Volatility Spillover between Oil and Energy Commodities

A research project submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investments

Submitted by: Dongfang Wei

Student Number: 2382217

Supervisor: Dr. Jones Odei-Mensah

Wits Business School

Date: February 2022

DECLARATION

I, Dongfang Wei, with student Number: 2382217, hereby declare that this research report is my own work except as indicated in the references and acknowledgments. It is submitted in fulfilment of the requirements for the award of Master of Management in Finance and Investments degree at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Signature: ……Dongfang Wei……

Signed at ……Wits Business School (WBS)……

On the ……28th…… day of ………February……… 2022

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my supervisor, Dr. Jones Odei-Mensah for his guidance during this research. His support and encouragement helped me complete my research successfully. I also like to thank my family, who gave me great emotional and financial support. Finally, I would like to thank my lecturers and classmates for their enthusiastic assistance and inspiration.

TABLE OF THE CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Energy is an indispensable resource for economic development and one of the main concerns of market participants and academics. The extreme volatility of energy prices, especially those triggered by the financial crisis in 2008 and the COVID-19 epidemic in 2020, makes it important to investigate the volatility spillover between energy markets.

Oil, natural gas and ethanol are chosen for this paper because the rise and fall in oil prices have a profound impact on a country's financial system. In addition, natural gas and ethanol are substitutes for oil, which have been shown in the earlier literature to have a long-term relationship with oil prices. This relationship has changed subsequent to the financial crisis.

The study analyses the volatility spillover and dynamic correlation between oil and natural gas and ethanol markets using VAR-BEKK-GARCH and VAR-DCC-GARCH models with weekly frequencies from June 2005 to December 2020. The sample is divided into five subintervals using the two significant events mentioned above as crisis periods.

The empirical results of the study show that there is a bidirectional volatility spillover from the oil to ethanol and natural gas markets during the full sample period. The volatility spillover results vary across markets in different subperiods, but there are more significant cases in the crisis and post-crisis periods. The average dynamic correlation coefficients between these three markets are low, which however increases to a higher figure during the crisis period.

1. INTRODUCTION

1.1 Introduction to the study

Extreme volatility is prevalent in both energy and commodity prices, which has drawn much attention among scholars. Since 2008, it has been observed that the increase in the development of energy financialization has made energy prices very volatile (Ji, Li & Sun, 2019). Especially during the 2020 coronavirus outbreak, there was a great demand shock and fold over to a price shock in the energy market. According to the Global Energy Review 2020 (IEA, 2020b):

> *Energy demand contracts by 6%, the largest in 70 years in percentage terms and the largest ever in absolute terms. The impact of COVID-19 on energy demand in 2020 would be more than seven times larger than the impact of the 2008 financial crisis on global energy demand.*

Subsequent Global Energy Review 2021 confirmed the 4% drop of the global energy demand in the whole 2020, which is actually five times larger than 1% decline in the 2008 financial crisis (IEA, 2021).

In April 2020, oil price dropped by nearly 5% in the first quarter (IEA,2020b). Brent Crude price based on June contracts fell by 8.9% at less than $26 a barrel. West Texas Intermediate (WTI) price even turned negative to $37.63 a barrel (Walker, 2020).

As the basis of economic development, oil price fluctuations deeply affect all aspects of production and distribution and tighten the nerves of producers and investors. However, natural gas and ethanol, as the commodities well-known to be closely related to oil, their prices didn’t seem to be affected during the same period. Therefore, it raises the interest in studying the volatility spillover effects between oil, natural gas and ethanol.

The economic theory implies that oil and natural gas are substitutes for consumption as well as complements. Their prices are linked by both demand and supply and are shown as follows: The increase in oil prices would increase the demand and prices for natural gas as a substitute. The rise in oil prices caused by rising demand may improve the production of natural gas as a co-product of oil extraction, thereby reducing natural gas prices (Villar & Joutz, 2006). Villar and Joutz (2006) demonstrate that the relationship between crude oil and natural gas has been historically stable, consistent with the economic theory.

Ethanol is also a substitute for oil (Chang & Su, 2010), which is the same as natural gas. Many studies found a strong connection between oil and agriculture commodities (Balcilar, Chang, Gupta, Kasongo, & Kyei, 2016; Nazlioglu, S., Soytas, 2011) and considered high oil prices as the main factor pushing up agricultural prices. The reason for this is because of the increase in crop use in biofuel production, including ethanol and biodiesel. Put another way, soaring oil prices trigger an increase in the demand for biofuels such as ethanol, which in turn causes a rise in the price of agricultural products used as raw materials for producing biofuels.

Investigating volatility spillover between oil, natural gas and ethanol is of great significance. It provides a deeper comprehension of the information and risk transmission mechanisms among these three markets so that policymakers can improve regulatory efficiency and take timely and relevant measures to prevent the spread of risks among markets (Wang & Guo, 2018). In addition, volatility is one of the major indicators of investment risks (Karali & Ramirez, 2014). Therefore, investors can develop hedging strategies based on this and diversify and optimize their portfolios (Lin & Li, 2015).

So far, the literature analysing the volatility transmission between oil, natural gas and ethanol is relatively limited. For oil and natural gas, more attention is paid to the price linkage between them. The traditional view is that they have a long-term equilibrium relationship (Hartley, MedlockIII & Rosthal, 2008) while the more recent view is that this long-term relationship has weakened or decoupled (Brigida, 2014; Erdös, 2012, Lin & Li, 2015). However, just a few studies examine the volatility spillover between oil and natural gas and even fewer articles have considered the volatility spillover effect across different periods (Lovcha & Perez-Laborda, 2020). For oil and ethanol, more research is interested in volatility spillover effects of oil and agricultural products (especially corn), since corn is the raw material for biofuels as a substitute for oil (Trujillo-Barrera, Mallory & Garcia, 2012; Katrakilidis, Sidiropoulos & Tabakis, 2015; Chiu, Hsu, Ho & Chen, 2016). Not surprisingly, the volatility spillover effect can be found. Nevertheless, very limited literature directly discovers the volatile transmission between ethanol and the oil market and considers the spillover effect over time.

Given the reasons above, this paper hopes to explore the volatility transmissions between crude oil, natural gas and ethanol, thus providing helpful information for investors and policymakers, as well as filling the gap in academics.

1.2 Context of the study

1.2.1 *Oil market*

Since the mid-1950s, oil has become the world's most essential source of energy. It serves as a critical component of the world's economy as it is the lifeblood for many global industries. In 2019, oil constituted 31% of the total worldwide primary energy demand (IEA, 2020a), still holding the highest share.

The overall trend of world oil production and consumption is increasing year by year. According to BP Statistical Review of World Energy – all data, 1965-2019, oil production along with consumption grew by an average of 1.46% and 1.32% respectively per year over the 20-year period from 1999 to 2019. Hence, the significant fluctuations in oil prices will inevitably have an influence on the macroeconomic development of countries around the world.

The price of oil has been volatile and fluctuating throughout the 20^{th} century. The first oil crisis broke out for political reasons in 1973. The Organization of Petroleum Exporting Countries (OPEC) implemented oil production cuts as well as announced oil embargoes and export suspensions to protect their national interests and achieve higher oil profits (Hamilton, 1983). These actions increased oil prices from less than $3 a barrel to nearly $12 a barrel, causing the oil crisis. The second oil crisis occurred in 1979. There was a drastic oil supply drop because of the Iranian revolution coupled with the war between Iran and Iraq, leading oil price to surge from an average of $14 a barrel to $36.83 a barrel in 1980, up more than 150%. These two oil crises resulted in an economic recession in oil-consuming countries such as the United States (Painter, 2014).

After the second oil crisis, non-OPEC countries increased their oil production to cut the shares of OPEC countries, weakening their influence on oil prices. At the same time, oil futures were launched to mitigate the wild fluctuation of the oil prices (Razek & Michieka, 2019). As a result, oil prices maintained around $20 to $40 a barrel from 1980 to 2000.

From 2003 to 2006, the high economic growth of the global economy, especially in emerging countries such as China, drove up the consumption of oil. At the same time, the devaluation of the U.S. dollar brought an inflow of capital into the commodity market, further raising the price of oil, causing it to rise approximately twofold during this period (Griffin, 2007).

There was a peak during 2007 and 2008. Due to the development of financial markets, oil futures were invested by a large number of speculative funds, pushing the price of oil to $145 a barrel, which was the highest price in the history of crude oil (Enwereuzoh, 2019).

Since then, because of the 2008 global financial crisis, investors' risk appetite has plummeted and speculative financial factors have subsided, with oil prices crashing by about 75% to $33.87 a barrel within half a year as funds were pulled out from the crude oil futures market (Enwereuzoh, 2019).

2014 and 2016 have seen another round of massive oil prices drop. After the financial crisis, oil prices have gradually recovered as a result of global easy monetary policies. However, supply surpluses of the oil driven by technological breakthroughs in the extraction of shale oil, as well as demand reduces of the oil caused by the slow global economic recovery triggered a 77.5% decline in oil prices (Zhu, 2017).

The most recent oil price shock was in 2020. The outbreak of the Covid-19 epidemic forced countries to cut off traffic and take measures such as lockdown, which significantly limited the demand for oil and brought its price down far from the level of the financial crisis.

Considering the large fluctuations in the oil prices since the 20th century, and the environmental protection issues, oil’s alternative energy sources are increasingly emphasized (Szklo & Schaeffer, 2006).

1.2.2 *Natural gas market*

A new chapter in global climate and environmental governance has begun with the signing of the Paris Agreement, which aims to reduce global warming to a certain range. One hundred ninety-five countries have joined the Agreement and target to achieve a goal of carbon neutrality. As a consequence, increasing the use of cleaner energy instead of high emission energy becomes an inevitable choice for all parties. Natural gas, the greenest burning fossil fuel, provides many environmental advantages in terms of air quality and greenhouse gas emissions compared to oil. Specifically, its combustion produces about 20% lower CO2 emissions. As of 2018, natural gas combustion accounted for 21 percent of CO2 emissions from the energy sector, well behind coal (44 %) and oil (35%). (IEA, 2019a).

In addition, natural gas is considered a close traditional substitute for oil (Erdös, 2012; Chiou-Wei, Chen & Zhu, 2019). It has abundant reserves in the world with excellent prospects for development and can replace 100% of the fuel functions of gasoline, diesel and kerosene. Therefore, the demand for natural gas is constantly being increased to replace the demand for oil. Since 2005, natural gas has grown more market share than any other energy source, accounting for nearly one-third of the aggregate growth in energy demand over the past decade (IEA, 2019a)

However, natural gas is not a perfect substitute for oil. The growth of natural gas has not yet driven down the consumption of other fuels. Oil demand has been strong as ever, growing at an annual rate of more than one million barrels a day (IEA, 2019a).

