# Study of the Influence of Oil Prices on Stock Markets' Indices and Macroeconomic Factors in OPEC Countries and Top Economies and the Prediction of Future Oil Prices

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# Abstract

Oil as one of the main fossil fuel energy sources, its price changes and fluctuation has the ability to influence the local economy or even the world economy. Especially for the oil-exporting countries, like OPEC countries, they have big influence on the oil prices. Whilst the proof of oil prices themselves have been examined, the influence of the oil prices on the relationship between different indices and between macroeconomic is not clear and the usage of Holt-Winter model on the oil price prediction has not been proofed.

The aim of this thesis was to determine influence two oil prices (WTI and Brent crude oil prices) on the relationship between top economies in the world (Japan, the UK and the US). To achieve this the simple regression model, the VAR and the VECM model was including to examine the relationship of oil prices with indices and macroeconomic factors. The cointegration tests were used first to test whether they are stationary or non-stationary. Then, the VAR and the VECM model were employed to examine the short-run and long-run relationship between them. In addition, the Holt-Winter model was applied to test its predictability by estimate the oil prices.

This thesis was the first to investigate the influence of oil prices on the relationship between different indices between OPEC countries and top economies' stock indices. The key findings were that the oil prices changes' conditions have influence on the relationship between different indices but limited. Secondly, by using the Holt-Winter model indicates that the oil market is inefficient where the prediction period had large difference between real period data. Thirdly, this thesis concluded that the oil prices and macroeconomic variables had causality relationship. These indicate that it is necessary to consider the influence of oil prices when analyse the world economy.

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Finally, I would like to thank my parents and other family members for their encouragement, support and accompaniment along the journey.

# Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

# General Introduction

## Background

Fossil fuels are the main energy sources used in the world for electricity production. Even though there are various kinds of renewable energy, like wind power, solar energy and hydropower, the world is highly reliant on fossil fuels. Marques, Fuinhas and Pereira (2018) stated that hydropower and solar PV have the ability to emulate fossil fuels, although currently, only fossil fuels can meet peak electricity consumption. Moriarty and Honnery (2016) concluded that renewable energy may not completely replace fossil fuel in the future, due to its storage needs and the unpredictability of the various natural ecosystems. Arutyunov and Lisichkin (2017) found that the alternative sources of energy to fossil fuels could not replace the usage of fossil fuels by the end of the 21st century.

Oil is one of the main fossil fuels used in the world; oil consumption was over 35 billion barrels in 2016, and based on the current rate of consumption, oil reserves will last for about 47 years (Worldometer). Pirog (2005) stated that the production ratio of oil reserves has been proven to be a measure to influence the oil price. Therefore, it is necessary and crucial to investigate the oil market. Its price fluctuates over time and is vulnerable, which is due to the uncertainty of the oil supply and demand, and the continuing decline in world stocks of oil. The price is mainly influenced by the existing stocks of oil and the new oil supplies found, but it also depends on the interaction of demand and supply in the market.

Güntner (2014) found that increase in global aggregate demand could consistently raise oil prices and have a negative influence on the stock markets in oil-importing countries. Li and Zhao (2011) confirmed that the oil demand shocks (increase in oil prices) were more influential than oil supply shocks on oil price fluctuation.

The aggregate and precautionary oil demand shocks and lower relevance of exogenous supply shocks can also have time-varying influence, which Nadal, Szklo and Lucena (2017) evidenced in the 2008 financial crisis period and Gong and Lin (2018) proved through the effects on China's macro-economy.

Since the beginning of the twenty-first century, the price of oil has experienced a few sharp increases and decreases. After 2010, the economies of countries like China and Russia have slowed down their economic growth, and after 2014, Canada and the United States (US) strengthened their crude oil production, leading to a sharp decline in oil prices. Kim (2016) proposed that the oil price declines during 2008 to 2009 by the reduction of real oil demand measured by US stock market while 2014 to 2016 were determined by U.S. shale oil development comparing to oil supply increased by OPEC. However, Prest (2018) concluded that the large decline of the Brent crude oil price between 2014 and 2016 was mainly caused by the U.S. shale gas revolution, which was because of the shrinking oil demand in the world.

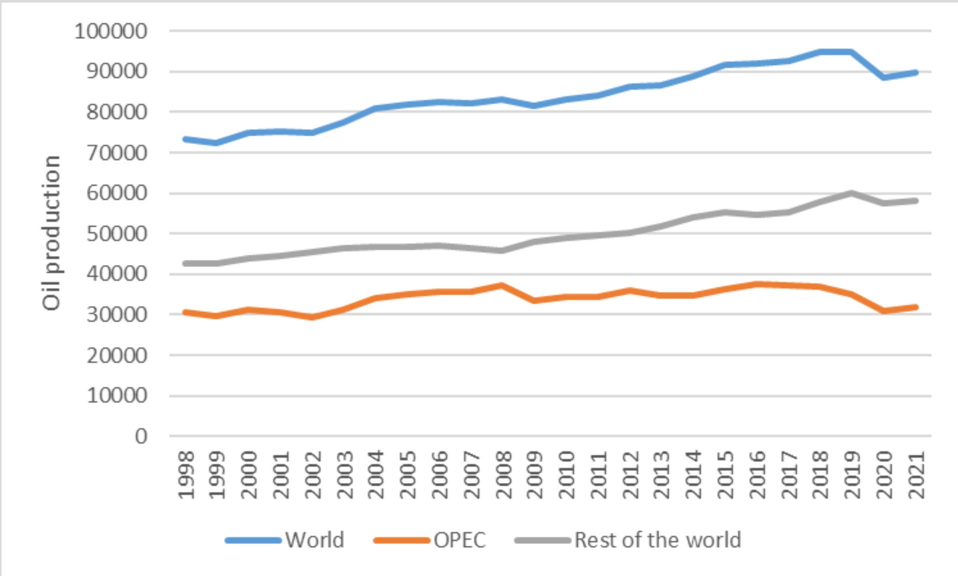
The Organization of the Petroleum Exporting Countries[1] (OPEC) countries comprises the main oil-producing organisations in the world, and their economies are influenced by decreases in oil prices. In 2015, Omoregie – the Lonadek Oil and Gas Consultant – stated that due to low oil prices, oil firms withdrew over $150 billion of investment. Also, the 'BP reports Q4 2015' reported that the profit in this quarter decreased by 51%, and the whole year's profit decreased by 38% compared with 2014. This steep decline in oil prices seriously affected the oil and gas industry.

OPEC countries do not have large oil reserves, but they play an important role in balancing the oil market. Kaufmann et al. (2004) revisited the influence of OPEC's decisions on the oil market through its quotas, production, and operable capacity. The results showed that OPEC still had a powerful influence on changes in oil prices. Furthermore, this paper indicated that some non-OPEC countries might present potential threats to the OPEC countries' major power over oil prices. Guidi, Russell and Tarbert (2006) concluded that the US and UK stock markets reacted to the

[1] OPEC countries list: Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, United Arab Emirates and Venezuela. Chart 1 shows the oil production from 1998 to 2021. The value of the OPEC countries' oil export was US$459.5 billion in 2021 which contained 47.8% of world total oil export value – US$982.6 billion. (Collected from World's Top Exports by W. Daniel)

OPEC policy decisions asymmetrically during the conflict period. Compared to non-conflict periods, oil markets need time to incorporate the decisions from OPEC countries.

Chart 1. Crude oil production from 1998 to 2021 *(in 1,000 barrels per day)*




*Data collected from Statista*

Razek and Michieka (2019) concluded that OPEC plays an important role in the balancing of the oil market. They also pointed out that non-OPEC countries' influence on the oil price should not be underestimated. Schmidbauer and Rösch (2012) found that OPEC announcements have an influence on the oil price expectation and volatility. In terms of expectation, the announcement of a cut decision leads to a negative influence, while a rise or maintenance of a price level has a positive influence. In addition, the advance announcement of a cut has a large positive influence on volatility. Mensi, Hammoudeh and Yoon (2014) and Loutia, Mellios and Andriosopoulos (2016) also concluded that the announcements from OPEC were significant and influential when there was a cut or maintenance in production. In addition, Mensi, Hammoudeh and Yoon (2014) found that the 'cut' and 'maintenance' announcements had strong influence on both the returns and volatility of WTI and Brent prices.

Güntner (2014) found that oil producers barely respond to speculative demand shocks in the same month. There is not enough evidence to demonstrate that the

OPEC countries reduce production while non-OPEC countries increase.

OPEC's policy decisions influenced the US and United Kingdom (UK) stock markets between 1986 and 2004 (Guidi, Russell and Tarbert, 2006). The authors also pointed out that the markets need time to absorb decisions from OPEC, and that during times of conflict there would be a time lag for the market to react, whereas outside of conflict periods, the market would react effectively and in a timely manner to OPEC's decisions.

Baumeister and Kilian (2015) used real data from June, 2014, when OPEC made an announcement that led to an oil price decrease of 44% in the second half of the year, and other commodities declined by approximately 10%. As Loutia, Mellios and Andriosopoulos (2016) stated, OPEC's decisions have an influence on oil price fluctuations. The effects would be significant when oil prices are low, and weak when the oil prices are high.

Gupta and Banerjee (2018) claimed that OPEC's news had sentimentally affected the US stock market. Good news from OPEC would affect US-listed firms negatively and bad news from OPEC would have the opposite effect. Also, Demirbas, Omar Al-Sasi and Nizami (2017) stated that oil price shocks were highly influenced by the demand and supply of oil and were especially affected by OPEC countries. The production of oil increase led to a higher price decline and the oil demand increase cause the oil price goes high. Naifar and Al Dohaiman (2013) stated that OPEC oil price fluctuations and the Gulf Cooperation Council[2] (GCC) countries' stock markets rely on their local policies. Among these studies, OPEC plays a very important role in oil price fluctuations.

The uncertainty of the OPEC meetings and production decisions can influence economies in other countries. Ji, Zhang and Zhang (2019) found that uncertainty could influence the oil securities market in China. Plante (2019) concluded that

[2] Gulf Cooperation Council (GCC) countries list: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates. GCC and OPEC both contain Kuwait, Saudi Arabia and United Arab Emirates which are the main oil exporting countries in the world. However, for GCC organization, their aim is to achieve unity among all members by economic and social cooperation. For OPEC organization, their aim is to achieve a stable and fair price for petroleum producers and the efficient supply of petroleum to other countries.

uncertainty leads to a higher level of oil price volatility. Due to the new announcement of the OPEC+ agreement in reaction to the United States shale revolution, Russia needed to maintain a low level of oil price and make a large loss in revenue (Akinfiev 2019).

The majority of the existing literature investigates macro-economic or economic growth following the impact of oil price shocks. The findings of Ftiti et al. (2016) relate the strengthening of the relationship between oil price and economic growth. They also concluded that oil shocks have a stronger effect in the long or mid-term than the short term. In addition, Salisu, Ndako and Adediran (2018) used high-frequency data to predict GDP in the selected countries, providing a better forecast result. Zhang and Wang (2019) employed a mixed-data sampling (MIDAS) model and concluded that the high-frequency data in the stock market offer an advantage to help investors and analysts to forecast the prices of crude oil in the future. They also suggest that using high-frequency data could help investors have a better strategy for their investment.

Nusair (2016) claimed that oil price shocks influence the GDP of the GCC countries, and that positive oil shocks were more influential than negative ones. Moreover, Van Eyden et al. (2019) used over a century of data from the countries of the Organisation for Economic Co-operation and Development (OECD) to analyse the influence of oil price volatility on economic growth. They found that it had a significant negative impact on local economies. This provides further evidence that the success of the economies of oil-producing countries are highly dependent on oil prices.

Bala and Chin (2018) stated that for African OPEC countries (Algeria, Angola, Libya and Nigeria), both positive and negative oil price changes had positive influence on inflation in these countries. Kumar (2019) found strong evidence that the oil price and exchange rate have a bidirectional nonlinear relation. In addition, the results show that positive and negative shocks of oil prices have positive and negative influences on exchange rates.

Sharp declines in oil prices significantly affect the world’s economy, especially in oil-producing economies and their stock markets. For instance, the large decrease in the oil price in 2015 had a major impact on the Malaysian economy, leading to a reduction of 10.5% in tax and 1.9% of GDP, and an increase in unemployment of 0.3% (Maji et al., 2017). Nyangarika and Tang (2018) concluded that the Russian economy is also highly dependent on its energy resources – any decline in oil prices would hit the Russian economy – and that international investors need to consider this effect.

This thesis aims to find some relationships within stock markets, macro-economic variables and crude oil prices. There are three chapters in this thesis to investigate. In the first chapter, the aim is to use stock market data from four OPEC countries (Ecuador, Nigeria, Saudi Arabia and the United Arab Emirates) and compare that with the stock market data of three developed countries (the S&P 500 from the US, the FTSE 100 from the UK and the Japan stock exchange). This chapter investigates the relationship between the Middle East and the African countries that are the main members of OPEC, and the highest-performing economies in the world. It aims to identify whether there is a cointegrated relationship between them, and if so, the type of correlation. These findings will provide investors with clear insight into the economic relationships between these countries. The reason why this thesis aims at the OPEC countries is that the OPEC is one of the biggest oil production organizations in the world. Their decisions on the oil production can influence world oil market. Therefore, to select the countries in this organization can reach a better result. In addition, as for the comparison group, this thesis selects the US, the UK and Japan, which are the top economical performing countries in the world. The discussion between these two groups gives a clearer result of the relationship between oil prices and other variables. It also can provide the different influences of oil prices changes to these two different groups.

In the second chapter, after investigating the relationship between oil prices and stock markets, it is also necessary to have an examination of the prediction of future oil prices. In this chapter, the West Texas Intermediate (WTI) oil price and the Brent oil price were selected to test the predictability of the oil prices. The aim of this is to check whether the oil prices are predictable and to what extent the oil price can be estimated. The results can provide information on future oil price predictability, which, combined with the results from Chapter One, can yield a better understanding of the oil prices' influence on the financial markets.

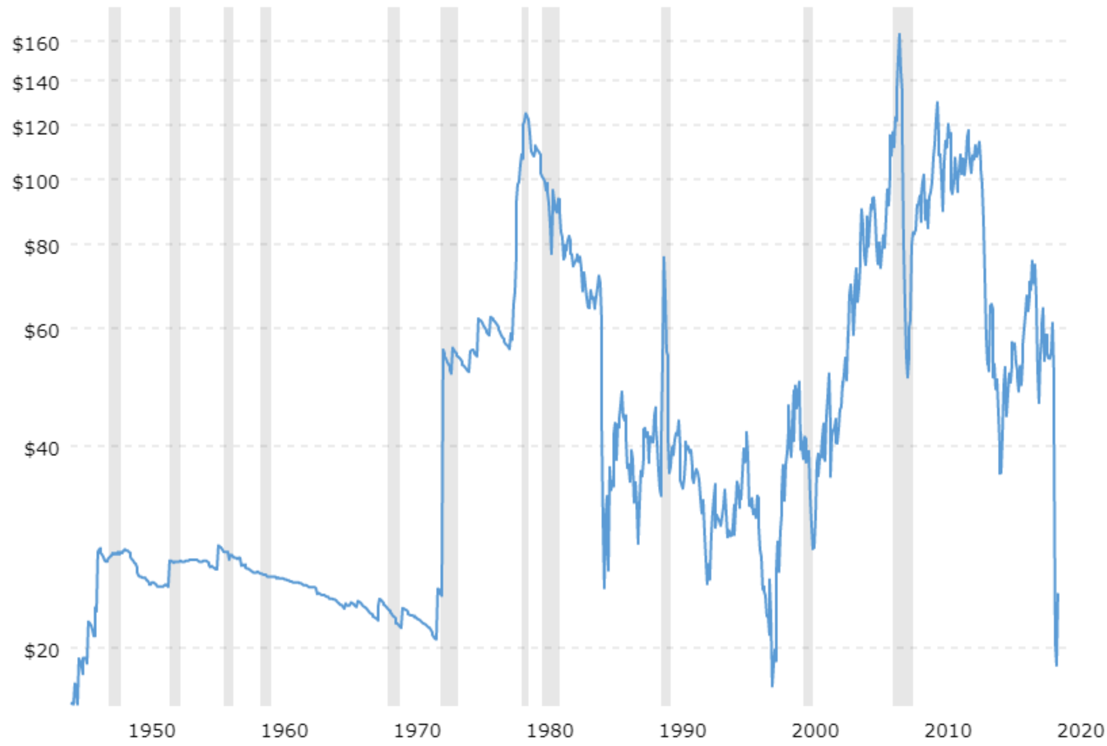
There is much investigation in various literatures into macro-economic variables such as inflation, exchange rates and interest rates. Therefore, in the third chapter, this paper aims to examine the relationship between these macro-economic factors in selected OPEC countries and compare the results from these OPEC countries with economically high-performing countries. These results can provide the premise that changes in the oil price affect the macro-economic situation in OPEC countries and non-OPEC countries. By assessing the results, not only can investors have a deeper understanding of the influence of oil price changes, but also the policy makers can set policies to shield against the harm caused by oil price changes.

The rest of the thesis is organized as follows: the investigations into the relationship between oil prices and selected stock indices, and how the oil price can influence the relationship between different indices, are reviewed in Section 2 (as Chapter 1). The prediction of the oil price by using the Holt-Winters model is analyzed in Section 3 (as Chapter 2). In Section 4, for further examination, the relationship between oil prices and macro-economic factors is introduced. In Section 5, the results from chapters 1 to 3 are then summarized and interpreted, and some limitations and future research are discussed.

# Oil market summary

According to Kimani (2019), the first commercial refinery was established in 1837 in Baku, Azerbaijan, to support heating and lighting for citizens. Then, in 1846, the first oil well was sunk in Baku, which supplied over 90% of the oil production needed. After this well was sunk, there were many other oil wells established around the world. In the meantime, the US became the largest oil producer in the world, following the discovery of oil in Oklahoma, in 1912, which was the settlement point of the West Texas Intermediate (WTI) price benchmark. Until the late 1950s, oil price and oil production were controlled by the US. In order to lower the competition of the US and balance the controlling power of oil prices and oil production, Saudi Arabia, Iran, Iraq, Kuwait and Venezuela teamed up and became OPEC. After that, OPEC become one of the most important and main oil exporting organizations in the world, having a strong influential effect on the oil price.

Chart 2. Historical oil price trend (WTI)




*Copied from macrotrends.net*

In history, there have been several times where the oil price experienced a sudden decrease or increase. For instance, during World War One (1914-1918), due to the increasing demand for oil to supply the needs of the war, the oil price doubled – from $0.81 per barrel to $1.98 per barrel. The discovery of the East Texas field in 1930 led to a great fall in the oil price – from $1.19 per barrel to $0.65 per barrel. The oil demand and oil price increased during World War II. Since then, war has made all governments realise the importance of oil reserves to their nation, which was very important during wartime for the control of oil production and oil prices.

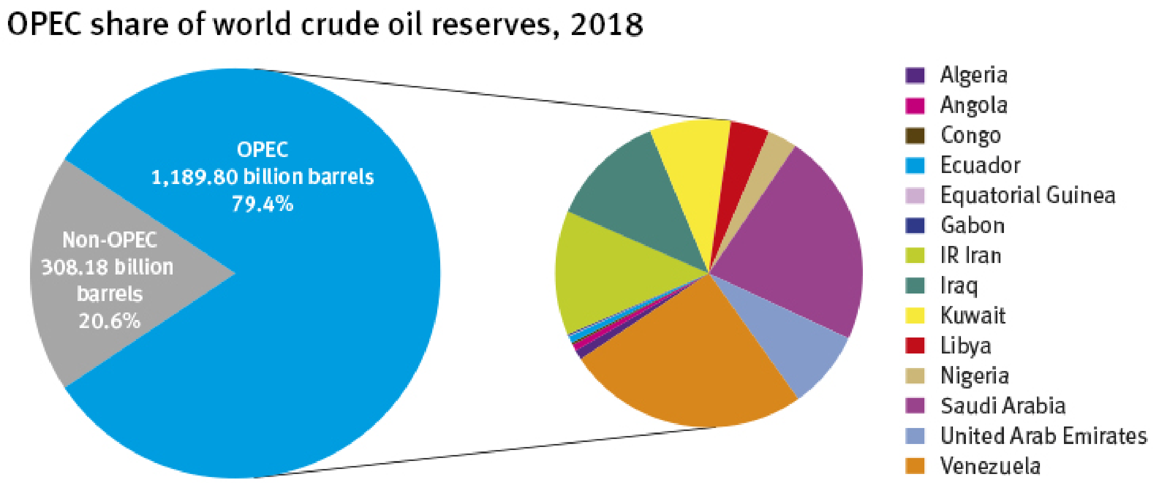
In 1973, the oil embargo announced by OPEC led to a sharp increase in the oil price – by over 400% in the Arab area, which was higher than the price in the US. Kimani (2019), Barsky and Kilian (2004) all agreed that OPEC's operation of the oil embargo was due to political factors – in order to gain more control of oil prices and oil production in the world. The decision was also made due to the mechanism of the

Bretton Woods system. OPEC tried to link the oil price directly to the price of gold, rather than the price of the US dollar. Thus, in order to gain more control of the oil prices, they changed the oil price system from being linked to the US dollar to being linked to gold, thus enabling an oil embargo. Without considering the political and moral factors, this behaviour emphasized that OPEC played an important role in the oil market and they had the power to influence both oil prices and oil production throughout the world.

