Volatility spillover

The results of the time-varying variance-covariance obtained from the diagonal BEKK GARCH (1,1) models for each country are shown in Table 3.4. AR (1) coefficients denote autocorrelation effects. Whilst 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. However, the most important coefficients to interpret are for 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. While (β_{ii}) parameters explain the persistence of shocks (the piecemeal decline of the influence of news). We also assess the stabilisation of the variance which consider a critical condition in the GARCH process. It can be achieved if the sum of the parameters A and B in a process is less than one. Moreover, if the sum of A and B values is close to one, this means that the process somewhat fluctuates around the mean value indicating 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 their 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 a 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 estimation coefficients of ARCH $A(\alpha_{ii})$ and GARCH effects $B(\beta_{ii})$ are highly statistically significant for the three countries.[24] All the ARCH parameters ($\alpha_{11}, \alpha_{22}, \alpha_{33}$ *and* α_{44}) derive positive values and statistically significant. This signifies 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. Where the lowest values of the ARCH effects among the models were found for the estimated coefficients of the clean energy production index, CO_2 emission and oil prices as represented by (α_{11}), (α_{33}) (α_{22}) respectively. To sum up, the estimated coefficients of the ARCHs show that the future

[24] Except the coefficient (α_{11}) for the UAE model which found to be insignificant.

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. This is solid evidence of the persistence of the impact of the past shocks on the current prices of the markets (at least one day). However, we found that the impact of the past shocks of the GCC energy stock markets have less persistence in comparison with 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 ($\beta_{11},\ \beta_{22}\ and\ \beta_{33}$). The steadiest GCC energy index is Kuwait energy stock price followed by Abu Dhabi and Saudi energy indexes as evidenced by the values (0.7494), (0.8879) and (0.9529) respectively. 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. We also detect long memory behaviour in our time series as the sum of these parameters for each model almost equal to one.

Table 3.4: 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.

3.4.3.2.2. Dynamic conditional correlations analysis

Table 3.5 shows 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 particular market can be largely attributed to endogenous shocks more than spillover across the markets. The sum of the DCC_α *and* DCC_β 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 3.5: Estimation results of multivariate GARCH asymmetric 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.

3.4.3.2.3. Time-varying conditional correlations

Figures 3.4, 3.5 and 3.6 display the dynamic conditional correlations for the market pairs obtained from the three multivariate GARCH models. The market pairs illustrate 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 interpret 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 (Bloomberg, 2018). For example, Saudi and the UAE have imposed a value-added tax (VAT) of 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.

Figure 3.4: Conditional covariance plots of diagonal BEKK GARCH (1,1) model

Saudi **UAE** **Kuwait**

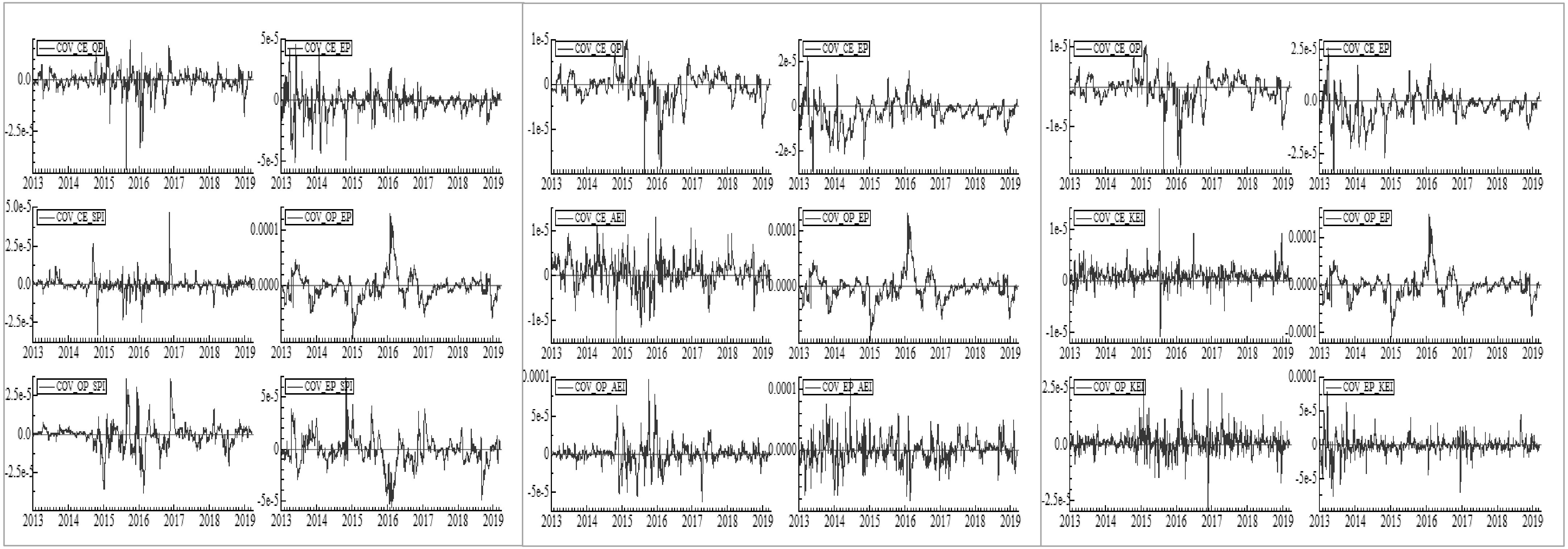


Figure 3.5: Conditional covariance plots of asymmetric DCC GARCH (1,1) model

Saudi **UAE** **Kuwait**

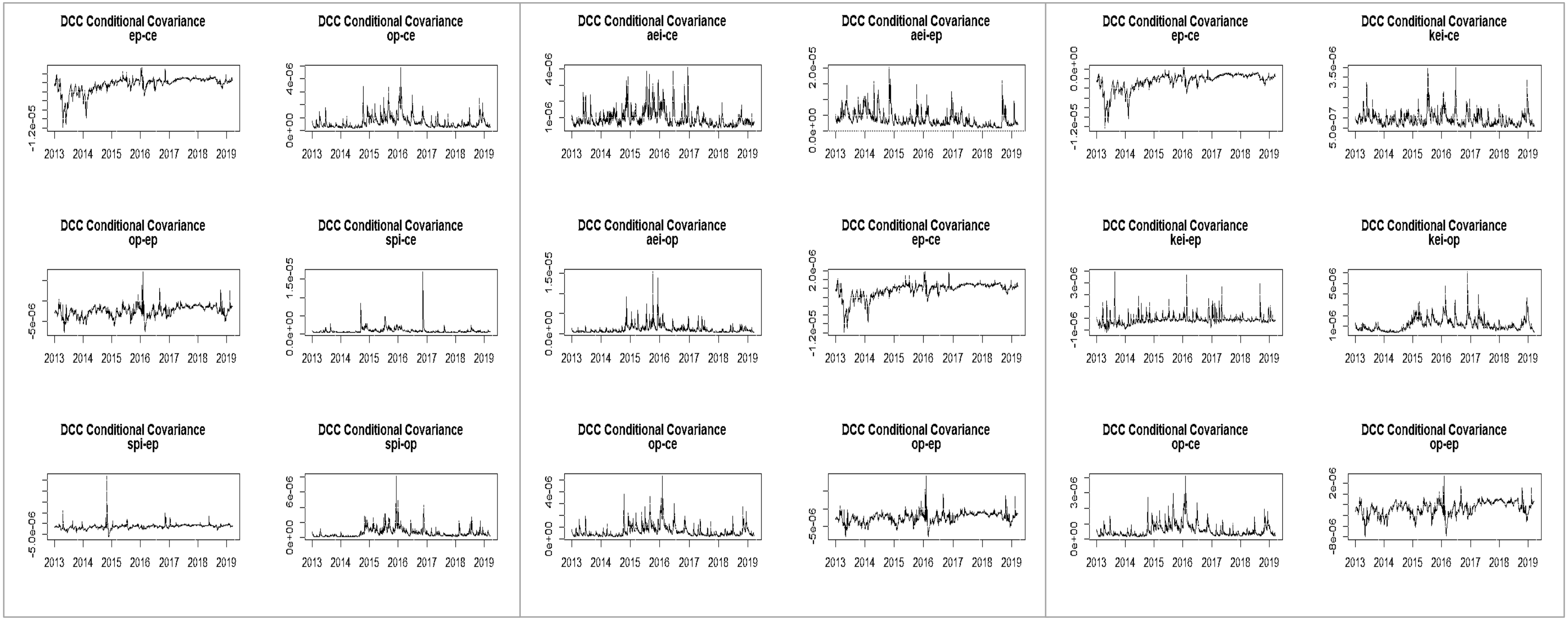
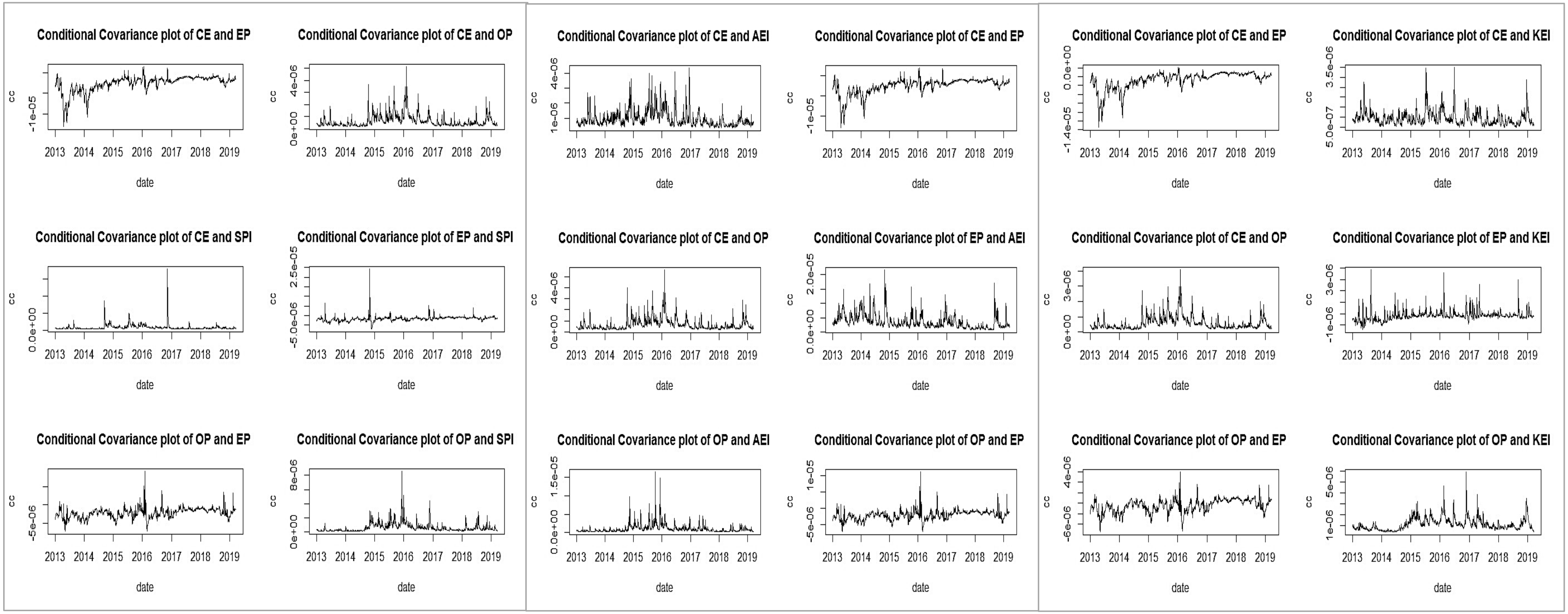


Figure 3.6: Conditional covariance plots of copula DCC GARCH (1,1) model

Saudi **UAE** **Kuwait**



3.4.3.3. Diagnostics tests and models comparison

Table 3.6 shows the results of the modified multivariate portmanteau tests developed by Hosking (1980) and Li-McLeod (1981). The results of Hosking test statistics confirm that the diagonal BEKK models for the Abu Dhabi and Kuwait markets can capture the spillover dynamics. This is because we are unable to reject the null of correct model specification up to the lag 20. Similarly, the Li-McLeod test indicates that the null of the correct specification can be not rejected. Therefore, the diagonal BEKK models were able to capture the conditional volatility dynamics for the two countries. However, for the Saudi model, it can be inferred that the BEKK GARCH was unable to fully capture the volatility dynamics. Where asymmetric and copula DCC GARCH models were

Table 3.6: Diagnostic test results

	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 the autocorrelation among the series no significant for lags.
2) *, ** and *** denote the significant level at 1%, 5% and 10% levels, respectively.

unable to totally explain the volatility spillover dynamics for the three countries. This is because the null of the correct model specification is rejected across all three models.

Table 3.7 compares the performance of the three empirical models using the Bayesian information criterion (BIC) as well as the Akaike information criteria (AIC).[25] We use the two statistics as the models that we are dealing with are non-nested. Both BIC and AIC confirm that the diagonal BEKK model is the best across the three countries as its statistical values are the lowest.

Table 3.7: 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

[25] Both AIC and BIC compare the quality of a set of models. The AIC is formulated as: AIC = -2(log-likelihood) + 2K, where BIC= *k log(n)- 2log (log-likelihood* $(\hat{\theta})$*)*. The optimal model shows the lowest statistical values of criteria.

3.4.3.4. Forecasting performance and evaluation

In this section, we provide forecasts for five days for all three models and countries. Tables 3.8, 3.9, 3.10, 3.11, 3.12, 3.13 and 3.14 report the forecasts which were calculated based on conditional mean, conditional variance-covariance and conditional correlation.

Table 3.8: Conditional mean forecast for diagonal BEKK, asymmetric DCC and Copula DCC

		Saudi				UAE				Kuwait			
	Day	CE	OP	EP	SPI	CE	OP	EP	AEI	CE	OP	EP	KEI
Diagonal BEKK	1	0.000625	-4.68E-05	-0.00148	0.000666	0.000639	-4.16E-05	-0.00148	0.000722	0.000632	-3.75E-05	-0.00143	-3.01E-05
	2	0.000253	-4.78E-05	0.001136	0.000175	0.000234	-4.28E-05	0.001211	-0.00013	0.000268	-3.88E-05	0.001253	3.34E-06
	3	0.000179	-4.78E-05	0.000647	0.000126	0.000145	-4.27E-05	0.000695	-7.50E-05	0.000197	-3.88E-05	0.000738	2.54E-06
	4	0.000164	-4.78E-05	0.000738	0.000121	0.000126	-4.27E-05	0.000794	-7.87E-05	0.000183	-3.88E-05	0.000837	2.56E-06
	5	0.000161	-4.78E-05	0.000721	0.00012	0.000122	-4.27E-05	-0.00077	7.85E-05	0.00018	-3.88E-05	0.000818	2.55E-06
Asymmetric DCC	1	0.000172	0.000908	-4.38E-05	-1.89E-05	0.000172	0.000908	-4.38E-05	0.000168	0.000172	0.000913	-3.97E-05	4.06E-05
	2	0.000172	0.000913	-3.97E-05	-1.46E-05	0.000171	0.000917	-3.52E-05	0.000171	0.000171	0.000917	-3.52E-05	4.02E-05
	3	0.000171	0.000917	-3.52E-05	-1.88E-05	0.000174	0.000906	-3.19E-05	0.00017	0.000174	0.000906	-3.19E-05	4.04E-05
	4	0.000174	0.000906	-3.19E-05	-1.72E-05	0.000174	0.000912	-3.08E-05	0.00017	0.000174	0.000912	-3.08E-05	4.02E-05
	5	0.000174	0.000912	-3.08E-05	-1.46E-05	0.000174	-0.00091	2.88E-05	0.000169	0.000174	0.000911	-2.88E-05	4.03E-05
Copula DCC	1	-0.00319	0.106205	-0.00594	-0.01691	-0.0063	0.023217	-0.00337	0.017241	-0.00019	0.009451	0.010992	0.005017
	2	0.000362	-0.05269	-0.00759	0.012532	0.003557	-0.01201	0.004716	0.010257	0.007149	-0.00785	-0.01724	-0.00268
	3	-0.00292	0.004078	-0.00219	-0.0104	0.015391	0.003308	-0.00019	0.000709	-0.0019	0.004723	-0.00967	0.008013
	4	-0.00833	0.002177	0.005386	-0.00406	-0.00572	0.038925	0.000302	-0.00166	-0.00748	0.01289	0.003863	0.000397
	5	0.000282	0.016495	-0.00702	0.002152	0.000298	0.057476	0.000892	0.009066	0.001327	-0.00681	0.000372	-0.00061