There has not yet been a unified international market for natural gas in the world like there is for crude oil. The natural gas market is currently broken down into three major regional markets: Asia, Europe and North America (Geng, Ji & Fan, 2017). Given the substitutability between oil and natural gas, in the early stages of the three regional markets, natural gas prices were international crude oil prices based. Subsequently, different regional natural gas markets have developed to varying degrees.

In the North American market, there is currently a competitive market system for natural gas, and its prices are mainly affected by market supply and demand. Meanwhile, its price has distinct seasonal changes, which is significantly higher in winter than in other seasons (Mu, 2007). In Europe, its price is based mainly on sources of competitive energy, such as international crude oil (Asche, Osmundsen & Sandsmark, 2006). However, the pricing mechanism has gradually transformed toward market supply and demand in recent years. In Asian markets, due to the immaturity of regional market development and the lack of natural gas trading centres, the price of long-term gas contracts is based on international crude oil prices (Neumann, 2009).

Many studies have linked natural gas with oil due to their strong relationship (Hartley et al., 2008; Brigida, 2014; Batten, Ciner & Lucey, 2017; Tiwari, Mukherjee, Gupta &

Balcilar, 2019). There are three main findings among these studies: the relation between oil and gas in econometrics is inconstant and may be time-dependable; oil plays a leading role in information transmission; and due to different reactions to positive and negative shocks, the linkages between oil and gas are generally asymmetric (Batten et al., 2017). However, some studies found that prices between them have decoupled in some countries (Erdös, 2012; Brigida, 2014; Lin & Li, 2015; Batten et al., 2017; Zhang & Ji, 2018; Parifanis & Dagoumas, 2018).

1.2.3 *Ethanol market*

Compared to natural gas, biofuels, dominated by Ethanol and Biodiesel, are deemed a technological substitute for oil (Chang & Su, 2010; Hassouneh, Serra, Goodwin & Gil, 2012). It can be mixed with gasoline or used alone in multi-fuel vehicles, which is also an unperfect substitute for oil. After the first oil crisis, fuel ethanol began to receive attention due to its renewable and environmentally friendly nature. Over these decades, its development in different countries has been supported by policies.

Brazil was the first country in the world to develop ethanol gasoline and was the first to achieve full coverage of ethanol gasoline for vehicles. As early as 1973, Brazil started the development of ethanol as an alternative to oil. Currently, Brazil is the second largest producer and consumer of ethanol gasoline in the world. Its fuel ethanol industry is extremely well developed, having replaced about more than half of the gasoline in the country (Lou, 2019).

The U.S. Congress issued the Renewable Fuel Standard in 2005, setting minimum requirements for the use of renewable fuels, including ethanol. Driven by strong government support and a significant increase in corn production, U.S. fuel ethanol production has been on the rise, surpassing Brazil to become the world's top producer of fuel ethanol in 2006 (Lou, 2019).

In Europe, fuel ethanol is used in almost all 28 European Union member states. The E.U. revised the Renewable Energy Directive in 2018, proposing a target of 32% of renewable energy use in the E.U. by 2030, with a target of 14% of renewable fuel use in transport.

Currently, several countries such as Canada, Sweden, the United States, Denmark, Spain, France and Japan are at different stages of development in the production of fuel ethanol from lignocellulose. They have signed several projects in the field of ethanol fuel production, thus promoting the industrialization of lignocellulosic ethanol (Soccol et al., 2010).

Global biofuel production broke the record of 154 billion liters in 2018, with the highest year-on-year growth rate of 7% in the five years, increasing by 100 billion liters, double which produced in 2017. Fuel Ethanol accounted for two-thirds of the growth (IEA, 2019b).

Because ethanol is an alternative choice for oil, many studies have paid attention to their price linkage. For example, Paris (2018), Gardebroek and Hernandez (2013) claimed that the growth of oil price may facilitate an increase in biofuels production because of the alternative effect. However, most studies are more interested in the relationship between the agriculture market and oil market instead of the direct connection between oil and biofuels (Kaltalioglu & Soytas, 2011; Nazlioglu, Erdem & Soytas, 2013; Yip, Brooks, Do & Nguyen, 2020). The reason is that Ethanol is agricultural-based energy (corn-based and sugarcane), which has a potential impact on agricultural market, thus strengthening the bond between the oil market and agriculture market.

Volatility spillover between oil and agricultural commodity markets began in many 2011 studies. This paper establishes the link between the oil market, natural gas and ethanol, and analyses the volatility effects on each market, as well as the causality between them to fill the lacunae in the extant literature.

1.3 Statement of the problem

As mentioned above, it is very important to study the linkage between oil and the selected energy commodities. On the one hand, energy investment and policy decisions can be better by investigating the relationship between these commodities. Simply put, policymakers could decide when to accelerate the development of one energy over the other, and investors could find arbitrage opportunities through their connections (Batten et al., 2017). On the other hand, understanding the relationship, especially the volatility spillover relationship between oil and other selected energy commodities, can help investors to identify the risks of and between each energy market and improve their welfare by making optimal hedging decisions to reduce uncertainty (Pindyck, 2004; Lin & Li, 2015).

Nonetheless, in the existing studies, Atil, Lahiani and Nguyen (2014) address that most of the research that analyse price transmission mechanisms between oil and natural gas focused on the linear relations between these prices. Compared to that, the number of papers investigating their volatility connection is surprisingly limited (Pindyck, 2004; Lin & Li, 2015; Parifanis & Dagoumas, 2018; Lovcha & Perez-Laborda, 2020). In addition, Lovcha and Perez-Laborda (2020) state that only a few literatures study oil and natural gas volatility spillover effects over time.

Moreover, McPhail (2011) mentions that it is limited to an analytical presentation of the impact of biofuels on the crude oil market; most of the studies concentrate on the linkage between the oil market and agriculture market, as stated above.

Therefore, these problems call for deeper exploration of the volatility transmission between crude oil, natural gas and ethanol in terms of time variation. This study thus fills the blank and provides investors and policymakers with a reference. Moreover, this study would be the first to investigate the volatility spillover between these three markets since most of the research just concentrates on part of them.

1.4 Objectives of the study

The study objectives are as follows:

- Examine whether volatility in crude oil prices have any explanatory impact on the volatility in natural gas, ethanol prices.

- Identify the direction of volatility spillover between crude oil, natural gas and ethanol markets over time.

1.5 Research questions

Consistent with the research objectives, this study answers the following questions:

- What is the extent and nature of volatility spillover effect from oil to other selected energy commodities?

- Does volatility spillover between crude oil and other selected energy commodities differ from the different sample periods?

1.6 Purpose and significance of the study

Lin and Li (2015) point out that the linkage exists across prices in various energy sectors, and their volatilities appear to be transmitted between markets. Oil is considered as one of the most vital energy commodities among the energy sectors, and its price fluctuations deeply affect a country's economy. Alternative energy commodities to oil can reduce a country's dependence on oil, thus attracting the interest of scholars (Tiwari et al., 2019). In this regard, natural gas and ethanol are traditional and technological alternatives for oil, making it meaningful to study their volatility spillover effect with oil.

As mentioned earlier, there is limited studies on the relationship between oil, natural gas and ethanol examine the volatility spillover effect. Moreover, those studies were published at an early stage, thus calling for an update in this field. This study fills this gap. It also considers the events of the financial crisis and the COVID-19 pandemic, dividing the data by pre-crisis, crisis and post-crisis periods, so as to examine the volatility spillover and the direction between markets in different periods.

Through this study, policymakers can capture the transmission of information among these three markets and formulate timely policies to prevent the spread of risks among them. At the same time, investors would take the result as a reference to enhance their portfolio diversification and risk management strategies to reduce investment losses.

1.7 Limitation of the study

This study has two main limitations. First is that it adopts weekly data in order to eliminate market noise, which may lead to bias of actual energy price trends. The second is that it focuses more on the volatility spillover effect itself without expanding the causes in detail.

2 LITERATURE REVIEW

2.1 Introduction

This section reviews the literature on the relationship between crude oil and other energy commodities. Although there are numerous studies in this field, not many examine the dynamic of risk transmission between crude oil, natural gas and ethanol. Due to the importance of other energy markets, this requires more attention. The literature in this chapter can be structured into two parts.: (i) the price link between oil and natural gas; (ii) the price relationship between ethanol and oil, as well as agricultural products and oil in terms of biofuels.

2.2 The relationship between oil and other energy commodities

2.2.1 *Price connection and volatility between crude oil and natural gas market*

Natural gas and oil prices are deemed to be correlated in economic theory. An increase in oil price may have a positive impact on the supply and a negative impact on the price of natural gas. Alternatively, it could have a positive effect on both demand and price of natural gas. (Villar & Joutz, 2006). Pindyck (2004) uses a Garch model to analyse the connectedness between the natural gas and crude oil prices from 1990 to 2003 in the U.S. markets. It is observed that the volatility of natural gas has a statistically small significant positive trend, and the demise of Enron does not attribute to an increase in volatility. Due to the limited length of the sample period, no evidence is found explaining a long-standing relationship between natural gas and crude oil.

In addition, Pindyck suggests the unidirectional volatility spillovers from oil to natural gas. What is more, the impulse responses are short-lived (i.e., half-life on the order of 5 to 10 weeks). Consequently, the study recommends that fluctuations in volatility could possibly influence the related derivative market (options on future contracts).

These markets have a duration lasting several months. Hence, the volatility spillovers could possibly influence the value of derivatives and investment decisions.

This is one of the first papers to examine volatility spillovers between natural gas and oil and make a crucial contribution to this field. It introduces the Enron collapse as a dummy variable and considers the change in volatility over time. However, most of the data used in this study are estimated and may deviate from the actual. Moreover, the fact that the sample period is from 1990 to 2003 makes the study deemed to be dated.

Similarly, Karali and Ramirez (2014) investigate a similar sample period (from 1994 to 2011) using a Multivariate Garch model. They conclude that there is indirect two-way volatility transmitted between crude oil and natural gas, and direct volatility transmitted from natural gases to crude oil returns. On the other hand, the study also finds evidence that volatility in the energy markets would significantly change during multiple major political, financial, and natural events.

Karali and Ramirez introduce some important events and macroeconomic variables that affect energy markets, considering the asymmetry of positive and negative shocks. For example, whether positive and negative shocks have different influences on the volatility of markets such as oil and gas. Their findings significantly extend previous research. Nevertheless, they do not take into account how volatility spillovers between markets change over time and, like Pindyck (2004), the paper is rather old.