Since the start of the 21st century, the oil price has experienced several ups and downs. Due to the US invasion of Iraq in 2003, which threatened the oil supply of Iraq, combined with the rapid rise of oil demand in the world, the oil price increased from $28.38 per barrel in 2000 to $146.02 per barrel in 2008. Then, the financial crisis severely hit the oil market and decreased the oil price from $147 per barrel (highest) to $32 per barrel (lowest) during the financial crisis from December 2007 to June 2009. In addition, the cut in oil production made by OPEC because of the abundance of newly-discovered US shale gas made the oil price rise again.

Therefore, seen from history, OPEC, since its establishment, has played an important role in the oil market, but without considering any political or moral factors. The OPEC countries have a large quantity of the oil reserves in the world. In addition, due to their large amounts of oil stocks, their actions and announcements could influence oil prices, which then influence world economies. These factors emphasize the importance of OPEC countries' role in the oil market. For example, an oil attack happened in Saudi Arabia in September 2019, leading to a surge in the oil price the following day. Also, the oil market had close connections with the world economy, which resulted in the oil price change influencing the profitability of firms, leading to changes in stock markets. Thus, it is worthwhile and necessary to investigate the oil price and OPEC countries in comparison with other top economies in the world. By analysing the OPEC countries in comparison with other countries in the world, this can generate a series of results to prove the importance of OPEC, and consequently, not only investors, but also researchers and policy makers could gain benefits.

Chart 3. The oil reserves of OPEC and non-OPEC countries

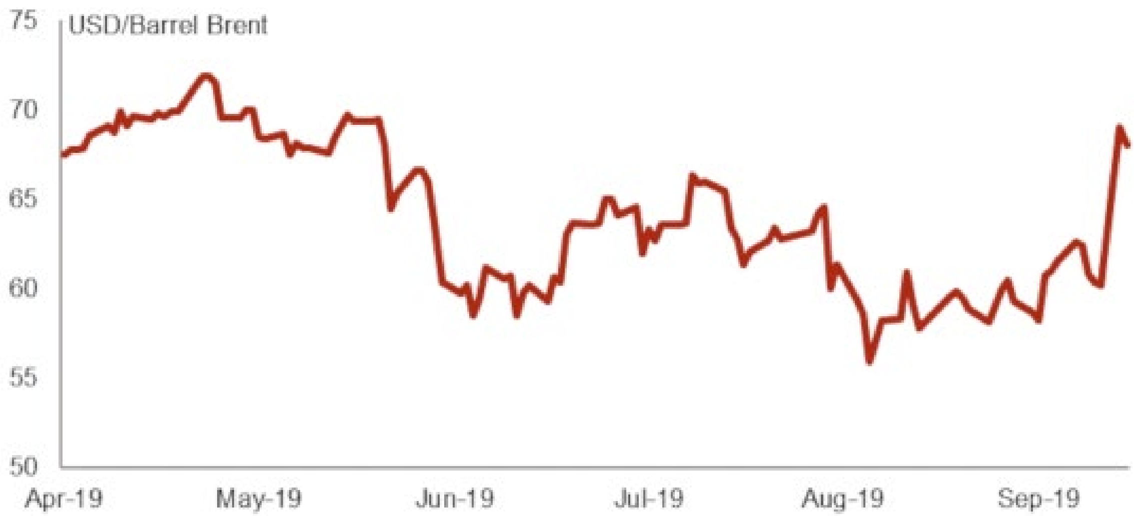



**OPEC proven crude oil reserves, at end 2018 (billion barrels, OPEC share)**

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Venezuela | 302.81 | 25.5% | Kuwait | 101.50 | 8.5% | Algeria | 12.20 | 1.0% | Gabon | 2.00 | 0.2% |
| Saudi Arabia | 267.03 | 22.4% | UAE | 97.80 | 8.2% | Ecuador | 8.27 | 0.7% | Equatorial Guinea | 1.10 | 0.1% |
| IR Iran | 155.60 | 13.1% | Libya | 48.36 | 4.1% | Angola | 8.16 | 0.7% | | | |
| Iraq | 145.02 | 12.2% | Nigeria | 36.97 | 3.1% | Congo | 2.98 | 0.3% | | | |

*Source: OPEC Annual Statistical Bulletin 2019.*

Chart 4. The oil price surge after the attack in Saudi Arabia in September 2019




Source: Bloomberg

# Findings, limitation and potential applications

This thesis focuses on the oil prices and oil price changes influence on other economic variables. This thesis find that the oil price changes have some influences on the stock markets in the selected countries (OPEC countries, the US, the UK and

Japan). It also concludes that it is important and necessary to consider the oil price as a condition when invest into different stock market. The investigation of the oil price can help investors to have a better management on their portfolio. In addition, the results show that the oil price changes can influence the macro-economic variables, such as exchange rate, interest rate and inflation. For example, the exchange rate, the results show that exchange rates are cointegrated with oil prices. This gives a sign to the investors who involve in the money market that when the oil price changes, they can take appropriate strategy to reallocate their portfolio to against the influence from the exchange rate to exchange rate. Moreover, policy makers can also pay attention to the oil price changes, it will help them to make the announcement and set the monetary policy in time to prevent the further economic fluctuation in this nation because of the oil price changes.

However, there are some limitations in this thesis. First, the data availability is not enough. If there is more available data from OPEC country, the result will be more complete and can have better comparison with other three countries. Second, including the machine learning or deep learning may lead to a better result. Third, the oil price changes can be set into different types which may lead to more specific results.

By the results finding in this thesis, investor and policy maker can get some benefits. The results show that when consider the oil price as a condition which can influence relationship between different stock markets. this gives an idea to investors to take the oil prices into consideration, which can help them to avoid the potential loss when they include different stock markets in their portfolio. For policy makers, this also give them a sign that the oil price changes can lead to a change on the macro-economic variables. It is necessary for them to have a look at the oil price changes or oil market. Based on the changes of oil price, they can make the announcements or the policy in an appropriate time to handle the shocks from the oil price changes.

# 1. **Chapter One: The relationship between oil prices and stock prices**

## 1.1 Introduction

The higher the oil price, the higher the cost of production and services that a firm must endure. This will decrease their level of earnings, leading to a decrease in the firm's financial performance. The oil price is related to macroeconomics, regarding which Tsai (2015) stated that in general, the higher the oil price, the higher the production costs of goods and services, which is then transmitted to the assets' price in the financial market by reducing their earnings.

Also, as noted by Sadorsky (1999), the analysis of US results shows that oil price shocks have a significant negative influence on stock markets, which emphasizes the effect of the price of oil on the cost of production, leading to the decline of firms' earnings. He also indicated that if the market is efficient, then the decline in the stock market is immediate, while if it is not efficient, there will be some time lag.

In addition, Masih, Peters and Mello (2011) found that there were two main ways in which oil price shocks would influence the stock market in South Korea. First, oil price shocks would influence the cost of production directly. Second, due to the influence of the potential decline of earnings, investors and shareholders may sell their shares to avoid losses, affecting stock prices indirectly in the financial markets.

Papapetrou (2001) investigated oil price shocks' influence on the Greek economy. He found that oil price shocks had an immediate negative influence on industrial production and employment. Then, the rise of the oil price would create an inflationary effect in the economy, caused by a decline in firms' production and earnings. Thus, oil price shocks have a negative impact on stock returns, which leads to an increase in the interest rate.

Furthermore, Chittedi (2012) indicated that an increase in the oil price could raise the cost of importing products, which may hurt the profitability of the firms listed on the Indian stock market. Additionally, the high oil price would increase the national price level, which would then lead to a rise in interest rates, hitting the stock market. He also mentioned that the value of stock prices was equal to the discounted value of dividends, which was influenced by economic activities.

Guo and Kliesen (2005) pointed out that both increases and decreases in the oil price could harm the economy. First, the uncertainty of future oil prices increases the rate of the business cycle, which slows down investment. Second, it is costly to reallocate assets in response to changes in oil prices. Guo and Kliesen's results showed that the US economy is influenced by changes in the oil price, which affects the GDP growth rate in that country.

Lardic and Mignon (2008) indicated that there are five ways in which the results of oil price changes are transferred to the economy. First, a rise in the oil price would reduce imports, which leads to a reduction in production, and the growth of output and productivity would be low, a consequence that had been agreed by G7 (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) countries and the European economic zone. Second, the rise would enhance the purchasing power of the oil-exporting countries compared to the oil-importing ones. Third, the increase in the oil price would lead to the increase of interest rates, and slow down economic growth. Fourth, the increasing oil price could generate inflation, which increases local price levels. Fifth, the increase of the oil price may lead to a change in a country's economic structure, and a delay in investment, due to higher production costs and/or a rise in the unemployment rate.

These literatures indicated that oil price changes could not only influence the economy at a national level, affecting inflation, interest rates and employment rates, but that their influence would also spread to financial markets. Therefore, it is important to investigate the relationship between oil prices and different stock markets. Therefore, my contribution is to find the effects of oil price changes on the relationship between different stock markets, which has not been studied before. This means that I will first find the relationship between different relevant stock markets, and secondly add the oil price changes as considerate variables, to test how oil price changes would influence relationships. As far as I know, this has not been studied before. Therefore, by finding the importance of oil prices, this can provide, in theory, an idea that the oil price is also a necessary variable to consider, because it has similar influences, like exchange rates and interest rates. Additionally, in practice, international investors can have a clearer understanding of how the oil price influences the relationship between different stock markets, and policy makers can set an emergency measure to deal with the sharp movement of oil prices to reduce the losses to their nation.

## 1.2 Aims and objectives

The aim of this chapter is to investigate the relationship between the stock markets of OPEC countries and economically high-performing countries according to oil prices. This chapter will combine the OPEC countries as a whole organisation in order to make a comparison with other stock markets – this would finally get the results of what the exact relationship between them is. The work will not simply analyse the stock market data from these countries, it will also consider the oil price as a variable in the analysis. This means that the analysis will identify how oil price changes influence the relationships between these countries.

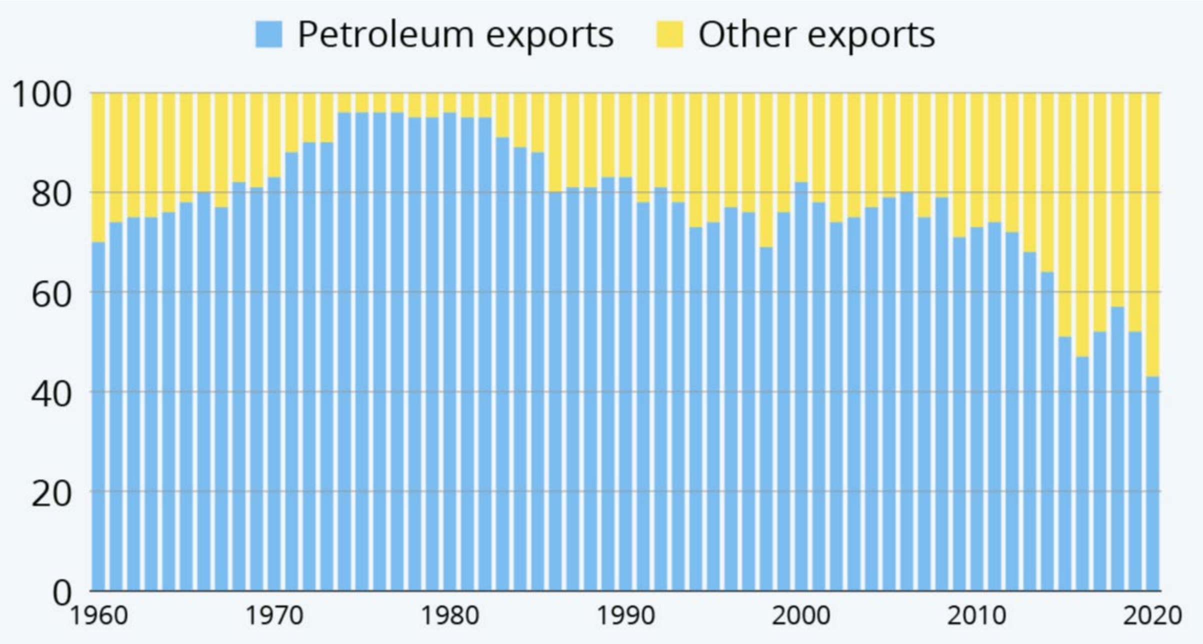
In the analysis process, this chapter will take the 2007-2008 financial crisis into consideration because it is a popular discussion topic that the relationship between oil prices and the stock markets has been subject to change – not only during the financial crisis, but also in the pre- and post-financial crisis periods. Therefore, this thesis aims to identify as many relationships between oil prices and the stock markets, and the OPEC stock markets and the top economies' stock markets, as possible.

## 1.3 Motivations for the chapter

Oil price fluctuations influence economies and stock markets across the world. Theoretically, the uncertainty of oil prices has a negative relationship with stock market returns. Most articles suggest that oil price shocks lead to a negative effect on stock markets (Sadorsky, 2001; Park and Ratti, 2008; Sim and Zhou, 2015; Kang, Gracia, Ratti, 2017; Xiao, 2018). Oil plays an important role in our world, and therefore oil-related firms and oil-related countries are influenced by changes in oil prices. As Nusair and Al-Khasawneh (2018) stated, changes in oil prices directly influence import and export prices, which in turn directly influence national income. Thus, national economies are affected when oil price shocks happen, and the effect spreads to the stock market.

As the main oil-exporting organisations, the economies of the OPEC countries are highly reliant on the export of oil. In 2021, Nigeria's value of petroleum exports contained 88.28% of total value of exports and for Saudi Arabia, its petroleum exports contained 70.56% (data collected from opec.org). The changes in the oil prices will influence the volume and value of the oil export in OPEC countries and the effects of the oil price changes should lead to more obvious changes in their economies. Thus, different reactions to the same oil price changes could be caused by OPEC countries having a different influence than other countries in the world. Analysis of the difference between these countries according to the conditions of changing oil prices could provide a general guide for the reader – and investors – of the exact relationship between them.

Chart 5. OPEC Countries' value of petroleum as percentage of total exports




*Copied from Statista*

The existing literature has not conclusively identified the relationship between the OPEC countries and the economically top-performing countries with regard to the effects of oil price shocks/fluctuation. OPEC countries' economy are highly depended on the oil export and its price changes will directly influence the local economy and affected the oil-related companies, which indirectly influence local stock markets. Therefore, the literature has tended to research how oil price shocks affect different stock markets. Therefore, in this thesis, I will try to answer the following two questions:

1) What are the relationships between these stock markets and between oil prices and these stocks?
2) Is the relationship between stock price indices in different countries influenced by oil price shocks/fluctuations?

By answering these questions, I hope to generate a clear result of the relationship between the stock markets of the OPEC countries and the economically top-performing countries. The economically top-performing countries are the UK, the US and Japan. The reason why including three economically top-performing countries is that these group of countries can have comparison with the OPEC to figure in the same time period how are the influence of the oil price changes to these two different groups of countries. In addition, by also including the condition of the oil prices, I hope to provide another guide for readers, investors and portfolio managers in order to better understand the relationships between these countries. These results can help readers to understand the influence of the oil prices on different stock markets especially for international investors who holding the stocks in OPEC countries and economically top-performing countries.

## 1.4 Hypotheses

### *1.4.1. Hypothesis 1: There is a positive relationship between changes in oil prices and the OPEC stock markets, while the relationship between oil prices and leading economies' stock markets is negative.*

The first hypothesis is to investigate the relationship between the oil price and stock markets. It is assumed that the oil price will influence the stock market differently in these two separate groups of countries. The oil price changes will positively influence the OPEC countries' stock markets, while the US, UK and Japanese stock markets will respond negatively to oil price changes.

It is expected that for the OPEC countries, as the main oil-exporting organisations, an increase in oil prices would enhance their local economies and therefore lead to an increase in the returns from the stock market. The changes in the oil prices will influence macroeconomic factors such as inflation and interest rates. Papapetrou (2001), Chittedi (2012) and Arouri and Rault (2012) examined oil prices and the GCC stock markets (the GCC is another group of oil-exporting countries). They found that they were cointegrated and that an increase in oil prices could benefit these stock markets. In addition, Nusair and Al-Khasawneh (2018) stated that the oil price and the GCC stock markets were bound by co-movement, increasing and decreasing simultaneously. Therefore, I want to investigate if OPEC countries, the main oil-exporting countries, would have a similar result to that seen in the GCC countries. In addition, Gupta and Banerjee (2018) claimed that good news from OPEC would negatively affect US-listed firms. As far as I know, not all the OPEC countries have been studied, thus I will extend the investigation to some other OPEC countries.

It is widely believed that oil price shocks have a negative influence on the stock markets of developed countries. Jimenez-Rodriguez (2015) analysed the relationship between the US stock market and oil prices, and concluded that there was a negative relationship. In addition, Kang and Ratti et al. (2017) found that the positive demand shocks resulted in a negative impact on the US stock returns, and that the influence would last for a long time. Thus, I try to use the single regression model and cointegration test to test the cointegration within these stock markets.

I will use the single regression model and cointegration test to investigate the relationship between oil price stock markets. The previous literature had proved some relationship between oil price and stock markets. I will test their relationship from 01/01/1990 to 31/12/2017 to see during this time period what exact relationships existed among oil prices and stock markets.

### *1.4.2. Hypothesis 2: The stock markets of OPEC countries have a long-term relationship (a cointegration[3] relationship) with the stock markets of economically high-performing countries (the US, the UK and Japan), so changes in the price of oil will influence this relationship between these stock markets.*

Saadi-Sedik and Petri (2006) stated that the Jordanian stock market was not cointegrated with developed countries, but that the Arab stock markets were cointegrated. Abbes and Trichilli (2015) also found that the Islamic stock market was integrated with similar economic countries, but that there was no cointegration

[3] Cointegration test is used to investigate between different time series in the long term if there is a correlation. Cointegration relationship means that different non-stationary time series are integrated together that they cannot deviate from the equilibrium point in the long term (defines as over a year). It is believed that the oil price changes can influence the economy in the world. An increase in the oil price normally hit the economy which can sperate the influence stock markets and usually result in a negative way. Therefore, the influence of fluctuation of the oil price can have a long-term relationship with stock markets.

relationship with developed countries. The authors also pointed out that including the developed and developing countries' stocks could achieve diversification. Al Nasser and Hajilee (2016) claimed that the emerging stock markets in countries like Mexico and Russia – which are oil-exporting countries – had no long-term relationship between them, rejecting the cointegration relationship.

However, there are still some other authors and literature that have provided some evidence showing that developing countries have had a long-running relationship with developed countries. Zaimović and Berilo (2014) found that there was no diversification opportunity to invest in the German and Bosnian stock markets during the financial crisis. Majdoub, Mansour, and Jouini (2016) found that the French and the US conventional stock markets had a long-running relationship with Islamic stock prices. Also, Yarovaya and Lau (2016) concluded that UK investors saw no diversification benefits to invest into the Brazil, Russia, India, China and South Africa (BRICS) stock markets in which these stock markets were integrated.

These above literatures have provided the idea that not all the developing countries are co-integrated with developed countries, which also means that some of the developing countries' stock markets might have long-term relationships with developed stock markets. This offers the idea that I can investigate the relationship between these stock markets' relationship first, and then add the oil price as the variable into consideration to see how the fluctuation of the oil price could influence their relationship. I have expected to find that the oil price plays an important role between the stock markets of OPEC countries and selected stock markets of top-performing economies. Also, the fluctuation of the oil price (either going up or down) will enhance the negative relationship between these two groups of stock markets, and it will break down the positivity between them.

## 1.5 Literature review

This section includes literature that is relevant to oil prices and stock markets. The section's aim is to introduce the basic idea and the previous conclusions in these two markets. There are two parts to the section – diversification, and oil price and stock markets. The diversification part introduces the idea that a diversified portfolio can help investors and portfolio managers to achieve lower risk. Diversification can provide a reason why it is important to have a diversified portfolio, because it can help investors and managers to have a better portfolio. This section can also help readers to understand that an investment contains a variety of financial products that can help them achieve lower risk. The second part is related to oil prices and stock markets. In this section, all the collected literature is focused on oil prices and stock markets. Previous literature has analysed the influence of the oil price changes on the stock markets. This includes different forms of oil price changes, similar oil price changes' varying influence on different types of countries (oil-exporting and oil-importing), and other factors such as inflation and exchange rates. The literature section offers the idea that oil price changes influence the stock markets. Thus, this chapter aims to analyse the influence of the oil price changes on the relationship between different stock markets.

### *1.5.1 Diversification*

Diversifying one's portfolio is a wise strategy for investors or portfolio managers – to create a portfolio with lower risk than those not diversified. A diversified portfolio includes more than one asset. The diversified portfolio can be multi-national or multi-industry. Ideally, the well-diversified portfolio only takes systematic risks in something that is essentially safe, such as national Treasury bonds. Thus, it is very important to find the appropriate and most suitable assets in order to combine them as a bundle to achieve diversification. It is risky to randomly choose different assets without any analysis and consideration, because randomly-chosen assets may beat the market in the short term, but their rise in value cannot last for a long time and their risk is very high. Therefore, before a portfolio can be created, it is a priority to investigate the relationship between those potential assets, and this will provide a guide in regard to which assets should be included and which assets should be avoided. For investors, if the relationship between the oil prices and stock markets can be figured out, this relationship will help them to have a better control over their portfolio and to achieve a better allocation of their assets. Additionally, consider oil as a consideration, the relationship between different stock markets is tested. Based on the investigation, investors can manage their asset allocation based on the changes of the oil prices to avoid potential loss to achieve diversification.