Table 3.9: Conditional covariance forecast for diagonal BEKK

		Saudi					UAE					Kuwait			
		CE	OP	EP	SPI		CE	OP	EP	AEI		CE	OP	EP	KEI
Day 1	CE	1.57E-05	1.17E-06	2.58E-06	4.75E-07	CE	2.03E-05	1.17E-07	-1.35E-06	8.83E-07	CE	1.69E-05	1.64E-06	2.75E-06	-3.49E-07
	OP	1.17E-06	3.58E-05	-5.17E-06	2.55E-06	OP	1.17E-07	3.75E-05	-5.75E-06	-1.55E-06	OP	1.64E-06	3.47E-05	-5.64E-06	3.40E-07
	EP	2.58E-06	-5.17E-06	0.000225	4.01E-06	EP	-1.35E-06	-5.75E-06	0.000224	-1.01E-05	EP	2.75E-06	-5.64E-06	0.000222	1.01E-06
	SPI	4.75E-07	2.55E-06	4.01E-06	3.62E-05	AEI	8.83E-07	-1.55E-06	-1.01E-05	7.62E-05	KEI	-3.49E-07	3.40E-07	1.01E-06	2.19E-05
Day 2	CE	1.57E-05	1.16E-06	2.56E-06	4.64E-07	CE	2.03E-05	1.17E-07	-1.35E-06	8.83E-07	CE	1.69E-05	1.63E-06	2.72E-06	-1.41E-07
	OP	1.16E-06	3.61E-05	-5.21E-06	2.57E-06	OP	1.17E-07	3.78E-05	-5.80E-06	-1.41E-06	OP	1.63E-06	3.50E-05	-5.72E-06	4.90E-07
	EP	2.56E-06	-5.21E-06	0.000226	4.01E-06	EP	-1.35E-06	-5.80E-06	0.000225	-9.17E-06	EP	2.72E-06	-5.72E-06	0.000223	7.41E-07
	SPI	4.64E-07	2.57E-06	4.01E-06	3.65E-05	AEI	8.83E-07	-1.41E-06	-9.17E-06	7.80E-05	KEI	-1.41E-07	4.90E-07	7.41E-07	2.40E-05
Day 3	CE	1.57E-05	1.15E-06	2.54E-06	4.53E-07	CE	2.03E-05	1.17E-07	-1.35E-06	8.83E-07	CE	1.69E-05	1.62E-06	2.69E-06	2.12E-08
	OP	1.15E-06	3.64E-05	-5.24E-06	2.59E-06	OP	1.17E-07	3.80E-05	-5.84E-06	-1.28E-06	OP	1.62E-06	3.52E-05	-5.79E-06	6.11E-07
	EP	2.54E-06	-5.24E-06	0.000227	4.01E-06	EP	-1.35E-06	-5.84E-06	0.000226	-8.25E-06	EP	2.69E-06	-5.79E-06	0.000224	5.29E-07
	SPI	4.53E-07	2.59E-06	4.01E-06	3.67E-05	AEI	8.83E-07	-1.28E-06	-8.25E-06	7.97E-05	KEI	2.12E-08	6.11E-07	5.29E-07	2.54E-05
Day 4	CE	1.57E-05	1.14E-06	2.53E-06	4.43E-07	CE	2.03E-05	1.17E-07	-1.35E-06	8.83E-07	CE	1.69E-05	1.61E-06	2.65E-06	1.48E-07
	OP	1.14E-06	3.66E-05	-5.27E-06	2.60E-06	OP	1.17E-07	3.82E-05	-5.88E-06	-1.15E-06	OP	1.61E-06	3.55E-05	-5.86E-06	7.09E-07
	EP	2.53E-06	-5.27E-06	0.000228	4.01E-06	EP	-1.35E-06	-5.88E-06	0.000227	-7.39E-06	EP	2.65E-06	-5.86E-06	0.000226	3.59E-07
	SPI	4.43E-07	2.60E-06	4.01E-06	3.70E-05	AEI	8.83E-07	-1.15E-06	-7.39E-06	8.13E-05	KEI	1.48E-07	7.09E-07	3.59E-07	2.64E-05
Day 5	CE	1.57E-05	1.13E-06	2.51E-06	4.33E-07	CE	2.03E-05	1.17E-07	-1.35E-06	8.83E-07	CE	1.69E-05	1.60E-06	2.62E-06	2.47E-07
	OP	1.13E-06	3.69E-05	-5.30E-06	2.62E-06	OP	1.17E-07	3.84E-05	-5.93E-06	-1.03E-06	OP	1.60E-06	3.58E-05	-5.93E-06	7.87E-07
	EP	2.51E-06	-5.30E-06	0.000229	4.00E-06	EP	-1.35E-06	-5.93E-06	0.000228	-6.57E-06	EP	2.62E-06	-5.93E-06	0.000227	2.23E-07
	SPI	4.33E-07	2.62E-06	4.00E-06	3.72E-05	AEI	8.83E-07	-1.03E-06	-6.57E-06	8.28E-05	KEI	2.47E-07	7.87E-07	2.23E-07	2.71E-05

Table 3.10: Conditional correlation forecast for diagonal BEKK

		Saudi					UAE					Kuwait			
		CE	OP	EP	SPI		CE	OP	EP	AEI		CE	OP	EP	KEI
Day 1	CE	1	0.049337	0.043352	0.019897	CE	1	0.004244	-0.02002	0.022443	CE	1	0.067933	0.044994	-0.01815
	OP	0.049337	1	-0.05771	0.070946	OP	0.004244	1	-0.06273	-0.02895	OP	0.067933	1	-0.06434	0.012326
	EP	0.043352	-0.05771	1	0.044436	EP	-0.02002	-0.06273	1	-0.07758	EP	0.044994	-0.06434	1	0.014424
	SPI	0.019897	0.070946	0.044436	1	AEI	0.022443	-0.02895	-0.07758	1	KEI	-0.01815	0.012326	0.014424	1
Day 2	CE	1	0.048717	0.042988	0.019374	CE	1	0.004231	-0.01997	0.022181	CE	1	0.067194	0.0443	-0.00701
	OP	0.048717	1	-0.05769	0.070864	OP	0.004231	1	-0.06287	-0.02595	OP	0.067194	1	-0.06472	0.01692
	EP	0.042988	-0.05769	1	0.044158	EP	-0.01997	-0.06287	1	-0.06917	EP	0.0443	-0.06472	1	0.010122
	SPI	0.019374	0.070864	0.044158	1	AEI	0.022181	-0.02595	-0.06917	1	KEI	-0.00701	0.01692	0.010122	1
Day 3	CE	1	0.048107	0.042628	0.018866	CE	1	0.004219	-0.01993	0.021944	CE	1	0.066469	0.043616	0.00102
	OP	0.048107	1	-0.05767	0.070784	OP	0.004219	1	-0.063	-0.02319	OP	0.066469	1	-0.06509	0.020418
	EP	0.042628	-0.05767	1	0.043886	EP	-0.01993	-0.063	1	-0.06146	EP	0.043616	-0.06509	1	0.006999
	SPI	0.018866	0.070784	0.043886	1	AEI	0.021944	-0.02319	-0.06146	1	KEI	0.00102	0.020418	0.006999	1
Day 4	CE	1	0.047507	0.042272	0.018373	CE	1	0.004206	-0.01988	0.02173	CE	1	0.065756	0.042942	0.007006
	OP	0.047507	1	-0.05765	0.070704	OP	0.004206	1	-0.06313	-0.02064	OP	0.065756	1	-0.06546	0.023144
	EP	0.042272	-0.05765	1	0.04362	EP	-0.01988	-0.06313	1	-0.05436	EP	0.042942	-0.06546	1	0.004649
	SPI	0.018373	0.070704	0.04362	1	AEI	0.02173	-0.02064	-0.05436	1	KEI	0.007006	0.023144	0.004649	1
Day 5	CE	1	0.046917	0.041919	0.017895	CE	1	0.004194	-0.01984	0.021534	CE	1	0.065055	0.042277	0.011553
	OP	0.046917	1	-0.05763	0.070625	OP	0.004194	1	-0.06326	-0.01828	OP	0.065055	1	-0.06583	0.025292
	EP	0.041919	-0.05763	1	0.043361	EP	-0.01984	-0.06326	1	-0.04781	EP	0.042277	-0.06583	1	0.00284
	SPI	0.017895	0.070625	0.043361	1	AEI	0.021534	-0.01828	-0.04781	1	KEI	0.011553	0.025292	0.00284	1

Table 3.11: Conditional covariance forecast for asymmetric DCC

		Saudi					UAE					Kuwait			
		CE	OP	EP	SPI		CE	OP	EP	AEI		CE	OP	EP	KEI
Day 1	CE	1.94E-05	-1.33E-06	3.60E-07	6.90E-07	CE	1.94E-05	-1.35E-06	3.57E-07	6.22E-07	CE	1.77E-05	-1.44E-06	2.97E-07	6.44E-07
	OP	-1.33E-06	2.02E-04	-1.43E-06	2.39E-06	OP	-1.35E-06	2.02E-04	-1.42E-06	-1.48E-06	OP	-1.44E-06	1.94E-04	-1.41E-06	-1.70E-07
	EP	3.60E-07	-1.43E-06	2.48E-05	3.88E-07	EP	3.57E-07	-1.42E-06	2.48E-05	2.56E-07	EP	2.97E-07	-1.41E-06	2.43E-05	5.01E-07
	SPI	6.90E-07	2.39E-06	3.88E-07	7.31E-05	AEI	6.22E-07	-1.48E-06	2.56E-07	3.53E-05	KEI	6.44E-07	-1.70E-07	5.01E-07	1.71E-05
Day 2	CE	1.77E-05	-1.36E-06	3.13E-07	6.52E-07	CE	1.64E-05	-1.36E-06	2.79E-07	5.33E-07	CE	1.64E-05	-1.40E-06	2.68E-07	6.15E-07
	OP	-1.36E-06	1.94E-04	-1.40E-06	2.30E-06	OP	-1.36E-06	1.86E-04	-1.36E-06	-1.35E-06	OP	-1.40E-06	1.86E-04	-1.37E-06	-1.77E-07
	EP	3.13E-07	-1.40E-06	2.43E-05	4.00E-07	EP	2.79E-07	-1.36E-06	2.40E-05	2.37E-07	EP	2.68E-07	-1.37E-06	2.40E-05	4.87E-07
	SPI	6.52E-07	2.30E-06	4.00E-07	7.50E-05	AEI	5.33E-07	-1.35E-06	2.37E-07	3.18E-05	KEI	6.15E-07	-1.77E-07	4.87E-07	1.65E-05
Day 3	CE	1.64E-05	-1.36E-06	2.77E-07	7.41E-07	CE	1.76E-05	-1.51E-06	2.77E-07	5.26E-07	CE	1.76E-05	-1.55E-06	2.69E-07	6.25E-07
	OP	-1.36E-06	1.86E-04	-1.37E-06	2.15E-06	OP	-1.51E-06	1.88E-04	-1.37E-06	-9.96E-07	OP	-1.55E-06	1.88E-04	-1.38E-06	-1.79E-07
	EP	2.77E-07	-1.37E-06	2.40E-05	3.72E-07	EP	2.77E-07	-1.37E-06	2.29E-05	2.16E-07	EP	2.69E-07	-1.38E-06	2.29E-05	4.67E-07
	SPI	7.41E-07	2.15E-06	3.72E-07	7.70E-05	AEI	5.26E-07	-9.96E-07	2.16E-07	3.02E-05	KEI	6.25E-07	-1.79E-07	4.67E-07	1.60E-05
Day 4	CE	1.76E-05	-1.52E-06	2.75E-07	7.14E-07	CE	1.60E-05	-1.46E-06	2.49E-07	4.83E-07	CE	1.60E-05	-1.49E-06	2.43E-07	5.88E-07
	OP	-1.52E-06	1.88E-04	-1.38E-06	1.94E-06	OP	-1.46E-06	1.81E-04	-1.32E-06	-1.01E-06	OP	-1.49E-06	1.81E-04	-1.33E-06	-1.84E-07
	EP	2.75E-07	-1.38E-06	2.29E-05	3.46E-07	EP	2.49E-07	-1.32E-06	2.15E-05	1.99E-07	EP	2.43E-07	-1.33E-06	2.15E-05	4.46E-07
	SPI	7.14E-07	1.94E-06	3.46E-07	6.93E-05	AEI	4.83E-07	-1.01E-06	1.99E-07	2.78E-05	KEI	5.88E-07	-1.84E-07	4.46E-07	1.56E-05
Day 5	CE	1.60E-05	-1.47E-06	2.46E-07	6.36E-07	CE	1.48E-05	-1.39E-06	2.25E-07	4.65E-07	CE	1.48E-05	-1.41E-06	2.21E-07	5.57E-07
	OP	-1.47E-06	1.81E-04	-1.33E-06	1.82E-06	OP	-1.39E-06	1.72E-04	-1.26E-06	-9.95E-07	OP	-1.41E-06	1.72E-04	-1.26E-06	-1.83E-07
	EP	2.46E-07	-1.33E-06	2.15E-05	3.19E-07	EP	2.25E-07	-1.26E-06	2.02E-05	1.83E-07	EP	2.21E-07	-1.26E-06	2.02E-05	4.26E-07
	SPI	6.36E-07	1.82E-06	3.19E-07	6.45E-05	AEI	4.65E-07	-9.95E-07	1.83E-07	2.61E-05	KEI	5.57E-07	-1.83E-07	4.26E-07	1.52E-05

Table 3.12: Conditional correlation forecast for asymmetric DCC

		Saudi					UAE					Kuwait			
		CE	**OP**	**EP**	**SPI**		**CE**	**OP**	**EP**	**AEI**		**CE**	**OP**	**EP**	**KEI**
Day 1	**CE**	1	-0.02906	0.011461	0.016923	**CE**	1	-0.02906	0.011461	0.023597	**CE**	1	-0.02911	0.011321	0.036636
	OP	-0.02906	1	-0.02173	0.01545	**OP**	-0.02906	1	-0.02173	-0.0184	**OP**	-0.02911	1	-0.02147	-0.00424
	EP	0.011461	-0.02173	1	0.008112	**EP**	0.011461	-0.02173	1	0.007196	**EP**	0.011321	-0.02147	1	0.02389
	SPI	0.016923	0.01545	0.008112	1	**AEI**	0.023597	-0.0184	0.007196	1	**KEI**	0.036636	-0.00424	0.02389	1
Day 2	**CE**	1	-0.02911	0.011321	0.016758	**CE**	1	-0.02917	0.01112	0.023394	**CE**	1	-0.02917	0.01112	0.036688
	OP	-0.02911	1	-0.02147	0.015781	**OP**	-0.02917	1	-0.02128	-0.01808	**OP**	-0.02917	1	-0.02128	-0.00428
	EP	0.011321	-0.02147	1	0.008579	**EP**	0.01112	-0.02128	1	0.007616	**EP**	0.01112	-0.02128	1	0.023795
	SPI	0.016758	0.015781	0.008579	1	**AEI**	0.023394	-0.01808	0.007616	1	**KEI**	0.036688	-0.00428	0.023795	1
Day 3	**CE**	1	-0.02917	0.01112	0.016985	**CE**	1	-0.02997	0.011532	0.022947	**CE**	1	-0.02997	0.011532	0.036649
	OP	-0.02917	1	-0.02128	0.015551	**OP**	-0.02997	1	-0.02159	-0.01774	**OP**	-0.02997	1	-0.02159	-0.00426
	EP	0.01112	-0.02128	1	0.00806	**EP**	0.011532	-0.02159	1	0.00743	**EP**	0.011532	-0.02159	1	0.023787
	SPI	0.016985	0.015551	0.00806	1	**AEI**	0.022947	-0.01774	0.00743	1	**KEI**	0.036649	-0.00426	0.023787	1
Day 4	**CE**	1	-0.02997	0.011532	0.017387	**CE**	1	-0.02998	0.011552	0.022933	**CE**	1	-0.02998	0.011552	0.036669
	OP	-0.02997	1	-0.02159	0.015217	**OP**	-0.02998	1	-0.02162	-0.01777	**OP**	-0.02998	1	-0.02162	-0.0043
	EP	0.011532	-0.02159	1	0.008216	**EP**	0.011552	-0.02162	1	0.007417	**EP**	0.011552	-0.02162	1	0.023787
	SPI	0.017387	0.015217	0.008216	1	**AEI**	0.022933	-0.01777	0.007417	1	**KEI**	0.036669	-0.0043	0.023787	1
Day 5	**CE**	1	-0.02998	0.011552	0.017353	**CE**	1	-0.02996	0.011559	0.022985	**CE**	1	-0.02996	0.011559	0.036679
	OP	-0.02998	1	-0.02162	0.015443	**OP**	-0.02996	1	-0.02163	-0.01777	**OP**	-0.02996	1	-0.02163	-0.0043
	EP	0.011552	-0.02162	1	0.008185	**EP**	0.011559	-0.02163	1	0.007368	**EP**	0.011559	-0.02163	1	0.02378
	SPI	0.017353	0.015443	0.008185	1	**AEI**	0.022985	-0.01777	0.007368	1	**KEI**	0.036679	-0.0043	0.02378	1