Unlike Pindyck (2004), Hartley et al. (2008) observe a long-term inverse relationship between oil and gas prices in America using the VECM model from the period of 1990 to 2006 through marginal competition between natural gas and residual fuel oil. Similarly, Zamani (2016) also finds evidence of an indirect relationship. However, the latter study argues that demand shocks are the primary component that explains the inverse relationship between crude oil and gas markets, which differs from the former study.

Aloui, Aïssa, Hammoudeh and Nguyen (2014); Atil et al. (2014) analyse the crude oil and natural gas prices from 1997 to 2011 and 2012 with copula-Garch and NARDL, respectively. Both studies notice asymmetric and nonlinear structures between oil and natural gas. Although, Aloui et al. (2014) discover that the crude oil and gas markets tend to be closely comoved in bull markets (rising markets). Meanwhile, this relationship does not exist in bear markets.

Although, the study implies that investors should include fuels and energy trades together as pair trades in their portfolios during a bullish market. The study also concludes that low economic growth (bear markets) and technological improvements in extraction weakens the connection between crude oil and gas. If a recession seems to deteriorate this relationship - recessions become more prolonged and more frequent, these two commodities' prices will slowly drift apart.

Similarly, some papers also point out that the long-term correlation between crude oil and gas has weakened. Brigida (2014) examines the cointegrating relationship between the price of crude oil and natural gas by adopting an error correction model (ECM). The results display a long-term equilibrium relationship between these two prices. Nevertheless, it is worth noting that their price decoupled temporarily at the beginning of the 21st century.

Erdös (2012) investigates the link between oil and natural gas prices in Europe and the U.S. He suggests that European and the U.S. prices of oil and natural gas had a long-term equilibrium relationship before 2009 (this relation was broken in the U.S. after 2009). Some subsequence studies confirm the result of the U.S. oil-gas price decoupling (Lin & Li, 2015; Zhang & Ji, 2018; Parifanis & Dagoumas, 2018). Among them, Lin and Li (2015) take the samples from January 1992 to December 2012 and find bidirectional volatility spillovers between the crude oil market and natural gas market in both U.S. and Europe. They also address the cointegrated relation between crude oil prices and natural gas prices in Europe and Japan, which is different from the finding of Zhang and Ji (2018) that there is a temporally gas-oil price decoupled in European and Asian markets.

Similarly, Caporin and Fontini (2017) adopt the VECM model and confirm that the long-term equilibrium of oil-gas price since 2009 has no longer existed. Batten et al. (2017) assess factors of supply and demand shock, as well as infrastructure and technological improvement. Also, they learn that the prices of crude oil and gas are independent of each other.

Most of these articles suggest that there was a long-term relationship between natural gas and oil. However, over some periods, this long-term relationship has weakened or disappeared. It is therefore very interesting to study the volatility spillover relationship between oil and natural gas over time.

It can be found that the literature introduced above focuses more on investigating the price symmetry, cointegration and decoupling between crude oil and natural gas when analysing the oil-gas nexus. However, risk transmission, that is, volatility spillovers between these markets, has not been fully explored after much evidence of decoupling have shown. This research thus intends to extend the existing literature by exploring the volatility transmission between crude oil and gas.

2.2.2 *Price linkage and volatility between ethanol, agricultural and crude oil*

The link between crude oil and biofuel prices captures the attention of many academic scholars, investors, and policymakers. As there is a rapid development in using biofuels as a substitute for crude oil, Timilsina, Mevel and Shrestha (2011) discover that the production of biofuels is highly responsive to the oil prices. McPhail (2011) examines the impact of biofuels on the crude oil market using VAR model, finding that instead of supply expansion, just demand expansion caused by policymaking has a significant impact, which responds negatively to the oil prices.

However, this interest has renewed the nexus of agricultural commodities and crude oil under the indirect influence of biofuels. As there is a substitution effect that exists between oil and biofuels, an upturn in oil prices could boost biofuel production. This would further lead the agricultural market to be hit by a positive demand shock, bringing the price of oil and agricultural commodities more closely linked (Paris, 2018).

In an earlier study, Hassouneh et al. (2012). suggest a positive correlation between the prices of biodiesel, sunflower, and crude oil. More recently, a paper confirms the long-term relationship between the price of oil and agricultural commodity in terms of the potential effect of biofuel production (Paris, 2018). It states that most agricultural products are virtually unaffected by oil prices in the long term without considering biofuel production. Although these two studies confirm the correlation between oil and agriculture commodities under the impact of biofuels, they do not explore the direct relationship between oil and biofuels.

To this extent, certain papers confirm a long-run causal relationship between crude oil, ethanol and the price of specific agricultural commodities (Katrakilidis et al, 2015; Chiu, et al, 2016). Furthermore, Chiu et al. (2016) also find a positive and permanent impact of a positive crude oil price shock on ethanol prices. Biofuel introduction could bring down high oil prices. However, these two papers do not have an extension for the volatility spillover effect.

Trujillo-Barrera et al. (2012) use the crude oil future prices to investigate the volatility spillover effect of crude oil on both ethanol and corn. The results identify strong evidence of volatility spillover from the crude oil market to both the ethanol and corn futures markets over the period from 2006 to 2011. Interestingly, crude oil price volatility attributes almost 15% on both ethanol and corn price volatility during stable period. However, during the global financial crisis, this value reached 45%. They also identify that there is a spillover effect from corn to the ethanol market, but no apparent indication from ethanol to corn market.

Some studies take time variability into account. Gardebroek and Hernandez (2013) introduce multivariate Garch model and DCC model to determine whether the volatility of both oil and ethanol boosts the price of corn in the market in the U.S. from 1997 to 2011. Interestingly, the study reveals no indication of volatility spillover from oil or ethanol to corn. Strangely, A shock in corn price results in short run shock in the volatility price of ethanol. Their results also suggest volatility transmission from oil to ethanol and the other way around.

Similarly, Wu and Li (2013) investigate corn, ethanol and crude oil in China between September 2003 to August 2012 by using univariate EGarch and BEKK-MVGarch models. However, their findings are different from the conclusions of Gardebroek and Hernandez (2013). In particular, their study advises that the volatility in crude oil spillover to corn and ethanol, but there is no evidence suggesting that corn or ethanol influences the price volatility of crude oil. In addition, the study also puts forward that the relationship between these three commodities has strengthened after September of 2008.

These papers all analyse the volatility spillover effect between the oil and ethanol markets, and all demonstrate that volatility in the oil market is transmitted to the ethanol market. Though, there are different conclusions about the spillover from the ethanol market to the oil market, which may be due to the different regions and sample intervals where the data are taken. In addition, these studies were published ten years ago that the topic needs to be explored further as the market changes at a rapid pace.

Lu, Yang and Liu (2019) study the volatility spillover between crude oil and corn, soybeans, and wheat before and after the 2008-2009 financial crisis. Their results suggest a two-way volatility transmission existed during the crisis. In the post-crisis period, only a unidirectional volatility spillover is observed from the corn to oil market, which can be explained by subsidies from the government for biofuel production. Despite the fact that this study does not directly analyse the volatility transmission between oil and biofuels, particularly ethanol, it is reference worthwhile to compare the difference in volatility spillover between markets before and after the financial crisis.

2.3 Summary

Understanding the linkage between oil, natural gas, and other agricultural commodities is essential for economic and sustainable development. The studies suggested above related to oil and natural gas tend to provide inconsistent results. For example, Pindyck (2004) finds weak evidence that crude oil price volatility influences natural gas prices and vice versa. Furthermore, the study also notices that the transmission effect does not strengthen during extreme events (i.e., the demise of Enron).

Meanwhile, other studies observe an indirect relationship between natural gas and crude oil. Hence, this relationship significantly changes during major events. Interestingly, Aloui et al. (2014) find evidence that the occurrence of recessions could weaken the relationship between natural gas and crude oil.

Given that many studies focus on the global financial crisis period (almost ten years ago). Knowing that technology is constantly improving and effective ways to process energy commodities are constantly being discovered, these studies may be considered dated. Hence, it’s necessary to revisit these studies and determine whether the results align with their findings.

Lastly, the studies above also suggest a link between crude oil and agricultural commodities which is a concern. Although volatility spillovers between crude oil and ethanol have been analysed in many papers, the Authors suggest volatility transmission in terms of different periods, such as pre-crisis, post-crisis and during 2008 and 2020 crisis haven’t been well researched. Therefore, this study aims at filling these gaps.

3 METHODOLOGY

3.1 Data collection and sampling

This study employs weekly data of crude oil (WTI), natural gas (NG), and ethanol (EN) spot prices that are derived from Bloomberg. The reason for using weekly data is that it avoids serious bid-ask spreads and reduces potential biases from some sparsely traded stocks compared to daily data. These biases may come from non-trading and non-synchronous trading problems (Sakthivel, Bodkhe & Kamaiah, 2012). These raw prices are then converted to natural logarithms, and taken first-order difference to obtain the return series: $R_t = 100 \times ln(P_t \,/\, P_{t-1})$, Where R_t is the returns at day t, P_t is the price at day t, P_{t-1} is the price at day t-1.

The sample covers from 06 June 2005 to 28 December 2020. As a consequence, 813 observations for each series and 2439 observations for full sample. The period selection is based on several reasons. First, oil prices have greatly fluctuated since 21 century, as mentioned in Chapter 1. Second, prices of crude oil and natural gas were decoupled after 2009; and crude oil and ethanol were suggested to have a stronger correlation after September of 2008, regarding Chapter 2. Third, major events that influenced the global economy are covered in the selected period, including the 2008 Global financial crisis, 2010 sovereign debt crisis and 2020 COVID pandemic. To measure the volatility relationship between oil and other selected energy commodities in different periods in terms of the impact of the crisis, this paper works with five subperiods showing below:

- 06^{th} June 2005 to 31^{st} December 2007 (Pre-crisis 1)
- 07^{th} January 2008 to 28^{th} December 2009 (Crisis 1)
- 04^{th} January 2010 to 28^{th} December 2015 (Post-crisis 1)
- 04^{th} January 2016 to 30^{th} December 2019 (Pre-crisis 2)
- 06^{th} January 2020 to 28^{th} December 2020 (Crisis 2)

3.2 Econometric methodology

MGARCH (multivariate GARCH) models are mostly used to examine the volatilities and co-volatilities of multiple markets. Among them, BEKK (Engle and Kroner, 1995) and Dynamic Conditional Correlation – DCC (Engle, 2002) are widely adopted to study the volatility spillover effects and co-movement among different markets in energy economics and finance (Chen, Zheng & Qu, 2020). This study employs the VAR-BEKK-GARCH model and VAR-DCC-GARCH model to investigate the volatility spillover effect and dynamic correlations among oil, natural gas, and ethanol.