Jorion (1985) stated that an international portfolio was a popular choice for international investors in order to achieve a better portfolio and a larger profit. He also mentioned that previous literature on this subject was only focused on the model of using previous data to do the forecast. This was not wrong, but Jorion chose to also consider estimation risk in his study. The results of this addition demonstrated a greater diversification of portfolios with more certain (rather than overestimated) future returns. Thus, this study suggested that diversification was related more to the reduction of risks than to an increase in profits. Ahuja (2015) also concluded that a suitable amount of financial assets included in a portfolio could achieve lower risk by analysing the diversification opportunities in the Karachi Stock Exchange.

The random choice of financial products may also lead to reduced risk portfolios. Gilbert and Burton (1994) analysed the Wall Street Journal for the random choice of darts and found no evidence to support the notion that the professors' decisions could beat the market. However, in 1997, Atkins and Sundali analysed 204 dart samples and 204 professional samples in order to identify whether randomly chosen portfolios could truly beat those portfolios chosen by professionals. Their results showed that only half of the dart portfolios performed well in the following month and the following six months respectively, while all of the professionally chosen portfolios performed as expected in the same time periods.

Apart from the luck factor, it is also necessary to have some financial and investment knowledge in order to make a better investment in financial markets. Abreu and Mendes (2010) found that the level of education and the source of information for the financial assets matters. A higher level of education and more specific information acquired would help investors to achieve a better combination of diversified portfolios. Abreu and Mendes also stated that investors with suggestions from portfolio managers could perform better.

Mouna and Jarboui (2015) focused on the influence of financial literacy on portfolio diversification. They concluded that investors with low income, a low level of knowledge and less experience were less likely to achieve diversification in their investment.

International investment is a way for investors and portfolio managers to achieve diversification. Meric and Meric (1989) found that the longer the time period that was analysed, the better the estimation of the future movement of the international stock markets. In addition, they concluded that the international portfolio is more diversified than the multi-industry portfolio: even if an investor chose to invest in the same industry across the world, an international portfolio would achieve lower risk. Bergin and Pyun (2016) also claimed that investors became more attracted to overseas investment, which could help them to combine two or more assets with a lower correlation to achieve diversification and gain benefits from it.

Markellos and Siriopoulos (1997) examined diversification from 1974 to 1994 by combining European stocks with US and Japanese stocks. They stated that international investors wanted to achieve diversification of their investments, and that was dependent on the integration of selected markets. They found that this would benefit US and Japanese investors. Based on the result of cointegration tests, Markellos and Siriopoulos confirmed that the European markets had a weak integration with the other two developed markets – this indicated that they had no co-movement. Gilmore and McManus (2002) concluded that US investors could benefit from including three selected European countries to achieve better diversification, because the US stock market was weakly correlated with the Central European markets.

However, the results showed that the emerging Asian stock markets had long-term relationships with global markets, except China, India and the Philippines. Mohti et al. (2019), using the detrended cross correlation analysis (DCCA) model, concluded that the emerging Asian stock markets were strongly integrated with global markets. On the other hand, they found that in the frontier markets, only the Pakistan stock market had a long-term relationship with the US and Japanese stock markets. The result indicated that the frontier market could generate bigger diversification benefits than emerging markets.

Within the international investment field, it is also popular for investors to combine their investments in stock markets in both developed and developing countries. Due to the different situations of these two kinds of countries, it seems that the opportunities for diversification occur more. Lessard (1973) found that the co-movement between developed countries was stronger than in developing countries. The result showed that there was large potential return in combining stocks in developed and developing countries. Saadi-Sedik and Petri (2006) concluded that the stock markets in the Arab area were cointegrated, which indicated that there was very little or no opportunity to achieve diversification by selecting these stock markets. Additionally, the results showed that the Jordanian stock market had no cointegration relationship with other emerging and developed stock markets. Therefore, it is wise to choose to invest in these two groups of markets to gain diversification benefits. Katircioğlu, Alkhazaleh and Katircioglu (2018) found that even though Jordan is a highly oil-related country, movement of the international oil price had no significant effect on its stock market.

Abbes and Trichilli (2015) investigated the potential diversification benefits between the Islamic stock market and some developed countries in the world, during both economically stable and unstable time periods. They found that the Islamic stock market was partially integrated with different economic groups and that they had a long-term equilibrium with similar economic groups. In the short term, there was no integration relationship between the Austrian Islamic market and the European Islamic market. They also found low levels of short-term integration between European–Asian, European–American and Latin–Islamic markets, which provided short-term diversification benefits. Furthermore, during the time period of the financial crisis, the Islamic stock markets were able to provide diversification benefits.

Jawadi, Jawadi and Cheffou (2018) analysed the oil market and the Islamic stock market, which could test the dependency of the Saudi Arabian oil market and investigate potential diversification opportunities for investment in the Islamic stock market. The authors stated that investment in the oil market and the Islamic stock market could provide a diversified portfolio with a higher return and reduced risk. The authors also found that when oil price shocks happen, the impact would not be immediately seen in the stock markets – there are some time lags in the response to the shocks. These findings provide investors with time to manage their portfolio and thus afford them some time benefits.

The higher the level of information availability and international investment, the more stock markets in the world are moving together. Zaimović and Berilo (2014) found that the German stock market, as a mature market, performed well before the financial crisis. In addition, combining the German stock market and the Bosnian stock market in order to achieve diversification would decrease risk during both the post- and pre-financial crisis periods. However, it seemed that both markets were hit by the crisis and that there was no opportunity to have a diversified portfolio by including these two stock markets during the financial crisis.

Al Nasser and Hajilee (2016) found that in the short term, emerging stock markets (Brazil, China, Mexico, Russia and Turkey) were integrated with developed markets (the US, the UK and Germany), which eliminates the diversification opportunity in the short term, while for the long-term investment, only the German stock market had a significant integration relationship with emerging stock markets, which means that other developed stock markets could combine with emerging stock markets to achieve diversification in long-term investments.

By using the generalized autoregressive conditional heteroskedasticity (GARCH) model on eight markets around the world, De Santis and Gerard (1997) tested the capital asset pricing model (CAPM) model. They found that changes in the US stock market had a widespread effect, especially the decline in the US stock market. The decline in the US stock market could lead to a total decline in the international portfolio. Moreover, they found that increasing the level of integration between these stock markets did not significantly change the returns of international portfolios.

Furthermore, Phylaktis and Ravazzolo (2005) and Driessen and Laeven (2007) both found that there appeared to be diversification benefits between developing and developed countries. The former researchers found that the Pacific Basin attracted more overseas investment from investors' portfolios, which might increase the integration level  and would eliminate diversification opportunities. However, they found that the US and Japanese markets had no significant influence on Pacific Basin stock markets, which generated the opportunity of gaining diversification benefits. In addition, for the latter group, after investigation of the US, European and Far East stock markets, they found that both in the long term and short term, they generated a large profit for international portfolios.

Gulf Cooperation Council (GCC) countries, like the OPEC countries, play an important role in the energy market. Akoum et al. (2012) stated that the GCC countries' stock markets had no significant short-term co-movement with oil prices, which provide diversification opportunities, while in the long term they had co-movement, which had no chance for diversification. Also, they indicated that the financial crisis could have enhanced the diversification benefits in the short term. Moreover, Al-Yahyaee and Mensi and Sensoy et al. (2019) found that during the financial crisis time period, energy markets and precious metal markets were correlated weakly with GCC countries' stock markets, which provided them with a choice to achieve diversification. They also indicated that commodities could offer a large reduction in risk. Furthermore, Mortaz (2019) stated that investing into different energy assets in the same geographical area could reduce risks. The result also showed that the larger the geographical area invested in, the better the portfolio.

Yarovaya and Lau (2016) investigated the diversification benefits of UK investors holding Brazil, Russia, India, China and South Africa (BRICS) and Mexico, Indonesia, South Korea and Turkey (MIST) stocks. They concluded that the UK stock market was integrated with the BRICS and MIST stock markets, apart from the Chinese stock market. They also indicated that the negative shocks from the UK stock market could influence the Brazil, South Africa and Mexico markets. Naser and Ahmed (2016) concluded that the reactions of the Brazil and India stock markets were negative to oil price shocks, while the Chinese stock market responded positively. Interestingly, at the beginning, the Russian stock market responded positively, but after four months this response changed to negative. Finally, the impacts of the shocks on the Chinese stock market were the smallest amongst the four countries studied. Mensi and Shahzad et al. (2017) investigated the relationship between BRICS countries and three developed stock markets (the US, the UK and Japan). They concluded that the Chinese stock market provided the largest risk reduction after the financial crisis. The authors also reminded the investors of the need to consider the time variation of diversification benefits when holding a diversified portfolio.

The results showed that the East Asian stock market had the same interdependent relationship with oil, while the Chinese and Japanese stock markets were weakly correlated with oil – Cai et al. (2017) concluded that this may be due to the Chinese government's influence and the strength of the Japanese economy. The results also showed that the combination of oil and stocks could reach a lower risk portfolio in the short term, while the portfolio diversification benefits decreased in the long term. All in all, the authors suggested that the combination portfolio of oil and East Asian stocks was a good choice in the short term to gain diversification benefits, while it was recommended for investors to invest in the long term.

Moreover, Islamic stock prices and the France, Indonesia, UK and US conventional stock markets were tested for their integration relationship, and it was found that all the markets had long-term relationships, except the UK and Islamic stock prices, which provided an opportunity to gain diversification benefits. In addition, Majdoub, Mansour and Jouini (2016) also concluded that the Indonesian market was weakly integrated with the developed stock markets in both conventional and Islamic stock prices, which provided diversification opportunities.

All the literature above analyses the diversification strategies among the selected markets' combinations. The idea of this section is to show the benefits of the diversified portfolio. The diversified portfolio is always accompanied with a lower risk when combining the same profitable ability. By using a diversification strategy, investors and portfolio managers can also understand which markets have the same movement trend, and which have the opposite movement trend. Therefore, it is important to understand the relationship between different financial markets. This can help investors and managers to create a diversified portfolio to reduce their risks, and it can also help them to gain more benefits and profits.

Diversification strategy is not only suitable for short-term investment, but can also be used for long-term investment. Developed countries (such as the US, the UK, and Japan) have been examined or tested many times and, based on the findings of these studies, it would be better or more appropriate to investigate other developing countries. Combining developed and developing countries may also be a choice for investors. It seems that the stock systems in developing countries are not complete, which means that they may not absorb global information as fast as developed countries. Also, the economies of developed countries are more likely to rely on local economic activities and local policies.

For the reasons described above, I aim to try and reach the conclusion that oil price changes can influence the relationship between different stock markets. This would help others to be more confident in their investments. Combining two or more markets that are not cointegrated is a good way to diversify a portfolio. The selected markets may or may not have a weak fluctuating trend with each other. Thus, it would help investors to avoid some events that may lead to the loss of all of their assets.

### *1.5.2 Oil prices and the stock market*

In this part, all the literature that analyses the oil prices and stock markets is collected. The selected literature states that oil price changes have some influence on different stock markets. To have a clear understanding of the influence of the changes of oil prices can help readers to have a better investment strategy. However, these articles mainly focus on the relationship between oil prices and stock markets. This can provide the first major contribution of this chapter – that the introduction of these articles could help readers to understand that this thesis tries to analyse the impacts of oil prices changes on the relationship between stock markets, which can help investors and managers to adjust their portfolio after various oil price changes.

Apart from oil price changes, the uncertainty of oil prices could also influence stock markets. Jones and Kaul (1996) and Sadorsky (1999) found that both oil prices and oil price volatility could influence stock markets. Sadorsky concluded that oil price shocks have a significantly negative influence on the stock market. This author also pointed out that a change in the price of oil has larger effects on economic activities than the other way round. Besides this, oil price shocks positively influence interest rates and industrial production. Therefore, the evidence shows that oil price shocks are important indicators of stock returns.

Masih, Peters and De Mello (2011) focused on the influence of oil price fluctuations and volatility on the emerging market in South Korea. The authors concluded that there were two influences on the Korean market: 1) oil price shocks increase the costs for some companies; and 2) firms make some changes in order to solve the problem that shocks might bring in the future. Both scenarios affect the stock market. Also, South Korea is highly reliant on fossil fuel sources, because of its fast industry development, and so its stock markets are influenced by the price uncertainties of these fuels. This would also apply to other developing countries that require a lot of these fuel sources to develop.

In addition, the hedging opportunities for the Asian stock markets (China and Japan) in regard to the energy risks (oil, gas and coal) are interesting points to investigate. Batten et al. (2017) concluded that the degree of the integration level is time-varying, and that the Asian stock market has become more integrated with global stock markets. However, the integration level between the Asian stock markets and the energy market changed as a result of the financial crisis. The authors concluded that the time-varying correlation between energy and stock could provide diversification benefits for investors and generate positive time-varying returns.

Moreover, Africa's emerging stock markets and advanced markets could also generate diversification benefits for the portfolio holder (Mensah and Alagidede, 2017). In addition, the authors claimed that the African stock markets would be a good choice to guard against any crises in advanced markets. However, if the investors or the portfolio managers not only combined Africa’s stock markets with advanced markets, but also combined the South African stock market with other African stock markets, this would lead to a reduction in diversification.

Raza et al. (2016) investigated the asymmetric effect of gold and oil prices and their volatilities on the emerging stocks’ prices. The reason why the authors tried to analyse the asymmetric effect was that cointegration could be initiated if positive and negative influences were cointegrated. The authors also employed a nonlinear ARDL (NARDL) model to analyse the asymmetric effect and structural break. The results showed that the impact of prices and volatilities on the stock market was nonlinear, which was asymmetric. The results also showed that gold and oil prices have a negative impact on their stock price in both the short and long term. Finally, the emerging markets were more easily affected and more vulnerable to the uncertainty of oil and gold prices.

The influence of the oil price changes on the stock markets could vary through time. Miller and Ratti (2009) studied six countries’ stock markets with reference to crude oil prices, from 1971 to 2008. They found that during 1971 to 1980, and from 1988 to 1999, they had positive and significant cointegrating coefficients. They also found that in the long term, the international stock market prices had an opposite trend on the oil price. Apergis and Miller (2009) indicated that the oil price structural shock had an influence on the stock markets and that the oil price changes had the power to explain the changes of the stock return adjustments.

The analysis of the GCC stock markets showed that the oil return predictability has changed in different periods (Fayyad and Daly, 2011). The price of oil was not predictable during the stable oil price period, but it was predictable in all countries except Kuwait and Bahrain during the period of the financial crisis. During the oil price boost and decline period, the stock markets of the GCC countries had bigger reactions to the oil price changes than the US and UK markets. Furthermore, the oil price shocks due to the financial crisis lasted for a long time. Arouri and Rault (2012) found that the GCC stock markets were cointegrated with fluctuations in oil prices. Increases in oil prices benefited all of the stock markets in this group of countries, except for Saudi Arabia.

In addition, Wong and El Massah (2018) aimed to investigate the causality relationship between oil price and the GCC countries, and to find out how long the GCC countries were able to absorb the oil price changes for. The results showed that the Kingdom of Saudi Arabia (KSA), UAE and Kuwait were significantly influenced by changes in the price of oil. The results also showed that the GCC markets could themselves affect the price of oil, which indicates that there are interconnections between oil prices and the stock markets of the GCC countries. In addition, the influence of oil price shocks or other stock market changes would immediately affect other members of the GCC group in the first week, but all of the influence would be absorbed by the market for the following 5–6 weeks.

The oil price changes could influence the behaviour of the stock market in the S&P 500 in the US. Chen (2010) tried to gather evidence to prove that higher oil prices would lead the stock market to turn into a bear market. The results showed that a higher oil price led to an increased possibility of pushing the stock market from a bull market to a bear market. In addition, Chen found some evidence to claim that the higher the oil price, the longer the time period that stock markets would stay in the bear market status, which proved his hypothesis that the high oil price has the power to turn the bull market into a bear market.

A new model called quantile-on-quantile (QQ) tests the relationship between oil prices and the stock market in the US. Compared to the OLS or quantile regression, the QQ model could combine the two benefits together to see how the oil price could influence the US stock market. First, Sim and Zhou (2015) concluded that a large negative oil price shock would lead to a positive effect on well-performing stock markets. Second, the authors concluded that a positive shock had a weak and insignificant influence on the stock markets, which showed that the relationship between oil prices and stock market returns was unequal.

The quantile-on-quantile (QQ) model is a new model created by Sim and Zhou (2015) to test the relationship between oil prices and the stock market. Sim and Zhou (2015) concluded that a large negative oil price shock would lead to a positive effect on well-performing stock markets. However, the positive oil price shocks have a weak and insignificant influence on the stock markets. Later, Tchatoka, Masson and Parry (2018) also used the QQ model to test the oil price shocks' influence on the main crude oil countries. They found that negative oil price shocks lead to a higher return in stock markets. In addition, they stated that the influence of oil price shocks also depends on the condition of the stock markets – whether they perform well or perform poorly.

Apart from the linear relationship between oil prices and stock market returns, nonlinearity also needed to be tested. Jimenez-Rodriguez (2015) identified that there are significant differences in the influence of oil price shocks between Canada, Germany, the UK and the US. When considering the linear condition, all countries except Canada had a significant negative relationship with the oil price. Under the nonlinearity condition, the increase in the price of oil had a negative influence on the stock markets of all four countries. Comparing these linear and nonlinear effects, nonlinearity would have a bigger impact on the stock market. Finally, the author stated that oil price shocks would have a bigger impact during stable time periods.

Narayan and Gupta (2015) revisited over 150 years of data from 1859 to 2013 in order to test the relationship between oil prices and stock returns, using four approaches, firstly, the authors would use the data for as long as possible. Secondly, they employed a time-series predictive regression model because it allowed persistent and internal oil price variables. Third, they employed the in-sample and out-sample variable together. Finally, they tested whether the oil price could predict US stock prices. The results showed that the US stock returns can be predicted, regardless of whether the oil price was positive or negative; however, a negative oil price had a better predictable power than a positive one.

Significant spillovers had been found between the crude oil market and the stock market when Ewing and Malik (2016) employed univariate and bivariate GARCH models that included structural breaks in the model. However, when the structural break was not considered, there was no evidence to support the spillover effect. In addition, the GARCH-jump model was employed in the study and showed that time-varying jumps existed in stock returns. In addition, Shahzad et al. (2018) claimed that the Islamic equity market could not escape being hit by the global financial crisis. However, the results showed that the oil market experienced higher risk than the Islam equity market, which led to a spillover effect. The results also showed an asymmetric effect in both the oil market and the Islamic equity market. Furthermore, spillover effects were not asymmetric from upside and downside quantiles when Wen et al. (2019) investigated the relationship between oil and the US stock market. However, the risk of the spillover effect had been strengthened, and had been more significant since the financial crisis.

Diaz, Molero and Perez de Gracia (2016) investigated the relationship between stock returns and oil price volatility in the G7 countries. The authors concluded that an increase in the oil price would lead to a negative impact on the stock market of these countries. The results also indicated that world oil price volatility is a better indicator of the stock market than the national one. Lee, Yang and Huang (2012) concluded that there was no Granger causality relationship between the oil price and G7 stock indices. However, the authors stated that the various individual industries were differently influenced by the oil price. At the country level, Germany was most affected, followed by the US and France. At the industrial level, the IT and consumer staples sector were most influenced by oil price shocks. The authors found that the influence was positive and the effects were larger and stronger from the stock market side, rather than the opposite way.

The investigation into the Chinese stock market showed that oil price shocks had significant positive influences on the market and five sector returns, which employed the CBOE crude oil volatility index (OVX) as the measure of oil price volatility (Luo and Qin, 2017). Moreover, Christoffersen and Pan (2018) found that after the financialisation of the commodity markets in 2004, oil volatility became a very useful variable to predict the future return of stocks, because oil price changes would influence the stock market economically, which therefore influences the economy of a country. They also concluded that oil price uncertainty was a strong variable to drive overall stock market prices.

In addition, the OVX could also be combined with the Chinese stock markets to examine how the Chinese market reflects the changes in oil prices, especially focusing on the asymmetric effects. Xiao et al. (2018) divided the OVX shocks into positive and negative. The results showed that OVX changes had an influence on the Chinese market. The unexpected changes in the OVX influenced the stock market negatively, and this was significant during the bear market period of the Chinese market. Also, positive OVX changes caused larger impacts on the stock market than negative ones. Therefore, there was an asymmetric effect. Finally, the reform in 2013 weakened the influence of the OVX shocks, which indicated that control from the Chinese government would help the Chinese stock market to weather any OVX shocks.