Table 3.13: Conditional covariance forecast for copula DCC

		Saudi					UAE					Kuwait			
		CE	OP	EP	SPI		CE	OP	EP	AEI		CE	OP	EP	KEI
Day 1	CE	1.60E-05	-3.32E-06	4.11E-07	5.10E-07	CE	2.48E-05	-3.80E-06	3.18E-07	8.70E-07	CE	1.44E-05	-2.54E-06	4.94E-07	7.40E-07
	OP	-3.32E-06	7.49E-04	-3.68E-06	-2.82E-06	OP	-3.80E-06	8.92E-04	-2.48E-06	4.60E-06	OP	-2.54E-06	4.79E-04	-3.05E-06	-4.27E-07
	EP	4.11E-07	-3.68E-06	4.87E-05	3.07E-07	EP	3.18E-07	-2.48E-06	1.77E-05	2.66E-07	EP	4.94E-07	-3.05E-06	9.01E-05	1.13E-06
	SPI	5.10E-07	-2.82E-06	3.07E-07	3.51E-05	AEI	8.70E-07	4.60E-06	2.66E-07	5.48E-05	KEI	7.40E-07	-4.27E-07	1.13E-06	2.37E-05
Day 2	CE	1.58E-05	-4.49E-06	5.26E-07	1.16E-06	CE	2.64E-05	-4.06E-06	4.90E-07	1.11E-06	CE	1.33E-05	-2.41E-06	4.65E-07	7.08E-07
	OP	-4.49E-06	1.36E-03	-4.99E-06	-4.93E-06	OP	-4.06E-06	8.70E-04	-2.47E-06	5.64E-06	OP	-2.41E-06	4.56E-04	-3.27E-06	-4.34E-07
	EP	5.26E-07	-4.99E-06	4.79E-05	1.31E-06	EP	4.90E-07	-2.47E-06	1.76E-05	3.48E-07	EP	4.65E-07	-3.27E-06	9.25E-05	1.14E-06
	SPI	1.16E-06	-4.93E-06	1.31E-06	5.83E-05	AEI	1.11E-06	5.64E-06	3.48E-07	9.64E-05	KEI	7.08E-07	-4.34E-07	1.14E-06	2.41E-05
Day 3	CE	1.45E-05	-4.44E-06	4.62E-07	1.08E-06	CE	2.47E-05	-4.00E-06	4.27E-07	1.03E-06	CE	1.73E-05	-2.69E-06	5.51E-07	7.83E-07
	OP	-4.44E-06	1.45E-03	-2.12E-06	-5.59E-06	OP	-4.00E-06	8.29E-04	-2.48E-06	5.28E-06	OP	-2.69E-06	4.35E-04	-2.85E-06	-3.13E-07
	EP	4.62E-07	-2.12E-06	4.89E-05	1.18E-06	EP	4.27E-07	-2.48E-06	1.84E-05	3.58E-07	EP	5.51E-07	-2.85E-06	1.08E-04	1.43E-06
	SPI	1.08E-06	-5.59E-06	1.18E-06	6.68E-05	AEI	1.03E-06	5.28E-06	3.58E-07	9.87E-05	KEI	7.83E-07	-3.13E-07	1.43E-06	2.31E-05
Day 4	CE	1.44E-05	-4.32E-06	4.57E-07	1.25E-06	CE	4.55E-05	-5.44E-06	5.06E-07	1.24E-06	CE	1.62E-05	-2.55E-06	6.10E-07	8.03E-07
	OP	-4.32E-06	1.37E-03	-2.69E-06	-5.70E-06	OP	-5.44E-06	7.81E-04	-2.37E-06	4.52E-06	OP	-2.55E-06	4.11E-04	-3.06E-06	-3.57E-07
	EP	4.57E-07	-2.69E-06	4.59E-05	1.16E-06	EP	5.06E-07	-2.37E-06	1.75E-05	3.20E-07	EP	6.10E-07	-3.06E-06	1.07E-04	1.46E-06
	SPI	1.25E-06	-5.70E-06	1.16E-06	7.07E-05	AEI	1.24E-06	4.52E-06	3.20E-07	8.36E-05	KEI	8.03E-07	-3.57E-07	1.46E-06	2.64E-05
Day 5	CE	2.06E-05	-4.95E-06	4.90E-07	1.58E-06	CE	4.32E-05	-5.55E-06	4.37E-07	1.15E-06	CE	2.08E-05	-2.82E-06	6.32E-07	8.64E-07
	OP	-4.95E-06	1.28E-03	-3.11E-06	-5.45E-06	OP	-5.55E-06	8.21E-04	-2.38E-06	4.16E-06	OP	-2.82E-06	3.97E-04	-3.15E-06	-3.63E-07
	EP	4.90E-07	-3.11E-06	4.50E-05	9.44E-07	EP	4.37E-07	-2.38E-06	1.66E-05	2.88E-07	EP	6.32E-07	-3.15E-06	9.98E-05	1.32E-06
	SPI	1.58E-06	-5.45E-06	9.44E-07	6.58E-05	AEI	1.15E-06	4.16E-06	2.88E-07	7.18E-05	KEI	8.64E-07	-3.63E-07	1.32E-06	2.46E-05

Table 3.14: Conditional correlation forecast for copula DCC

		Saudi					UAE					Kuwait			
		CE	OP	EP	SPI		CE	OP	EP	AEI		CE	OP	EP	KEI
Day 1	**CE**	1	-0.03034	0.014725	0.021514	**CE**	1	-0.02549	0.015187	0.02358	**CE**	1	-0.03063	0.013719	0.040038
	OP	-0.03034	1	-0.01926	-0.01742	**OP**	-0.02549	1	-0.01972	0.020795	**OP**	-0.03063	1	-0.0147	-0.00401
	EP	0.014725	-0.01926	1	0.007433	**EP**	0.015187	-0.01972	1	0.008533	**EP**	0.013719	-0.0147	1	0.024447
	SPI	0.021514	-0.01742	0.007433	1	**AEI**	0.02358	0.020795	0.008533	1	**KEI**	0.040038	-0.00401	0.024447	1
Day 2	**CE**	1	-0.03058	0.019098	0.038292	**CE**	1	-0.0268	0.022727	0.021957	**CE**	1	-0.03086	0.013242	0.039525
	OP	-0.03058	1	-0.01953	-0.0175	**OP**	-0.0268	1	-0.01992	0.019475	**OP**	-0.03086	1	-0.0159	-0.00414
	EP	0.019098	-0.01953	1	0.024685	**EP**	0.022727	-0.01992	1	0.008445	**EP**	0.013242	-0.0159	1	0.024219
	SPI	0.038292	-0.0175	0.024685	1	**AEI**	0.021957	0.019475	0.008445	1	**KEI**	0.039525	-0.00414	0.024219	1
Day 3	**CE**	1	-0.0306	0.017327	0.03469730	**CE**	1	-0.02796	0.020015	0.020877	**CE**	1	-0.03103	0.012762	0.039086
	OP	-0.0306	1	-0.00797	0.01795512	**OP**	-0.02796	1	-0.0201	0.018456	**OP**	-0.03103	1	-0.01316	-0.00312
	EP	0.017327	-0.00797	1	0.02066815	**EP**	0.020015	-0.0201	1	0.008401	**EP**	0.012762	-0.01316	1	0.028654
	SPI	0.034697	-0.01796	0.020668	1	**AEI**	0.020877	0.018456	0.008401	1	**KEI**	0.039086	-0.00312	0.028654	1
Day 4	**CE**	1	-0.03078	0.01779	0.039204	**CE**	1	-0.02887	0.017941	0.02005	**CE**	1	-0.03116	0.014671	0.038743
	OP	-0.03078	1	-0.01075	-0.01834	**OP**	-0.02887	1	-0.02026	0.017697	**OP**	-0.03116	1	-0.01464	-0.00343
	EP	0.01779	-0.01075	1	0.020378	**EP**	0.017941	-0.02026	1	0.008368	**EP**	0.014671	-0.01464	1	0.02752
	SPI	0.039204	-0.01834	0.020378	1	**AEI**	0.02005	0.017697	0.008368	1	**KEI**	0.038743	-0.00343	0.02752	1
Day 5	**CE**	1	-0.03045	0.016091	0.042819	**CE**	1	-0.02948	0.016308	0.020678	**CE**	1	-0.03101	0.013882	0.03816
	OP	-0.03045	1	-0.01293	-0.01874	**OP**	-0.02948	1	-0.02037	0.017118	**OP**	-0.03101	1	-0.01586	-0.00367
	EP	0.016091	-0.01293	1	0.017352	**EP**	0.016308	-0.02037	1	0.008342	**EP**	0.013882	-0.01586	1	0.026671
	SPI	0.042819	-0.01874	0.017352	1	**AEI**	0.020679	0.017118	0.008342	1	**KEI**	0.03816	-0.00367	0.026671	1

We evaluate the forecasts based on the conditional variance using two evaluation measures: mean absolute error (MAE) and root mean square error (RMSE).[26] Table 3.15 shows the MAE and RMSE results of the three models. The results confirm the accuracy of the models as the average magnitude of the errors is minor for all the forecasted values.

Table 3.15: 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

It can also be concluded that both the diagnostics and forecasting tests as shown in Tables 3.7 and 3.15 respectively confirm that the diagonal BEKK outputs are the most accurate. Therefore, the final statistical step is to 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. The values of the RMSE shown in Table 3.16 are slightly lower for the BEKK (1,1) estimates for all three energy stocks.

[26] Mean Absolute Error (MAE) and Root mean squared error (RMSE) are the most common statistical tools to evaluate accuracy for continuous variables by measuring the average magnitude of the errors. MAE defined as follows: $MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$ where RMSE $= \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}$

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 3.16: 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

3.5. Discussion of results

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. This was particularly obvious for the three GGC energy stock prices. The volatilities and their persistence in the GCC energy returns were less than other markets. 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 following 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 Corp (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 the sectors of banking and energy. (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; C. Sun et al., 2019). We explore that the impact of establishing ETS in developed countries can reach oil-exporting countries. 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.

3.6. Conclusion

We examine 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 Arabi, the UAE and Kuwait. This is to explore the possibility of the presence of multifaceted links between the GCC energy markets and the recent rapid energy use transformations worldwide. We use daily data over the period from January 02, 2013, to March 20, 2019, to apply 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 find strong evidence on the presence of volatilities in the three GCC energy stock markets and that they are influenced by past shocks related to other markets. However, the most powerful deriver of the volatilities is the past shocks in the GCC markets themselves (endogenous shocks). Abu Dhabi's energy price is largely influenced by its past shocks followed by Kuwait and Saudi energy markets. We also find that the volatilities in all the markets under consideration are highly persistent; though the GCC energy stock markets are more consistent compared to other markets. We also detect short and long-term persistence in the conditional variance of all the time series, but the long-run persistent volatilities are more pronounced especially for oil and CO_2 emission prices. This work helps policymakers in oil-producing countries to design appropriate mechanisms to speed up revenue diversification policies. It also promotes investors to assess the likelihood of alternative portfolios and hedge their strategies. Examining the various types of dependence structure among the same markets would be an interesting topic for future researches.

Chapter 4: Wavelets Based on A Dependence Structure between the GCC Energy Equities and Select Global Energy Markets

4.1. Introduction

The oil price plunge in 2014 has triggered a new stream of literature investigating its underlying reasons. Some research reasoned such drop to macroeconomic factors, e.g., weak global economy and an oil supply glut due to a slowdown in the Chinese economy (Timilsina, 2014; Ratti and Vespignani, 2014; Mohaddes and Pesaran, 2017; Monge et al., 2017; Marchionna, 2018). Others have linked such a fall to the rapid expansion in global renewable energy production and the application of the emissions control systems (Omri et al., 2015; Reboredo, 2015; Bauer et al. 2015; Khan et al., 2017).

Several studies have discussed the causal links between oil price swings and stock prices at aggregate or industry-level (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Angelidis et al., 2015; Alsalman and Herrera, 2015; Ghosh and Kanjilal, 2016; Alsalman, 2016; Kumar, 2017). Others have investigated the impact of the emission trading schemes on oil price swings (e.g., Scholtens and Van Der Goot, 2014; Bauer et al., 2015; Chang et al., 2020). Some researchers discussed how the emission trading schemes boost profits of clean energy companies (Hammoudeh et al., 2014a; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019). While Stern (1993), Stern (2000), Oh and Lee (2004), Payne (2012), Chevallier (2012), Tan and Wang (2017) and Ji et al. (2018) have investigated the like among renewable energy growth and oil price changes.

There is still uncertainty, however, whether the recent expansion in global clean energy production as well as CO_2 emission allowances impacted conventional energy stock prices. Furthermore, the nature of the dependence structure between these elements in multiple time horizons remains unclear. The objective of this chapter is to investigate how global clean energy production, CO_2 emission and oil price fluctuations have influenced the fossil energy stock index of three GCC heavy oil-exporting countries namely, Saudi, UAE and Kuwait. Using the same dataset of chapter 3, we develop a dependence structure of wavelet multi-resolution decomposition for each of the GCC markets.

Our empirical results indicate that global clean energy production, oil prices and CO_2 emission is positively correlated with the GCC energy stock prices at lower frequencies (higher scales). This was confirmed by the wavelet correlation (WC) analysis. From the wavelet cross-correlation (WCC), we find evidence that changes in the global clean energy production index and CO_2 emission price positively leads the three GCC energy markets at low frequencies. However, oil price can only lead Kuwait energy stock price at the same level of frequencies. Both techniques uncover that the Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets. Besides, the oil price is found to be the primary moderator for the three GCC energy stocks in comparison with the clean energy production and CO_2 emission price.

This chapter documents three contributions to energy economics literature. First, this is the first study to analyse the role of global clean energy production and CO_2 emission price in deriving the GCC energy stock prices. Next, we have used different time scale approaches to identify the leading variable in the correlated pairs. Finally, we focus on industry-level data for GCC energy prices which is likely linked more closely to global energy market trends.

The rest of the chapter 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 provided in Section 4, followed by a discussion of these results in Section 5. Finally, Section 6 concludes this study.

4.2. Literature review

Since Hamilton's (1983) paper that investigated the dependence structure between oil price changes and US stock returns, several published followed and analysed such a link in three key streams. Most earlier studies have investigated the effect of oil price changes on the aggregate stock market indexes/returns (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Angelidis et al., 2015; Ghosh and Kanjilal, 2016; Bastianin et al., 2016; Bouri et al., 2017; Ferreira et al., 2019; Balcilar et al., 2019; Mokni, 2020; Ashfaq et al., 2020; Wang et al., 2020). Fewer scholars focused on the influence of oil price shifts on the industry-level stock market indices /returns (e.g., Alsalman and Herrera, 2015; Alsalman, 2016; Kumar, 2017; Badeeb and Lean, 2018; Xiao et al., 2018; Nazif Çatık et al., 2020; Ferreira et al., 2020). Lastly, several authors have integrated the crude oil-stock prices dependence structure with some respective factors such as exchange rate, gold, gas, coal, carbon, or clean energy prices (Lescaroux and Mignon, 2008; Anoruo, 2011; Masih et al., 2011; Hammoudeh et al., 2014a; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Toparlı et al., 2019; Lin and Chen, 2019; Chang et al., 2020; Morema and Bonga-Bonga, 2020). Together, the three types of studies were conducted using two different time perspectives: (i) standard timescales (short and long terms) or (ii) multi timescales (short, middle and long terms).

The next sections exhaustively discuss the three streams of studies considering the two-time scale techniques.

4.2.1. Oil price and stock market indexes dependence structure

The vast majority of authors focused on the correlation between oil price volatility and the aggregate stock market indexes /returns (e.g., Marsh and Merton, 1987; Anoruo, 2011; Tiwari et al., 2019; Alqahtani et al., 2020; Xiao and Wang, 2020; Wang et al., 2020; Peng et al., 2020; Hung, 2020). Xiao and Wang (2020); Wang et al. (2020) found that oil price boosts significantly Ganger cause a decrease in both the stock markets of China and BRICS respectively. This view is supported by Tiwari et al. (2019) who used a nonparametric conditional causality test for the oil price-BRICS equities relationship. Similarly, Anoruo (2011) and Peng et al. (2020) implemented linear and nonlinear causality tests to assess the impact of oil prices on the US and China stock markets respectively. They provided empirical evidence on the negative causality from oil price changes to the stock returns. Alike, Hung (2020) documented the same evidence on the causal relationship between oil price and some European stock returns using a time-varying analysis. Nevertheless, Bouri et al. (2017) found that the causality-in-variance between oil prices and the stock market of China is absent between 2013-2016. Furthermore, Alqahtani et al. (2020) discovered a positive Ganger causality between oil prices and the stock market returns of the GCC.

Recently, few articles have used the historically-decomposed oil price shocks, following Kilian's (2009) approach, to analyse the dependence structure among oil price and the aggregate stock market indexes/ returns (e.g., Park and Ratti, 2008; Kilian and Park, 2009; Apergis and Miller, 2009; Kang et al., 2015; Angelidis et al., 2015; Bastianin et al., 2016; Zhang, 2017; Ji et al., 2020; Mokni, 2020). Generally, empirical findings were sensitive to the employed methodological approach. While Kilian and Park (2009) and Kang et al. (2015) applied a structural VAR and revealed that the joint long-run effects of oil price shocks on the US stock market returns were 22% and 25.7% respectively. On contrary, Apergis and Miller (2009), Angelidis et al. (2015) and

(Zhang, 2017) reported moderate or no relation between oil price shocks and the US stock market returns using various volatility models.

Similarly, Bastianin et al. (2016), Ji et al. (2020) and Mokni (2020) provided further details about the impact between the structural oil price shocks and equities. Mokni (2020) stated that the influence of supply shocks is negatively moderate for a set of stock prices in oil-exporting and importing countries, while the impact of aggregate demand shocks is significantly positive on stock returns. Regarding oil-specific demand shocks, Mokni (2020) uncovered that these types of shocks increase stock returns of oil-exporting economies and reduce returns for oil-importing ones. Bastianin et al. (2016) and Ji et al. (2020) reported the same evidence for stock returns by applying to G7 and BRICS countries.

On the other hand, novel empirical studies used multi timescales of wavelets to capture various dependency levels between oil price changes and the aggregate stock market indexes/returns (e.g., Jammazi and Aloui, 2010; Jammazi, 2012; Akoum et al., 2012; Jammazi and Reboredo, 2016; Ftiti et al., 2016; Huang et al., 2016; Wu et al., 2020). Although they used various multiple wavelet decomposition analyses, the results were nearly the same. For example, Jammazi (2012) used a sequence of square-shaped wavelets namely 'the Haar Trous decomposition' to study the dependence structure between oil and the US, UK, Japan, Germany and Canada stock market prices. The results uncovered the dependency between the pairs among multiple time horizons. Jammazi and Reboredo (2016) utilised the same model and reported similar results when analysing the impact of oil prices on Morgan Stanly Capital International (MSCT).