3.2.1 *VAR-BEKK-GARCH(1,1) Model*

VAR-BEKK-GARCH is superior to some traditional GARCH models, as it has less computational complexity when fewer parameters are required in analysing the spillover effect among several markets (Stelzer, 2008; Yu, Zha, Stafylas, He & Liu, 2020). More importantly, BEKK-GARCH (Engle and Kroner, 1995) ensures the positive definiteness of the variance-covariance matrix.

In the VAR model, each explanatory variable is a regression on its own lagged value, the lagged values of other endogenous variables and a random error term. This paper choose the VAR(1) model. The conditional mean equations for the chosen three energy commodities can be presented as follows:

$$R_{1,t} = C_1 + a_1 R_{1,t-1} + b_1 R_{2,t-1} + c_1 R_{3,t-1} + \varepsilon_{1t} \tag{1}$$

$$R_{2,t} = C_2 + a_2 R_{1,t-1} + b_2 R_{2,t-1} + c_2 R_{3,t-1} + \varepsilon_{2t} \tag{2}$$

$$R_{3,t} = C_3 + a_3 R_{1,t-1} + b_3 R_{2,t-1} + c_3 R_{3,t-1} + \varepsilon_{3t} \tag{3}$$

$$\varepsilon_t \mid I_{t-1} \sim N(0, H_t) \quad (4)$$

Where $R_{1,t}$, $R_{2,t}$ and $R_{3,t}$ are the weekly returns of ethanol, natural gas and oil price series respectively; C_1, C_2 and C_3 are the constant vectors; a_1, b_2, and c_3 can capture the mean spillover of 3 markets on themselves, when b_1 and a_2 access the mean spillover across ethanol and natural gas market. c_1 and a_3 represent the mean spillover across the ethanol and oil market. c_2 and b_3 are the mean spillovers across the natural gas and oil market respectively; ε_{1t}, ε_{2t} and ε_{3t} are the residual series of the VAR(1) model for the three markets. I_{t-1} denotes the market information available up to time t-1.

The full BEKK-GARCH(1,1) model can be written as Equations (5), (6), (7), (8):

$$\varepsilon_{i,t} = \nu_{i,t} h_{i,t},\ \nu_{i,t} \sim N(0,1) \quad (5)$$

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (6)$$

Where $\nu_{i,t}$ is the standard normal distribution residue; $h_{i,t}$ is the conditional variance (GARCH(1,1) process).

$$\mathbf{H}_t = \mathbf{CC}' + \mathbf{A}' \varepsilon_{t-1} \varepsilon_{t-1}' \mathbf{A} + \mathbf{B}' \mathbf{H}_{t-1} \mathbf{B} \quad (7)$$

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix} \qquad C = \begin{pmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{pmatrix}$$

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \qquad B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \quad (8)$$

Where H_t is the conditional variance-covariance matrix, $h_{11,t}$, $h_{22,t}$, $h_{33,t}$ are the conditional variances of the ethanol market, natural gas market and oil market respectively while $h_{ij,t(i\neq j)}$ represents the conditional covariance of market i and j; C is the 3×3 upper triangular constant matrix; Matrix A and B are square arrays when A is the ARCH coefficients and B is the GARCH coefficients of the model. A high ARCH parameter indicates the high short-run volatility where the impact of the shock is more significant in the subsequent period. The diagonal elements a_{11}, a_{22}, a_{33} in the Matrix A denote the ARCH effect of the fluctuations of the three markets; the non-diagonal elements $a_{ij(i\neq j)}$ mean the impact conduction among the three markets. A high GARCH parameter implies the high long-run volatility where the effects of a shock are more persistent. The diagonal elements b_{11}, b_{22}, b_{33} in the Matrix B represent the GARCH effect of the volatility of the three markets themselves; the non-diagonal elements $b_{ij(i\neq j)}$ suggest the volatility transmission across the three markets. The sum of the ARCH and GARCH coefficient means the degree of persistence. Volatility spillover effects last longer when the result is closer to 1.

3.2.2 *VAR-DCC-GARCH(1,1) Model*

DCC-GARCH (Dynamic Conditional Correlation) model was first developed by Engle (2002). It relaxes the constraints of the CCC-GARCH (Constant Conditional Correlation) model on the correlation coefficient matrix, and a variable conditional correlation coefficient is used to characterize the time-varying of the volatility correlation between different series. Therefore, it has outstanding computational advantages and is more practical for studying dynamic correlations among time-varying variables. The model decomposes the matrix H_t are given by the equations below:

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, H_t), \quad H_t = D_t R_t D_t \tag{9}$$

$$D_t = \mathrm{diag}\left(\sqrt{h_{i,t}}\right) \tag{10}$$

Where ε_t is the residual vector consisting of the residuals of the three markets obtained from the VAR model; ψ_{t-1} is the market information available at time t-1; H_t is the dynamic condition covariance matrix; D_t is the conditional standard deviations diagonal matrix; $h_{i,t}$ is the GARCH process; R_t is the dynamic correlation coefficient matrix, which dynamic process is determined by the following two equations:

$$R_t = \text{diag}\,(Q_t)^{-1}(Q_t)\text{diag}\,(Q_t)^{-1} \tag{11}$$

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1(e_{t-1}e'_{t-1}) + \theta_2 Q_{t-1} \tag{12}$$

Where e_{t-1} is the standardized residue term, Q_t represents a symmetric positive definite matrix; $\bar{Q}$ is the unconditional covariance matrix of the standardized residual obtained from the GARCH process. θ_1 and θ_2 are the coefficients of the DCC-GARCH model that satisfy $\theta_1 \geq 0$, $\theta_2 \geq 0$, $\theta_1 + \theta_2 < 1$ (the more the value closer to 1, the stronger persistence of the correlation) (Odei-Mensah & Premaratne, 2018; Boubakri & Guillaumin, 2015).

3.3 Ethical Consideration

This study applies for ethical clearance and permission through the University of the Witwatersrand Human Research Ethics Committee (Non-medical). Consent form, participant information sheet and a few other forms do not apply due to the secondary data this study used and no participants included. Data collection begins once ethical permission is obtained from the committee. For safety purposes, the password is set for the document of the data collected from Bloomberg Terminal and Equity RT. All the secondary data are deleted when the research project is completed.

4 RESULTS AND DISCUSSION

4.1 Introduction

This chapter uses the data obtained from Bloomberg to measure the volatility spillover and time-varying correlations between oil, natural gas, and ethanol markets in different periods. Section 4.2 interprets the results of the descriptive statistics. Section 4.3 explains the results of VAR-BEKK-GARCH and VAR-DCC-GARCH. Section 4.4 summarizes the chapter.

4.2 Descriptive Statistics

Figure 1 illustrates the time series of the weekly returns of ethanol, natural gas and oil market. It can be obviously observed that they were highly volatile from June 2005 to December 2020. In other words, they are all volatility clustering. In addition, the overall movement pattern of these three commodities seems similar, with strong fluctuations around 2008, 2014, and 2020. Natural gas generally follows oil throughout the whole period, while this is less obvious for ethanol. Among them, oil fluctuates particularly dramatically in the period of crisis 2, reaching the trough and rebounding to a peak shortly after of the entire period. However, there were no outliers for ethanol and natural gas during the same period.

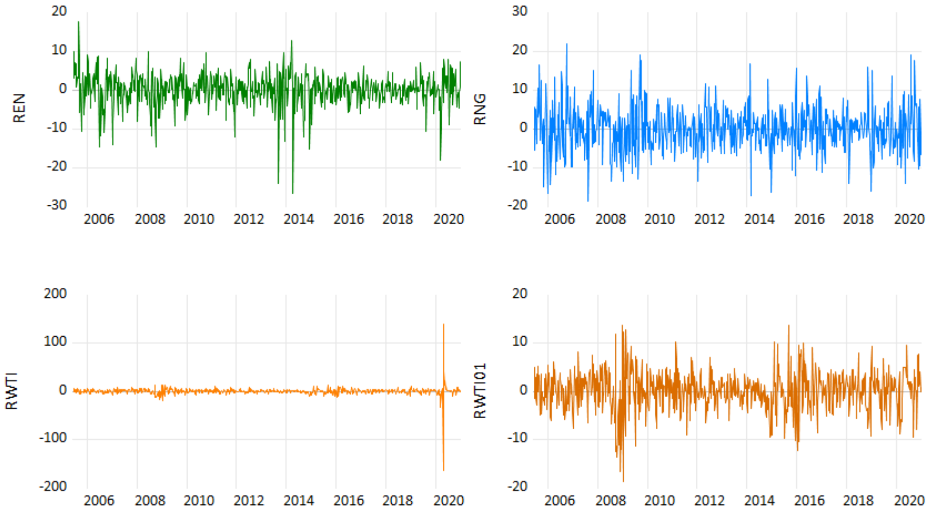

Figure 1: Weekly returns of ethanol, natural gas, and oil market

Note: REN and RNG are ethanol and natural gas raw returns respectively. RWTI is raw oil returns, outliers occur due to high volatility of oil prices in April 2020. RWTI01 is oil returns excluding outliers.

Table 1 demonstrates the summary statistics of three markets' returns in different periods. In the first three sub-periods (Pre-crisis 1, Crisis 1, Post-crisis 1), ethanol has the highest mean returns while natural gas has the lowest. In Pre-crisis 2, natural gas and oil have the highest and lowest mean returns respectively. However, the situation is reversed in Crisis 2. Ethanol is the only commodity with positive mean returns over all the sub-periods, meaning its returns are stable. Across all periods, ethanol and natural gas returns reach their highest values in Pre-crisis 1. Oil returns, on the other hand, hit the peak and trough in Crisis 2. Moreover, the standard deviation for natural gas is the highest over almost all sub-periods. This indicates that natural gas prices were comparatively more volatile than that of ethanol and oil, and it is the riskiest of the three commodities in the short term. In the long run, oil is the most volatile of the three commodities, with a standard deviation of 8.8168 in the Full Period compared to 4.0361 and 5.5210 for ethanol and natural gas. This oil volatility is particularly notable in Crisis 2, where its standard deviation reached 31.7071, more than six times higher than the lowest one. In terms of skewness, ethanol has the lowest and negative coefficient among all sub-periods, compared to the opposite for natural gas. As expected, mean returns for the crisis periods are significantly different from other periods. Moreover, the standard deviation of oil is distinctly greater in the crisis periods than in other periods.