Dutta, Nikkinen and Rothovius (2017) implemented the adjusted GARCH model to investigate the effect of uncertainty of oil prices on the Middle East and African stock markets. The authors indicated that the OVX was a good predictor of the oil market. Applying the OVX also allows investigation of the transmission between different markets. The authors found that oil price uncertainty had a significant influence on half of the markets. In addition, the influence of this uncertainty was persistent, which proved that the stock return volatility was directly related to, and affected by, the previous information. Thus, the OVX played an important role in explaining returns and volatility.

An opportunity to gain diversification benefits had been found between the US, UK and Nigerian stock markets, because Oloko (2018) found that the correlation between these stock markets was low. Also, the results showed that the benefits would also appear during times of financial crisis. Oloko concluded that the high efficiency of the developed countries' policies led to a higher stock value when compared with pre-crisis time periods, while inefficient policies made the Nigerian stock value remain at the same level. Finally, the author suggested that the Nigerian government should enhance investors' confidence, which would help the Nigerian stock market to perform well.

Tursoy and Faisal (2018) examined the influence of gold and crude oil prices on Turkey's stock market. The main aim of this paper was to analyse the long-term equilibrium relationship between prices. By employing the ARDL and a combined cointegration test, the authors concluded that there was a negative relationship between oil and gold in the long term. They also found that the gold price had a negative relationship with stock prices, while oil had a positive relationship with stock prices, both in the short and long term. Moreover, the Granger causality test showed that stock prices and gold prices interacted. There was not, however, any evidence of Granger causality between stock prices and oil prices, which indicated that the oil market was a good choice to transfer assets to in order to avoid potential losses from the stock and gold markets.

Oil demand and oil supply changes can also influence stock market returns in the US. Kang, Ratti and Yoon (2015) found that positive aggregate demand shocks can negatively influence stock returns and volatility, and that this negative influence would last for several months. However, a sudden reduction in oil production would lead to a significant increase in stock returns and volatility that could last for 24 months. Furthermore, the implied covariance between stock returns and volatility has been bigger since the financial crisis of 2008.

Phan and Nguyen (2019) tested the predictability of Indonesia’s stock market. They stated that there is much published literature related to developed countries or emerging markets such as China, India and South Africa. Thus, the authors decided to target the Indonesian market in order to provide new evidence. They concluded that macro-economy factors have the ability to predict Indonesia’s stock market, especially the exchange rate. Also, the authors found strong evidence to support the fact that the composite, basic materials and financial indices could be predictable out-of-sample.

These literatures have mainly focused on the influence of oil price changes or oil price volatility on the stock markets and analysed the relationship between different stock markets. In common, these articles pointed out that changes in oil prices and uncertainty would affect the stock markets, especially for some developing countries and emerging markets. In addition, these articles showed that changes happening in one stock market would lead to a change in other stock markets. . Furthermore, some papers confirm that the oil price changes are influential on the oil- related companies. These papers are in common to state that the oil price changes are negatively correlated with the stock markets with different degree. For example, the influence of the oil price changes may influence the developing countries longer and heavier while for developed countries in a shorter time and less influential. This might because developed countries' government is more complete in management, and they have more experience on handle the oil price changes which makes them to take action in time to against the oil price changes. This raised the possibility that oil price changes may affect the relationship between different stock markets. This is also the gap that this thesis tries to fill.

Apart from the normal investigations into the relationship between oil prices and the stock market, there are many studies that have examined the relationship between them through different aspects. Many researchers would love to separate the oil price shocks into different categories, such as oil-demand shocks, oil-supply shocks or, even more specifically, oil-specific demand shocks and aggregate demand shocks. Researchers have also looked into the same oil price shocks' influence on oil-exporting and oil-importing countries. Furthermore, some studies have analysed the influence of the financial crisis on the relationship between the oil price and stock markets. However, the industrial level of the stock market and the specific sectors are other aspects to be considered in future studies.

#### *1.5.2.1 Different kinds of oil shocks*

There are different kinds of oil price shocks, such as general, oil-demand and oil-supply shocks: more specifically, oil-specific demand shocks and aggregate demand shocks. Different kinds of oil price shocks may have varying influences on individual stock markets.

Differently from the previous research, Abhyankar, Xu and Wang (2013) indicated that the rise in oil price is not always a bad influence on the Japanese stock market. The authors found that the demand-side oil price shock is positively correlated to Japanese stock returns. The authors also stated that a negative impact on the stock market is due to specific demand shocks, and that the effects do not change the expected return – the cash flow.

Cunado and Perez de Gracia (2014) examined the influence of oil price shocks on the stock markets of European countries from 1973 to 2011. The authors proposed different specifications that they could use to categorise the oil price shocks into either demand or supply shocks. They found evidence from some European countries that explained the relationship between oil price shocks and stock returns. The changes in oil prices or oil price uncertainty had a negative impact on the stock markets of the selected countries and the impact was consistent. It has also been emphasised that the reasons for oil price change mattered – the oil-supply shocks had greater negative effects compared to oil-demand shocks when these shocks lead to the oil price increase. Elian and Kisswani (2018) also proved that the supply-side oil price shocks had a negative impact on Kuwait stock returns. They also found that there is a long-term relationship between oil prices and the Kuwaiti stock market. The result also showed that the Kuwait stock returns had a bidirectional causality with the Brent oil price, while it only had a unidirectional causality with the West Texas Intermediate (WTI) oil price.

However, not all the supply-side shocks had large or influential impacts on the stock markets. Bastianin and Manera (2018) confirmed that supply-side shocks had no significant influence on volatility when they investigated the influence of oil price shocks on the volatility of the US stock market. They also stated that a positive aggregate demand oil shock would influence US stock market prices immediately, while an unexpected rise in the oil demand could also cause volatility to increase, but with a time lag.

The time-varying correlation was significant in both these markets (US and Chinese). In addition, Broadstock and Filis (2014) found that the US stock market was more sensitive to shocks than the Chinese, which showed a higher correlation between the US market and oil price shocks. The US market showed a positive relationship with aggregate demand shocks, but this was not echoed in China's market. In addition, the authors also indicated that the difference between the two markets may be due to the specialist policy of the Chinese market. Thus, when considering developing stock markets, investors need to be aware of local policies.

In the US, not only the different types of the oil prices can influence the stock markets, but also the uncertainty of policies. Kang, Perez de Gracia and Ratti (2017) concluded that when compared with oil supply-side shocks, the aggregate demand shocks had positive effects on the stock performance of oil or gas firms. Also, the influence of the oil-supply and oil-demand effect would be enhanced by the uncertainty of policies. In addition, policy uncertainty shocks would negatively affect market returns.

Ready (2017) employed a novel method to test the relationship between oil prices and the stock market. This study divided oil price changes into either demand or supply driven, believing that the demand- and supply-driven oil prices would have varying influences on different kinds of oil-related firms. The author found that oil-demand shocks (which defined as returns to an index of oil producing companies) had positive correlations with stock returns, while supply shocks had significantly negative correlations with stock returns. Ready concluded that those firms relying on oil input were significantly connected to oil-demand shocks, while those firms depending on consumer expenditure were connected to supply shocks. This study also suggested that holding oil-related stocks was not always harmful to oil price shocks.

Hu et al. (2018) employed the nonlinear ARDL to simultaneously investigate the long-term cointegration and the dynamic interactions integration between oil price shocks and the stock market. The authors claimed that oil price movement was mainly driven by the aggregate demand shock and the oil market-specific demand shock, in which supply shocks only contributed a little. Furthermore, the influence of the oil price shocks was insignificant in the long term in China's stock market. The authors stated that in the short term, only the aggregate demand shocks have an asymmetric effect on China's stock market, due to the positive and negative shocks. Finally, the results showed that the demand shocks caused by economic booms or crises could not be absorbed in the short term.

Both types of changes would influence stock returns in the US. Thorbecke (2019) found that supply-driven changes performed differently both before and after oil production changes in 2010. Before the global financial crisis, oil prices had a negative relationship with stock returns; this relationship was reversed after the recovery of oil production in 2010. This research also claimed that oil price was just one factor in the multi-factor asset pricing model. This author provided a different result that showed that oil prices did not always have a negative relationship with the stock market.

Melichar and Atems (2019) revisited the oil prices changes in the US that were caused by internal reasons between 2006 and 2015, and studied how these changes influenced commodity prices. In order to distinguish the different influences of the oil price shocks, the sample was divided into the earlier time and the late time, according to the 2006 renewable fuel policy. The authors found that over the whole sample period, the relationship between the oil-demand shocks and the commodity prices were significantly positive, while for the oil-supply shocks and the commodity prices the relationship was not significant. Before the 2006 policy was established, the evidence suggested that the aggregate demand oil price shocks would make the commodity prices rise. However, after 2006, the commodity prices were more sensitive to oil-specific demand shocks.

In this section, these articles have considered different types of oil price shocks to see how the different oil price shocks could influence the stock markets. Simply put, the oil prices shocks can be divided into supply-side and demand-side shocks. These two different types of oil price shocks have different influences on stock markets. Oil demand-side shocks always lead to a positive effect on the stock markets, while oil supply-side shocks always bestow a negative effect on stock markets. This provides potential for further study – that it is necessary to distinguish between the type of oil prices shocks in order to have a better understanding of their influences on stock markets.

#### *1.5.2.2 Oil-exporting and oil-importing countries*

Furthermore, not only various kinds of oil price changes can have different influences on the stock markets, but also, diverse kinds of countries will be affected in individual ways, such as oil-exporting and oil-importing countries. The same oil price changes may lead to multiple effects on different countries. Degiannakis, Filis and Arora

(2018) stated that the degree of the oil price shocks' influence differed between oil-exporting and oil-importing countries.

Park and Ratti (2008) analysed the influence of oil price shocks on the stock markets of the US and on 13 European countries from 1986 to 2005. By selecting more than one country, this study aimed to provide a better explanation and eliminate any country-specific effect. The results showed that oil price shocks had a significant influence on the stock market in the same month or the following month. It was also shown that the global oil price was a better variable to explain the influence of shocks. Within these 14 countries, Norway had a significant positive relationship between oil price shocks and stock markets and, with the exception of Norway and the US, there was no evidence to show an asymmetric influence of oil price shock on stock markets among oil-importing European countries.

Using the dynamic conditional correlation asymmetric GARCH (DCC-GARCH-GJR) model, Filis, Degiannakis and Floros (2011) examined the time-varying correlation between oil price and the stock markets of some oil-importing and oil-exporting countries. The results showed that there was no difference in the correlations between the stock markets and oil prices of oil-importing and oil-exporting countries. However, it was found that the correlation would change due to specific demand shocks, like war and financial crises. Nguyen and Bhatti (2012) found that oil price changes had different influences on an oil-consuming country (China) and an oil-exporting country (Vietnam), where Vietnam's stock market had a positive correlation with world oil prices, while the Chinese stock market did not show this.

Turkey, as a developing and oil-importing country, was sensitive to oil price changes. Berk and Aydogan (2012) found that oil price shocks only had significant effects after the 2008 financial crisis. In addition, when the authors added the financial liquidity condition into the model, both the oil price and the stock return were influenced. Wang, Wu and Yang (2013) concluded that oil price shocks had a greater impact on oil-importing countries than oil-exporting countries. They also found that the aggregate and precautionary demand shocks caused co-movement in the stock market only in oil-exporting countries. Pandey and Mayank (2019) found that in India, which is highly relres on the foreign crude oil supply, only the energy industry index was influenced by the oil shocks and global oil production. Also, the authors found that the domestic oil price in India was influenced by the supply side, while there was no evidence to suggest that oil demand would influence the price of oil in India.

Similar to Turkey, Mexico is also a highly oil-dependent country, where oil accounts for up to 11% of its total exports and constitutes 30% of the government's budget (Reyes and Benitez, 2016). Delgado, Delgado and Saucedo (2018) concluded that the Mexican exchange rate had a significant and negative influence on the stock markets. In addition, an increase in the price of oil would have a significant negative influence on the exchange rate and would also lead to a positive impact on the Mexican stock prices. This finding was due to the fact that the oil price increase would lead to an appreciation in the value of the peso, which would then generate a positive impact on the Mexican stock market.

Moreover, Mexico is not only a crude oil exporting country, but it also imports refined oil every year and, therefore, its economy is highly related to the price of oil. Singhal, Choudhary and Biswal (2019) also included the price of gold as another analysis target in order to observe the difference between oil and gold. The results indicated that an increase in the price of gold would benefit the stock market in Mexico, while an increase in the price of oil had the opposite effect. Also, changes in gold prices did not influence the exchange rate, while changes in oil prices had a negative impact on the exchange rate. These findings implied that the price of oil plays an important role within the Mexican economy, and this information could help portfolio managers and policy makers to consider the influence of oil prices when they make decisions.

Hamdi et al. (2019) employed quantile regression analysis (QRA) to test the relationship between oil price volatility and the sectoral stock markets of GCC countries. The reason why they chose the GCC countries was not only because the GCC countries were the main oil-exporting countries, but because these countries also differed from other countries, since they were affected by local policies that would lead to a different result. The chosen time period for this study – from 2006 to 2017 – included the post-Iraqi financial crisis and many oil crises. The authors concluded that oil price volatility has a different influence on the sectoral stock markets based on the level of these markets; for instance, the energy, industrial, financial and basic material sectors are positively related to oil price volatility. Furthermore, the authors concluded that in a bear market, the stock indices would sensitively react to oil price volatility compared to middle and high markets. Finally, in the long term, the GCC stock markets were predictable, which showed that the price of oil was integrated with the stock markets of the GCC countries.

In addition, oil-exporting countries were significantly influenced by the oil price shocks, especially the oil or gas firms in the markets. Basher, Haug and Sadorsky (2018) divided the eight oil price shocks into four categories: oil-supply shocks, oil-demand shocks, speculative oil-demand shocks and oil-market-specific idiosyncratic oil price shocks. The results showed that between these eight oil-exporting countries, shocks significantly influence the local stock markets, except for Mexico. Indeed, Mexico was not affected by either the demand-side shocks or the supply-side shocks. The authors mentioned that this was due to the fact that Mexico has no large oil or gas companies.

The oil price fluctuation could influence both oil-exporting and oil-importing countries. Sharma et al. (2018) investigated oil prices in relation to the Indian stock market, which was worth analysing in order to provide investors and policy makers with information about the oil price and its impacts on the Indian economy. The authors found that there was no cointegration relationship between the international crude oil market and the Indian stock market by using the cointegration test, which means that it lacked a long-term relationship. They also found that there would be a negative influence when a standard deviation shock occurs. Moreover, over a 12-week period, the negative effect of the standard deviation shocks stayed the same, while the impact of the oil price shocks increased as time passed.

Le and Chang (2015) examined three different characteristics of oil countries – oil-based, oil-import and oil-export economies. The authors also considered including a structural break during the 1997 to 2013 time period. The results showed that oil price shocks had a causal relationship with the three Asian stock markets. The Malaysia and Singapore stock markets showed positive reactions to the oil price shocks. Japan also responded positively, but not with significance. When the time period was divided into three, the authors found that Malaysia was affected negatively in the pre-financial crisis time period and that Japan experienced a negative impact during the post-financial crisis time period.

Ji et al. (2018) employed the SVAR and GARCH model to investigate the risk of spillover effects between three stock markets in the BRICS countries and their reactions to oil shocks. The authors divided the oil price shocks into three categories – oil-supply shocks, aggregate demand shocks and oil-specific demand shocks. In addition, the study would look into oil-exporting and oil-importing countries. The results showed that the relationship between oil price shocks and stock returns was time-varying, and usually it was positive. During the financial crisis period, the BRICS stock markets increased risks significantly, and risk spillover existed between stock returns, except for Brazil and India. Furthermore, the authors found asymmetric effects in the stock markets of Brazil, Russia and India.

Global events may have different influences on oil-exporting and oil-importing countries. Phan, Tran and Nguyen (2019) found that the uncertainty of crude oil prices has a negative and statistical forecasting power on corporate investment. This provided a guide to investors about the relationship between uncertainty and the stock market they invest in. In addition, the authors found that oil-exporting countries are more heavily affected by uncertainty than oil-importing countries. Meanwhile, the explanatory power of this uncertainty became less useful during the financial crisis period.

Moreover, the oil-exporting countries may not always benefits form a higher oil price. Fardmanesh (1991) found that the booming in oil price for five selected oil-exporting countries (Algeria, Ecuador, Indonesia, Nigeria and Venezuela) negatively influence the local economy. The increase in the oil price increases the oil revenues, the spending efforts and their world price level. However, the agricultural sector had been contracted and expand the manufacturing sectors. These negative influences of oil price increase were significantly in developing oil-exporting countries which highly rely on manufacturing and agricultural sectors.

In conclusion, not only the different types of oil price changes lead to different influences on stock markets, but also, different kinds of countries should be considered, such as oil-exporting and oil-importing countries. The results of these literatures showed that the influences of the oil price shocks are not significant in both oil-exporting and oil-importing countries. However, basically, the oil prices shocks have a negative influence on oil-importing countries and a positive influence on oil-exporting countries. This also suggests the potential for further investigation that might divide the objectives into two groups – oil-importing and oil-exporting countries.

#### *1.5.2.3 Other factors (exchange rates, financial crises and alternative energy)*

Last but not least, there are many other factors that could influence or be influenced by oil price changes. Like pre-, during and post- financial crisis time periods, the impacts of oil price changes may be different. Also, oil price changes may not only influence stock markets – they may also affect other macro-economic variables, such as output, exchange rates, and interest rates, which could have an indirect influence on stock markets.

By looking at the macro-economy, oil price shocks had a negative correlation with industrial production and employment, and this kind of influence can be quickly absorbed (Papapetrou, 2001). The results also indicated that positive oil price shocks have a negative influence on stock returns. Finally, the author pointed out that stock returns react negatively to interest rate shocks. Filis (2010) also found that the oil price and the stock market had significant positive influences on the Consumer Price Index (CPI) in Greece. The author also indicated that oil price shocks had a negative influence on the stock market, but a positive impact on industrial production.

Narayan and Narayan (2010) investigated the impact of oil prices on Vietnam's stock market. The results showed that stock prices, oil prices and the exchange rate had long-term relationships, and that they were cointegrated. This result was not, however, consistent with the theoretical estimations. It seemed that it was due to the increasing foreign investment and the change of local investment structure. This study therefore indicated that local impacts were more powerful than oil price shocks. In addition, Basher, Haug and Sadorsky (2012) employed the SVAR model to investigate the oil price, exchange rates and emerging stock markets. The results showed that in the short term, positive oil shocks would hit both the stock market and the US dollar exchange rate. Also, a sudden increase in emerging market economic activities would lead to an upward trend of the oil price, although this seemed to be a price bubble.

By mainly looking at the oil price influence on stock prices and returns, rather than production levels, Sadorsky (2001) employed the multi-factor market model to analyse the relationship between risks and the returns of oil and gas firms in Canada (which is the fifth largest oil-producing country in the world). The authors deployed the crude oil price, the exchange rate and the interest rate as the variables in order to investigate how oil and gas companies react to these changes. The results showed that the stock returns have a positive relationship with the price of crude oil. However, the exchange rates between Canadian and US dollars and the interest rates had negative influences on the stock returns. In addition, the authors found that Canadian oil and gas stocks were less risky than the stock market, which was not a recommended choice to guard against inflation.

Different industries may be influenced in various ways by oil price shocks. Elyasiani, Mansur and Odusami (2011) investigated the four types of oil-related industries in the US stock market, which contains 13 different sectors, for their reactions to oil returns and oil returns’ volatility changes. The authors stated that it was important to figure out the macro-economic factors’ influence on stock returns. The authors found strong evidence to claim that oil price fluctuation caused systematic risks in the stock market at the sector level, and they also concluded that various types of oil-related sectors had different effects. The authors also found that the variance of the return was time-varying, and that the influence of the oil shocks had a high durability.

In addition, the condition of the stock markets – like bear or bull markets – could be influenced differently by oil price shocks. Zhang and Liu (2019) indicated that international oil price shocks have a stronger influence on the bear market than the bull market, and that the shocks are driven by the oil supply and aggregate demand. Also, oil supply shocks influence high energy-consuming industries more than others. The oil aggregate demand shocks influence the cyclical industries the most. Thus, it is necessary for investors to consider this relationship when they create a portfolio.

Ono (2011) found that apart from Brazil, the other countries in the BRICS all had significant positive reactions to oil price indicators. In addition, only India demonstrated asymmetric effects from oil price shocks. Also, the Russian and Chinese cases showed that oil price shocks influenced volatility in stock returns, while the other two countries had no statistical evidence for this. Mensi et al. (2018) investigated the long- and short-term movement between oil and gold prices with the BRICS stock markets. The authors concluded that the test could confirm that the oil price and the stock indices of the BRICS had strong co-movement and that this relationship had been strengthened since the 2008 financial crisis. However, there was no evidence to support the gold price having co-movement with the stock indices of the BRICS, and the authors suggested that the gold market was, therefore, a good choice to avoid loss during the financial crash time period.

In addition, stock markets are not only influenced by the oil price; they are also affected by interest rates, exchange rates, industrial production and inflation. Al-hajj, Al-Mulali and Solarin (2018) employed the nonlinear ARDL model and found that all of the sectors in Malaysia's stock market were cointegrated, except for the plantation sector. Using the ARDL model, all of the sectors in the stock market were shown to have responded negatively to the oil price, except the aggregate stock. This indicated that Malaysia's stock market was easily influenced by oil price changes. For the rest of the variables considered, an increase in the interest rate and inflation would have a negative impact on the stock market. Either increasing or decreasing the exchange rate would negatively influence the stock market. Finally, the authors concluded that in the long term, an asymmetric relationship existed between these variables.