In a similar vein, both Jammazi and Aloui (2010) and Huang et al. (2016) combined both wavelet analysis with different multivariate vector autoregression models to investigate the influence of oil prices on the returns of a selected number of stock in developed countries. Results of papers confirmed the existence of only a long-term interdependence relationship. On contrary, Jammazi and Aloui (2010) and Huang et al. (2016), Ftiti et al. (2016) postulated that the dependence structure between the oil and stock market of G7 countries was evident in the short and medium terms. Furthermore, Akoum et al. (2012) argued that dependence between oil prices and the GCC stock markets is inconspicuous while utilising the wavelet coherency approach.

4.2.2. Oil price and industry-level stock market dependence structure

Another strand of literature draws attention to the impact of oil price volatility on sectoral stock market prices/ returns (e.g., Gogineni, 2010; Alsalman and Herrera, 2015; Chiek and Akpan, 2016; Alsalman, 2016; Kumar, 2017; Badeeb and Lean, 2018; Xiao et al., 2018; Mensi et al., 2020; Nazif Çatık et al., 2020; Ferreira et al., 2020). Most authors have focused on the response of the US industries' returns to oil price changes. For instance, Alsalman and Herrera (2015); Kumar (2017) examined the dependence structure among oil prices and a number of the US industries (e.g., automobiles, financials, industrials and telecom). The authors found limited evidence on volatility transmission from oil prices to the estimated equity sectors. Similarly, Gogineni (2010) stated that the effect of oil prices on the US stock market industries is limited to the short term. This view is supported by both Badeeb and Lean (2018) and Mensi et al. (2020) who estimated the response of the US Islamic equity market to oil price shifts and found weak linkages between oil and Islamic stock prices.

The effect of oil price changes on industries' returns has also been investigated in other countries. For example, Chiek and Akpan (2016) examined the impact of oil price fluctuations on gas industry firms listed on the Nigerian stock market. Besides, Ferreira et al. (2020) assessed the influence of oil prices on the Brazilian oil-sensitive sectoral stock returns. Both types of research confirmed the short-termed impact of oil price shocks. Nazif Çatık et al. (2020) reported similar findings on the relationship between the Turkish stock exchange rates and oil prices. Alsalman (2016) and Xiao et al. (2018) used an oil price uncertainty measure, as an alternative to the actual oil prices, to examine its impact on sectoral stock returns. While Alsalman (2016) claimed that there is no significant impact between oil price uncertainty and US industries, Xiao et al. (2018) on the other hand, reported that oil price uncertainty significantly and negatively affects the Chinese industries' returns.

The use of multi-scale perspectives for studying the link between oil price swings and equities behaviour at an industry-level is documented in few studies (e.g. Ftiti and Hadhri, 2019; Pal and Mitra, 2019; Shao and Zhang, 2020; Zhang et al., 2020). Both Shao and Zhang (2020) and Zhang et al. (2020) analysed the dynamics between oil prices and renewable energy firms sectors. Shao and Zhang (2020) argued that the impact of oil price changes on seven clean energy metals indexes in China is significant and positive at different time scales. Similar conclusions were reported by Zhang et al. (2020) who discussed the effect of exogenous oil price shocks on three different clean energy stock prices in the EU. They stated that oil supply shocks are the strongest moderator of oil prices relative to other types of shocks. Likewise, Ftiti and Hadhri (2019) investigated the causal relationship between oil prices and the Dow Jones Islamic Market returns. They detected that the wavelet approach produces more significant results compared to the standard timescales techniques. While Pal and Mitra (2019) stated that the causal relationship between oil prices and the key global automobile stock returns are mostly observed over long time scales.

4.2.3. Oil price and other related variables to stock markets dependence structure

Other papers have considered other related variables to better understand the linkages between oil price swings and stock market movements (e.g. Lescaroux and Mignon, 2008; Anoruo, 2011; Masih et al., 2011; Hammoudeh et al., 2014a; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Toparlı et al., 2019; Lin and Chen, 2019; Chang et al., 2020; Morema and Bonga-Bonga, 2020). Some researchers have used macroeconomic variables and found that, in particular, exchange rates, interest rates, GDP growth and inflation are significant moderators for the relationship between oil prices and stock returns over the short term (Lescaroux and Mignon, 2008; Masih et al., 2011; Toparlı et al., 2019).

Another strand of literature has examined the moderation role of gold prices such as (Wanat et al., 2015; Morema and Bonga-Bonga, 2020). Whereas Wanat et al. (2015) reported that both oil and gold prices do not granger cause some EU stock markets. Morema and Bonga-Bonga (2020) postulated that both oil and gold prices significantly and positively influence selected south African stock prices.

Global warming and climate change mitigation policies and their impact on commodity prices and stock returns have been discussed in several papers such as (Scholtens and Goot, 2014; Hammoudeh et al., 2014; Bauer et al., 2015; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019; Chang et al., 2020). Bauer et al. (2015) showed that restrictions imposed on the conventional energy markets would decrease oil, gas and coal market revenues. Other studies such as Scholtens and Goot (2014) exploited the impact of the EU's Emission Trading Scheme on carbon price in fossil fuel markets. They found that these restrictions raise carbon prices that in turn boost several EU aggregate stock market indexes. Chang et al. (2020) showed that the increase in stock market returns leads to a rise in carbon levels in Taiwan.

A group of scholars studied the link between the carbon emission market and clean/electricity energy companies (Hammoudeh et al., 2014a; Tian et al., 2016; Zhang et al., 2018; Dutta et al., 2018; Bhat, 2018; Lin and Chen, 2019). They argued that the boom in clean energy sources, as a substitute for fossil sources, will increase production costs and prices of conventional energy sources. Thus, customers will find it more feasible to shift their consumption towards cleaner energy sources thus expanding the revenue for clean energy companies. Dutta et al. (2018) used the VAR-GARCH model and found that an increase in CO_2 emission price positively impacts alternative energy firm's revenues over the short run. Similar evidence was found by applying on renewable energy companies in China (Lin and Chen, 2019) and five emerging countries of the BRICS (Bhat 2018).

Other papers have studied the potential impact of CO_2 emission prices on the electricity industry (Hammoudeh et al., 2014a; Tian et al., 2016; Zhang et al., 2018). Tian et al. (2016) and Zhang et al. (2018) have applied to the EU and China, they concluded that the emission trading systems raise electricity prices over the short term. Hammoudeh et al. (2014) presented a comprehensive analysis for the impact of oil, gas, coal, electricity prices on the US emission trading index. The results indicate that the increase in crude oil or natural gas prices push down CO_2 emission prices, while higher electricity prices increase CO_2 emission levels over the short term.

Fewer studies applied multi-time scale wavelet analysis to examine the relationship between oil prices and other related variables to stock markets (Mensi et al., 2018; Kalmaz and Kirikkaleli, 2019; Jiang et al., 2020; Alshammari et al., 2020). Jiang et al. (2020) stated that CO_2 emission prices in China negatively impact coal prices at lower and higher frequencies (short and long term). While the effect on the clean energy stock market only occurs in the middle and lower frequencies (middle and long term). Both Mensi et al. (2018) and Alshammari et al. (2020) studied the dependence structure among oil, gold and stock prices. Whereas Mensi et al. (2018) detected that oil prices negatively affect five of the largest stock markets of the BRICS at low frequencies (long term) and they reported no significant relationships between the gold price and the stock markets. In contrast to Mensi et al. (2018), Alshammari et al. (2020) found that a surge in oil price cause growth in the Kuwait stock market at low frequencies (long term) where gold price has a short-term negative impact. Finally, Kalmaz and Kirikkaleli (2019) reported long-term causal effects at low frequencies between carbon levels, energy consumption and energy growth in the Turkish stock market.

4.3. Methodology and data

4.3.1. Methodology

We follow Percival and Walden's (2000) and use the maximal overlap discrete wavelet transforms (MODWT) to estimate the coefficients of multiscale wavelet correlation (WC) and wavelet cross-correlation (WCC) among the respective variables. Up to six levels of wavelets were performed to cover from daily to monthly frequencies. The timescales determined as scale 1 (1-2 days), scale 2 (2-4 days), scale 3 (4-8 days), scale 4 (8-16 days), scale 5 (16-32 days) and scale 6 (32-64 days). For the cross-correlation, a lag of 22 days has been selected, like the approximate number of trading days per month.

To identify the MODWT, we initially specify discrete wavelet transforms (DWT) as a core component of the MODWT. Two main wavelet functions called the father wavelet ϕ (the scaling function) and the mother wavelet ψ (the wavelet function) by:

$$\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi\left(\frac{t-2^j k}{2^j}\right) \qquad (4.1)$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(\frac{t-2^j k}{2^j}\right) \qquad (4.2)$$

where $j = 1, \ldots, J$ represents the scaling parameter and k is a shifting parameter, the expansion of wavelet function gives a discrete signal $y(x)$ in $(L^2 \in \mathbb{R})$ as symbolised by:

$$y(x) = \sum_k v_{J,k}\, \phi_{J,k}(x) + \sum_k \omega_{J,k}\, \psi_{J,k}(x) + \sum_k \omega_{J-1,k}\, \psi_{J-1,k}(x) + \cdots + \sum_k \omega_{1,k}\, \psi_{1,k}(x)$$

$$= S_j(x) + D_j(x) + D_{j-1}(x) + \cdots + D_1(x), \qquad (4.3)$$

where k vary between 1 to the number of coefficients in the specified element, J denotes the number of multiple scales. The term of $S_{J,k}$ is known as smooth and $D_{J,k}$ is the detail of wavelet transform coefficients (approximations). They are integrated over time as follows:

$$S_{J,k}(x) = \int_{-\infty}^{\infty} \phi_{J,k} y(x) dx \qquad (4.4)$$

$$D_{j,k}(x) = \int_{-\infty}^{\infty} \psi_{j,k} y(x) dx \qquad (j = 1,2, \dots . J). \qquad (4.5)$$

where the smooth coefficient ($S_{J,k}$) depicts the underlying smooth behaviour at the scale $2J$ (the highest-level of the coarse-scale), the detailed coefficient $D_1(x), D_2(x), \dots, D_j(x)$ describes deviations of length from the smooth behaviour.

The MODWT is almost identical to DWT as they have the same two filters, but for co-movement analysis, the MODWT asymptotically produces a more efficient wavelet variance estimator (Percival and Walden, 2000). Consider $\{\tilde{h}_{j,l} : l = 0, \dots, L_{j-1}\}$ is the wavelet filter for a size 2^j of two time series while $L_j = (2^j - 1)(L - 1)$ is the length of the filter. Thus, it can be described the stochastic process by:

$$W_{j,t} \simeq \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-1} \qquad (4.6)$$

where $X = x, y$ gives a signal when X has been filtered to obtain the wavelet function of MODWT, the signal can only be captured if it is present and finite. Therefore, wavelet variance for scale λ_j of signal X can be expressed as follows:

$$\sigma_{X,t}^2(\lambda_j) \simeq var\,\{\widetilde{W}_{j,t}\} \tag{4.7}$$

it can be decided the presence of wavelet variance for the scale λ_j when the impact of time is absent meaning that $\sigma_{X,t}^2(\lambda_j) = \sigma_X^2(\lambda_j)$. About the wavelet co-variance for the scale λ_j, it can be estimated by:

$$\sigma_X(\lambda_j) = cov\,\{\widetilde{W}_{x,j,t}, \widetilde{W}_{x,j,t}\} \tag{4.8}$$

hence, the MODWT coefficient of the wavelet correlation is can be obtained by:

$$\rho_X(\lambda_j) = \frac{cov\,\{\widetilde{W}_{x,j,t}, \widetilde{W}_{y,j,t}\}}{\left(var\,\{\widetilde{W}_{x,j,t}\}\,var\,\{\widetilde{W}_{y,j,t}\}\right)^{\frac{1}{2}}} = \frac{\sigma_X(\lambda_j)}{\sigma_x(\nu_j)\sigma_y(\lambda_j)} \tag{4.9}$$

Whiles the wavelet cross-correlation can be obtained if we suppose a delay τ in one variable as formulated by:

$$\rho_{X,\tau}(\lambda_j) = \frac{\sigma_{X,\tau}(\lambda_j)}{\sigma_x(\lambda_j)\sigma_y(\lambda_j)} \tag{4.10}$$

4.3.2. Data and further preliminary statistics

In this chapter, we use the same dataset as the third chapter. We employ logarithmic first differences of the daily data for the S&P Global Clean Energy Production Index (CE), Brent crude oil price (OP), CO_2 emission price (EP) and the three GCC energy stock indexes; Saudi petrochemical index (SPI), Abu Dhabi energy index (AEI) and Kuwait energy index (KEI) (more information about the data has been discussed on pages 83 to 87).

We also report in Table 4.1 six diagnostic statistical tests. First, a variance ratio test called Lo-MacKinlay (1988) is used to test the random walk hypothesis of the series. The null hypothesis is that the series follows a geometric Brownian motion (GBM) or random walk. We can see that clean energy production and CO_2 emission price rejects the null of the random walk. Where oil price and the three GCC energy markets do not reject the null. It means that these four series follow a random walk. Second, we employ the runs test, which is considered an alternative test to examine autocorrelation among the variables. The test's null hypothesis is the absence of autocorrelation. All the series reject the null, except for the Kuwait energy index. This gives a preliminary indication of the presence of a dependence structure among the series.

To check the dependence structure in our time series, we apply four memory tests to discover long memory processes across lags. The first two tests: Hurst-Mandelbrot and Lo's R/S statistic are allocated to reveal long-run dependence. The statistical results show that none of the six series rejects the null of the absence of long memory. Where both Gewke and Porter-Hudak (1983) and Robinson & Henry (1998), which quantify the extent of the long memory process by estimating the fractional differencing parameter *d*, indicate that clean energy production, CO_2 emission price and Saudi petrochemical index exhibit moderate long memory.[27]

Table 4.1: further descriptive statistics

Variables	Variance Ratio Test	Runs	Lo's R/S statistic	Hurst-Mandelbrot	Gewke and Powter-Hudak	Robinson & Henry
CE	5.18867 (0.000)	-2.878 (0.000)	1.3387	1.47653	0.12790 (0.000)	0.10278 (0.000)
OP	-0.83336 (0.404)	2.94100 (0.004)	1.7480	1.67616	0.01725 (0.480)	0.01030 (0.558)
EP	-4.52554 (0.000)	2.91691 (0.003)	0.8353	0.71404	0.21899 (0.000)	0.20258 (0.000)
SPI	1.37375 (0.169)	-2.0668 (0.036)	1.5350	1.59470	0.02706 (0.007)	0.03657 (0.000)
AEI	-0.44837 (0.653)	2.59356 (0.009)	1.2715	1.24521	0.01952 (0.424)	0.00793 (0.652)
KEI	-0.37284 (0.709)	0.859477 (0.390)	1.3704	1.37056	0.02635 (0.282)	0.03075 (0.080)

Note: the critical values for Hurst-Mandelbrot and Lo's R/S statistics test are 90%: [0.861, 1.747], 95%: [0.809, 1.862] and 99%: [0.721, 2.098].

[27] If 0<d<0.5, that indicates long memory.

4.4. Results

The wavelet correlation (WC) analysis produces two kinds of results: (i) the correlation of the GCC energy equities with the three respective variables: global clean energy production index, oil price and CO_2 emission price for the lower timescales (high frequencies) is near to zero; and (ii) there is a positive correlation between the pairs for the higher timescales (low frequencies). For the wavelet cross-correlation analysis (WCC), we prove that there is no lead/lag relationship between the respective pairs at low scales. For the higher scales, we find that changes in both the clean energy production index and CO_2 emission price positively leads the three GCC energy markets. While oil price can only influence Kuwait energy stock price at the same level of scales. Overall, the wavelet correlation of the Abu Dhabi energy index was more sensitive to changes in the three global energy indexes relative to Saudi and Kuwait energy indexes. Besides, oil price correlation effects on the three GCC energy equities are stronger than the correlation effects of clean energy production and CO_2 emission price.

The wavy lines in the wavelet correlation graphs can be interpreted as follows: the lines U and L represent the maximum limits for the confidence interval of 95%, while the middle line denotes the wave correlation coefficient. For the wavelet cross-correlation, if the highest value of the correlation coefficient is found at lag 0, there is no discernable lead-lag relationship among the pairs. However, if the highest value is found at a lag t, the first series lags behind the second series; and if the highest values are found at the negative lag (lead)t, the first series leads the second series.

4.4.1. Wavelet results of the Saudi petrochemical sector

4.4.1.1. The wavelet correlation

Figure 4.1 shows the standard wavelet correlation of the Saudi petrochemical index with global clean energy production index, oil price and CO_2 emission price. The Saudi energy returns/clean energy production wavelet correlation is near to zero across all six scales. However, the wavelet correlations of the Saudi energy sector with both crude oil and CO_2 emission prices are found to be positively remarkable at scale 5, which represents 16-32 days. The greatest wavelet correlation across all pairs is detected between the Saudi petrochemical index and oil price at scale 5. Otherwise, the values of the wavelet correlation coefficients are negligible. Consequently, we can reject the null hypothesis of no correlation between the pair with a 95% confidence level.