Table 1: Descriptive statistics for three markets returns

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Pre-crisis 1								
REN	0.4919	17.4980	-14.7884	4.9612	-0.3830	4.2558	12.0806	0.0024***
RNG	0.0630	21.8325	-18.7759	6.8178	0.1108	3.5446	1.9303	0.3809
RWTI	0.4466	8.0597	-7.7133	3.2047	-0.2346	2.4223	3.0922	0.2131
Crisis 1								
REN	-0.1915	9.9290	-14.6044	4.1221	-0.6547	4.3981	15.8991	0.0004***
RNG	-0.2797	18.8987	-13.7141	6.5471	0.1974	3.1081	0.7261	0.6956
RWTI	-0.2031	13.6018	-18.7177	6.1119	-0.4528	3.4850	4.5724	0.1017
Post-crisis 1								
REN	-0.1048	12.6654	-26.6785	4.2884	-1.4683	10.7276	891.2602	0.0000***
RNG	-0.2920	16.5921	-17.1859	4.5789	0.0618	4.4173	26.3965	0.0000***
RWTI	-0.2422	13.6090	-10.1786	3.3513	0.0363	4.4976	29.3194	0.0000***
Pre-crisis 2								
REN	-0.0094	6.9960	-10.6244	2.4338	-0.4421	4.4396	24.8558	0.0000***
RNG	-0.0288	15.9258	-16.1284	4.9443	0.0517	4.1196	11.0096	0.0041***
RWTI	0.2430	10.1138	-12.3932	3.7852	-0.2377	3.4439	3.6841	0.1585
Crisis 2								
REN	0.0777	7.9187	-18.1099	4.8052	-1.0706	5.5208	23.7008	0.0000***
RNG	0.2429	18.8661	-14.2386	6.9618	0.3725	3.0600	1.2104	0.5460
RWTI	-0.4714	139.1383	-163.4927	31.7071	-0.9908	21.5805	756.5198	0.0000***
Full Period								
REN	0.0188	17.4980	-26.6785	4.0361	-0.9901	8.3371	1096.4100	0.0000***
RNG	-0.1299	21.8325	-18.7759	5.5210	0.1653	4.0939	44.1823	0.0000***
RWTI	-0.0133	139.1383	-163.4927	8.8168	-3.0242	223.6828	1648951	0.0000***

Note: ***, ** and * indicate 1%,5%,10% significance levels respectively.

Table 2 exhibits the result for the unit root test, where Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are adopted. The results suggest that all series in all stages are significant, meaning they are all stationary in all sub-periods and the entire period.

Table 3 shows that the Spearman Rank correlation between oil and ethanol is almost always higher than that of oil and natural gas. Although in Pre-crisis 1, the Spearman Rank correlation between oil and natural gas is slightly higher than that of oil and ethanol (0.2888 compared to 0.2327). The three commodities were positively correlated for all the sub-periods as well as the full period. Moreover, the highest correlation coefficient for the full sample period does not exceed 0.3, implying the low Spearman Rank correlation of these three commodities. However, during the crisis periods, it can be clearly observed rapid increases in the correlation coefficients of the three commodities.

Table 2: Unit root test

		Pre-crisis 1	Crisis 1	Post-crisis 1	Pre-crisis 2	Crisis 2	Full Period
REN	ADF	-7.0473*** (0.0000)	-8.4080*** (0.0000)	-13.1085*** (0.0000)	-11.9086*** (0.0000)	-4.7822*** (0.0017)	-18.9435*** (0.0000)
	PP	-7.1201*** (0.0000)	-8.3330*** (0.0000)	-13.1383*** (0.0000)	-11.8368*** (0.0000)	-4.7903*** (0.0016)	-20.4402*** (0.0000)
RNG	ADF	-9.6850*** (0.0000)	-8.1698*** (0.0000)	-14.5158*** (0.0000)	-9.9668*** (0.0000)	-6.6934*** (0.0000)	-23.5497*** (0.0000)
	PP	-9.7223*** (0.0000)	-8.2395*** (0.0000)	-14.2933*** (0.0000)	-10.3140*** (0.0000)	-6.6809*** (0.0000)	-23.2491*** (0.0000)
RWTI	ADF	-9.6241*** (0.0000)	-8.4580*** (0.0000)	-14.0880*** (0.0000)	-10.4680*** (0.0000)	-8.8952*** (0.0000)	-24.3254*** (0.0000)
	PP	-9.6213*** (0.0000)	-8.7918*** (0.0000)	-14.1041*** (0.0000)	-10.0320*** (0.0000)	-9.5137*** (0.0000)	-33.3984*** (0.0000)

Note: Value in the bracket is the P-value. ***, ** and * indicate 1%,5%,10% significance levels

Table 3: Spearman Rank Correlation matrix

Pre-crisis 1	REN	RNG	RWTI
REN	1		
RNG	0.1262	1	
RWTI	0.2327	0.2888	1

Crisis 1	REN	RNG	RWTI
REN	1		
RNG	0.3909	1	
RWTI	0.5477	0.3863	1

Post-crisis 1	REN	RNG	RWTI
REN	1		
RNG	0.0796	1	
RWTI	0.2224	0.1836	1

Pre-crisis 2	REN	RNG	RWTI
REN	1		
RNG	0.0749	1	
RWTI	0.2106	0.107	1

Crisis 2	REN	RNG	RWTI
REN	1		
RNG	0.3301	1	
RWTI	0.3166	0.1531	1

Full Period	REN	RNG	RWTI
REN	1		
RNG	0.1512	1	
RWTI	0.2787	0.2123	1

4.3 Empirical Results and Discussion

4.3.1 *Empirical results of VAR-BEKK-GARCH model*

Table 4 and Table 5 show the estimated results of the VAR-BEKK-GARCH(1,1) model for all periods.

In Pre-crisis 1, it can be observed that a_{13}, a_{21}, a_{23} and a_{31} are significant at 10%, 1%, 10% and 1% significant level respectively. What is more, b_{13}, b_{31} and b_{32} are significant at the significant 1% level. Therefore, there was bidirectional volatility spillover between the ethanol market and oil market, as well as between the natural gas market and oil market. In other words, risks in the oil market were passed on to the ethanol and gas markets and vice versa. Additionally, it can be found that short-term shocks from the natural gas market spillover to the ethanol market.

In Crisis 1, a_{21} and a_{23} are significant at both the 1% significant level while a_{31} and a_{32} are significant at 5% and 10% significant level respectively, b_{12} and b_{23} are also significant at 5% level, indicating that volatility in the ethanol market spillover to the natural gas market and the other way around. This conclusion also applies to the natural gas market and oil market. That is to say, price fluctuations in the natural gas market led to price instability in the ethanol market and oil market, and vice versa. In addition, there was unidirectional volatility spillover from the oil market to the ethanol market, meaning that risks in the oil market were transmitted to the ethanol market, while the reverse was not valid. Interestingly, the coefficients of the ARCH term and GARCH term from the oil to other markets are much larger than in Pre-crisis 1, representing that the volatility spillover effects from the oil market to other markets were more persistent before the crisis.

In Post-crisis 1, coefficients of a_{13}, a_{21}, a_{31}, a_{32} b_{12} and b_{32} are all significant at different confidence levels (1%, 5% and 10%), which can be concluded that there was one-way volatility spillover from the oil market to natural gas market, and double-sided volatility transmission between ethanol market and oil market, as the same as between ethanol market to natural gas market. In this regard, oil price volatility drove ethanol price volatility. Ethanol price fluctuations affected and were affected by both natural gas and oil price fluctuations. Similar to Crisis 1, more persistent volatility spillover effects were found compared to Pre-crisis 1 from the oil market to other markets.

In Pre-crisis 2, it is interesting to find that there's only unidirectional volatility spillover from ethanol market to natural gas market, and from oil market to ethanol market, but not the other way around: a_{12}, a_{31}, b_{12} and b_{31} are significant at 10%, 1%, 1% and 5% significant level respectively. This means that risks from the oil market were transmitted to the ethanol market, and risks from the ethanol market were converted to the natural gas market

In Crisis 2, volatility spillover from the natural gas market to the oil market and vice versa since b_{23} and b_{32} are significant at 1% and 5% significant level respectively. In other words, price fluctuations in the natural gas market and oil market transmitted to each other. Moreover, short-term shocks from the ethanol market influenced the natural gas market, that is one way volatility spillover from the ethanol market to the natural gas market (a_{12} is significant at 1% significance level). For the long-term volatility spillover, it can be found from the oil market to the ethanol market when b_{31} is significant at 5% significance level. Therefore, price fluctuations in the oil market caused ethanol price fluctuations. In addition, volatility spillover effects from the oil market to the natural gas market lasted longer than the Pre-crisis 2.

Based on the full sample period, a conclusion can be made from the results that the ethanol market's volatility spillover to the oil market and vice versa. Volatility transmission can also be found between the natural gas market and oil market: a_{13}, a_{31}, a_{32}, b_{13}, b_{31}, b_{32}, b_{23} are all significant. That is to say, ethanol and natural gas price fluctuations were influenced by oil price volatility and the other way around.

Table 4: Estimated results of VAR-BEKK-GARCH(1,1) model for three periods

Parameter Variable	1:Enthanol Pre-crisis 1	2: Natural Gas Crisis 1	3: Oil Post-crisis 1
C(1,1)	0.9164(1.5664)	2.5771(6.1849)***	1.4294(5.9486)***
C(2,1)	3.0902(4.9407)***	1.9452(2.9747)***	3.1809(9.4739)***
C(2,2)	-0.0120(-0.0080)	0.0000(0.0000)	1.7693(3.1078)***
C(3,1)	2.2296(5.7025)***	2.5047(5.5034)***	0.2727(2.0074)**
C(3,2)	-0.0121(-0.0067)	-0.0001(-0.0001)	-0.0508(-0.1190)
C(3,3)	0.0000(0.0000)	0.0000(0.0000)	0.0000(0.0000)
A(1,1)	0.1643(1.8501)*	0.7015(5.2555)***	0.4850(9.2818)***
A(1,2)	-0.1979(-1.0798)	0.0741(0.4216)	0.0394(0.4341)
A(1,3)	-0.1632(-1.8280)*	-0.1162(-0.7343)	-0.0537(-2.1732)**
A(2,1)	0.1634(2.7311)***	-0.3014(-3.9628)***	-0.0971(-1.9360)*
A(2,2)	-0.0036(-0.0311)	0.0568(0.5690)	0.3807(5.5628)***
A(2,3)	0.0920(1.6653)*	-0.3587(-4.0311)***	-0.0046(-0.1891)
A(3,1)	-0.5598(-3.6945)***	0.1848(2.0842)**	0.1634(2.2388)**
A(3,2)	-0.2326(-0.7547)	0.1721(1.6694)*	-0.3676(-2.5821)***
A(3,3)	0.0962(0.6664)	0.7354(6.4036)***	0.2398(9.9148)***
B(1,1)	0.9177(23.9355)***	-0.4110(-1.5366)	0.8008(22.6415)***
B(1,2)	0.0349(0.5755)	-0.6306(-2.1972)**	-0.2374(-2.2615)**
B(1,3)	0.1419(2.7762)***	-0.2674(-1.0227)	0.0118(1.3168)
B(2,1)	-0.0410(-1.6040)	0.1119(1.2381)	-0.0447(-0.4241)
B(2,2)	0.8712(27.6605)***	1.0388(20.7455)***	-0.3296(-3.2323)***
B(2,3)	0.0086(0.1867)	0.1088(1.9896)**	-0.0275(-1.0791)
B(3,1)	-0.4046(-4.3165)***	0.0800(0.7192)	-0.0059(-0.3117)
B(3,2)	-0.8839(-4.5877)***	-0.0686(-0.7092)	0.2519(1.6985)*
B(3,3)	0.5691(4.1374)***	0.6970(6.1143)***	0.9717(156.8144)***