Different sectors may be influenced by the oil price shocks in various ways. Narayan and Sharma (2011) proved their four hypotheses. To begin with, oil price shocks have a different influence on the various sectors in the market. In addition, the influence of oil price shocks would not appear in the market immediately, because there is a time lag. Moreover, only six sectors proved the threshold effect, and the difference was due to the turnover rate. Finally, both the small and large firms have a significant relationship with oil price; however, the relationship changes from positive to negative as firm size grows.

In Chinese markets, oil price shocks are also influenced differently in the various respective sectors and industries. Cong et al. (2008) concluded that oil price shocks have an insignificant influence on most stocks in the Chinese market. However, for the manufacturing index and oil firms, their return increases after oil price shocks, compared to other indices and other industries. Meanwhile, oil-related companies – such as mining and petrochemicals – are directly influenced and their prices will increase due to rises in the price of oil. The authors did not find any evidence to support an asymmetric influence between the selected companies.

Moreover, Nandha and Faff (2008) investigated the influence of oil price movement on global equity prices. The analysis of 35 global indices showed that the relationship between oil prices and stock returns was negative, with the exception of mining, oil and gas firms. These results supported the previous literature, which stated that the relationship between them was negative. This study also suggested that international portfolios should consider including some oil-based stock in order to hedge the oil price risk. However, the authors also found some evidence to support asymmetric effects between the global indices and equity prices.

Arouri (2011) indicated that the influence of the oil price changes on the different sectors was diverse in Europe, and if this was only investigated at the market level then it might hide some serious consequences for individual sectors. In addition, the structure of European countries was varied. German and French markets, for instance, are mature and include a number of different sectors, while small countries like Switzerland may only include a few different industries in the market. The results showed that nine out of 12 sectors had significant reactions to the oil price shocks– six sectors (including healthcare and financial) responded negatively to the shocks, while the oil and gas, basic materials and consumer services sectors responded positively to the shocks. In addition, the results showed that oil price shocks have an asymmetric effect on European stock markets.

Moreover, when dividing the influences at the industrial level or national level, the influences may be different. Mohanty et al. (2011) also found that oil price shockshad a positive relationship with the stock markets of GCC countries at the country level. At the industrial level, only 12 of the 20 sectors were positively influenced by oil price shocks. The authors also stated that asymmetric effects on the stock market occurred both at the country level and at the industry level. Later in 2018, Mohanty, Onochie and Alshehri (2018) found that there was a significant positive relationship between oil price shocks and stock returns, which occurred at an aggregate and industry level. The authors also concluded that an increase in oil revenue would raise the government spend, which could help to boost the economy in Saudi Arabia. On the other hand, the low oil price would lead to a slow development of the Saudi Arabian economy, which was a negative impact.

Li, Zhu and Yu (2012) tried to fill the gap in the relationship between oil prices and stock markets at the industrial level in China's stock market. The results showed that oil price increases have a significant and positive influence on industrial stocks in the long term. The authors argued that this phenomenon was because other influential factors have a stronger effect than oil prices. Based on the Granger causality test, the results showed that Granger causality only appeared in the long-term relationship between oil prices and the stock market – in the short term it was unidirectional. Thus, the authors suggested that the Chinese stock market could become a hedging target against the rising trend of the price of oil.

However, there was no significant linear relationship between the Islamic composite index and the oil price shocks, neither in the short term nor the long term (Badeeb and Lean, 2018). In addition, the authors found a nonlinear relationship between them by using the NARDL method. In the short term, the Islamic stock market reacted positively to changes in the price of oil, while the relationship turned negative in the long term. The authors also concluded that various sectors had different sensitivities to changes in the oil price, suggesting that investors should choose basic materials, oil and gas when oil prices increase, and consumer goods when oil prices decrease.

Huang, Huang and Wang (2018) used the Brent oil price and the different sector stock indices from Morgan Stanley Capital International to test the length of the indices response to oil price changes. The results showed that diverse sectors responded to oil price shocks in different time periods. The authors concluded that in the short term, all of the sectors tended to have a similar coherence relationship with the price of oil. However, in the long term there was a lead-lag effect. In addition, the results also showed that the transportation, utilities and consumer discretionary sectors lagged behind other sectors. Due to this lagging effect, there was an opportunity to hedge risk by using the various response times of the different sectors.

Not only financial crises could have an influence on the relationship between oil prices and stock markets, but also some other non-financial factors could affect it, such as war and terrorist attacks. Filis, Degiannakis and Floros (2011) concluded that during such times, the correlation between oil price and stock market returns was negative and had been strengthened. However, during financial crises or boom periods, the correlation was positive. The results also suggested that the oil market was not a wise choice for diversifying investment portfolios or for hedging risk by reducing stock market losses during periods of financial crisis. Also, Aloui, Nguyen and Njeh (2012) investigated 25 emerging markets and claimed that the global beta market had a negative relationship with emerging market returns during the financial crisis period, which indicated that it was an opportunity to add emerging stocks into portfolios to hedge the risks.

Moreover, Nusair and Al-Khasawneh (2018) investigated the effect of oil price shocks on the stock markets of GCC countries by using quantile regression analysis. The authors allowed the structural break caused by the global financial crisis during the sample period and tested the asymmetric effects of the positive and negative oil price shocks on the stock market. The results showed that positive oil price shocks were more powerful during bull market periods, while negative oil price shocks were stronger during bear market periods. In addition, there were asymmetric effects.

Finally, the authors suggested that there was co-movement between the oil market and the stock markets of the GCC countries because they were increasing and decreasing together.

The 2008 financial crisis significantly influenced some relationships between oil markets and stock markets. Managi and Okimoto (2013) found that after the 2007 structural break, the relationship between oil price and clean energy switched to a positive relationship. Also, the authors mentioned that there was a similar reaction when the technology stock price was applied. In addition, Tsai (2015) examined the response of the stock returns before, during and after the financial crisis. The author then used the data of 682 US firms, and the results showed that before the financial crisis, firms of all sizes were negatively affected by oil price shocks, especially large firms. However, both during and after the crisis, medium-sized firms were positively affected by the shocks. The results also showed that there was an asymmetric influence of both positive and negative shocks during and after the financial crisis period.

Moreover, investigating the nonlinear cointegration of the price of crude oil and the Indian stock market could eliminate some structural break problems. Ghosh and Kanjilal (2016) found that the test rejected the equilibrium relationship between the price of oil and the Indian stock market for the whole sample period. By using the threshold cointegration tests, the authors found that there was only a cointegration relationship in Phase III, which was the post-2009 time period. This finding also suggested that the Indian stock market's structure has changed since 2009. In addition, the authors suggested that for long-term investment, the Indian stock market was not a wise choice with which to diversify portfolios. Moreover, the results showed that the increase in the price of oil would not directly transfer to the stock market. It would lead to a financial deficit first, because the import cost would increase, then it would affect the stock market. Thus, the oil price would still influence the stock market, but indirectly.

In addition, Ali, Azmi and Khan (2019) examined the time-varying relationship between oil prices and the disaggregated stock market in India. The authors stated that there were time-varying relationships between oil prices and the stock market.

Before the 2007–2008 financial crisis, the oil price and the stock market were not correlated, which was of benefit for diversification. However, positive correlation began after the crisis and eliminated the chance of gaining benefits because of diversification. Also, Ferreira et al. (2019) concluded that many indices were weakly correlated with the oil price before the financial crisis. However, the correlation was strengthened after the financial crisis and, in addition, the relationship became positive. There was a co-movement phenomenon, which means that the increase in the price of oil led to a higher stock return.

It is widely believed that changes in oil prices would influence alternative-oil firms and that an increase in the price of oil would benefit these firms. Thus, Henriques and Sadorsky (2008) aimed to investigate how sensitive the alternative-oil firms are to changes in the price of oil. Based on the result of the Granger causality test, the authors concluded that the oil price changes could explain the movement and reaction of the stock prices of the alternative energy companies. The other results also indicated that oil price changes had no significant influence on the alternative energy firms. However, the shocks of technology stock prices had a bigger power to influence the stock price of alternative energy stock, which provides a guide to investors and managers to help them make better investments.

Kumar, Managi and Matsuda (2012) focused on alternative energy stocks, which provide various options to replace oil use. The authors also took technology stocks into consideration because technology firms were sensitive to changes in energy prices. The results showed that the three clean energy indices selected had positive relationships with the price of oil – when the oil price increases, so does the clean energy stock return.

Reboredo (2015) employed copulas to investigate the relationship between oil prices and renewable energy stocks. The author hoped that this would provide a complete result of the movement trend of oil prices and stocks, and determine whether they were dependent or independent of each other. This research aimed to fill the gap left by the previous literature, which was mainly focused on the average effects of oil price changes on renewable energy stocks. Reboredo stated that there was co-movement between the price of oil and renewable energy stock prices, because they were increasing and decreasing together. This is because a rise in the price of oil would help the development of the renewable energy industry. Reboredo also suggested that green policy makers needed to consider the relationship between the price of oil and the renewable energy industry.

Benkraiem et al. (2018) investigated the relationship between the S&P 500 stock index and some energy prices (WTI, gasoline, heating, diesel and natural gas). The authors tested the quantile cointegration relationship between them, and also aimed to identify any asymmetric effects and nonlinear relationships, both in the short term and the long term. First, the authors found that the short-term relationship between the WTI oil price and the S&P 500 was negative. Second, they found that natural gas and WTI crude oil are substitutes for each other, and it seemed that natural gas had become more and more important in the market due to its often-higher predictability. The authors also mentioned that it was good for investors to look at oil-substitute assets in order to hedge the risk of oil price shocks.

The results of examining the volatility spillovers and co-movements between oil prices and the stock prices of major energy firms from 2001 to 2016 showed that the volatility of oil price was time-varying and correlated with gas and oil firms (Antonakakis et al., 2018). In addition, oil price volatility was influenced by firm-level volatility. Finally, the authors concluded that the optimal portfolio weights strategy is better than the optimal hedge ratio strategy, which would be more effective in reducing risks and diversifying, because the optimal portfolio strategy did not differ in the three time periods.

It was widely believed that this sector is very easily affected by changes in the price of oil. However, Pal and Mitra (2019) found that the price of oil and the automobile stock price have a co-movement trend, and that the movement was significant during the 2000–2002 and 2006–2009 time periods. These findings go against the original belief that the oil price has an opposite movement with the automobile industry. Thus, the authors disagreed with the suggestion of combining the oil and automobile markets to achieve diversification during financial crisis time periods. The authors suggested instead that investors need to be aware of sudden changes in the global financial situation.

There are also many other factors that can influence the stock markets. Managi and Okimoto (2013) stated that the financial crisis led to a structural break between the oil price and stock markets. Also, alternative energy can influence the effects of oil prices on the stock markets. The lower the alternative energy costs, the lower the competitiveness of oil, which then influences the stock markets. In addition, diverse industrial sectors can be influenced differently by the stock markets, and the size of the firms also needs to be considered. Moreover, the changes of the exchange rate also matter, and this could also influence the stock markets. Further study can also take more factors into consideration and see each effect on the stock markets.

### *1.5.3 Summary of the Literature Review*

The literature reviewed above confirms that oil prices influence stock markets around the world; this has been investigated by exploring the relationship between oil prices and stock markets. Papapetrou (2001), Mohanty et al. (2011) and Singhal, Choudhary and Biswal (2019) indicated that oil prices could affect countries' economies. Therefore, it is necessary and important to have a better understanding of the relationship between oil prices and stock markets.

The literature can be divided into different topics and discussions. First, Filis, Degiannakis and Floros (2011), Badeeb and Lean (2018) and Benkraiem et al. (2018) pointed out and agreed that oil price shocks had a negative impact on stock markets in the selected sample. However, Managi and Okimoto (2013), Pal and Mitra (2019) and Ali, Azmi and Khan (2019) contended that the 2008 global financial crisis reversed the relationship from negative to positive, which was a sign to investors that they needed to adjust their investment strategy to adapt to the new situation. Additionally, Le and Chang (2015) and Wen et al. (2019) said that the financial crisis enhanced the negative relationship. Thus, this chapter tries to obtain a sample, including the financial crisis period, to see how the financial crisis influenced the impact of the oil price on the relationship between stock markets.

In addition, demand and supply oil price changes may have different influence on stock markets. Furthermore, the same oil price shocks may have diverse impacts on different types of countries, such as oil-importing compared to oil-exporting countries, and developed countries compared to developing countries. Melichar and Atems (2019) agreed that the oil demand price shocks had significant impacts on stock markets, while the influence from the oil supply shocks was not significant. Thus, this chapter is going to investigate which OPEC countries are the main oil-exporting countries, and which economies are highly reliant on the oil price, because oil prices influence the volume of oil exports and the uncertainty of the oil price may affect the macro economy in these countries, and thus, ultimately, lead to changes in the stock market. The OPEC countries that could maximise the influence of the oil price on the stock markets are the countries that will be selected.

Papapetrou (2001), Filis (2010), Al-hajj, Al-Mulali and Solarin (2018) and Thorbecke (2019) found that the oil price has a negative relationship with the stock market, while Kumar, Managi and Matsuda (2012), Reyes and Benitez (2016) and Ferreira et al. (2019) suggested that oil price changes have a positive influence on the stock markets. Also, Papapetrou (2001), Guo and Kliesen (2005), Elyasiani, Mansur and Odusami (2011) and Phan and Nguyen (2019) studied the influence of some macroeconomic variables' influence on the stock markets, such as interest rates, exchange rates and the growth of GDP. Therefore, this chapter studies this area further. The main aim of this chapter is using the oil price as a condition to figure out how will the oil price changes influence the relationship between different stocks markets. First, this chapter including the comparing group of OPEC countries and three economical top-performing countries which have not been done before. It is worthy to take consideration on the OPEC which is the main oil exporting organization in the world. Second, choose the oil price changes as a condition to investigation the relationship between different stock markets is a method to help investors and policy makers to have a better understanding how important the oil price changes to the stock market. It will help them to have a better strategy on based the fluctuation of oil prices.

The findings of this chapter will benefit researchers and investors, so that when they want to investigate the relationship between different stock markets, oil price is also an important variable that needs to be considered. It is worth considering the influence of the oil price when investing in either oil-exporting or oil-importing countries, because oil price changes will influence the relationship between these two kinds of countries. Moreover, the analysis will also benefit policy makers; they should also pay attention to the oil price changes, as they influence national production and the earnings of firms. The makers of policy can then establish some relevant policies to help guard against times when large oil price changes occur. This will help them to reduce potential losses or gains due to oil price changes.

## 1.6 **Data and methodology**

### *1.6.1 Data description*

This chapter investigates the relationship between the stock markets of four OPEC countries (Ecuador, Nigeria, Saudi Arabia and the United Arab Emirates) and three economically high-performing countries (the US, the UK and Japan), and the influence of oil price changes on their relationships. The reason why I chose the OPEC countries is because the OPEC countries have played an important role in the oil markets since the 1950s. As Penrose (1979) stated, the emergence of OPEC has diversified oil production in the world, which has in turn reduced the control of the oil supply to make the oil price decline and to meet the price competition between countries. The aim of the OPEC countries has been to combat the controlling power of the US from 1912, when oil was discovered in Oklahoma. Also, Loderer (1985) found that OPEC countries had the power to influence the oil price by their actions and announcements. Starting from five countries, OPEC now has 14 members, and is the main oil exporting organisation in the world. OPEC's decisions on oil producing, exporting or cooperation with other countries influence the oil price, which then spreads influence to financial markets.

Even now, the US is still a net oil exporting country, even though it imports a large amount of oil. Much research has investigated the relationship between oil prices and the US economy and stock markets, which emphasise the importance of oil price effects on the US economy. Thus, I select the US stock market (the S&P 500 index) as a research object, because the US has played an important role since 1912, when they found oil in Oklahoma. In addition, including the US stock market is an appropriate comparison with other countries, which will make the result more reliable and more convincing.

The UK and Japan, both high-performing economies, are both net oil importing countries. Therefore, changes in the oil price will influence the profitability of firms, leading to changes in earnings, which will ultimately be reflected in the financial markets. Adding these two top economies to this chapters' research is useful in order to make a good comparison with the US. First, these three countries are oil importing countries. Second, including the UK and Japanese stock markets can create a contrast with the US stock markets and generate more complete results. When combining the research with that of OPEC countries, there will be two groups of countries – oil exporting and oil importing countries. By selecting these two groups, I can investigate the influence of the oil price on their stock markets, which also provides an opportunity to investigate the influence of the oil price changes on their relationships.

As for the oil price, I have chosen to use the WTI (West Texas Intermediate) and Brent spot oil prices. After the Oklahoma oil was found, it was first set as the West Texas Intermediate oil price benchmark. It then became the leading world oil price benchmark. Thus, the WTI spot oil price has been selected for investigation, as has the Brent oil price, which is contrasted with the WTI price, because these two oil benchmarks are designed for different areas. The Brent oil price benchmark was originally designed for the European markets, but now it extends to Africa. Therefore, the two oil prices will be used to test the relationship between oil prices and stock markets. Due to their benchmarks relating to different areas, the analysis results of these two kinds of oil price benchmarks may be different. The difference in the results can provide suggestions for researchers and investors when they choose to study and/or invest in different stock markets, and the advice can help them to choose which oil price benchmark should be included.

All the data for the indices were collected from Investing.com or the local stock market exchange and Thomson Reuters' Datastream. The oil prices were collected from Datastream, from 29/06/2001 to 01/10/2019. The reason why I chose this time period is because the data availability of OPEC that I can access is from 29/06/2001, and I want to study the whole time period of the stock markets. All the frequency of the data is on a daily basis. During this time period, the oil price has experienced several periods of increases and decreases, and this time period also includes the 2008 financial crisis. This will provide data on how during different oil price changes time periods, the oil price changes can influence the relationship between stock markets. In addition, because of the financial crisis, the world economy was hit heavily, possibly destroying the original relationship. This time period will therefore provide contrasting results.

However, not all the OPEC countries' stock market data are available during this time period. Iraq, for example, has incomplete records, so all the lifetime data that is possible to gather will be collected. For Saudi Arabia, the data have been collected from 1998 to 2019; for United Arab Emirates, the data have been collected from 2001 to 2019; for Ecuador, the data have been collected from 2012 to 2019; for Nigeria, the data have been collected from 2012 to 2019. Therefore, the data will be set into two analysis groups to see what relationship exists between these stock markets and oil prices.

For the single regression model, I will use all the available data to run the regression with two oil prices. This will provide results including the entire available data to see what relationship exists between stock markets and oil prices. Second, for Saudi Arabia, the United Arab Emirates, the UK, the US and Japan, I will divide their data into three time periods: pre-financial crisis, during the financial crisis and post-financial crisis (the 2008 financial crisis). This can generate a clearer result to show whether there appeared to be a structural break or not.

Then, in the second step, for the VAR model, the group includes Ecuador and Nigeria, Saudi Arabia, the United Arab Emirates, the UK, the US, Japan, the WTI crude oil spot price and the Brent crude oil spot price. The time period for this group is from 2012 to 2019. In the group, all the data will be bounded into different sets. For example, in the first group, one OPEC country, one economically top-performing country and one oil price will be allocated into one set – like Ecuador, the UK and the WTI crude oil spot price. The second set can be Ecuador, the UK and the Brent crude oil spot price. The rest of the sets follow in the same manner. In addition, all the stock markets and oil prices are combined to run the cointegration test to see the cointegration relationship between all these stocks and oil prices.

Table 1 Example of the data set in the first group

| Group 1 | OPEC countries' index | Top countries' index | Oil spot price |
|---|---|---|---|
| Set 1 | Saudi Arabia stock market index | UK stock market index | Brent oil spot price |
| Set 2 | Saudi Arabia stock market index | UK stock market index | WTI oil spot price |
| Set 3 | Saudi Arabia stock market index | US stock market index | Brent oil spot price |
| Set 4 | Saudi Arabia stock market index | US stock market index | WTI oil spot price |
| Set 5 | Saudi Arabia stock market index | Japanese stock market index | Brent oil spot price |
| Set 6 | Saudi Arabia stock market index | Japanese stock market index | WTI oil spot price |

## *1.6.1 Methodology*

### *1.6.1.1 Single regression model*

At the very beginning of the methodology part, the single regression model will be employed to test the linear relationship between the oil and stock markets. An explanation of a classical linear regression model can be found in Asteriou and Hall (2015). The regression model can provide an equation between two variables – for example, oil price changes and the stock market indices return. The results of the single regression model can tell us about the relationship between these two variables, such as whether it is positive or negative. It will not provide the causation relationship that will provide the correlation information. Therefore, for this method, I try to get the correlation relationship between oil price changes and oil price returns. For the single regression model, it simply provides the relationship between two variables. One considered as a dependent and the other variable assumed to be independent to figure the relationship between these two variables. The relationships can be defined by the coefficient of the parameters. In addition, the variance of the residuals is homoscedasticity. Furthermore, there is no autocorrelation. The benefit of the single regression model is that this model is simple and it can provide relationship between two variables by one coefficient between them. However, this model only considers the two variables themselves without consider any other influence and it also require the residuals are normally distribution.