4.4.1.2. The wavelet cross-correlation

Since the basic wavelet correlation does not capture the leads and lags effects between time series, the wavelet cross-correlation (WCC) approach is used with leads and lags up to 22 days (the working days per month). This is to enable identifying the leader among the pairs with multiple time scales. Figures 4.2, 4.3 and 4.4 illustrate the cross-correlation relationships for the Saudi model. There exists weak positive cross-correlation dynamics between Saudi energy equities and global clean energy production index at level 5 (16-32 days) and lags -18. A similar relationship is also revealed for CO_2 emission al level 3 (4-8 days) and lags -10 and -15. This implies that both variables positively and slightly lead the Saudi energy stock market. However, for the link with the oil price, we found that Saudi energy stock returns significantly and positively lead oil prices across different levels and lags. This is shown at level 4 (lags

14), level 3 (lags 5, 10 and 16) and levels 5 and 6 (lags 22). It implies that the null hypothesis of no interdependence between the pairs is rejected with a 95% confidence level.

Figure 4.1: Wavelet correlation of CE, OP and EP with SPI

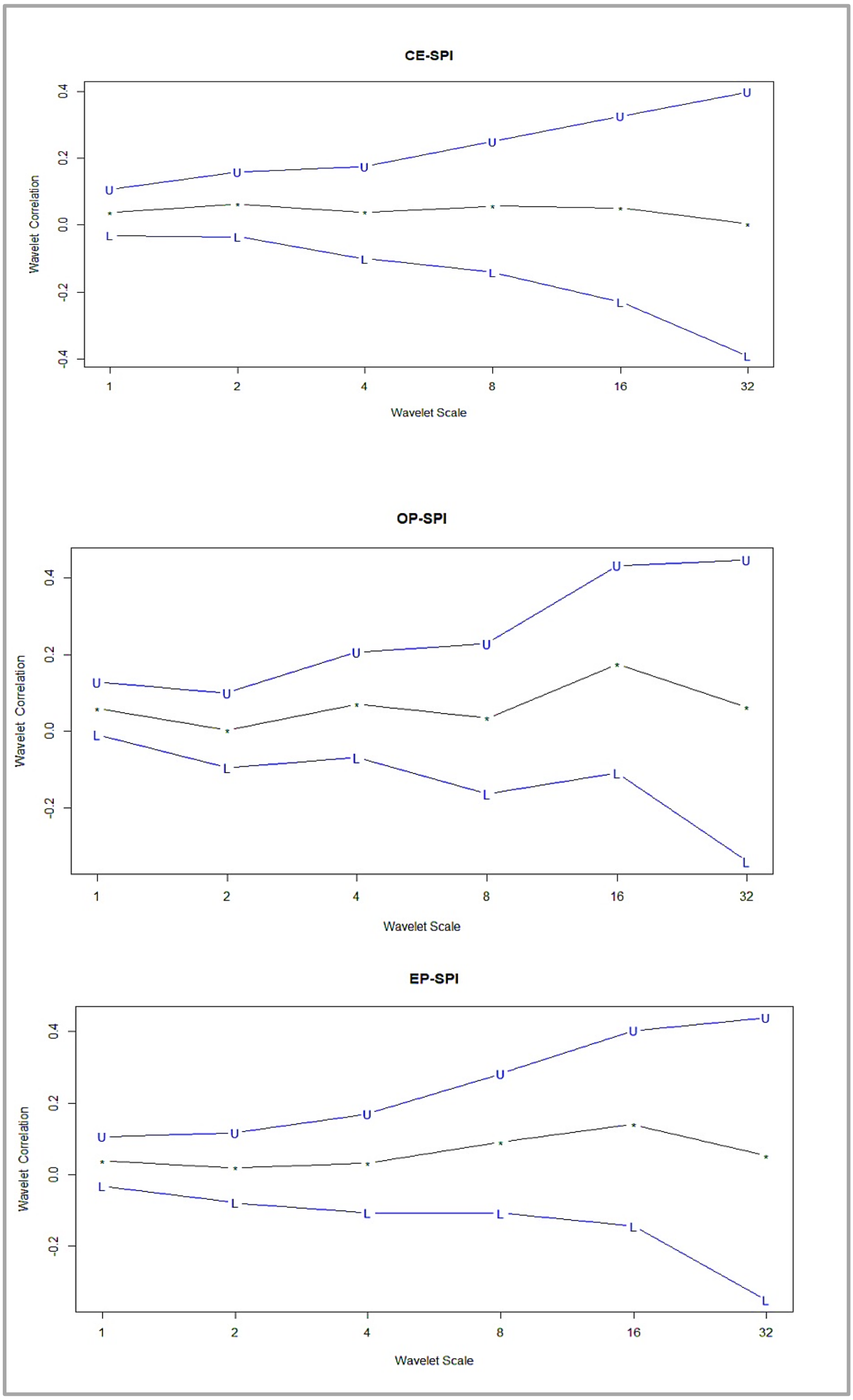


Figure 4.2: Wavelet cross-correlation for CE-SPI

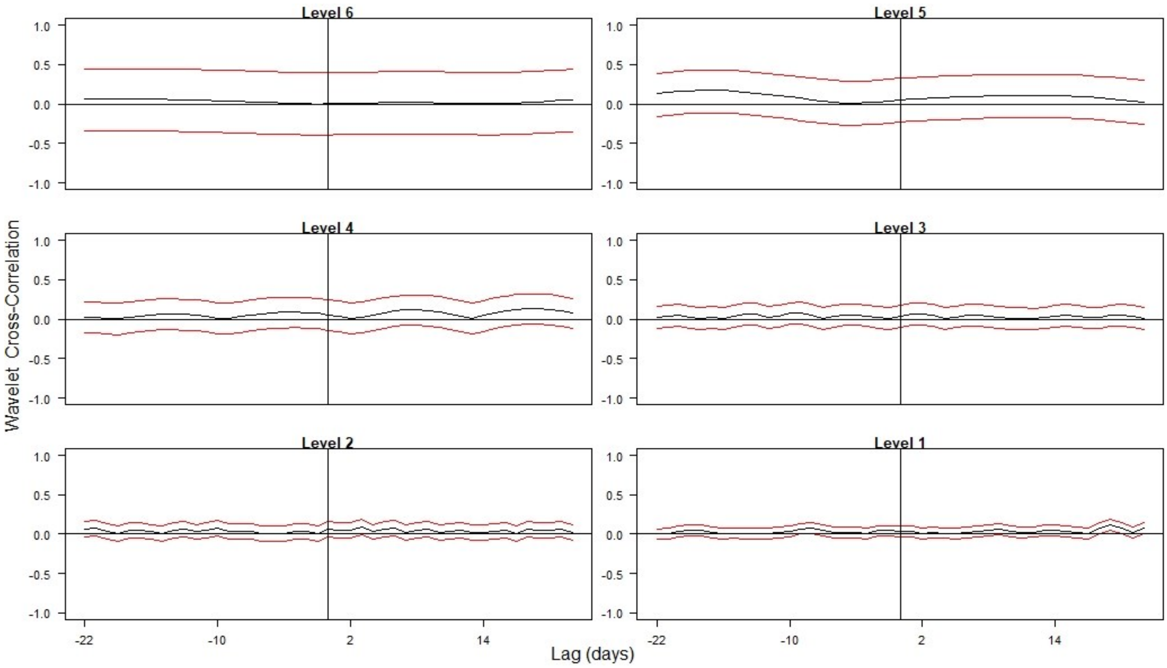


Figure 4.3: Wavelet cross-correlation for OP-SPI

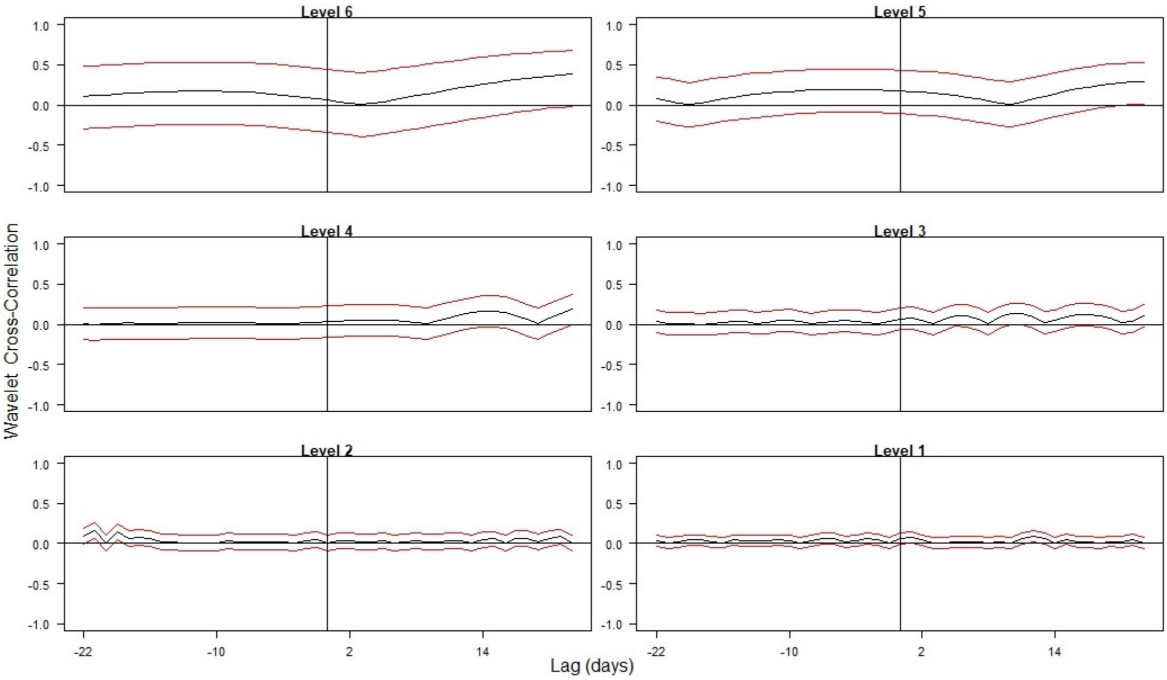
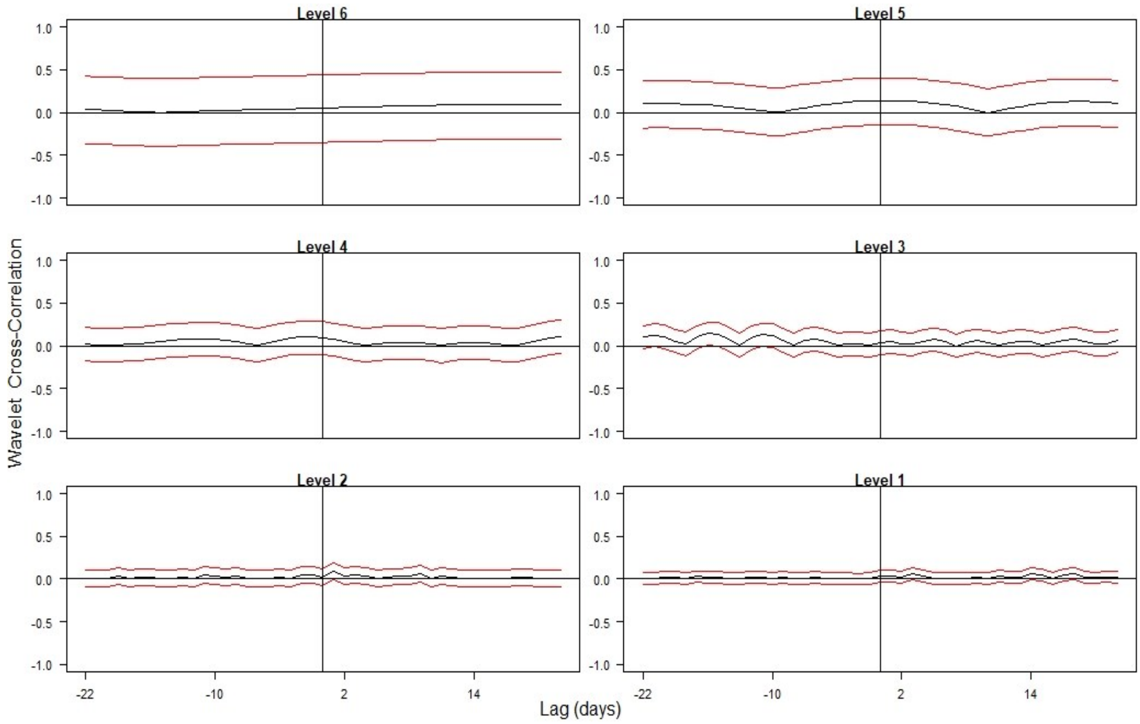


Figure 4.4: Wavelet cross-correlation for EP-SPI



4.4.2. Wavelet results of the UAE energy sector

4.4.2.1. The wavelet correlation

Figure 4.5 illustrates the correlation of the Abu Dhabi energy sector with the global clean energy production index, oil price and CO_2 emission price. Correlations in general dramatically increase after scale 5. Furthermore, the highest positive value of the correlation is at a scale of 6 for all variables, although the correlation of the global clean energy index is stronger. This scale corresponds to the period from 32 to 64 days and signifies the lower frequency in the equity markets. Overall, the wavelet correlation of the Abu Dhabi energy sector across all three frequencies increases as the scale rises. Therefore, it can be concluded that the correlation of the Abu Dhabi energy sector with the global clean energy index, oil price and CO_2 emission price is evidenced in the higher scales (lower frequency). Nevertheless, the correlation between the respective pairs is minimal in the high frequency (lower scales).

4.4.2.2. The wavelet cross-correlation

The wavelet cross-correlations of the Abu Dhabi energy index with global clean energy production index, oil price and CO_2 emission price is shown in Figures 4.6, 4.7 and 4.8. The cross-correlation analysis with clean energy production index and CO_2 emission price signifies minimal positive correlations across different levels, but the most significant correlation is at levels 3 and 4 with negative lags. This is evidence that both the global clean energy index and CO_2 emission price leads Abu Dhabi energy price at these scales. For the link with the oil price, there is higher positive cross-correlation at the last three levels under the lags 22. It implies that any increase in the Abu Dhabi energy stock price would raise oil prices.