Note: The value in the bracket is the t-value. ***, ** and * indicate 1%,5%,10% significance levels

Table 5: Estimated results of VAR-BEKK-GARCH(1,1) model for two periods

Parameter Variable	1:Enthanol Pre-crisis 2	2: Natural Gas Crisis 2	3: Oil Full Period
C(1,1)	1.9557(10.1970)***	-0.3634(-5.3785)***	0.5359(4.9391)***
C(2,1)	0.0149(0.0206)	2.9624(4.8509)***	-0.1741(-0.3180)
C(2,2)	2.2799(2.6445)***	-0.0003(-0.0005)	1.5889(5.6941)***
C(3,1)	-0.0399(-0.0980)	0.9961(0.6820)	0.7810(1.1571)
C(3,2)	1.1089(10.8991)***	-0.0010(-0.0005)	-0.9951(-1.9337)*
C(3,3)	0.0000(0.0000)	0.0000(0.0000)	1.4418(3.2854)***
A(1,1)	0.4501(4.6938)***	-2.9378(-8.5286)***	0.2171(8.7181)***
A(1,2)	0.2986(1.7251)*	-0.1639(-4.1708)***	0.0483(0.9527)
A(1,3)	-0.1134(-1.0643)	0.0708(0.6050)	-0.2143(-5.4642)***
A(2,1)	-0.0555(-1.2359)	-0.0216(-0.2628)	0.0262(1.3287)
A(2,2)	0.5629(6.8261)***	0.5678(3.1712)***	0.2257(5.4131)***
A(2,3)	0.0237(0.5338)	-0.1652(-0.4666)	0.0265(0.7692)
A(3,1)	-0.1796(-3.0669)***	-0.1652(-0.8057)	0.0667(4.1262)***
A(3,2)	0.0407(0.3602)	-0.0758(-0.7624)	-0.0567(-2.4366)**
A(3,3)	0.3910(6.8505)***	-0.1993(-1.0570)	0.8519(14.3397)***
B(1,1)	-0.0841(-0.5113)	-0.0839(-2.1367)	0.9669(119.5179)***
B(1,2)	-1.0712(-3.5004)***	0.0262(1.5140)	-0.0111(-0.4966)
B(1,3)	-0.1183(-0.6109)	0.0366(1.0121)	0.0502(1.6847)*
B(2,1)	0.0527(0.4978)	0.0320(1.1022)	0.0034(0.2369)
B(2,2)	0.3126(2.7912)***	-0.6269(-3.5096)***	0.9185(38.7072)***
B(2,3)	-0.0775(-1.4688)	-1.2364(-5.2542)***	0.0849(1.9232)*
B(3,1)	0.1996(2.1418)**	-0.0451(-2.0987)**	-0.0391(-3.0777)***
B(3,2)	-0.1638(-1.1904)	0.3238(2.1812)**	0.0673(3.0549)***
B(3,3)	0.8674(24.0201)***	-0.1436(-0.5711)	0.5585(6.8708)***

Note: The value in the bracket is the t-value. ***, ** and * indicate 1%,5%,10% significance levels

In order to verify the adequacy of the models, it is necessary to perform a diagnostic of the estimated models. Diagnosis of the MGARCH family models usually includes diagnosis of the mean equation as well as diagnosis of the variance equation. If there is no serial autocorrelation in the standardized residual series in the mean equation, the mean equation is considered to be correctly specified, and this diagnosis is usually tested with Ljung-Box (1978). If there is no serial autocorrelation in the residual square series, then the variance equation is also correct, and this diagnosis is usually tested with McLeod-Li (1983). When both tests accept the null hypothesis, that is no autocorrelation in the series, the VAR-GARCH-BEKK model is considered to be robust. Additionally, in the purpose of checking whether the result of the models is convincing, WALD test is also applied. When WALD test rejects the null hypothesis: $a_{\mathrm{ij}} = b_{\mathrm{ij}} = 0$ or $a_{\mathrm{ji}} = b_{\mathrm{ji}} = 0$, it means there are volatility spillovers from i to j or from j to i.

Table 6 displays the results of Ljung-Box and McLeod-Li. Given the results that all the values are insignificant, the conclusion can be made that the VAR-GARCH-BEKK models for all the sample periods are specified correctly.

Table 7 reports the results of WALD test. In Pre-crisis 1, the null hypothesis $a_{23} = b_{23} = 0$ (A23=B23=0) is rejected because the value is insignificant, meaning that there's no volatility spillover effect from the natural gas market to the oil market. Other than this, the rest of the WALD results for Pre-crisis 1 are in line with the results of BEKK. Similarly, A32=B32=0 is also insignificant for Crisis 1, representing that the conclusion obtained from the BEKK results that volatility from the oil market transmitted to the natural gas market should be rejected. A12=B12=0, A21=B21=0, A31=B31=0 and A23=B23=0 are all significant, confirming the other results of BEKK for Crisis 1. In addition, WALD test for other sub-periods and the full period are all consistent with the results of BEKK since the corresponding values are significant.

Table 6: Results of Ljung-Box and McLeod-Li

		Pre-crisis 1	Crisis 1	Post-crisis 1	Pre-crisis 2	Crisis 2	Full Period
Ljung-Box	REN	1.4872 (0.9145)	1.7443 (0.8833)	5.5473 (0.3528)	4.4192 (0.4908)	3.0856 (0.6868)	6.9216 (0.2265)
	RNG	2.7186 (0.7433)	3.5666 (0.6133)	2.7588 (0.7371)	19.5062 (0.1600)	4.9205 (0.4257)	8.7324 (0.1202)
	RWTI	0.9641 (0.9654)	3.8871 (0.5658)	1.6285 (0.8978)	7.2250 (0.2044)	2.2599 (0.8121)	3.7484 (0.5862)
McLeod-Li	REN	4.0094 (0.5481)	5.3524 (0.3744)	0.4998 (0.9921)	4.1558 (0.5272)	2.3374 (0.8008)	0.9743 (0.9646)
	RNG	2.6659 (0.7513)	7.9343 (0.1599)	8.2646 (0.1423)	4.9786 (0.4185)	2.5393 (0.7706)	7.9237 (0.1605)
	RWTI	5.5729 (0.3500)	4.4000 (0.4934)	3.6405 (0.6023)	4.7240 (0.4505)	2.0397 (0.8436)	5.0885 (0.3261)

Note: The Ljung-Box and McLeod-Li values are the T-value. Value in the bracket is the P-value. ***, ** and * indicate 1%,5%,10% significance levels

Table 7: Results of WALD test

Null Hypothesis	Pre-crisis 1	Crisis 1	Post-crisis 1	Pre-crisis 2	Crisis 2	Full Period
A12=B12=0	1.1676 (0.5578)	5.4831* (0.0645)	5.7851* (0.0554)	15.9794*** (0.0003)	18.2676*** (0.0011)	1.0410 (0.5942)
A21=B21=0	9.8236*** (0.0074)	16.8104*** (0.0002)	6.1886** (0.0453)	1.6294 (0.4428)	1.2252 (0.5419)	3.3953 (0.1831)
A13=B13=0	7.7944** (0.0203)	3.0590 (0.2166)	4.8106* (0.0902)	2.6576 (0.2648)	4.2498 (0.1194)	29.8579*** (0.0000)
A31=B31=0	67.8428*** (0.0000)	4.6400* (0.0983)	5.1808* (0.0750)	14.8066*** (0.0006)	6.3169** (0.0425)	17.2203*** (0.0002)
A23=B23=0	2.8283 (0.2431)	16.6129*** (0.0002)	1.4114 (0.4938)	2.4072 (0.3001)	29.2499*** (0.0000)	4.8002* (0.0907)
A32=B32=0	24.1943*** (0.0000)	2.7868 (0.2482)	9.5425*** (0.0085)	1.4488 (0.4846)	4.7758* (0.0918)	9.8380*** (0.0073)

Note: The WALD value is the Chi-Squared value. Value in the bracket is the P-value. ***, ** and * indicate 1%,5%,10% significance levels

4.3.2 *Empirical results of VAR-DCC-GARCH model*

Table 8 illustrates the estimated results of VAR-DCC-GARCH(1,1) model. All the coefficients are positive and significant at 5% level. Additionally, the sum of A(1) and B(1), A(2) and B(2), A(3) and B(3) are close to and less than one (0.98, 0.95 and 0.99 respectively), indicating that the volatility is highly persistent. Interestingly, oil has short-run persistence of shocks compared to the long-run ethanol and natural gas have. $\theta 1$ and $\theta 2$ represent the short-term and long-term persistence of shocks on the dynamic conditional correlation respectively. Apparently, long-term persistence of shocks is more important in the prediction of the DCC. The values of Ljung-Box and McLeod-Li are all insignificant, meaning that the model is robust.

Figure 2 reflects the dynamic correlation coefficients between the three markets. In general, the correlation between the three markets is positive. It can be clearly observed that there are significant changes in the dynamic correlation coefficients around several major events, especially during and after the two crises. During Crisis 1, the correlation coefficient reached the highest points of 0.35, 0.35 and 0.3 for ethanol and natural gas, ethanol and oil, natural gas and oil respectively. During Crisis 2, the correlation coefficient between ethanol and natural gas as well as ethanol and oil hit another peak. However, which between natural gas and oil achieved a trough to -0.2. Moreover, the average correlation coefficients between ethanol and natural gas, ethanol and oil, natural gas and oil is 0.15, 0.25 and 0.1 respectively. This indicates that the three markets have relatively weak relationships with each other. Ethanol and oil are the most dynamic correlated among the three markets, which is similar to the results of the Spearman Rank correlation matrix.