I will regress each stock market return against two oil prices separately. After regressing each group of data, I can get a series of results to see these relationships between stock market returns and oil prices. The result can generally provide information on the relationship between stock indices and oil price changes – whether they are positive or negative.

First, the single regression model will be applied, which is written as:

$$Y_i = \alpha + \beta X + u_i \,, \quad i = 1,2,3 \ldots \tag{1}$$

where $Y_i$ stands for the indices return of the countries selected, $X_i$ denotes the oil price return and $\beta$ stands for the sensitivity of the indices reacting to the change in oil prices. $\beta$ also provides the relationship between oil price returns and stock market indices returns. If $\beta$'s value is negative, the relationship between them is negative. This also means that for an increase in the oil price return, it would highly probably lead to a decrease in the stock market return. The $\alpha$ denotes the coefficient and the $u_i$ represents the disturbance, which is assumed to have a normal distribution.

The formula will then be written in a different style and the changes of the indices and the oil price will be used thus:

$$r_{i,t} = \hat{\alpha} + \hat{\beta}_i x_t \tag{2}$$

where $r_{i,t}$ and $x_t$ represent the changes of the indices and oil price is represented from t-1 to t, respectively. All the variables in this step are assumed to be independent and identically distributed.
In the single regression model, the oil price and stock market indices will not be used directly. They will be calculated as the return for each day. The changes will be computed as follows:

$$r_{i,t} = \log y_{i,t} - \log y_{i,t-1} \quad (3)$$

where $y_{i,t}$ is the stock index i or oil price i at time t and the $y_{i,t-1}$ presents the index and oil price at time t-1. The $r_{i,t}$ represents the returns of the stock index price return and the oil price return. The reason why to use the log return in this chapter is because the log return is better than the simple returns. The log return can have additive returns over time while the simple returns cannot. For example, if first year return for year one is 50% and for year two is -50%, the simple return for two year is 0 while the log return is -25%. The log return can reflect the real return for the oil prices.

At the end of the simple regression model, I will get a series of results that can simply explain the correlation relationship between each stock market selected and two kinds of oil prices. The aim of doing the simple regression model is to find the correlation relationship between them, which provides the first results of what relationship exists between them. I expect to get the result that in the whole time period, oil prices are positively correlated with the OPEC stock markets' indices and negatively correlated with the three top stock markets' indices. In addition, during the financial crisis, oil prices had a positive relationship with all the stock market indices. After doing the single regression model test, then the cointegration test and the VAR model will be employed.

### *1.6.1.1 Cointegration model*

#### *1.6.1.1.1 Cointegration test*

In order to empirically solve the relationship between the OPEC countries and the economically high-performing countries, this chapter technically and basically focuses on the correlation analysis and the cointegration analysis. The cointegration techniques that will be used to analyse the data will be in the spirit of those used by Saadi-Sedik and Petri (2006), who when using the cointegration test found that the Amman Stock Exchange (ASE) is cointegrated with Arab stock markets but not cointegrated with other emerging or developed stock markets. In addition, the cointegration test is widely used in financial analysis, such as by Sharma and Giri (2018). They found that there is no cointegration relationship between the oil market and the Indian stock market. The existence of cointegration will imply a long-term relationship between the stock markets. The cointegration test will be used to investigate the long-term relationship between oil prices and stock markets' indices, and between OPEC stock markets' indices and economically high-performing countries' stock market indices.

Cointegration test is a method to investigate the relationship between two or more variable in the long-term (which is defined as over one year in this chapter). If the tested variables are co-integrated, which states that these variables have long-run relationship between them, and their individual movement cannot deviate from the equilibrium. This will help the readers to have a better understanding of the relationship between oil prices and stock markets, which provide them a guide to manage their portfolio. Bahmani-Oskooee and Nasir (2004) and Natsiopoulos and Tzeremes (2022) applied the autoregressive distributed lag (ARDL) approach to test the cointegration which the ARDL approach can skip the process of unit root test and it can apply to the variables that are integrated of different order of I(1) and I(2) in a small sample size while the variables cannot be I(2). In addition, this model requires that there is no autocorrelation between error terms. Granger, Huang and Yang (2000) applied Gregory and Hansen two stage model to consider the structural breaks which fail to deal within the Engle-Granger cointegration test. Moreover, this chapter employs Johansen cointegration test, this method allows to have more than one cointegrating relationship between examining variables. Also, it does not need to choose the dependent variables, where Mostafavi (2012) found that results from Johansen approach is more real and close to theory comparing to ARDL approach.

At the end of the cointegration test, the result will demonstrate whether the relationships between oil prices and stock indices or among stock indices are long-term relationships or not. It is very important for the chapter to do the following test and to provide evidence for Hypothesis 2. I believe that the oil price changes or fluctuations influence the relationships between stock markets. Thus, in the following test, when adding the oil price into the stock markets indices set, this can provide evidence of the relationship between two stock market indices and oil prices.

As a brief explanation of the Johansen method of cointegration (Johansen, 1991), the following equation defines a k-vector of non-stationary **I**(1) variables $X_t$ (stock market price indices) and assumes the vector has a VAR representation of the form:

$$X_t = A_1 X_{t-1} + \cdots + A_p X_{t-p} + \varepsilon_t \tag{4}$$

where $\varepsilon_t$ is a vector of innovations. The above equation can be reparametrized as follows:

$$\Delta X_t = \prod X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta X_{t-1} + \varepsilon_t \tag{5}$$

The rank of Π, taken from Equation 5, indicates the number of cointegrating relationships that exist between the variables (the stock markets). Based on the value of the rank, the cointegration technique demonstrates a long-term relationship between the oil-producing economies' stock markets and the developed economies' stock markets.

There are three possible results or outcomes for the rank value:

1. Zero rank: Π could have a rank of zero (r = 0), which implies that all residuals are non-stationary and that there is no long-run cointegration between the stock markets. This finding would imply that the OPEC countries and the economically high-performing countries have no relationship. Thus, it would be wise for investors to include these stock markets together to reach diversification.

2. Full rank: Π could be full rank (r = k), which implies that all residuals are stationary only because all variables are I(0). Thus, none of the variables are integrated and so cannot be cointegrated. Hence, a long-run linkage, from the

perspective of cointegration, would not be feasible, because cointegration first requires that all variables are integrated. If the variables are not integrated, then it is implausible for them to be cointegrated.

3. Partial rank: Π could have a rank value between 0 and k ($0 < r < k$), where k is the number of variables in the model (in this case, it is the number of stock markets whose interlinkages are the subject of analysis). In this context, a rank between 0 and k implies that the OPEC stock markets are cointegrated with the stock markets of the top three economies. If they are cointegrated, then they might be driven by similar stochastic trends that bind them together and prevent them from moving too far away from one another. The higher the value of the rank, the lower the number of stochastic trends, and thus the more interlinked, intertwined or cointegrated the stock markets. Such a turn of events would provide evidence that some long-term relationships exist between the stock markets. In addition, if $r = k-1$, then this suggests that the markets are perfectly and completely integrated, and thus they are driven by the same stochastic trend and are generally not distinguishable from each other from the perspective of diversification.

In this chapter, the Johansen Cointegration test is employed to test the cointegration between different variables. Apart from this cointegration test, there still have Engle-Granger two-step method and Autoregressive Distributed Lag (ARDL) cointegration technique. Comparing to the Engle-Granger test, the Johansen test can avoid the issue of choosing the dependent variables. In addition, the Johansen test allows for investigating into more than one cointegrating relationship among all the variables. It also requires a large sample size where the small sample size led to unreliable results.

Stata will be used to do the cointegration test in this chapter to show whether the variables selected in this study are cointegrated. It also includes the hypotheses in this test. For the rank 0, the null hypothesis is that there is no cointegration relationship between all of the variables, and the alternative hypothesis is that the variables are cointegrated. For the rank 1, the null hypothesis is that there is one cointegration relationship amongst all of the variables, and the alternative hypothesis is that there is more than one cointegration relationship amongst all of the variables. The hypotheses for the rest of the ranks are done in the same manner.

With regard to the results provided by the Stata, the trace statistics and the max statistics should be checked. The comparison of these two statistics with the 5% critical value informs the decision on whether to reject the null hypothesis. If the value of the trace statistics is larger than the critical value, then the null hypothesis is rejected and the alternative hypothesis is accepted. The null hypothesis cannot be rejected when the value of the trace statistics is smaller than the critical value.

Whether these stock markets are cointegrated with oil prices can be simply concluded based on these results. If they are cointegrated then this means that they have a long-term association relationship, or they display the same trend in the long term. If it is shown that there is no cointegrated relationship between them, then they have different movement trends. In the former situation, there would be no diversification benefit to including all of these stocks in an investment portfolio; however, there would be a diversification benefit by including the stocks for the latter situation in investment portfolios.

The cointegration test is not, however, enough to explain the relationship between oil prices and all of the stock markets included in the thesis. If it is proven that there are cointegration relationships, then the vector error correction model (VECM) model will be employed to further examine the findings. If they are not cointegrated, then the unrestricted VAR model will be used to investigate further.

*1.6.1.1.2 Lag length selection and unit root test*

It is very important to confirm the lag length before doing the unit root test. I will include two lag length criteria to identify how much lag I will use. They are the Akaike information criterion (AIC) and the Bayes information criterion (BIC), which are the most common lag length selection criteria. AIC is a type of the lag selection in the measurement of goodness of fit of the estimated model. BIC selected models with different numbers of parameters. BIC has a larger penalty for additional parameters than AIC. In addition, AIC is better at making asymptotically equivalent to cross validation while BIC is suit for consistent estimation. I will then decide how many terms to go back when doing the autoregression process. The lower lag will be chosen to do the further test. This is also necessary in order for me to go for the unit root test.

For the unit root test, I will employ the augmented Dickey-Fuller (ADF) test to test the null hypothesis of a unit root of a time series sample. If the value of the ADF is negative, the larger the negative number, the higher the probability to reject the null hypothesis of a unit root. This can help me to identify the time series data in which lag order is stationary or non-stationary. Thus, by confirming that all the time series are non-stationary $I(1)$, then the cointegration test can be run. Based on the result by Dicky and Fuller (1979), the Dickey-Fuller test can start with a AR(1) model:

$$y_t = \rho y_{t-1} + u_t \tag{6}$$

where $y_t$ is the variable of oil price return or stock market indices return, $\rho$ is the coefficient, and $u_t$ is the white noise.

Then, the regression model can be written as following:

$$\Delta y_t = (\rho - 1) y_{t-1} + u_t \tag{7}$$

where Δ is the first difference operator and $u_t$ is the white noise. The test for unit root is to test the value of $\rho$. The null hypothesis is $H_0$: $\rho = 1$ equivalent to a unit root that fail to reject $H_0$.

By glazed at the later version of augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979 and Granger, Huang and Yang 2000), the ADF test can be employed as equation below:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + (\rho - 1)\Delta y_{t-1} + (\rho - 1)\Delta y_{t-2} + \cdots + (\rho - 1)\Delta y_{t-p+1} + u_t \tag{8}$$

In addition, the equation can be written as:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + (\rho - 1) \sum_{p=1}^{k} \Delta y_{t-p} + u_t \tag{9}$$

where $\alpha$ is a constant, $\beta$ is the coefficient with time trend and $p$ is the lag order of autoregression process, $\Delta$ is the first difference operator and $u_t$ is the white noise. Same as the Dickey-Fuller test, the null hypothesis is $H_0$: $\rho = 1$ and $y_t$ is said to have a unit root when failing to reject $H_0$.

#### *1.6.1.2 Error correction model and vector error correction model*

In order to investigate the cointegration relationship between the OPEC countries and the economically high-performing countries, the error correction model (ECM) will be employed to identify the true relationship. Badeeb and Lean (2018) used the unrestricted error correction model (UECM) to test nonlinear cointegration between oil prices and the stock market. Their research inspired the use of the ECM in this chapter.

The basic VECM will be used to test the relationship between oil prices and stock indices. This will identify the short- and long-term relationships between the variables.

By using the VECM and VAR models, I can identify what causation relationship exists between them. The result of the VAR model will generate a series of results that can explain how one variable in the test can be explained by other variables in the model. In this chapter, I will put two stock market indices and one oil price into one group set. Thus, there will be 20 data sets. Each set contains one of the OPEC countries, one of the economically high-performing countries and one of the oil prices. Each data set will be run through the VAR model. The result will provide three equations to explain what relationship exists among these variables.

At the very beginning, the model is set within the two variables of a long-run equilibrium relationship:

$$Y_t = KX_t \tag{10}$$

where $Y_t$ stands for the value of the indices and $X_t$ represents the oil price. This is the single long-term equilibrium between indices and oil price. Then, taking the lag version of Equation 10, it is extended further:

$$y_t = k + x_t \tag{11}$$

where the lower-case $y_t$ and $x_t$ represent the lag version of the indices and the oil price.

Within the ECM, the basic model should be set as follows:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \alpha_1 y_{t-1} + u_t \tag{12}$$

In Equation 12, $x_{t-1}$ and $y_{t-1}$ represent the lag value of the oil price lag return and the stock indices lag return at time t-1, $u_t$ is the error term and $\beta_0$, $\beta_1$, $\beta_2$ and $\alpha_1$ are the coefficients. When $y_{t-1}$ is removed from both sides, the equation is as follows:

$$y_t - y_{t-1} = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \alpha_1 y_{t-1} - y_{t-1} + u_t \tag{13}$$

Simply:

$$\Delta y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t \tag{14}$$

The left-hand side $\Delta y_t$ is the change of $y_t$. To complete the ECM, the change of the $x_t$ needs to be inserted into the right-hand side of the equation. Then, on the right-hand side, plus and minus $\beta_1 x_{t-1}$ is inserted, which becomes:

$$\Delta y_t = \beta_0 + \beta_1 x_t - \beta_1 x_{t-1} + \beta_1 x_{t-1} + \beta_2 x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t \tag{15}$$

Simply:

$$\Delta y_t = \beta_0 + \beta_1 (x_t - x_{t-1}) + (\beta_1 + \beta_2) x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t$$

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + (\beta_1 + \beta_2) x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t \tag{16}$$

It can also be written as:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t - (1 - \alpha_1)(y_{t-1} - \frac{(\beta_1 + \beta_2)}{1 - \alpha_1} x_{t-1}) + u_t \tag{17}$$

Equation 17 completes the ECM at the basic two variables because it contains the short-term and long-term equilibrium within one equation. The very first part of this equation is $\Delta y_t = \beta_0 + \beta_1 \Delta x_t$, which states the short-term relationship between them. The changes of one variable would lead to the changes of the other variable, assuming that $\gamma_1 = 1 - \alpha_1$ and $\gamma_2 = \frac{(\beta_1 + \beta_2)}{1 - \alpha_1}$. The $\gamma_1(y_{t-1} - \gamma_2 x_{t-1})$ is the error correction term that is similar to Equation 11, $y_t = k + x_t$. It is also suggested that these variables are cointegrated, which means that they have long-term relationships. In the long term, therefore, the changes of $x_t$ plus the error correction term could achieve long-term equilibrium.

Stata will be used to run the test, and the result will directly provide the coefficient and standard error. The result could also be used to define the long-term and short-term causality between the two variables by simply comparing the probability with the 5% significance value – if it is less than the 5% value then there is a significant long-term causality between the variables.

In addition, the coefficient and stand error of the lag value could be considered by comparing the probability of the result with the 5% significance value. If the value is less than 5%, it means that there is a short-term causality between the variables. Otherwise, there is no short-term causality.

Equation 17 would be re-written to:

$$\Delta y_t = \beta_0' + \beta_1 \Delta x_t - (1 - \alpha_1)(y_{t-1} - \beta_2' x_{t-1} - \varepsilon_{t-1}) + u_t \tag{18}$$

This part of Equation 18, $y_{t-1} - \beta_2' x_{t-1} - \varepsilon_{t-1}$, can be regarded as the error correction term:

$$ect_{t-1} = y_{t-1} - \beta_2' x_{t-1} - \varepsilon_{t-1} \tag{19}$$

Furthermore, it is necessary to test the linear hypothesis to confirm the short-term causality. By doing this, the null hypothesis that the coefficient is equal to zero is tested. At the same time, the probability will be identified, which could then be compared to 5%. If the probability is greater than 5%, it means that I cannot reject the null hypothesis and that the independent variables have no power to explain the changes of the dependent variables.

The single ECM will test each pair of variables in a bidirectional way, which would help to identify whether one variable is more influential than another. It could also help to identify whether the impacts of these variables are bidirectional or unidirectional.

After running the single ECM, the VECM will be employed to test more than two variables at the same time. Consider a VAR with h lags:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_h y_{t-h} + \epsilon_t \tag{20}$$

where $y_t$ stands for a K × 1 vector of variables, $v$ represents a K × 1 vector of parameters, $A_1 \sim A_h$ is the K × K matrices of parameters and $\epsilon_t\ (0, \Sigma, \mathrm{iid})$ is K × 1 disturbances. Equation 16 is then re-written into the VECM, which is:

$$\Delta y_t = v + \Pi y_{t-1} + \sum_{i=1}^{h-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{21}$$

where $\Pi = \sum_{j=1}^{j=h} A_j - I_k$ and $\Gamma_i = -\sum_{j=i+1}^{j=h} A_j$.

Doing the same tests in Stata, but with more than two variables, will give the coefficient and stand error of each parameter. The conclusions of the long-term and short-term relationships between the cointegrated variables can then be inferred by analysing the results.

### 1.6.1.3 Vector autoregression model

The VAR model is one of the most popular and most flexible models in financial analysis. As Henriques and Sadorsky (2008) indicated, one of the advantages of the VAR model is that it does not need to identify which variables in use are internal or external, which means that all of the variables are dependent on the lagged value. The VAR model – as explained by Wong and El Massah (2018) – is employed in this chapter.

To investigate the relationship between stocks and oil prices, the methodology is set up as follows:

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + u_t \tag{22}$$

where $'Y_t = (Y_{1,t}, Y_{2,t}, \ldots\ Y_{n,t})'$ denotes a time-series variable vector $(k \times 1)$ and $t = 1, \ldots, T$. Also, $(k \times 1)$ and $\Pi_i$ are coefficient matrices, $c$ is a $(k \times 1)$ vector of white noise with a zero mean and $\sum$ is a covariance matrix. In this chapter, $Y_t$ represents the value of oil price returns and stock indices returns. This is the method used to identify the short-term causality, and it creates two sets of variables. The first data set includes all of the variables collected in order to identify any short-term relationships between them. The second set of data contains all of the variables that are not cointegrated, which means that they have no long-term relationships.

When considering the two-dimensional vector of $Y$, the VAR(1) can be shown as follows:

$$Y_t = \begin{pmatrix} Y_{1,t} \\ Y_{2,t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 \\ \pi_{21}^2 & \pi_{22}^2 \end{pmatrix} \begin{pmatrix} Y_{1,t-2} \\ Y_{2,t-2} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} \tag{23}$$

where $cov(u_{1,t}, u_{2,t}) = \sigma_{12}\ for\ t \neq s$.

The lag operators can be written as the univariate autoregressive (AR) process:

$$\Pi(L)Y_t = c + u_t \tag{24}$$

where $\Pi(L)Y_t = I_n - \Pi_1 L - \cdots - \Pi_p L^p$.

In addition, the general form of the VAR(p) can be written as:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \Theta X_t + u_t \tag{25}$$

where $X_t$ represents an exogenous variable matrix of $(m \times 1)$, and $\Theta$ represents a parameters matrix.

Similar to the VECM, the unrestricted VAR model will also be run using Stata. The results will provide a set of coefficient, stand error and probability, which differs from the VECM model. For example, if there were three variables included in the test, then the results will show the relationships between each variable by testing each as the dependent variable. This means that the test will generate three equations to explain the relationship of each variable.

The results will show the explanatory power of each lagged value of the variables included. The calculated probability will then be compared with the 5% significance value. If the value is less than 5%, then it means that the lagged value of this variable is significantly explaining the dependent variable in this equation. Otherwise, it is not significant in explaining the dependent variable.

After doing the very first test, each different variable will individually either have the dependent variables explained or not explained. Then, the joint short-term causality will be tested using Granger causality tests. Therefore, the Granger causality tests should be involved. Thus, this test will provide results that can identify the causality relationship between the variables being studied.