Figure 4.5: Wavelet correlation of CE, OP and EP with AEI

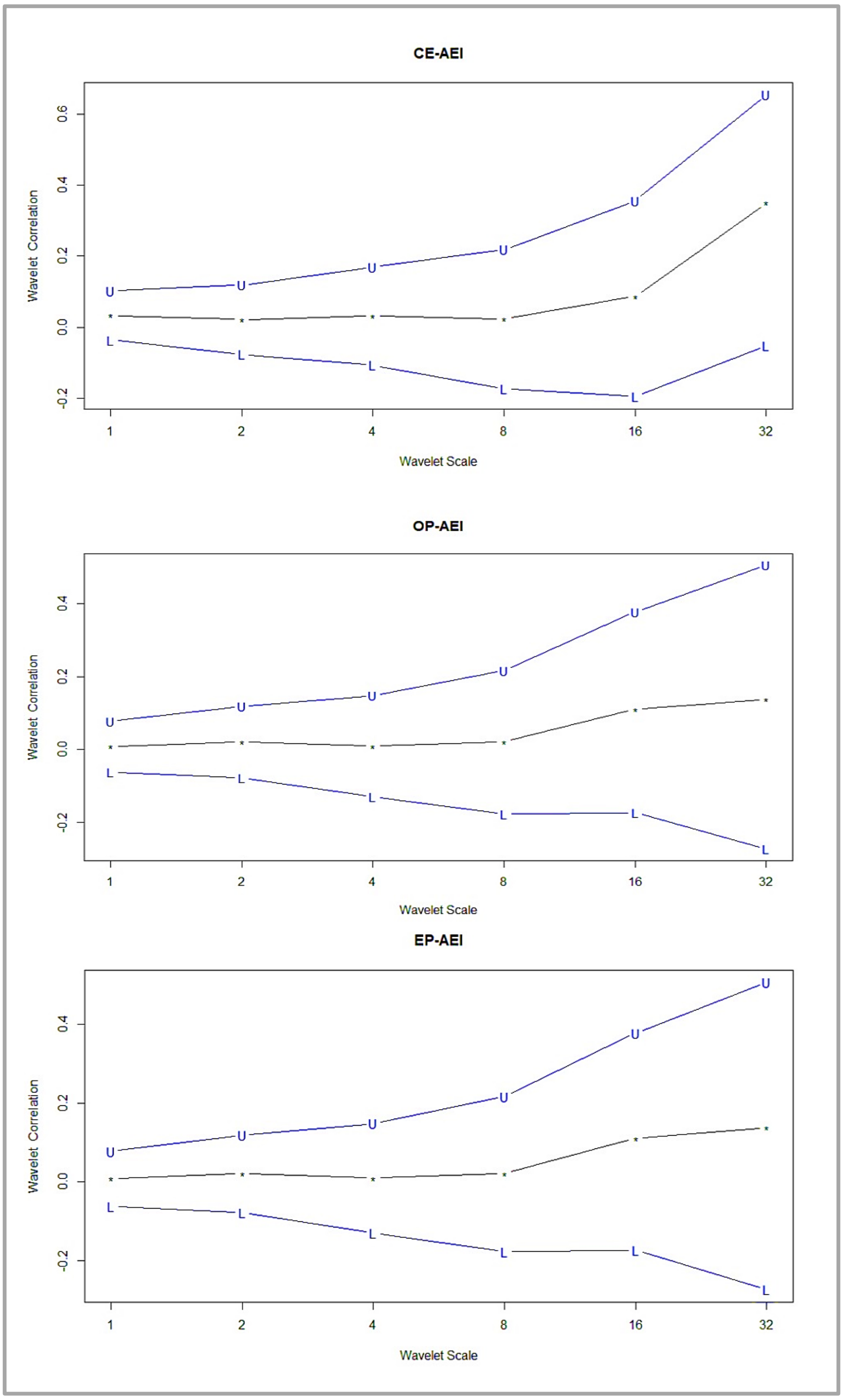


Figure 4.6: Wavelet cross-correlation for CE-AEI

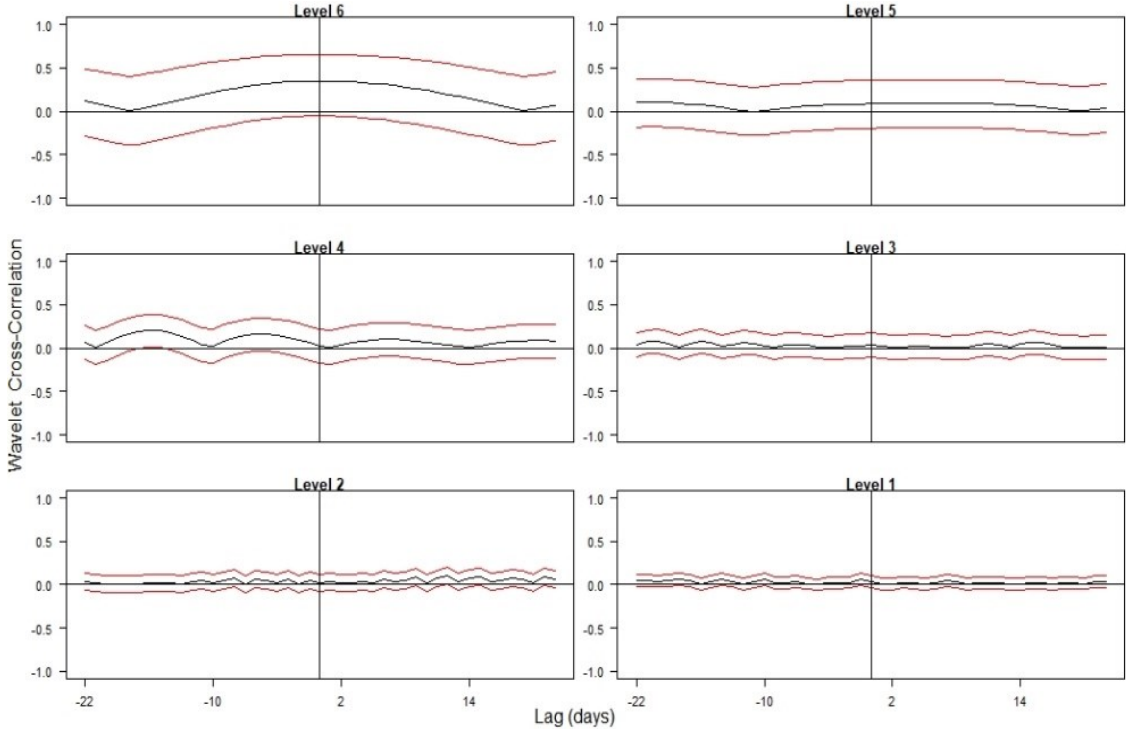


Figure 4.7: Wavelet cross-correlation for OP-AEI

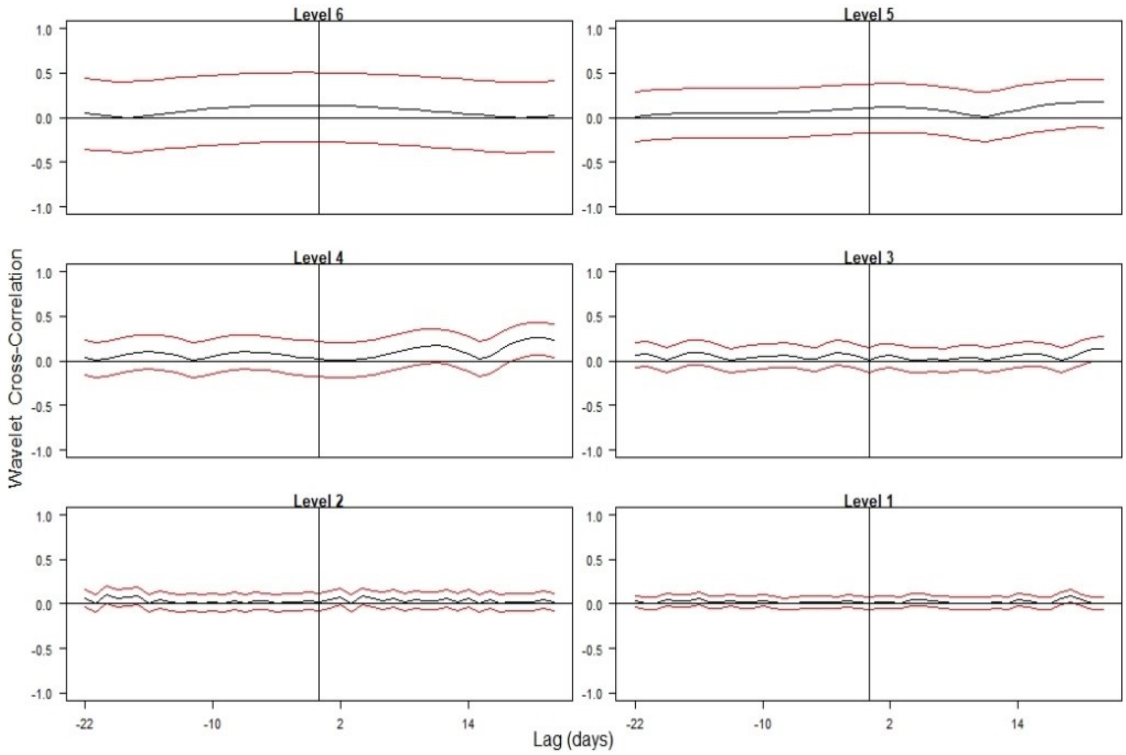
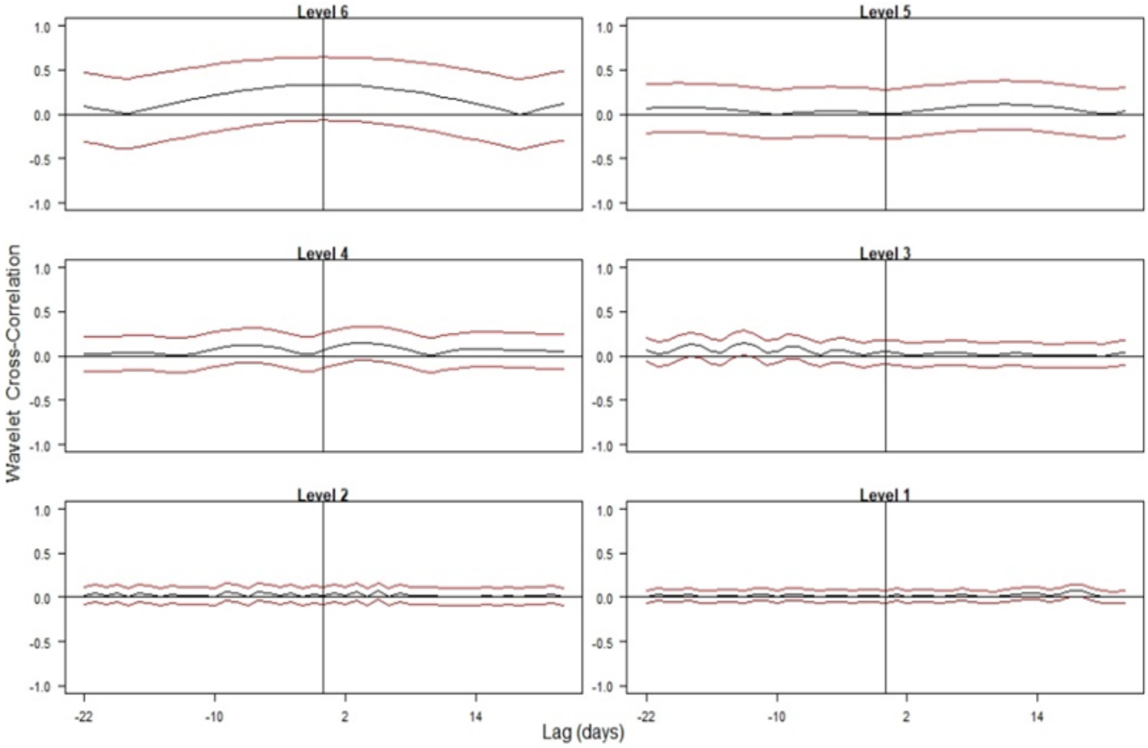


Figure 4.8: Wavelet cross-correlation for EP-AEI



4.4.3. Wavelet results of Kuwait energy sector

4.4.3.1. The wavelet correlation

Figure 4.9 shows the wavelet correlation of Kuwait energy index with clean energy production index, oil price and CO_2 emission price. Overall, the wavelet correlation of the Kuwait energy index with the respective variables is low. While the wavelet correlation with oil price is positively distinguished at scale 5, which represents 16-32 days. This is only evident at the higher scales (lower frequencies).

4.4.3.2. The wavelet-cross correlation

Figures 4.10, 4.11 and 4.12 exhibit the cross-coronation of wavelets of Kuwait energy index with clean energy production index, oil price and CO_2 emission price. There is evidence that the clean energy production index and CO_2 emission price slightly and positively leads Kuwait energy market at the lag -14 of level 4 and the lag -22 of level 6 respectively. For Kuwait energy retunes and oil price, there exists a stronger positive cross-coronation at levels 3, 4 and 5 with the lags -13, -19 and -22 respectively. Therefore, oil price swings positively lead Kuwait energy stock prices at these scales.