Table 8: Estimated results of VAR-DCC-GARCH(1,1) model

Variable	Coefficient	Standard Error	T-Statistic	P-value
C(1)	0.2781**	0.1287	2.1616	0.0307
C(2)	1.8311***	0.4808	3.8082	0.0001
C(3)	3.4178***	0.7921	4.3151	0.0000
A(1)	0.0801***	0.0188	4.2717	0.0000
A(2)	0.1392***	0.0272	5.1118	0.0000
A(3)	0.6185***	0.0853	7.7220	0.0000
B(1)	0.9044***	0.0219	41.3515	0.0000
B(2)	0.8060***	0.0302	26.7144	0.0000
B(3)	0.3770***	0.0730	5.1644	0.0000
$\theta 1$	0.0102**	0.0046	2.2429	0.0249
$\theta 2$	0.9862***	0.0069	144.0835	0.0000
Ljung-Box and McLeod-Li Test				
Ljung-Box	REN		4.9838	0.4179
	RNG		7.5821	0.1808
	RWTI		3.7515	0.5857
McLeod-Li	REN		1.2188	0.9431
	RNG		4.3797	0.4961
	RWTI		2.6009	0.7612

Note: ***, ** and * indicate 1%,5%,10% significance levels

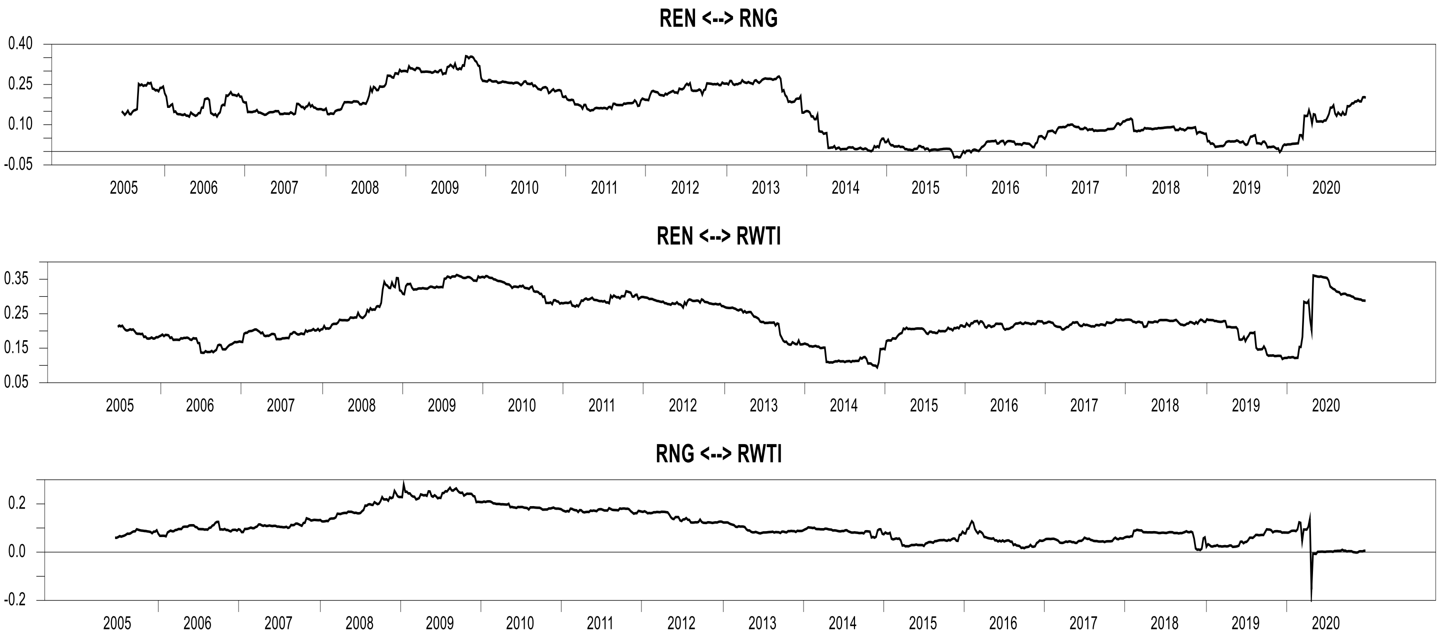

Figure 2: The dynamic conditional correlation (DCC) between ethanol, natural gas and oil

4.4 Summary and discussion

This chapter examines the volatility spillovers and dynamic correlations between ethanol, natural gas, and oil markets using the VAR-BEKK-GARCH and VAR-DCC-GARCH models. Different findings are presented for different subperiods.

Firstly, volatility spillover effect cannot be found between the ethanol and natural gas market over the full period, representing that there is no risk transmission across the ethanol and natural gas markets. However, volatility spillover can be found in the sub-periods. In Pre-crisis1, the natural gas market volatility spillover to the ethanol market. During Crisis 1 and Post-crisis 1, there was bidirectional volatility transmission between the ethanol market and natural gas market. When it comes to Pre-crisis 2 and Crisis 2, volatility spillover can be observed from the ethanol market to the natural gas market. As we know, fertilizers are the essential input in corn and sugarcane production, which is the raw materials of ethanol, while natural gas is an important source of input to produce the fertilizers. Whistance and Thompson (2010) pointed out that natural gas prices could be affected by one-tenth to one-quarter percent by corn-ethanol production under the U.S. biofuel policies. Therefore, the different results in different periods may be the combination of the production and demand conditions in various periods and the biofuel policies introduced by the countries.

Secondly, for the full period, volatility from the ethanol market spillover to the oil market and vice versa – ethanol price fluctuations and oil price fluctuations were affected by each other. Interestingly, there was volatility spillover from the oil market to the ethanol market in all the sub-periods, while it can be just examined in Pre-crisis 1 and Post-crisis 1 the other way around. Particularly, the findings for Pre-crisis 1, Crisis 1 and Post-crisis 1 are basically in line with the results of Trujillo-Barrera et al. (2012) and Gardebroek and Hernandez (2013). The former identified a unidirectional volatility spillover from the oil market to the ethanol market over the period from 2006 to 2011. The latter found bidirectional spillover effect between these two markets during the period 1997 to 2011. And the results are expected when ethanol is a clean energy alternative to oil driven by national policies.

Thirdly, there was bidirectional volatility transmission between the natural gas market and the oil market in the full period. That is to say, risks spread between the natural gas and oil markets. And among the subperiods, only findings of Crisis 2 are consistent with this. Moreover, Unidirectional volatility spillover was found from the oil market to natural gas market in Pre-crisis 1 and Post-crisis 1, as well as from the natural gas market to the oil market in Crisis 1. This is somewhat different from the findings of Karali and Ramirez (2014) and Lin and Li (2015). They applied the data from 1994 to 2011 and from 1992 to 2012 respectively and reached similar conclusion that there is two-way volatility transmission between the natural gas and oil markets. The difference may lie in the fact that this paper divides the data for similar time span into various sub-periods. Interestingly, the spillover effect from the oil market to the natural gas market appear to be more durable in the crisis periods.

Finally, the dynamic correlation between these three markets is generally positive and modest. Particularly, the correlations changed considerably with major events. Especially in the periods of Crisis 1 and Crisis 2, the correlation coefficients between the three markets increase markedly, except oil and natural gas became negatively correlated during Crisis 2. The reason for the negative correlation is due to two aspects. One is the operational risk associated with the change in trading rules. The other is the oil demand crashed because of the epidemic, while the demand for natural gas did not decrease much because it can be used for heating.

5 CONCLUSION

5.1 Introduction

Because of the extreme volatility prevalent in energy prices, coupled with the rapid financialization of energy, understanding the volatility spillover effects between energy markets is of great importance for both the real economy and stock market participants. It is well known that oil is one of the most widely used energy sources in the modern era and is closely linked to a country's economy. However, its price has been fluctuating dramatically since the 20th century. Furthermore, as people become more environmentally conscious, natural gas and ethanol, which are cleaner alternatives to oil, are gaining more interest and attention.

Although there has been considerable literature in recent years examining the relationship between these three, most papers have taken into account linear relationships. In addition, studies on volatility spillovers among these three commodities are relatively old.

Therefore, this study uses more recent data to investigate the volatility transmission and dynamic correlation between these three markets to provide investors with references for portfolio optimization and risk management decisions.

This chapter briefly reviews the key findings of the study and makes recommendations for future research.

5.2 Summary of the key findings

In this paper, weekly data of oil, natural gas and ethanol spot prices from June 2005 to December 2020 are chosen. Moreover, these data are divided into five sub-periods according to pre-crisis, crisis and post-crisis, with VAR-BEKK-GARCH and VAR-DCC-GARCH being used. Several findings are obtained from the model results:

Firstly, throughout the full sample period, there were bidirectional spillovers from the oil market to the ethanol and natural gas markets. Specifically, oil price fluctuations caused ethanol and natural gas price fluctuations, as well as the other way around. Simply put, risks were passed from the oil market to the ethanol and gas market, and vice versa.

Secondly, the volatility spillover effect varies over time. In other words, the situation of a market's price volatility drives other markets' price volatility changes over time. Volatility was transmitted from ethanol market to natural gas market in Crisis 1 to Crisis 2 while the other way around can be observed from Pre-crisis 1 to Post-crisis 1. There was bidirectional volatility spillover between the ethanol market to the oil market in Pre-crisis 1 and Post-crisis 1 when volatility from the oil market spillover to the ethanol market in all the sub-periods. Unidirectional volatility transmission from the natural gas to the oil market is identified in Crisis 1 and Crisis 2, and vice versa in Pre-crisis 1, Post-crisis 1 and Crisis 2. In particular, the conclusions for Pre-crisis 1 to Post-crisis 1 are agreed with those of Trujillo-Barrera et al. (2012) and Gardebroek and Hernandez (2013) to some extent, and somewhat differ from Karali and Ramirez (2014) and Lin and Li (2015).

Thirdly, cases of volatility spillover from the oil market to the other two markets are more than the other way around, representing the dominance of oil in volatility spillover effect.

Fourthly, in the crisis and post-crisis period, there are more cases of significant volatility transmission, suggesting that the crises have had a non-negligible impact on volatility spillovers among these three energy markets. Specifically, volatility spillover interactions between the oil, natural gas and ethanol market raised from 4 in Pre-crisis 1 to 4 and 5 in Crisis 1 and Post-Crisis 1 respectively. In comparison, these increased from 2 in Pre-crisis 2 to 4 in Crisis 2. Moreover, the spillover effects from the oil market to the natural gas market were persistent in times of crisis.

Finally, the dynamic correlation between the three markets is generally positive and moderate, and their correlation increases in times of crisis.

Market participants should be aware of the above findings that the impact of extreme negative shocks (crises) can exacerbate spillover effects and investment risks among energy markets. Moreover, the total share of these three commodities in an investor's portfolio should not be too large for diversification purposes. Investing in these three commodities should be more effectively hedged by choosing other commodities or stocks that do not have volatility spillover patterns.

5.3 Recommendation for further studies

This paper is more concerned with the spillover effect. It does not give a specific explanation for the specific causes of it in different periods, so it can be improved on this basis in further research.