If there exits the cointegration relationship between these variables, there should exist the Granger Causality between them, for example running from $x_t$(oil price) to $y_t$(stock indices) or from $y_t$ to $x_t$.
In the first step of Granger Causality test, we should set and involve two variables, oil price returns ($x_t$) and stock index returns ($y_t$). Then we can have the equation for these two variables:

$$y_t = a_0 + \alpha_{1,i} y_{t-1} + \alpha_{2,i} y_{t-2} + \cdots + \alpha_{1,k} y_{t-k} + \epsilon_{y,t} \tag{26}$$

$$x_t = \beta_0 + \beta_{1,i} x_{t-1} + \beta_{2,i} x_{t-2} + \cdots + \beta_{1,k} x_{t-k} + \epsilon_{x,t} \tag{27}$$

The equation and equation can be written as below:

$$y_t = a_0 + \sum_{i=1}^{k} \alpha_{1,i} y_{t-i} + \epsilon_{y,t} \tag{28}$$

$$x_t = \beta_0 + \sum_{i=1}^{k} \beta_{1,i} x_{t-i} + \epsilon_{x,t} \tag{29}$$

where in these two equations, the null hypotheses are $H_0: \alpha_{1,1} = \alpha_{1,2} = \cdots = \alpha_{1,k} = 0$ and $H_0: \beta_{1,1} = \beta_{1,2} = \cdots = \beta_{1,k} = 0$, respectively and failing to reject the hypotheses indicate that there is no granger causality relationship.
In addition, the unrestricted Granger Causality test is shown as below:

$$y_t = a_0 + \sum_{i=1}^{k} \alpha_{1,i} y_{t-i} + \sum_{i=1}^{k} \alpha_{2,i} x_{t-i} + \epsilon_{y,t} \tag{30}$$

$$x_t = \beta_0 + \sum_{i=1}^{k} \beta_{1,i} x_{t-i} + \sum_{i=1}^{k} \beta_{2,i} y_{t-i} + \epsilon_{x,t} \tag{31}$$

Similar as the restricted Granger Causality test, the null hypothesis is $H_0: \alpha_{2,1} = \alpha_{2,2} = \cdots = \alpha_{2,k}$, failing to reject the null hypothesis implies that the oil price returns does not Granger cause stock index returns while failing to reject $H_0: \beta_{2,1} = \beta_{2,2} = \cdots = \beta_{2,k}$ indicates that stock index returns does not Granger cause oil price returns.

In addition, the linear hypotheses test could be used to look at a specific variable in the equation. In the linear hypotheses test, the null hypothesis is that the coefficient of the lagged independent value is equal to zero. If the probability is less than 5%, then the null hypothesis is rejected. If they are not zero, then they are significant in explaining the dependent variable.

At the end of the VECM and VAR models, I will get a series of result sets of the stock market indices. Each result set provides three equations in which each equation explains how the two variables can explain the third variable. By analysing the equation and other variables, such as stand error and probability, I can conclude that when adding the oil price into consideration, this will either change the relationship between stock indices or not. In addition, the result can also explain to what extent the oil price will influence the relationship between the stock indices. Moreover, by comparing all the results, I should get the result about which oil price has more power to explain which set of stock market indices, and this will also provide evidence to prove the second hypothesis.

## 1.7 Results

### *1.7.1 Single regression model result*

In this part, two groups of data will be tested to get the single regression model. The reason why there are two is due to data availability and the financial crisis. The first group is like an event study that includes the 2008 financial crisis. Thus, the data are collected for a longer period than the second group, which can totally cover the 2008 financial crisis period. Also, the periods before the financial crisis and after the financial crisis are equal in length. For the second group, all the selected stock indices will be tested together.

### *1.7.1.1 Single regression result of the first group*

In this part, the indices of the Saudi Arabia stock exchange (TASI), the United Arab Emirates stock exchange (ADX), the US stock market (S&P 500), the Tokyo stock market (TOPIX) and the UK stock market (FTSE 100) will be tested by the single regression model. The first group includes two OPEC countries stock markets' indices (TASI, ADX), three stock markets' indices (S&P 500, TOPIX, FTSE 100) and two oil spot prices (WTI, Brent). All the indices' data have been collected from 29/06/2001 to 01/10/2019. All the data have been collected from Thomson Reuters Datastream. Also, the WTI crude oil spot price and the Brent crude oil spot price have been collected from Datastream, from 29/06/2001 to 01/10/2019. In addition, all the data will be collected from 29/06/2001 to 04/01/2016 to test the changes of the linear relationship due to the financial crisis. The date set of the financial crisis is from 03/10/2007 to 31/07/2009. Before the date 03/10/2007 is the pre-financial crisis time period and after the date 31/07/2009 is the post-financial crisis time period.

Table 2 shows the single regression results of these five indices regressed with the WTI and Brent crude oil spot prices, starting from 29/06/2001 and ending at 01/10/2019. All the data (the percentage changes of each collected data) are assumed to be i.i.d (independent and identically distributed). Based on this result, it is clear to see that all the indices have a positive relationship with two oil prices, for which all the coefficients are positive. It also shows that Brent crude oil has a relatively stronger influence on these indices compared to WTI crude oil. The result shows that the FTSE100 index is the highest index correlated with two crude oil prices, while ADX is the lowest index correlated with crude oil prices. It is clear to see that for the whole period, the positive relationship between oil prices and stock markets' indices is significant where the p-value is less than 0.01.

Table 2. Regression model of five indices with WTI and Brent crude oil spot prices

| | ADX | TASI | S&P500 | TOPIX | FTSE100 |
|---|---|---|---|---|---|
| Panel A : With WTI | | | | | |
| Coefficient | 0.0355 | 0.0584 | 0.0823 | 0.0524 | 0.1206 |
| Standard error | 0.0082 | 0.0090 | 0.0076 | 0.0081 | 0.0068 |
| R-square | 0.0039 | 0.0089 | 0.0241 | 0.0088 | 0.0625 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Panel B : With Brent | | | | | |
| Coefficient | 0.0496 | 0.0905 | 0.1035 | 0.0696 | 0.1353 |
| Standard error | 0.0089 | 0.0097 | 0.0069 | 0.0087 | 0.0073 |
| R-square | 0.0064 | 0.0181 | 0.0448 | 0.0132 | 0.0669 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Notes: Data have been collected from 29/06/2001 to 01/10/2019. All the data are using percentage changes to run the regression model as in equation (1). In the single regression model, the percentage changes of the stock markets' indices are the dependent variables, while the percentage changes of oil prices are the independent variables.

Table 3, 4 and 5 presents the regression result of these five indices from 29/06/2001 to 04/01/2016, a period that contains the 2008 financial crisis. The data sets have been divided into three time periods: pre-financial crisis, during the financial crisis and post-financial crisis. I chose the time period from 03/10/2007 to 31/07/2009 as the financial crisis time period. The pre-financial crisis time period is started from 29/06/2001 and the post-financial crisis time period is ended at 04/01/2016. The pre-financial crisis and post-financial crisis time periods have the same time length.

It is easy to see that the financial crisis has its influence on the relationship between the oil price and stock market indices under the single regression model. Before the financial crisis, the coefficients of the results are relatively small compared to the time periods during the financial crisis and after the financial crisis. The 2007/2008 financial crisis enhanced the correlation level between the oil price return and the stock market indices return. From all these tables, even after the financial crisis, there is no set coming back to the correlation level before the crisis.

The results show that the Brent crude oil price is correlated closer with the four indices than the WTI crude oil price, except in the S&P500 case, and when the Brent is considered as the dependent variable, it shows that the financial crisis leads to a heavy influence on the relationship between its price and the stock markets.

Within these five indices, the ADX, TASI, FTSE100 and TOPIX indices show that their correlation relationship started to recover to its original level before the crisis at the post-time period. The Japanese stock indices had the largest recovery. However, for the S&P500 case, their relationship become closer after the financial crisis.

Table 3. Regression model of five indices with WTI and Brent crude oil spot prices (pre-financial crisis)

| | ADX | TASI | S&P500 | TOPIX | FTSE100 |
|---|---|---|---|---|---|
| Panel A : With WTI | | | | | |
| Coefficient | 0.0216 | 0.0036 | -0.0116 | 0.0250 | 0.0100 |
| Standard error | 0.0126 | 0.0186 | 0.0111 | 0.0128 | 0.0121 |
| R-square | 0.0018 | 0.0000 | 0.0007 | 0.0023 | 0.0004 |
| p-value | 0.0860 | 0.8470 | 0.2940 | 0.0520 | 0.4090 |
| Panel B : With Brent | | | | | |
| Coefficient | 0.0085 | 0.0154 | -0.0166 | 0.0168 | -0.0015 |
| Standard error | 0.0127 | 0.0188 | 0.0111 | 0.0129 | 0.0121 |
| R-square | 0.0003 | 0.0004 | 0.0013 | 0.0010 | 0.0000 |
| p-value | 0.5000 | 0.4120 | 0.1360 | 0.1930 | 0.9040 |

Notes: Data have been collected from 29/06/2001 to 04/01/2016. All the data are using percentage changes to run the regression model. In the single regression model, the percentage changes of the stock markets' indices are the dependent variables, while the percentage changes of oil prices are the independent variables.

Table 4. Regression model of five indices with WTI and Brent crude oil spot prices (during the financial crisis)

| | ADX | TASI | S&P500 | TOPIX | FTSE100 |
|---|---|---|---|---|---|
| Panel A : With WTI | | | | | |
| Coefficient | 0.0621 | 0.1057 | 0.1488 | 0.1109 | 0.2070 |
| Standard error | 0.0363 | 0.0272 | 0.0264 | 0.0261 | 0.0224 |
| R-square | 0.0061 | 0.0309 | 0.0629 | 0.0366 | 0.1524 |
| p-value | 0.0880 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Panel B : With Brent | | | | | |
| Coefficient | 0.1215 | 0.1677 | 0.1299 | 0.2521 | 0.2521 |
| Standard error | 0.0430 | 0.0319 | 0.0318 | 0.0265 | 0.0846 |
| R-square | 0.0165 | 0.0550 | 0.0339 | 0.1598 | 0.1598 |
| p-value | 0.0050 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 5. Regression model of five indices with WTI and Brent crude oil spot prices (post-financial crisis)

| | ADX | TASI | S&P500 | TOPIX | FTSE100 |
|---|---|---|---|---|---|
| Panel A : With WTI | | | | | |
| Coefficient | 0.0371 | 0.0901 | 0.2019 | 0.0437 | 0.1849 |
| Standard error | 0.0119 | 0.0134 | 0.0113 | 0.0152 | 0.0116 |
| R-square | 0.0058 | 0.0265 | 0.1602 | 0.0049 | 0.1326 |
| p-value | 0.0020 | 0.0000 | 0.0000 | 0.0040 | 0.0000 |
| Panel B : With Brent | | | | | |
| Coefficient | 0.0501 | 0.1422 | 0.1938 | 0.0796 | 0.2541 |
| Standard error | 0.0136 | 0.0150 | 0.0132 | 0.0173 | 0.0127 |
| R-square | 0.0081 | 0.0507 | 0.1134 | 0.0125 | 0.1924 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

### *1.7.1.2 Single regression result of the second group*

In this part, the indices of the Saudi Arabia stock exchange (TASI), the United Arab Emirates stock exchange (ADX), the Ecuador stock exchange (ECU), the Nigeria stock exchange (NSE), the US stock market (S&P 500), the Tokyo stock market (TOPIX) and the UK stock market (FTSE 100) will be run through the single regression test. The second group includes four OPEC countries' stock markets indices (TASI, ADX, ECU, NSE), three economically high-performing stock market indices (S&P 500, TOPIX, FTSE100) and two oil spot prices (WTI, Brent). All the indices' data have been collected from 03/01/2012 to 01/10/2019. All the data have been collected from Thomson Reuters Datastream. Also, the WTI crude oil spot price and the Brent crude oil spot price have been collected from Datastream, from 03/01/2012 to 01/10/2019.

Table 6 includes two more OPEC countries' stock indices, but with a shorter time period due to the data availability. I can see from Table 6 that except for the ECU and the NSE, all the other indices are significant under the 10% significance level. In addition, compared to the results in previous secter, it seems that the influence of the financial crisis had been weakened. This is because the coefficients became smaller in the time period during the financial crisis. The same changes in the oil prices have a smaller influence on these indices.

Table 6. Regression model of five indices with WTI and Brent crude oil spot prices

| | ADX | TASI | ECU | NSE | S&P500 | TOPIX | FTSE100 |
|---|---|---|---|---|---|---|---|
| Panel A : With WTI | | | | | | | |
| Coefficient | 0.0384 | 0.0644 | -0.0074 | 0.0156 | 0.1128 | 0.0206 | 0.1071 |
| Standard error | 0.0094 | 0.0108 | 0.0053 | 0.0103 | 0.0080 | 0.0124 | 0.0084 |
| R-square | 0.0082 | 0.0174 | 0.0010 | 0.0011 | 0.0888 | 0.0014 | 0.0748 |
| p-value | 0.0000 | 0.0000 | 0.1600 | 0.1310 | 0.0000 | 0.0960 | 0.0000 |
| Panel B : With Brent | | | | | | | |
| Coefficient | 0.0562 | 0.1160 | -0.0028 | 0.0177 | 0.0999 | 0.0576 | 0.1477 |
| Standard error | 0.0103 | 0.0117 | 0.0058 | 0.0113 | 0.0090 | 0.0136 | 0.0090 |
| R-square | 0.0146 | 0.0466 | 0.0001 | 0.0012 | 0.0577 | 0.0089 | 0.1179 |
| p-value | 0.0000 | 0.0000 | 0.6330 | 0.1190 | 0.0000 | 0.0000 | 0.0000 |

Notes: The four values in each vertical line represent coefficient, standard error, r-square and p-value.

Jimenez-Rodriguez (2015), Kang and Ratti et al. (2017) found that oil price changes lead to a negative influence on the developed countries’ stock markets. However, this chapter shows that the developed countries’ stock market indices have positive relationships with oil price changes. Even though the results show that in the pre-financial period, the three economically high-performing countries’ stock markets indices are negative, the values of the coefficients are insignificant. Abbes and Trichilli (2015) found that the financial crisis could yield some diversification benefits. However, the results indicate that a financial crisis leads to a closer relationship between oil price changes and indices, which cannot offer diversification benefits during a financial crisis.

### *1.7.2 Cointegration test and the VAR model result*

For the cointegration test and the VAR model, only the second group of data will be included to run the test. The reason for this is due to the availability of the data collected. In this part, this chapter tries to take all the data into consideration. Therefore, only the second group will be considered. In order to have a relatively long period and more stock market indices included, only the second group will be tested by the cointegration test and the VAR model. The unit root test is based on the Augmented Dickey–Fuller (ADF) test, in which a null hypothesis is: ‘the data series has a unit root against the alternative hypothesis of stationary’. For all the variables in this section, they are all calculated as logarithmic return. One of the benefits to using the log return rather than normal prices or indices is that the log returns provide a more stationary time series data. Moreover, the log version returns

can eliminate the non-stationary of the original data series, indicating I(0), which also approved by Granger, Huang and Yang (2000) on exchange rate.
The next step is to run the Johansen cointegration test. Each set of the data tested includes one OPEC country and one economically top-performing country. For instance, ADX and S&P500 is a data set. Therefore, there are 12 data sets.

Tables 7-9 are the results of the VAR model by using the combination of the ADX, three economically top-performing countries' indices and two spot oil prices. All the data are collected from Datastream and came from the same period. All the data used in the VAR model are calculated as its difference, which is calculated by the difference of their log value. In addition, all the coefficients of the VAR models are using p-value to see whether they are significant or not. 'a' means that these variables are significant at 1%, 'b' and 'c' present 5% and 10%, respectively. This can help us to see whether adding the oil prices as a condition will change the explanation power of one index to another.

Table 7. VAR results of ADX and S&P500 with WTI and Brent

| VAR | ADX(-1) | ADX(-2) | SP500(-1) | SP500(-2) | Constent |
|---|---|---|---|---|---|
| ADX | 0.0195* | 0.0551*** | 0.2171 | -0.0255* | 0.0261 |
| SP500 | 0.0449** | 0.0000* | -0.0148* | -0.0499*** | 0.0422 |
| ADX(WTI) | 0.0115* | 0.0535*** | 0.1934 | -0.0437** | 0.0301 |
| SP500(WTI) | 0.0420*** | -0.0017* | -0.0146* | -0.0629 | 0.0435 |
| ADX(Brent) | 0.0126* | | 0.2069 | | 0.0281 |
| SP500(Brent) | 0.0359** | | -0.0127* | | 0.0429 |

Note: The collected values in the table are coefficients. The superscripts ***, ** and * stand for the rejection of the null hypothesis at 1%, 5% and 10%.

Table 8. VAR results of ADX and FTSE100 with WTI and Brent

| VAR | ADX(-1) | ADX(-2) | FTSE100(-1) | FTSE100(-2) | Constent |
|---|---|---|---|---|---|
| ADX | 0.0092* | 0.0417** | 0.1554 | 0.0539*** | 0.0323 |
| FTSE100 | 0.0587 | -0.0226* | -0.0167* | -0.0309* | 0.0126 |
| ADX(WTI) | 0.0031* | 0.0423** | 0.1260 | 0.0463** | 0.0347 |
| FTSE100(WTI) | 0.0549 | -0.215* | -0.040** | -0.0320* | 0.0142 |
| ADX(Brent) | 0.0155* | | 0.1372 | | 0.0349 |
| FTSE100(Brent) | 0.0532*** | | -0.0163* | | 0.0112 |

Table 9. VAR results of ADX and TOPIX with WTI and Brent

| VAR | ADX(-1) | ADX(-2) | TOPIX(-1) | TOPIX(-2) | Constent |
|---|---|---|---|---|---|
| ADX | 0.0371* | 0.0523*** | 0.0215 | 0.0192* | 0.0350 |
| TOPIX | 0.1035 | 0.0192* | -0.0307* | 0.0429** | 0.0338 |
| ADX(WTI) | 0.0232* | 0.0474*** | 0.0132* | 0.0237* | 0.0352 |
| TOPIX(WTI) | 0.0843 | 0.0146* | -0.0368* | 0.0360* | 0.0382 |
| ADX(Brent) | 0.0317* | | 0.0174* | | 0.0360 |
| TOPIX(Brent) | 0.0881 | | -0.0423** | | 0.0391 |

Table 10. The example of the VAR model from Table 7

| | | Constant | ADX(-1) | ADX(-2) | SP500(-1) | SP500(-2) |
|---|---|---|---|---|---|---|
| Panel A : without oil price | | | | | | |
| | ADX | 0.0261 | 0.0195 | 0.0551 | 0.2171 | -0.0255 |
| $Y_t$ | SP500 | 0.0422 | 0.0449 | 0.0000 | -0.0148 | -0.0499 |
| Panel B : with WTI | | | | | | |
| | ADX | 0.0301 | 0.0115 | 0.0535 | 0.1934 | -0.0437 |
| $Y_t$ | SP500 | 0.0435 | 0.0420 | -0.0017 | -0.0146 | -0.0629 |
| Panel C : with Brent | | | | | | |
| | ADX | 0.0281 | 0.0126 | | 0.2069 | |
| $Y_t$ | SP500 | 0.0429 | 0.0359 | | -0.0127 | |

It is clear to see that from tables 7 to 9, all three economically top-performing countries' indices have the significant explanation of their lagged value to explain the ADX. Also, the p-value of the ADX lagged value shows that the coefficients are significant with the cases of FTSE100 and TOPIX, while for the S&P500 case, the lagged value of ADX is significant at the 10% level. This indicates that ADX and S&P500 or FTSE100 have influence on each other. The influences between them are bilateral.

After adding the WTI and Brent crude oil prices into consideration, their relationship stays the same. ADX and S&P500 or FTSE100 keep the bilateral influence on each other, with just a little reduction of the coefficients. For the TOPIX case, it keeps the explanation power from the ADX lagged value to TOPIX in the two oil prices cases. However, it moves the explanation power of the TOPIX lagged value to ADX in both oil price cases.

Markellos and Siriopoulos (1997) stated that investors seek to find diversification benefits by having an international portfolio that combines European stocks with US and Japanese stocks. Also, in this case, the combination of Japanese stocks and ADX stock could yield some benefits, because the results show that they do not have a significant explanation power to each other. However, Mohti et al. (2019) stated that Asian emerging stock markets had a long-term relationship with global markets, which denoted that the combination of different stock markets will lead to different results.

Mensi and Shahzad (2017) tested that the relationship between BRICS and US, UK and Japan stock markets indicated that the time variance was an important variable to be considered. The time period of the data included in this part does not include the financial crisis, which may lead to a different result when taking it into consideration.

That Japanese stock markets were weakly correlated with oil was concluded by Cai et al. (2017), who had the same opinion when considering the relationship between ADX and the Japanese stock market. By adding both oil prices as a condition, it still does not change the significance of the relationship between ADX and TOPIX. This indicates that there is a diversification benefit opportunity by combining the ADX and TOPIX.

Chen (2010) found that changes in the oil price had power to change the S&P500 from a bull market into a bear market when the oil price was high. However, in the VAR results, when adding the oil price as a condition, there is no significant influence on the S&P 500, and it will not change the explanatory power of the S&P500 to others.

Tables 11 to 13 show the VAR results of a combination of ECU and economically high-performing countries, with and without the condition of oil prices. Different from the ADX, without considering the oil price condition, there is no significant explanation power to each other between the ECU and economically high-performing countries' indices. This indicates that when only considering the ECU and one of the indices, they have no influence on each other, which can be a suitable investment combination for investors who want to avoid risks.

When adding the oil price condition, their relationship stays the same. Therefore, with or without the condition of the oil prices, the results of the VAR model show that the changes of the ECU and economically high-performing countries' indices have no influence on each other. This offers an opportunity for investors to achieve diversification by including these two sides' financial products.