Figure 4.9: Wavelet correlation of CE, OP and EP with KEI

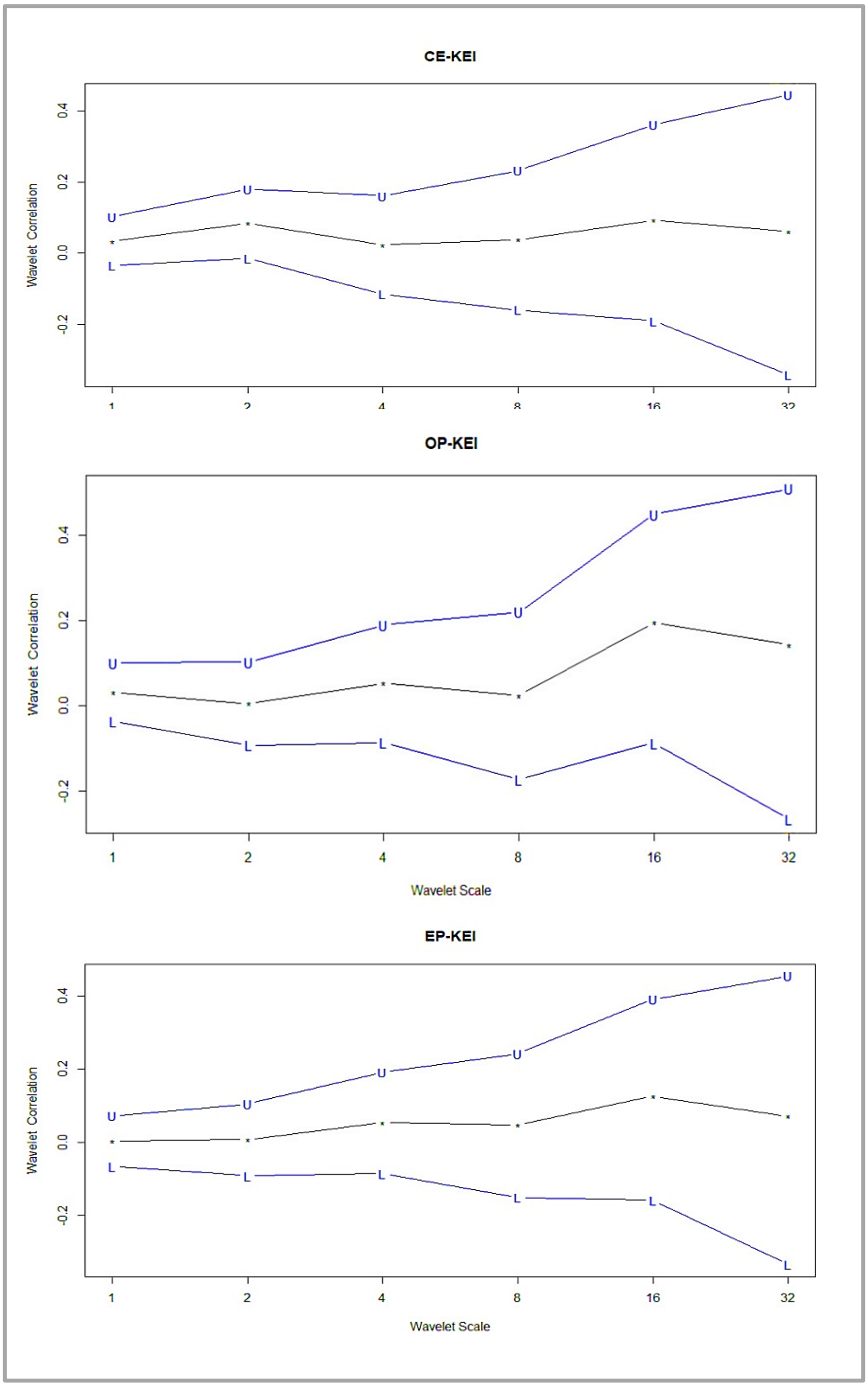


Figure 4.10: Wavelet cross-correlation for CE-KEI

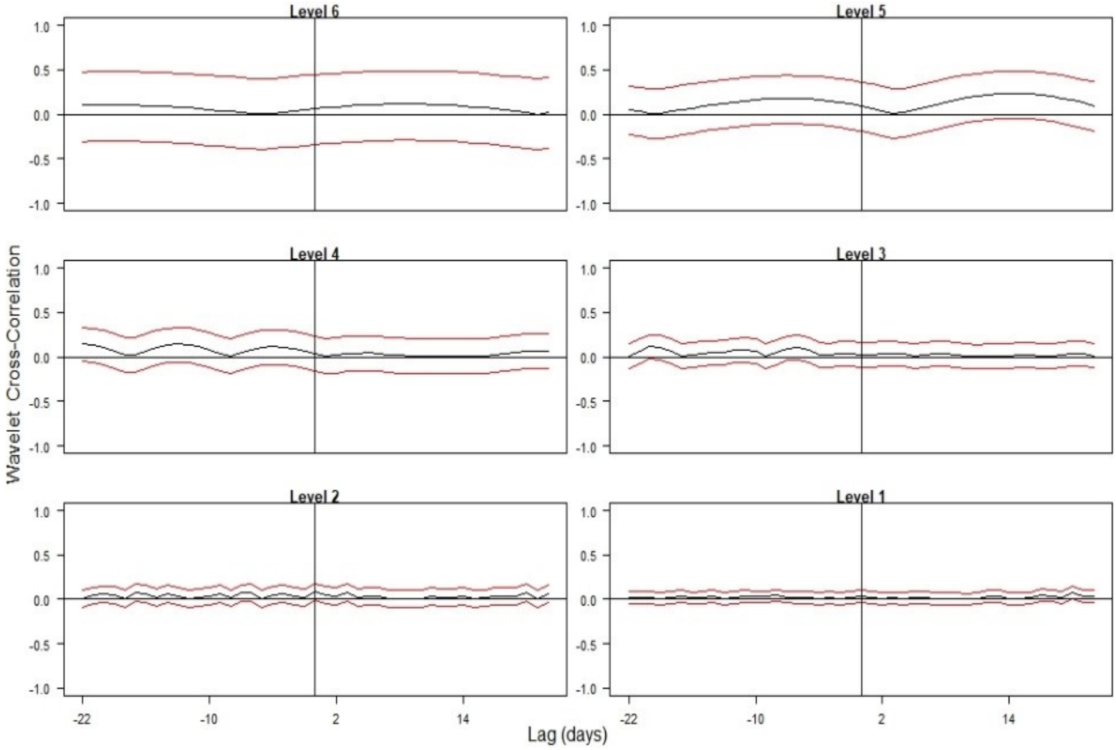


Figure 4.11: Wavelet cross-correlation for OP-KEI

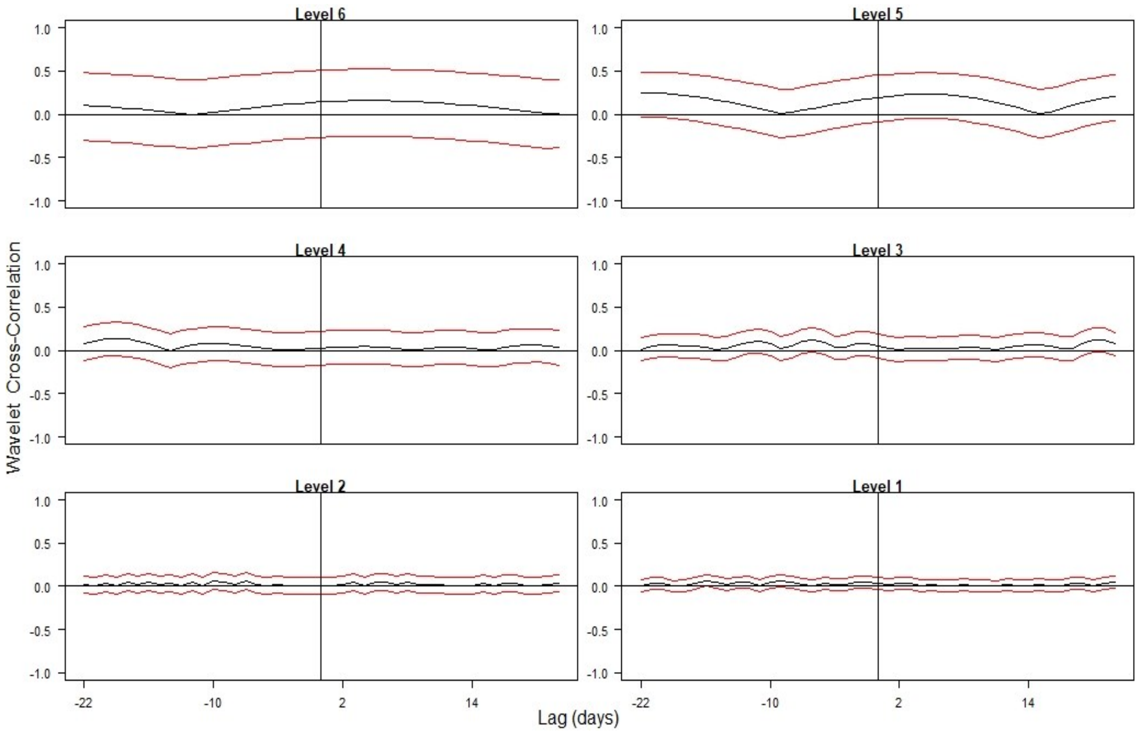
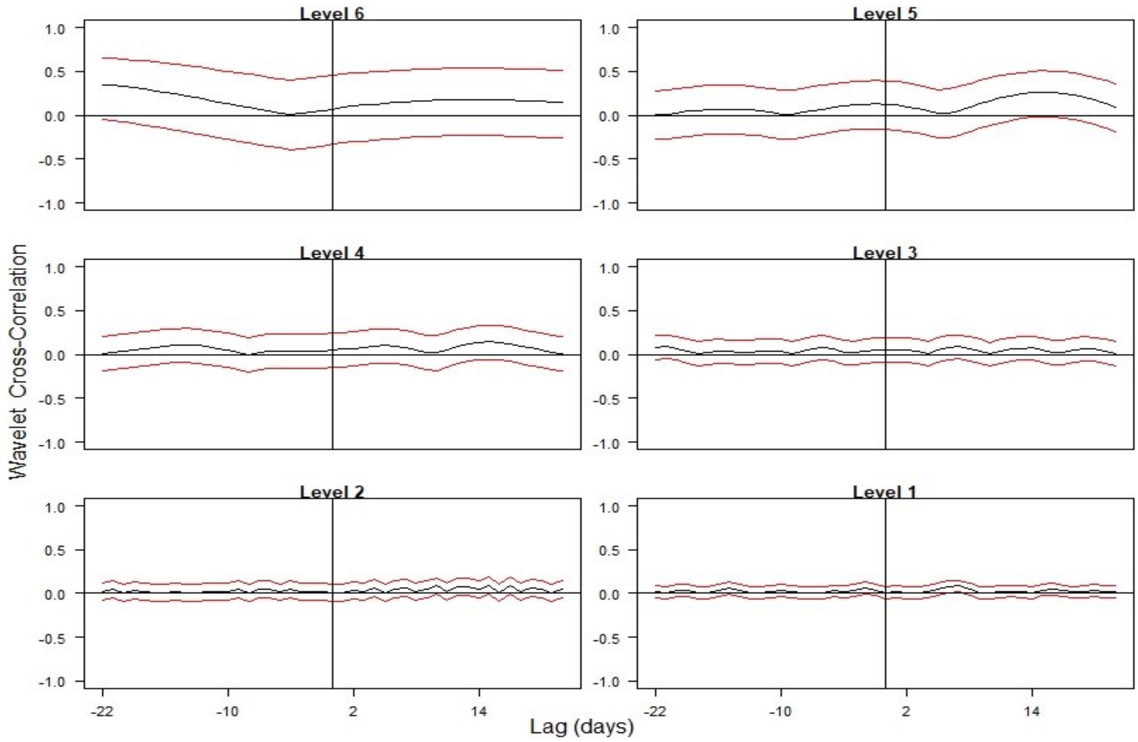


Figure 4.12: Wavelet cross-correlation for EP-KEI



4.5. Dissection of results

Our results mainly indicate that a positive and nominal wavelet correlation of the GCC energy stock prices exists at lower frequencies (higher scales) with the three global energy markets: global clean energy production, oil price and CO_2 emissions.

According to Orlov (2009) and Gallegati (2012), wavelet correlation at lower frequencies points out evidence of interdependence (or co-movement) between markets. This is because the innate co-movements of markets are sluggish; hence they require a longer horizon to be captured. Whereas wavelet correlation at higher frequencies indicates a contagion phenomenon.[28] This is due to financial shocks transformation between markets is quick; thus, it can be computed in a few days.

The positive link between oil price and the GCC stock returns comes in line with some previous works' findings (Hammoudeh and Choi, 2006; Arouri and Rault, 2010; Arouri et al., 2011; Mohanty et al., 2011). This is attributed to the macroeconomic performance of the GCC countries, which mainly depends on crude oil revenues. Thereby, any increase in oil price will lead to a boost in the GCC stock market prices, particularly the energy sector. However, limited evidence is found about the underlying reasons for the positive impact between the global clean energy production index and CO_2 emission price for the three GCC energy stock prices.

[28] Key studies such as those by Bodart and Candelon (2009), Orlov (2009) and Gallegati (2012) define contagion as an unexpected and direct transmission of shocks between markets/countries that mostly caused by surprising financial crises. While co-movements, interdependence are spillovers refer to normal association between markets during non-crisis periods.

There is no concrete theoretical model to describe a direct relationship between global clean energy production, EU ETS implementation and the energy stocks in the GCC region. However, we hypothesise that oil price changes play a crucial role in this relationship. Higher oil prices could lead to a higher demand for clean energy, as renewable energy sources are adequate substitutes for non-renewables, thus a rise in its production (Bhattacharyya, 2011). While lower oil prices could tempt heavy-oil businesses to consume higher levels of oil causing an increase in carbon emissions levels (Hussain et al., 2012; Nwani, 2017; Liu et al., 2020). This pushes the installations to demand extra emission allowances causing an increase in their prices. Finally, oil price, global clean energy production and CO_2 emission exhibit common links with global economic activity conditions, technology development and environmental issues (He et al., 2010; Barkhordari and Fattahi, 2017; Troster et al., 2018; Chen et al., 2018; Dong et al., 2019).

The distinctive nature of GCC stock markets can explain their behaviour in our empirical analysis. First, high percentages of the GCC energy company shares are owned by governmental institutions (Argaam, 2021).[29] Therefore, they are not fully and timely responsive to changes in global clean energy production, CO_2 emission and oil prices. The GCC stock markets are more sensitive to regional common issues such as wars, domestic regulations and government budgetary plans (Mensi, Hammoudeh, et al., 2017; Braunstein, 2019; Erdoğan et al., 2020; Alkhateeb and Mahmood, 2020).

[29] For example, the Abu Dhabi National Oil Company (ADNOC) hold 80% ownership of the ADNOC Distribution in the UAE. While the Saudi government is substantial shareholder by 98.18 %.

Finally, energy in GCC countries including fuel, gas and electricity are locally subsidised and sold based on governmental fixed rates.[30] This implies that the GCC energy companies' revenues coming from domestic sales would be less correlated with the dynamics of global energy prices.

[30] In 2016 the Saudi government announced a timeline to cut energy subsidies to improve the energy use efficiency and the government expenditure. Where in the UAE, the government release fuels prices to align with global energy prices (Morgan, 2016).

4.6. Conclusion

Using a multiscale approach of wavelets, we develop a dependence structure to investigate the impact of global clean energy production, oil price and CO_2 emission on the energy stock markets of the largest three oil exporters in the GCC region; Saudi, UAE and Kuwait. The purpose is to evaluate the effect of the recent boom in the global renewable energy industry and the EU ETS on the GCC conventional energy stock prices. Our findings indicate that the three global energy markets are weakly and positively correlated with the GCC energy stock prices at lower frequencies (higher scales). Besides, at the same level of frequencies, we found that changes in the global clean energy production index and CO_2 emission price positively influences the three GCC energy stock prices. Oil price is a stronger moderator for the three GCC energy equities at lower frequencies relative to other variables, especially for Kuwait's energy stock price. We also discover that the Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets. These findings carry important implications and guidelines for policymakers, portfolio managers and scholars who attempt to understand the dynamic nexus between GCC energy sectors and global energy markets behaviour. Future studies can explore these relationships over the long term using other statistical techniques. Future studies are encouraged to consider the potential impact of the recent US shale oil production on oil-exporting economies.

Chapter 5: Value at Risk and the Expected Shortfall for the GCC Energy Stock Markets via Three Long Memory ARCH/GARCH Models

5.1. Introduction

Since the mid-1990s when J.P. Morgan developed the first risk standardised approach to forecast future risks of financial markets, such approach become an ultimate goal for investors, financial managers, regulators as well as academics. Empirically, most scholars point out that the most effective risk quantifying techniques are value-at-risk (VaR) and the expected shortfall (ES) (e.g., Aloui and Hamida, 2014; Su, 2015; Mabrouk, 2017; Mensi et al., 2017; Liu et al., 2018). 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. The ES is a complementary tool to the VaR to quantifies the losses that are not covered by VaR under its confidence level (Gong and Weng, 2016; Mensi et al., 2017; Liu et al., 2018).

Predicting the risks of high volatile markets commonly uses 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). Where some authors developed VaRs 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). However, the literature has limited evidence of VaR and ES for conventional energy stock prices, especially for heavy oil-exporting countries like those in the GCC region. There is also a gap in understanding the crucial role of the statistical properties of high volatile markets' VaRs (e.g., excessive volatility, leverage effects, fat-tails, asymmetry and long memory). According to Cabedo and Moya (2003), returns for energy commodities prices mostly display a large skewness, kurtosis or follow a long memory process.

We quantify one step ahead VaR and the ES for the three energy stock prices indexes of Saudi and the UAE and Kuwait using three long memory ARCH/GARCH models: FIGARCH, FIAPARCH and HYGARCH. These models were used to capture potential leverage effects, fat-tails, asymmetry and long memory effects of our variables.[31] While the three global energy markets: clean energy production index, crude oil and CO_2 emission prices are used as regressors to explore their statistical long memory effects on the GCC energy equities.

To the best of our knowledge, this is the first study to undertake an analysis of VaR and ES for traditional energy sectors based on modelling (i) the statistical properties of volatility clustering, fractional integration and asymmetry in the selected energy markets (ii) and the effects of the three pre-mentioned regressors.

The remaining parts of this chapter 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, where Section 5 concludes this study.

[31] 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).

5.2. Literature review

Two literature strands emerged since 1996 when the basic VaR analysis was first introduced by J.P. Morgan to estimate potential financial market losses. The first strand 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; Chen et al., 2020). The second strand 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).

In the first group of studies, they mostly applied ARCH/GARCH class of models, in particular long memory volatility GARCH such as (Chin et al., 2009; Aloui and Hamida, 2014; Balibey and Turkyilmaz, 2014; Su, 2015; Günay, 2017; Mabrouk, 2017; BenSaïda et al., 2018). 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. This is mainly because that statistical features of high volatile time-series data for equity returns mostly point out fat-tail probability (Aloui and Mabrouk, 2010).

Critical stock market losses were also computed using more advanced techniques (Chen and Chen, 2013; Gong and Weng, 2016; Mensi, Shahzad, et al., 2017; Liu et al., 2018; 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 estimated 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 different results based on the GARCH and rolling-window approaches.

Aloui and Mabrouk (2010) is a major study that considered international financial markets spillovers when 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.

Overall, these studies highlight the gap of the VaR analysis for the conventional energy sectors, particularly for the largest oil exporters such as those in the GCC region. Besides, there a piece of evidence that spillover and dependence effects between markets play a critical role in the VaR analysis.

5.3. Methodology and data

5.3.1. Methodology

5.3.1.1. Long memory GARCH-type models

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. The international energy market indexes: global clean energy production, CO_2 emission and crude oil prices were used as explanatory variables.[32]

The three long memory time-varying volatility models have been used for two statistical reasons. VaR alone is incapable to account for volatility clustering in stock market fluctuations. This limitation could confound losses predicting, especially during crises, as a result of ignoring serial dependence over time (Danielsson, 2011; Nguyen et al., 2019). Besides, 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.

[32] 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).

- *The fractional integrated GARCH (FIGARCH) model:*

Baillie et al. (1996) expanded the standard GARCH to be an eventual fractional integration 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:

$$[\varphi(L)(1-L)^d]\varepsilon_t^2 = \omega + X_t + [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2) \qquad (5.1)$$

or

$$\sigma_t^2 = \omega + X_t + \beta(L)\sigma_t^2 + [1-\beta(L)]\varepsilon_t^2 - \varphi(L)(1-L)^d\varepsilon_t^2 \qquad (5.2)$$

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

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 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 which should be truncated.

- *The fractional integrated asymmetric power ARCH (FIAPARCH) model:*

Since the FIGARCH (p,d,q) model does not capture asymmetry and long memory feature in the conditional variance, Tse (1998) 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:

$$\sigma_t^{\delta} = \omega[1-\beta(L)]^{-1} + X_t + \{1-[1-\beta(L)]^{-1}\rho(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta} \quad (5.3)$$

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.

- *The hyperbolic GARCH (HYGARCH) model:*

Davidson (2004) 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 terms of the facts of volatility clustering, long memory feature and leptokurtosis, but it discounts asymmetry in the return distribution. The HYGARCH model can be defined as:

$$\sigma_t^{\delta} = \omega[1-\beta(L)]^{-1} + X_t + \{1-[1-\beta(L)]^{-1}\rho(L)[1+\alpha\{(1-L)^d\}]\}\varepsilon_t^2 \quad (5.4)$$

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

5.3.1.2. 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 innovation distribution.[33] The VaRs' formulas for long and short trading positions can be expressed as follows:

$$VaR_{long,t} = \hat{\mu}_t + skst_{\alpha}(v,k)\hat{\sigma}_t \qquad (5.5)$$

$$VaR_{short,t} = \hat{\mu}_t + skst_{1-\alpha}(v,k)\hat{\sigma}_t \qquad (5.6)$$

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 $\hat{\mu}_t$ and $\hat{\sigma}_t$ 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. It can be simplified as follows:

$$ES_{\alpha}(X) = E\{X|X \geq VaR_{\alpha}(X)\} \qquad (5.7)$$

---

[33] 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.

5.3.1.3. 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 $\hat{P} \equiv N/T$ is statistically equal to τ^*:

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

Following a binomial distribution, the null hypothesis of an accurate VaR can be rejected if the actual fraction of VaR exceptions is statistically different than τ^*.

5.3.2. Data and further preliminary statistics

We use the same dataset of the two previous chapters. Thus, we utilise log-differenced daily data for the S&P Global Clean Energy Index (CE), Brent crude oil price (OP), emission price (EP) and the three GCC energy stock indexes; Saudi petrochemical index (SPI), Abu Dhabi energy index (AEI) and Kuwait energy index (KEI) (more details about the data has been discussed from pages 83 to 85).

Following Daniel and Wood (1980), we apply various diagnostic tests. We preset the quantile-quantile (Q-Q) plots in Figure 5.1 to examine the distributional property of the six series. It can be noticed that all the Q-Q plots diverge from the straight line in both ends. This means 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).