Furthermore, it is believed that a negative shock to the financial time series may lead to an increase in volatility rather than a positive shock of the same magnitude. Therefore, it would be interesting for future studies to include the magnitude and directions of the volatility spillover among these commodities.

REFERENCE

Aloui, R., Aïssa, M. S. B., Hammoudeh, S., Nguyen, D. K. (2014). Dependence and extreme dependence of crude oil and natural gas prices with applications to risk management. *Energy Economics*, *42*, 332–342.

Asche, F., Osmundsen, P., Sandsmark, M. (2006). The UK market for natural gas, oil and electricity: Are prices decoupled? *The Energy Journal, 27(2)*, 27-40.

Atil, A., Lahiani, A., Nguyen, D. K. (2014). Asymmetric and nonlinear pass-through of crude oil prices to gasoline and natural gas prices. *Energy Policy, 65*, 567-573.

Balcilar, M., Chang, S., Gupta, R., Kasongo, V., Kyei, C. (2014). The relationship between oil and agricultural commodity prices: A quantile causality approach. *University of Pretoria, Department of Economics, Working Paper Series*, 68.

Batten, J. A., Ciner, C., Lucey, B.M. (2017). The dynamic linkages between crude oil and natural gas markets. *Energy Economics, 62*, 155-170.

Boubakri, S., Guillaumin, C. (2015). Regional integration of the East Asian stock markets: An empirical assessment. *Journal of International Money and Finance, 57*, 136-160.

Brigida, M. (2014). The switching relationship between natural gas and crude oil prices. *Energy Economics, 43*, 48-55.

Caporin, M., Fontini, F. (2017). The long-run oil–natural gas price relationship and the shale gas revolution. *Energy Policy, 64,* 511-519.

Chang, T., Su, H. (2010). The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods. *Energy, 35 (7)*, 2807–2813.

Chen, Y., Zheng, B., Qu, F. (2020). Modeling the nexus of crude oil, new energy and rare earth in China: An asymmetric VAR-BEKK (DCC)-GARCH approach. *Resources Policy*, *65,* 101545.

Chiou-Wei, S. Z., Chen, S. H., Zhu, Z. (2019). Energy and agricultural commodity markets interaction an analysis of crude oil, natural gas, corn, soybean, and ethanol prices. *The Energy Journal, 40(2)*, 265-296.

Chiu, F., Hsu, C., Ho, A., Chen C. (2016). Modeling the price relationships between crude oil, energy crops and biofuels. *Energy, 109,* 845-857.

Engle, R. F., Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory, 11(1995)*, 122-150.

Engle, R.F. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20(2002),* 339-350.

Enwereuzoh, P. A. (2019). *Crude oil shocks and stock returns in African stock markets.* (Master's thesis). University of the Witwatersrand.

Erdös, P. (2012). Have oil and gas prices got separated. *Energy Policy, 49,* 707-718.

Gardebroek, C., Hernandez, M. A. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics, 40*, 119–129.

Geng, J. B., Ji, Q., Fan, Y. (2017). The relationship between regional natural gas markets and crude oil markets from a multi-scale nonlinear Granger causality perspective. *Energy Economics, 67,* 98–110.

Griffin, J. M. (2007). The Future of World Oil Prices: Some Keys to the Puzzle (No. 1176-2016-93387, pp. 7-24).

Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy, 91(2)*, 228–248.

Hartley, P. R., Medlock III, K. B., Rosthal J. E. (2008). The relationship of natural gas to oil prices. *The Energy Journal, 29(3),* 47-65.

Hassouneh, I., Serra, T., Goodwin, B. K., Gil, J. M. (2012). Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships, *Energy Economics, 34*, 1507-1513.

International Energy Agency (IEA). (2019a, July). The Role of Gas in Today's Energy Transitions, Retrieved from https://iea.blob.core.windows.net/assets/cc35f20f-7a94-44dc-a750-41c117517e93/TheRoleofGas.pdf

International Energy Agency (IEA). (2019b, October). Renewables 2019, Retrieved from https://www.iea.org/reports/renewables-2019

International Energy Agency (IEA). (2020a, April). Global Energy Review 2019, Retrieved from https://www.iea.org/reports/global-energy-review-2019

International Energy Agency (IEA). (2020b, April). Global Energy Review 2020, Retrieved from https://www.iea.org/reports/global-energy-review-2020

International Energy Agency (IEA). (2021, April). Global Energy Review 2021, Retrieved from https://www.iea.org/reports/global-energy-review-2021

Ji, Q., Li, J. P., Sun, X. L. (2019). New challenge and research development in global energy financialization. *Emerging Markets Finance and Trade, 55(12)*, 2669-2672.

Kaltalioglu, M., & Soytas, U. (2011). Volatility spillover from oil to food and agricultural raw material markets. *Modern Economy, 02(02)*, 71–76.

Karali, B., Ramirez, O. (2014). Macro determinants of volatility and volatility spillover in energy markets. *Energy Economics, 46*. 413-421.

Katrakilidis, C., Sidiropoulos, M., Tabakis, N. (2015). An empirical investigation of the price linkages between oil, biofuels and selected agricultural commodities. *Procedia Economics and Finance, 33*, 313-320.

Lin, B. Q., Li, J. L. (2015). The spillover effects across natural gas and oil markets: Based on the VEC–MGARCH framework. *Applied Energy, 155*, 229-241.

Lou, Y. (2019). 美国燃料乙醇行业发展现状与启示 (Experiences and enlightenments of development of biofuel industry in American). *International Petroleum Economics, 27(9),* 99-106.

Lovcha, Y., Perez-Laborda, A. (2020). Dynamic frequency connectedness between oil and natural gas volatilities. *Economic Modelling, 84*, 181-189.

Lu, Y. X., Yang, L. G., Liu, L. H. (2019). Volatility spillovers between crude oil and agricultural commodity markets since the financial crisis. *Sustainability, 11(2),* 396.

McPhail, L. L. (2011). Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach. *Energy Economics, 33*, 1177-1185.

Mu, X. Y. (2007). Weather, storage, and natural gas price dynamics: Fundamentals and volatility. *Energy Economics, 29(1)*, 46-63.

Nazlioglu, S., Erdem, C., Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, *36,* 658–665.

Nazlioglu, S., Soytas, U. (2011). World oil prices and agricultural commodity prices: evidence from an emerging market, *Energy Economics, 33(3)*, 488-496.

Neumann, A. (2009). Linking natural gas markets: is LNG doing its job. *The Energy Journal, 30*, 187-200.

Odei-Mensah, J., Premaratne, G. (2018). Integration of ASEAN banking sector stocks. *Journal of Asian Economics, 59*, 48-60.

Painter, D. S. (2014). Oil and Geopolitics: The oil crises of the 1970s and the Cold War. *Historical Social Research / Historische Sozialforschung, 39(4)*, 186–208.

Parifanis, T., Dagoumas, A. (2018). Price and volatility spillovers between the US crude oil and natural gas wholesale markets. *Energies, 11(10),* 2757.

Paris, A. (2018). On the link between oil and agricultural commodity prices: Do biofuels matter? *International Economics, 155*, 48-46.

Pindyck, R. S. (2004). Volatility in natural gas and oil markets. *The Journal of Energy and Development, 30(1)*, 1-19.

Razek, N. H. A., Michieka, N. M. (2019). OPEC and non-OPEC production, global demand, and the financialization of oil. *Research in International Business and Finance, 50*, 201-225.

Sakthivel, P., Bodkhe, N., Kamaiah, B. (2012). Correlation and volatility transmission across international stock markets: A bivariate GARCH analysis. *International Journal of Economics and Finance, 4(3)*, 253-264.

Soccol, C., Vandenberghe, L., Medeiros, A., Karp, S., Buckeridge, M., Ramos, L., Pitarelo, A., Ferreira-Leitão, V., Gottschalk, L., Ferrara, M., Silva Bon, E., Moraes, L., Araújo, J., Torres, F. (2010). Bioethanol from lignocelluloses: Status and perspectives in Brazil. *Bioresource Technology, 101(13)*, 4820-4825.

Stelzer, R. (2008). On the relation between the VEC and BEKK multivariate GARCH models. *Econometric Theory, 24 (4)*, 1131-1136.

Szklo, A., Schaeffer, R. (2006). Alternative energy sources or integrated alternative energy systems? Oil as a modern lance of Peleus for the energy transition. *Energy, 31(14)*, 2513-2522.

Timilsina, G., Mevel, S., Shrestha, A. (2011). Oil price, biofuels and food supply. *Energy Policy, 39(12)*, 8098-8105.

Tiwari, A. K., Mukherjee, Z., Gupta, R., Balcilar, M. (2019). A wavelet analysis of the relationship between oil and natural gas prices. *Resources Policy, 60*, 118-124.

Trujillo-Barrera, A., Mallory, M., Garcia, P. (2012). Volatility spillovers in U.S. crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics, 37(2)*, 247-262.

Villar, J. A., Joutz, F. L. (2006). The relationship between crude oil and natural gas prices. *Energy Information Administration, Office of Oil and Gas, 1*, 1-43.

Walker, A. (2020, April 21). US oil prices turn negative as demand dries up. *BBC News*, Retrieved from https://www.bbc.com/news/business-52350082

Wang, Y., Guo, Z. (2018). The dynamic spillover between carbon and energy markets: New evidence. *Energy, 149*, 24-33.

Whistance, J., Thompson, W. (2010). How does increased corn-ethanol production affect US natural gas prices? *Energy Policy, 38(5)*, 2315-2325.

Wu, H. X., Li, S. P. (2013). Volatility spillovers in China's crude oil, corn and fuel ethanol markets. *Energy Policy*, *62*, 878-886.

Yip, P. S., Brooks, R., Do, H. X., Nguyen, D. K. (2020). Dynamic volatility spillover effects between oil and agricultural products. *International Review of Financial Analysis, 69*, 1-9.

Yu, L., Zha, R., Stafylas, D., He, K., Liu, J. (2020). Dependences and volatility spillovers between the oil and stock markets: New evidence from the copula and VAR-BEKK-GARCH models. *International Review of Financial Analysis, 68*, 101280.

Zamani, N. (2016). How the crude oil market affects the natural gas market? demand and supply shocks. *International Journal of Energy Economics and Policy, 6(2)*, 217-221.

Zhang, D., Ji, Q. (2018). Further evidence on the debate of oil-gas price decoupling: A long memory approach. *Energy Policy, 113*, 68-75.

Zhu, Q. B. (2017). 国际石油价格波动对我国对外贸易的影响研究 (The impact of international oil price fluctuation on China’s foreign trade). (*Master’s thesis*). Anhui University.