Figure 5.1: Normal Q-Q plots for the time series daily returns

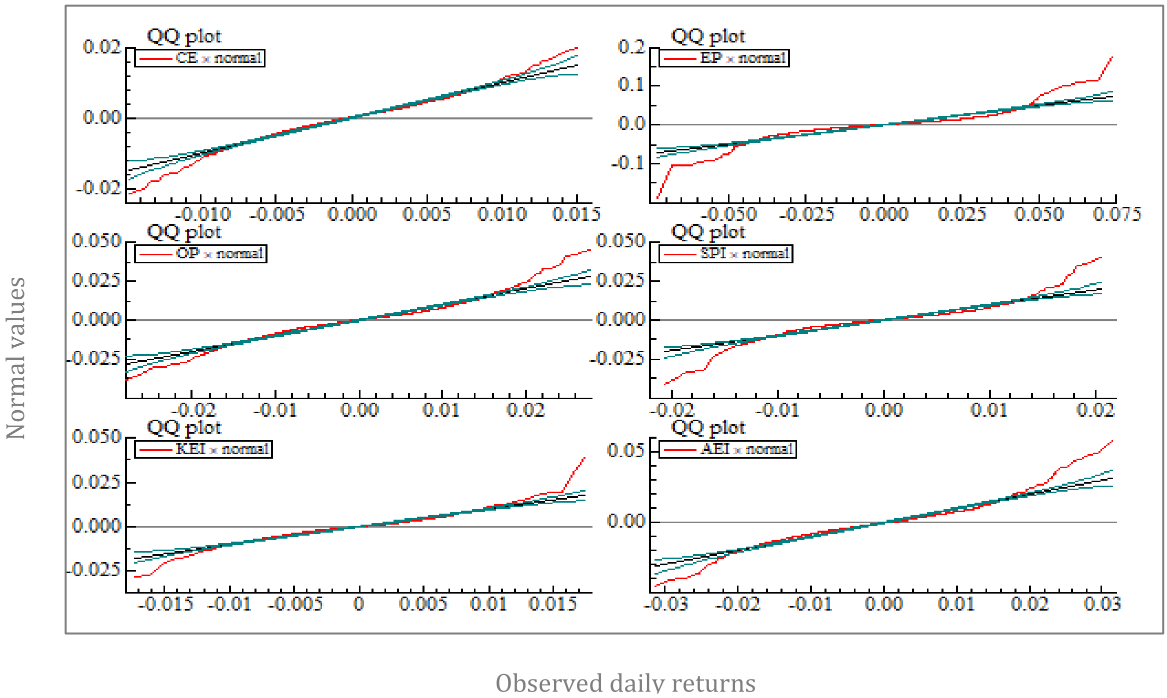
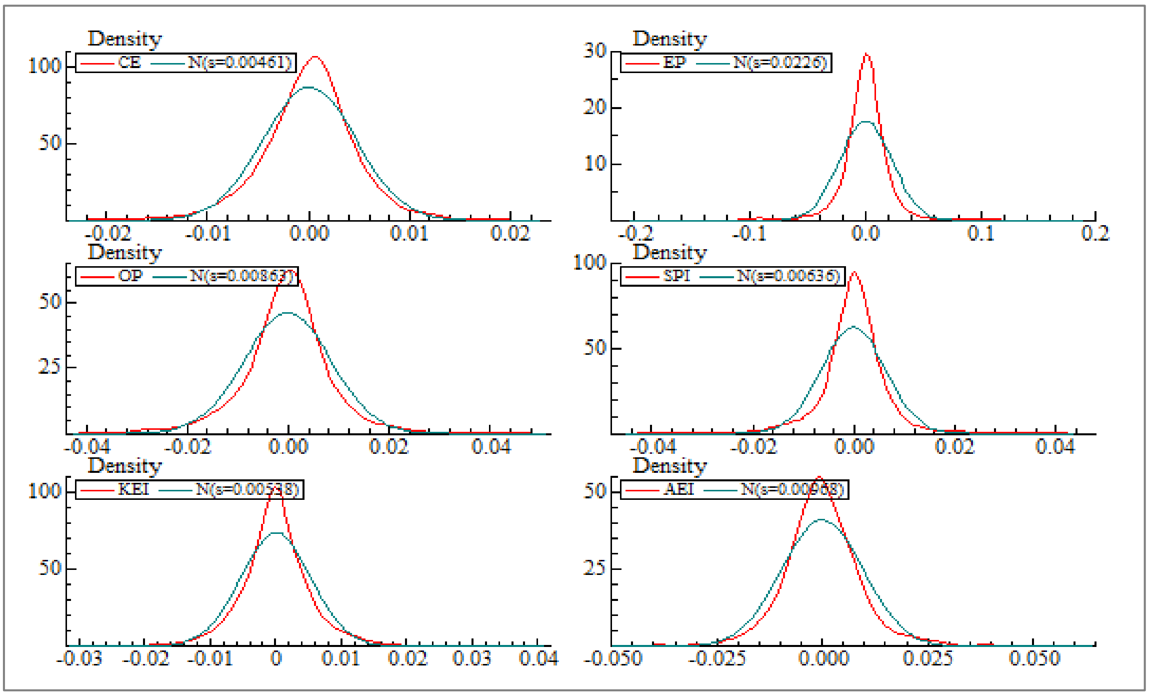


Figure 5.2 shows the normal probability plots of all the daily returns. The actual distributions of the six series greatly differ from their hypothesised normal distribution. In other words, we have clear evidence of positive Kurtosis and all the series are found to be Leptokurtic. Following our statistical result as well as the prior research on the same field, we decide to estimate the three GARCH models under the assumption of Student-t innovation's distributions.

Figure 5.2: Normal probability plots



5.4. Results

5.4.1. The three GARCH-type models results

Tables 5.1, 5.2 and 5.3 display the obtained results of the FIAPARCH, FIGARCH and HYGARCH models for the three GCC energy sectors. As shown, the long-range memory, ARCH, GARCH, asymmetry and asymmetric response phenomena are statistically evidenced across the different models. However, the regressors; global clean energy production, crude oil and CO_2 emission prices are statistically insignificant.

Table 5.1 shows the FIAPARCH model estimation of the three GCC energy markets. 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. This means that high volatility will be followed by high volatility and vice versa. While the long memory parameter value of the Abu Dhabi energy index is more than 0.5, but significant, implying anti-persistence. It means that a period of high volatility will 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.[34] 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

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

volatility in these two stocks compared to the good news. Where the asymmetric parameter for the Kuwait model is found negative indicating leverage effect. The power parameters (δ) are significant for the three models, implying that the functional form of the GARCH equations is not quadratic.

Table 5.1: FIAPARCH (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)	0.000131	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.

The goodness of fit test of the Ljung-Box with 10 lags rejects the null hypothesis and this indicates the absence of serial correlation within the variables.[35] Thus, it can be concluded that the estimated models can capture the volatility dynamics.

[35] The Ljung Box formula as follows: $Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j}$

The results of the FIGARCH (1,1) models for the three GCC markets are shown in Table 5.2. 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. Thus, 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.

Table 5.2: FIGARCH (1,1) results

	Saudi petrochemical index		Abu Dhabi energy index		Kuwait Oil & Gas index	
Parameters	Coefficient	P-value	Coefficient	Prob. value	Coefficient	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 5.3 presents the results of the HYGARCH models for the three GCC energy sectors. The long memory in volatility and anti-persistent behaviour in conditional volatility are confirmed 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 indicating that the GARCH elements are covariance stationary. The post estimation diagnostic test shows that the models capture the volatility dynamics.

Table 5.3: 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.

5.4.2. Performance assessment of the three GARCH-type models

To choose the best models for the value at risk (VaR) analysis, two key forecast measures namely Root Mean Square Error (RMSE) and mean absolute error (MAE) are conducted over an in-sample window of length 5. The results are shown in Table 5.4.

Table 5.4: Estimated model comparison

	RMSE			MAE		
Energy index	FIAPARCH	FIGARCH	HYGARCH	FIAPARCH	FIGARCH	HYGARCH
SPI	2.318e-005	2.308e-005	2.869e-005	2.056e-005	2.067e-005	2.652e-005
AEI	5.305e-005	4.643e-005	4.327e-005	4.734e-005	3.846e-005	3.495e-005
KEI	2.192e-005	2.516e-005	2.335e-005	2.185e-005	2.49e-005	2.321e-005

In the case of the Saudi petrochemical sector, the FIGARCH outperforms other models based on RMSE criteria while FIAPARCH is the best as per the MAE criteria. This is because the two measures show the minimum average magnitude of the errors. Both criteria indicate that HYGARCH is the best model for the Abu Dhabi energy index and FIAPARCH is the best for the Kuwait energy sector.

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

Table 5.5 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 lies between 95% and 99% confidence levels. Accordingly, we are unable to reject the null hypothesis of correct specification in the quantiles of the three indexes over both short and long-run positions, except the third quantile of the Saudi short trading position. This implies that the models are successful in capturing the critical losses for short and long positions across all different quantiles of the three markets.

Table 5.6 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 mostly computed and the FIGARCHs are valid in predicting the critical losses in the GCC energy indexes.

Table 5.7 reports the estimation results of VaRs and the expected shortfalls for the HYGARCH models. 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 99% and 99.5% short trading position quantiles of Saudi and Kuwait indexes respectively. Thus, the HYGARCH models are able to estimate the critical losses for the GCC energy indexes in different trading positions.

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 5.4.

Table 5.5: 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 5.6: 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 is the expected shortfall values.

Table 5.7: 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

5.5. Conclusion

We estimate one-day-ahead VaR and the expected shortfall for Saudi, Abu Dhabi and Kuwait energy stock prices over short and long trading positions. We use long memory ARCH/GARCH models: FIAPARCH, FIGARCH and HYGARCH applying on the same dataset of the two past chapters. In the GARCH model, we employ the three global energy indexes: clean energy production, crude oil and CO_2 emission prices as regressors to consider their impacts on the GCC energy volatilities. Our findings confirm (1) the asymmetry, fat-tails and long memory in the GCC energy price volatilities. (2) The rejection of the statistical influence of the three regressors on the GCC daily returns volatility. (3) that 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 carry three important policy implications and lessons for future research: first, it is recommended to forecast more than one-day-ahead VaR and the expected shortfall for the three GCC energy stocks. Second, since the three regressors are poor predictors of the GCC energy daily fluctuations, it will be interesting to see how they impact other major traditional energy sectors in different regions.[36] Finally, our work levy useful insights for risk managers, investors and financial institutions to better control the level of potential losses in their portfolios.

[36] As this could be attributed to internal factors (e.g., wars, government regulations and high levels of oil reserves).

Chapter 6: Conclusion

Since the Paris Agreement in 2015, when nearly 200 countries have shared a common goal of limit carbon dioxide emissions and better mitigate dangerous climate changes, the world has witnessed a global surge in renewable energy production and usage. Over four empirical chapters, this thesis has undertaken an in-depth and multi-methodological empirical analysis on the nexus between global energy markets and the conventional energy stock prices in the largest GCC oil exporter nations – Saudi Arabia, UAE and Kuwait – by posing and attempting to answer four research questions.

Chapter 2 posed the following research question: what is the impact of the structural oil price shocks and the US stock market on the stock markets of the three countries while considering the various foreign ownership shares of these markets? To answer the question, we used monthly data from June 2002 to June 2019 and employed Killian's, (2009) alternative pioneering approach in a Structural VAR. We first decomposed the underlying causes of oil price changes into three shocks: oil supply shock, oil aggregate demand shock and oil specific demand shock. Next, we examined the impact of these shocks on the GCC stock prices while controlling for the potential impact of the US stock index and local stock market foreign share regulations.

We found that oil supply shock reduces Saudi stock prices during the first two months; following this, prices revert until the impact fades away after the fifth month. However, the magnitude of the decline in the stock prices driven by the aggregate demand shock is larger. Oil-specific demand shock, at 95% confidence intervals, significantly reduces the stock market for six months until fading away. The US stock market and other stock market shocks also have significant and negative impacts during the first three months, showing a less-inclined decrease in the stock market prices until the fifth month, after which the impact fades away. While the influence of these shocks on the Dubai stock market is similar to the impact of the estimated shocks on the Saudi stock market, except for the influence of aggregate demand and oil-specific demand shocks. An aggregate demand shock boosts Dubai stock prices with a powerful effect, starting from the second month until the fifth month. An oil-specific demand shock temporarily increases the stock market prices in the first two months, followed by a gradual decrease until the seventh month. Finally, oil supply shock leads to an immediate increase in the Kuwaiti stock prices in the first two months and then a gradual decrease until the fifth month. The impact of a global aggregate demand shock, in contrast, increases during the first month and then slowly reverts in the second month. Following this, a gradual upward trend is once more visible until the fifth month. An oil-specific demand shock, which statistically is significant within a 95% confidence interval, increases the Kuwaiti stock prices in the first two months, reverting gradually back until the sixth month. Finally, the impact of the US stock market and other shocks on Kuwait stocks is similar to the previous analyses.

The obtained results of chapter 2 have mostly come in line with our expectations. The stronger negative impact of oil supply shock on Dubai relative to the Saudi and Kuwait stock markets could be in part due to the Dubai stock market structure, consisting of a considerable number of transportation and service companies that increasingly use fuel. (Balcılar et al., 2017). Moreover, the UAE has a small proven reserve of crude oil

(OPEC, 2018).[37] Unexpectedly, the Kuwait stock market temporarily benefits from oil supply shock, as Kuwait exports a high percentage of its production unlike the other two countries (Awartani and Maghyereh, 2013).[38] A global aggregate demand shock interim reduces the Saudi stock market and rise stocks in Dubai and Kuwait. One possible justification is that the Saudi stock market heavily contains energy and petrochemical companies, which their activity is associated with the global business cycle condition.[39] This is in comparison to Dubai and Kuwait stocks, which have more diversified business activities, such as real estate, tourism and financial services. Finally, The negative responses of the three GCC stock markets to oil-market-specific demand shock are anticipated, as the stocks are susceptible to the political events in the Middle East, which are often the primary source of the precautionary demand of crude oil (Kim and Hammoudeh, 2013; Balcilar et al., 2017). Also, the GCC governments usually hold non-sustained financial surpluses driven by the political concerns in the region (Nusair and Al-Khasawneh, 2018).[40]

Chapter 3 has been carried out to discover the volatility spillover effects and co-movement among global clean energy production, crude oil price, CO_2 emission price

[37] UAE's proven reserve of crude oil amounts to 97,800 (million barrels), while Saudi Arabia and Kuwait have 266, 26 and 110, 50, respectively (OPEC, 2018).

[38] The percentage of crude oil exports out of produced oil in Kuwait is 76.2%, while the levels are 69.9% and 64.7%, respectively, in Saudi Arabia and the UAE (OPEC, 2018).

[39] For example, Saudi stock market growth mainly relies on the revenues of the Saudi Basic Industries Corporation (SABIC), which is a global leading company in the diversified chemicals industry.

[40] The GCC policymakers build annual spending plans based on consistent prices of crude oil (Kim and Hammoudeh, 2013).

and the conventional energy sectors of the three GGC countries. The main research question posed in this chapter was: is the current volatility in the GCC conventional energy stock prices influenced by the past shocks on the three global respective variables? To answer the research question we used three multivariate GARCH models: diagonal BEKK GARCH (1,1), asymmetric DCC GARCH (1,1) and copula DCC GARCH (1,1) models for each country over the period from January 02, 2013, to March 20, 2019.

The results show that the present volatilities in the three GCC energy stock markets are influenced by the past shocks on the three global respective variables, but the greatest influence comes from the past endogenous shocks on the GCC markets themselves. The volatility of Abu Dhabi energy prices is the most sensitive to its past shocks followed by Kuwait and Saudi markets. We also find that the volatilities in all the variables under consideration are highly persistent; though the GCC energy stock markets are more stable compared to other markets. The steadiest GCC energy index is Kuwait energy stock price followed by Abu Dhabi and Saudi energy indexes. Both short and long-term persistence in the conditional variance of all the time series are confirmed, but the long-run persistent volatilities are more definite especially for the variables; oil and CO_2 emission prices.

Overall, this study strengthens the idea that the current volatility in the GCC conventional energy stock prices is influenced by the past shocks of other variables; but the past shocks coming from these markets themselves were more powerful. 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 following 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 Corp (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 the sectors of banking and energy. (capital market authorities in Saudi and Dubai, 2020).

The research question posed in Chapter 4 has been addressed as follows: do global clean energy production, CO_2 emission and oil price fluctuations influence the energy stock prices of the three GCC countries? To answer the question we relied on the same dataset for chapter 3 developing a dependence structure of wavelet multi-resolution decomposition for each of the GCC markets. The results indicate a positive and nominal wavelet correlation of the GCC energy stock prices at lower frequencies (higher scales) with the three global energy markets: global clean energy production, oil price and CO_2 emissions. We also found that oil price is the leading moderator relative to other variables in deriving price trends in the GCC markets. Moreover, Abu Dhabi energy index is more sensitive to swings in the three perspective markets compared to Saudi and Kuwait energy markets.

The wavelet correlation at lower frequencies, which points out evidence of interdependence (or co-movement) between markets, is understood. This is because the innate co-movements of markets are sluggish; hence they require a longer horizon to be captured (Orlov, 2009 and Gallegati, 2012). Similarly, the positive link between oil price and the GCC stock returns is due to the macroeconomic performance of the GCC countries, which mainly depends on crude oil revenues. Thereby, any increase in oil price will lead to a boost in the GCC stock market prices, particularly energy sectors. However, the positive impact of the global clean energy production index and CO_2 emission price on the three GCC energy stock prices comes in contrast with the main assumption of the study.

There is no concrete theoretical model to describe the positive relationship between global clean energy production, EU ETS implementation and the energy stocks in the GCC region. However, we hypothesise that oil price changes play a crucial role in this relationship. Higher oil prices could lead to a higher demand for clean energy, as renewable energy sources are adequate substitutes for non-renewables, thus a rise in its production (Bhattacharyya, 2011). While lower oil prices could tempt heavy-oil businesses to consume higher levels of oil causing an increase in carbon emissions levels (Hussain et al., 2012; Nwani, 2017; Liu et al., 2020). This pushes the installations to demand extra emission allowances causing an increase in their prices. Finally, oil price, global clean energy production and CO_2 emission exhibit common links with global economic activity conditions, technology development and environmental issues (He et al., 2010; Barkhordari and Fattahi, 2017; Troster et al., 2018; Chen et al., 2018; Dong et al., 2019).

The research question posed in Chapter 5 was given as follows: what are the maximum financial risks that can hit the GCC stock markets; while considering the external impact of the clean energy production index, crude oil and CO_2 emission prices? To answer the question we applied three long memory ARCH/GARCH models: FIGARCH, FIAPARCH and HYGARCH to capture potential leverage effects, fat-tails, asymmetry and long memory effects in the time series. We employed the three global energy indexes: global clean energy production, crude oil and CO_2 emission prices as regressors. Our results show the maximum financial risks for the GCC stock markets. We also confirmed (1) the asymmetry, fat-tails and long memory in the GCC energy price volatilities; (2) the rejection of the statistical influence of the three regressors on the GCC daily returns volatility; and (3) that FIAPARCH produces the most accurate VaR and the expected shortfall for Saudi and Kuwait energy sectors. Finally, we discovered that HYGARCH performs better for the Abu Dhabi energy index.

The thesis's findings have significant implications for policymakers, portfolio managers and scholars to understand the response of the GCC, as an example of oil-exporting economies, to market dynamic transformations between renewable and non-renewable global energy markets. Future studies are recommended to examine the proposed nexus using long-term statistical techniques and to consider some of the recent global incidences and dynamics, such as the US shale oil production expansion, on the oil-exporting economies and energy markets.

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