Table 11. VAR results of ECU and S&P500 with WTI and Brent

| VAR | ECU(-1) | ECU(-2) | SP500(-1) | SP500(-2) | Constent |
|---|---|---|---|---|---|
| ECU | -0.1235 | -0.0501*** | 0.2149* | -0.0083* | 0.0194 |
| SP500 | 0.0531* | -0.0438* | -0.0066* | -0.0404** | 0.0430 |
| ECU(WTI) | -0.1225 | -0.0509*** | 0.0163* | -0.0080* | 0.0198 |
| SP500(WTI) | 0.0516* | -0.0414* | -0.0085* | -0.0547*** | 0.0443 |
| ECU(Brent) | -0.1176 | | 0.0153* | | 0.0188 |
| SP500(Brent) | 0.0563* | | -0.0082* | | 0.0407 |

Table 12. VAR results of ECU and FTSE100 with WTI and Brent

| VAR | ECU(-1) | ECU(-2) | FTSE100(-1) | FTSE100(-2) | Constent |
|---|---|---|---|---|---|
| ECU | -0.1257 | -0.0525*** | 0.0197* | -0.0155* | 0.0217 |
| FTSE100 | -0.0026* | -0.2487* | -0.0017* | -0.0285 | 0.0159 |
| ECU(WTI) | -0.1170 | | 0.0149* | | 0.0192 |
| FTSE100(WTI) | 0.0070* | | -0.0286* | | 0.0143 |
| ECU(Brent) | -0.1174 | | 0.01264* | | 0.0193 |
| FTSE100(Brent) | 0.0020* | | -0.0060* | | 0.0130 |

Table 13. VAR results of ECU and TOPIX with WTI and Brent

| VAR | ECU(-1) | ECU(-2) | TOPIX(-1) | TOPIX(-2) | Constent |
|---|---|---|---|---|---|
| ECU | -0.1229 | -0.0482*** | 0.0088* | -0.0160** | 0.0202 |
| TOPIX | 0.0223* | 0.0394* | -0.0146* | 0.0452*** | 0.0363 |
| ECU(WTI) | -0.1170 | | 0.0086* | | 0.0191 |
| TOPIX(WTI) | 0.0334* | | -0.0225* | | 0.0415 |
| ECU(Brent) | -0.1176 | | 0.0076* | | 0.0192 |
| TOPIX(Brent) | 0.0246* | | 0.0300* | | 0.0415 |

The result in the situation when including the ECU and other leading economies indicates that the investors could gain diversification benefits, regarding which Saadi-Sedik and Petri (2006) also stated that the Jordanian stock markets were not cointegrated with developed countries. The results also prove that the oil market will not influence the relationship between the ECU and the three leading economies'

stock markets, about which Sharma and Giri (2018) also found that there was no cointegration relationship between the Indian stock market and the oil market.
In addition, like the OPEC countries, GCC countries play an important role in the energy markets. Akoum et al. (2012) stated that the GCC countries had a long-term relationship with oil prices, which provide no diversification benefits. Al-Yahyaee et al. (2019) found that the time period was important when analysing the relationship between stocks and oil prices. In addition, Mortaz (2019) claimed that it was also necessary to consider the geographical area of the countries.

Moreover, Yarovaya and Lau (2016) stated that the UK stock market was integrated with the BRICS and MIST stock markets. These papers pointed out that it is important and necessary to identify the details of the stock markets selected. Even though the selected countries or stock markets are in the same group or located in the same area, it is still necessary to have a deeper investigation into their relationship. Differently from the ADX, the relationship between the ECU and leading economies' stock markets provides the opportunity of gaining diversification benefits when considering oil prices.

Tables 14 to 16 show the VAR model results of the combination of the NSE and three leading economies' indices with and without the oil prices. Similar to the ADX cases, without considering the oil prices condition, the NSE and the S&P500 or the FTSE100 have a bilateral influence on each other. However, the TOPIX cases show no influential affects for each other.

When adding WTI crude oil price as the condition, this keeps the explanation power of the NSE to the S&P500 and the FTSE100, and it changes the significant level from the S&P500 and the FTSE100 to the NSE, from a 1% level to 5% and 10% levels. This indicates that when considering the WTI crude oil prices, the influence of the changes in the S&P500 and FTSE100 to the NSE becomes less; this tells us that we need to pay more attention to the changes in the NSE, which may influence the S&P500 and the FTSE100. The TOPIX cases show nothing different. In addition, including the condition of the Brent crude oil price keeps the bilateral influences between the NSE and the S&P500 or the FTSE100. In addition, when adding the Brent crude oil prices, the TOPIX lagged two values have explanation power to the

NSE. Therefore, in this case, the oil prices condition has the power to keep or remove the influence of one index to the other.

Similar to the ADX case, with or without the consideration of the oil prices, the relationship between the Japanese stock markets and the oil price does not change, because including the oil price increases the explanation power of TOPIX to the NSE or the NSE to TOPIX. Le and Change (2015) found that the Japanese stock markets responded to the oil price shocks positively, but with no significance.

For the cases of the S&P500 and the FTSE100, by adding the oil prices into consideration, the influences of the S&P500 and the FTSE100 to the NSE become not significant. Arouri and Rault (2012) pointed out that increases in the oil prices will benefit GCC countries; they stated that oil price changes will influence oil-related countries like the OPEC countries. Also, Fayyad and Daly (2012) stated that the GCC countries had a bigger reaction to the oil price changes than the US and the UK. This could be one reason why adding the oil prices as a condition removes the explanation power of the S&P500 and the FTSE100 to the NSE.

Table 14. VAR results of NSE and S&P500 with WTI and Brent

| VAR | NSE(-1) | NSE(-2) | SP500(-1) | SP500(-2) | Constent |
|---|---|---|---|---|---|
| NSE | 0.3173 | -0.0150* | 0.0732 | 0.0336* | 0.0056 |
| SP500 | -0.0643 | 0.0338*** | -0.0078* | -0.0351* | 0.0432 |
| NSE(WTI) | 0.3116 | -0.0166* | 0.0522** | 0.0060* | 0.0097 |
| SP500(WTI) | -0.0667 | 0.0331** | -0.0059* | -0.0509*** | 0.0447 |
| NSE(Brent) | 0.3125 | | 0.0582*** | | 0.0083 |
| SP500(Brent) | -0.0556 | | -0.0077* | | 0.0425 |

Table 15. VAR results of NSE and FTSE100 with WTI and Brent

| VAR | NSE(-1) | NSE(-2) | FTSE100(-1) | FTSE100(-2) | Constent |
|---|---|---|---|---|---|
| NSE | 0.3124 | 0.0180* | 0.0766*** | 0.0432*** | 0.0075 |
| FTSE100 | -0.0417*** | 0.0355** | 0.0027* | -0.0283* | 0.0146 |
| NSE(WTI) | 0.3098 | -0.0176* | 0.0491** | 0.0211* | 0.0112 |
| FTSE100(WTI) | -0.0452*** | 0.0239* | -0.0276* | -0.0265* | 0.0157 |
| NSE(Brent) | 0.3110 | | 0.0551*** | | 0.0100 |
| FTSE100(Brent) | -0.0367** | | -0.0046* | | 0.0562 |

Table16. VAR results of NSE and TOPIX with WTI and Brent

| VAR | NSE(-1) | NSE(-2) | TOPIX(-1) | TOPIX(-2) | Constent |
|---|---|---|---|---|---|
| NSE | 0.3221 | -0.0202* | -0.0125* | 0.0302** | 0.0095 |
| TOPIX | 0.0004* | -0.0280* | -0.0135* | 0.0506*** | 0.0398 |
| NSE(WTI) | 0.3144 | -0.0222* | -0.0256* | 0.0250* | 0.0125 |
| TOPIX(WTI) | -0.0121* | -0.0020* | -0.0242* | 0.0405** | 0.0416 |
| NSE(Brent) | 0.3132 | | -0.0164* | | 0.0116 |
| TOPIX(Brent) | -0.0093* | | -0.0292* | | 0.0421 |

In addition, Oloko (2018) found that US and UK investors could gain diversification benefits from holding Nigerian stock, where the correlation was low. Sim and Zhou (2015) found that the positive effect on the US stock markets was insignificant to weak. Therefore, without considering the condition of the oil prices, the results may indicate that the influences between two markets are bilateral. However, when including the oil prices into consideration, their relationship may be changed.

Tables 17 to 19 show the VAR results of TASI and leading economies' index with and without the oil price condition. Between the TASI and the S&P500, with or without the condition of both crude oil prices, these two indices keep the bilateral influence between them. For the situation between the FTSE100 and the TASI, the results of the VAR model only show that the FTSE100 has significant explanation power to the TASI; however, with the condition of both oil prices, the relationship between the TASI and the FTSE100 stays the same. In the cases of TASI and TOPIX, with and without the condition of oil prices, TASI has the explanation power to TOPIX while TOPIX has insignificant explanation power to TASI.

Table 17. VAR results of TASI and S&P500 with WTI and Brent

| VAR | TASI(-1) | TASI(-2) | SP500(-1) | SP500(-2) | Constent |
|---|---|---|---|---|---|
| TASI | 0.1203 | -0.0545*** | 0.1937 | 0.0089* | -0.0007 |
| SP500 | 0.0892 | -0.0231* | -0.0271* | -0.0482*** | 0.0433 |
| TASI(WTI) | 0.1081 | -0.0506*** | 0.1524 | 0.0034* | 0.0046 |
| SP500(WTI) | 0.0868 | -0.0242* | -0.0234* | -0.0591*** | 0.0435 |
| TASI(Brent) | 0.1125 | -0.0596 | 0.1847 | -0.0028* | 0.0022 |
| SP500(Brent) | 0.0908 | -0.0264* | -0.0232* | -0.0535*** | 0.0432 |

Table 18. VAR results of TASI and FTSE100 with WTI and Brent

| VAR | TASI(-1) | TASI(-2) | FTSE100(-1) | FTSE100(-2) | Constent |
|---|---|---|---|---|---|
| TASI | 0.1258 | -0.0429** | 0.1135 | 0.0077* | 0.0073 |
| FTSE100 | 0.0347** | -0.0312** | -0.0129* | -0.0239* | 0.0146 |
| TASI(WTI) | 0.1137 | -0.0402** | 0.0709*** | 0.0025* | 0.0106 |
| FTSE100(WTI) | 0.0242* | -0.0254* | -0.0356* | -0.0202* | 0.0145 |
| TASI(Brent) | 0.1176 | -0.0474*** | 0.0976 | -0.0057* | 0.0090 |
| FTSE100(Brent) | 0.0308* | -0.0294* | -0.0136* | -0.0179* | 0.0128 |

Table 19. VAR results of TASI and TOPIX with WTI and Brent

| VAR | TASI(-1) | TASI(-2) | TOPIX(-1) | TOPIX(-2) | Constent |
|---|---|---|---|---|---|
| TASI | 0.1430 | | 0.0022* | | 0.0096 |
| TOPIX | 0.1747 | | -0.0470*** | | 0.0379 |
| TASI(WTI) | 0.1244 | | 0.0009* | | 0.0121 |
| TOPIX(WTI) | 0.1511 | | -0.0487*** | | 0.0411 |
| TASI(Brent) | 0.1295 | | -0.0008* | | 0.0109 |
| TOPIX(Brent) | 0.1456 | | -0.0535*** | | 0.0407 |

Park and Ratti (2008) tested the influence of oil price shocks on the US and European countries, and found that oil price shocks had significant influence on these stock markets. The result states that the oil prices influence the performance of the stock markets. In this chapter, the consideration of the oil prices does not change the relationship between the TASI and the S&P500 and the FTSE100. This indicates that oil price changes affect all three indices.

Papapetrou (2001) and Filis (2010) claimed that macro-economic variables could also influence the performance of the stock markets. Narayan and Narayan (2010) also indicated that the exchange rate, oil prices and stock prices had long-term relationships. This pointed out that not only oil price changes can influence the stock markets, but also other factors.

Differently, for the scenario of TASI and TOPIX, the VAR results show that the TASI lagged value has significant explanation power to the TOPIX, while the TOPIX does not, with or without the oil price condition. Therefore, when considering including the TASI in the portfolio, the investors should pay attention to the different financial markets included.

## *1.7.3 Test of the DJT (Dow Jones Transportation Average) and the MSCIWE (MSCI World Energy Index)*

Apart from the OPEC countries' stock markets, this chapter also takes the Dow Jones Transportation Average (DJT) and the MSCI World Energy Index (MSCIWE) into consideration. The reason for including these two indices is that the OPEC stock indices are the whole stock markets' indices, which include all the industries in the markets. Only focusing on the DJT and MSCIWE can provide a result showing how the oil price changes influence energy-related industrial indices. The results show that the oil price changes have a larger influence on these two indices.

Table 33 shows the single regression results of the DJT and the MSCIWE with WTI and Brent crude oil spot prices, starting from 29/06/2001 and ending at 01/10/2019. In the regression model, the DJT and MSCIWE are assumed to be the dependent variables and the crude oil prices are assumed to be the independent variables. Due to the positive number of the coefficients of all the results, it was concluded that the relationships between the DJT and the MSCIWE with two crude oil prices are positive. Comparing these two indices, the MSCIWE has a stronger correlation relationship with the two crude oil prices. Table 34 indicates the regression results from 29/06/2001 to 04/04/2016, which includes the 2008 financial crisis. The results show that the financial crisis had influenced the relationship between the DJT and the MSCIWE with the two crude oil spot prices. Due to the impacts of the financial crisis, the coefficients between the DJT with the two crude oil spot prices change from negative to positive (coefficients). The reason why the relationship between them changes from negative to positive is due to the influence of the financial crisis. The impact of the financial crisis made the oil price and stock market become closer and have co-movement. For the MSCIWE, the financial crisis strengthens its correlation relationship with the two oil prices. Different from the previous stock indices, after the financial crisis, their relationships do not weaken after time passes; however, their correlation level becomes higher.

Tables 35 to 42 are the VAR results of the four OPEC countries' indices with the DJT and the MSCIWE. Without consideration of the oil price condition, the DJT has the explanation power to the ADX at 0.01 and to the NSE and the TASI, both at 0.05. In addition, the ADX, the NSE and the TASI have explanation power to the DJT at a 5% significance level. For the case of the ECU, there is no significant explanation power running from each other. Different from the DJT, the MSCIWE has explanation power to four OPEC countries' stock markets at the 0.01 level, while at 0.1 level to the ECU. In the opposite way, the ADX has the explanation power at the 0.05 level to the MSCIWE. The NSE and the TASI have the 0.01 significant level explanation power to the MSCIWE.

When adding the WTI crude oil price as a consideration, for the ADX case, there is no change in the relationship between them. For the ECU case, it stays the same with the DJT case – that they have no explanation power from each other. In the MSCIWE case, the explanation power from the MSCIWE to the ECU becomes insignificant at the 10% level. For the NSE, the consideration of the WTI totally reduces the significant level of the explanation power of the DJT and the MSCIWE to the NSE, keeping the same significant level power from the NSE to them. Different from the scenario of the NSE, the TASI has the explanation power to the DJT at the 0.01 level. Furthermore, the WTI removes the explanation power from the DJY to the TASI.

Taking the Brent crude oil price as a consideration is similar to the consideration of the WTI crude oil price. The difference is that the NSE has the explanation power to the MSCIWE at the 0.1 level and at the 0.05 level from the MSCIWE to the NSE. It is clear to see that oil prices have the power to make some changes to the relationship between different stocks, especially in regard to the energy indices. Additionally, the results show that the consideration of the oil prices could give OPEC countries' stock more explanation power to the DJT and the MSCIWE.

### *1.7.4 Summary*

Previously published literatures mainly focus on the relationship between the oil price and different stock markets, or the relationship between different stock markets. The results from the previous papers confirmed that oil price changes will influence the stock markets, and different stock markets influence each other. Therefore, this chapter estimates the influence of oil price changes on the relationship between different stock markets. This is a combination of the previous aims, and can help readers and investors have a better understanding of the effects of oil price changes on the different stock markets, assisting them to have a better, more diversified portfolio.

The findings in the single regression model showed that all the stock markets' indices are correlated positively with two crude oil spot prices (WTI and Brent), which denies Hypothesis 1. All the coefficients obtained from the single regression model are significant and positive. Then, taking the financial crisis into consideration, the results show that the financial crisis had the power to significantly enhance the relationship between oil price changes and stock markets' indices. The coefficients become larger, which indicates that the same change in the oil prices leads to a large percentage change in the indices based on the single regression model. In addition, after the financial crisis, the correlation level between the oil price and stock market indices still did not come back to the level before the financial crisis. Moreover, in the analysis of the second group, the results also show that all the stock market indices are correlated with the two oil prices, except the ECU and the NSE.

Due to the logarithmic return of all the variables calculated, the logged return eliminates the non-stationary properties of these variables, which indicates that there is no need for cointegration test. Then, in the VAR model test, the result shows that the oil price changes' conditions have influence on the relationship between different stock markets' indices; however, the influence is limited, and only in a few cases can the oil price changes truly affect relationships. In the case of the scenario including the ECU, by adding the oil prices changes as the condition, this would not change the relationship between them where they have no explanation power to each other. Also, for the cases that include the TOPIX, the Japanese stock market, whether the oil prices are considered as a condition or not, it can provide diversification benefits for investors when they include these assets with leading economies' stock markets. Moreover, it is clear to conclude that the influence of the oil prices changes is limited, which may be because of other factors, such as inflation, production and exchange rates; these macro-economic variables have influence on the relationship between stock markets at the same time. In addition, in the extra test of the DJT and the MSCIWE, the results show that adding oil prices into the VAR model will influence the explanation power of the stocks; however, most cases stay the same.

Comparing to the previous papers, this chapter indicates oil price is one of the conditions can influence the relationship between different stock markets in the selected countries. In addition, this chapter includes the OPEC countries and economical top-performing countries as a comparison group to provide guide how oil price will influence their stock markets. The results show between US stock market (S&P500) has explanation power to Nigerian stock exchange (NSE) while when take oil price into consideration can remove the explanation power. This fills the gaps that other paper does not looking into influence of the oil price on relationship between different stock markets but only between oil prices and stock markets. In addition, the influence of oil prices can be different based on different oil prices. Therefore, apart from the stock markets, it is still necessary to take the oil price into consideration to when involving the stock markets selected in this chapter.

For investors and portfolio managers, the oil price changes provide a sign for them, especially for international one that they can reallocate their assets based on those changes. If the oil price changes remove the explanation from one stock markets to another one, it might be good for them to include these two stock markets to achieve diversification and reduce risks. For policy makers, the oil price change can influence the stock markets and local economy that they should make the announcements or take any action on the policy to against the influence of the oil price changes. In addition. the oil price changes can also influence foreign investment into local financial markets where they should take some actions to protect the local investors and handle the massive investment external.

Therefore, future studies should be directed to: 1) investigating the structural break caused by the financial crisis; 2) considering other macro-economic factors – not only the oil prices changes, but also elements such as exchange rates and inflation and production levels, to see when considering these variables together how the variable changes would influence the relationship between different stock markets; 3) investigating if there a nonlinear relationship that would appear between OPEC countries' and leading economies' stock markets, and would the oil price changes or other factors influence the relationship?; and 4) investigating the predictability of the oil price effects on the stock markets.

# 2. Chapter Two: Prediction of oil prices

## 2.1 Introduction

The predictions of financial products are important. The aim of the estimate of the future movement of a financial asset or a market is to provide a guide to investors, or to help readers to manage their investments and their assets. In addition, using different models to do the predictions also can help researchers to figure out in what situations a particular model is the most appropriate one. Moreover, analysing the future movements of the markets or assets can help investors and countries to avoid some potential losses, or it can even help to gain some benefits.

As oil is one of the main fossil fuel energy sources in the world, it is important to have an investigation into its price movement, and it is necessary to have an estimation of future oil prices. The fluctuations of oil prices and their uncertainty provide an opportunity of investigation into oil price prediction.

In the previous chapter, the results showed that oil price changes can influence the relationship between oil prices and stock market returns, which indicates the importance of oil prices in financial markets. It is necessary to investigate the changes in the oil prices and to conduct some tests on the prediction of the oil prices. The reasons for this are that the estimation of the oil prices will provide a template to investors and researchers to enable them to conduct a better investigation of other financial products in the markets.
In addition, the accuracy of prediction of future oil prices can also be important. The more accurate the prediction, the more accurate the investment strategies and the direction of the research that will be set. Therefore, different models can have varying results. The selection of the models should be taken into consideration – basically, the lower the error of the results, the higher the predicted ability of the model. Moreover, some researchers use machine learning programmes to help them to make an estimation of oil prices.

Based on the previous chapter, I concluded that oil price changes have an influence on the relationship between oil prices and stock market returns. Thus, the aim of this chapter is to make a further investigation into the predictability of oil prices. The reason why this chapter is going to test the predictability is that the if the oil price is predictable, not only the investor can benefit from the oil price estimation, but also the policy makers can set the appropriate policy to handle the fluctuation of the oil price. The Holt-Winter's and ARIMA model will be used in this chapter to test the predictability which have not been done before. This model is suitable for prediction of time series data.

Albuquerquemello and Medeiros et al. (2018) tried to find the most appropriate method to forecast the oil price following the decrease in prices after 2014. In this paper, they tested the self-exciting threshold auto-regressive – SETAR – model. This model can automatically switch regimes after the threshold, which results in 2% of root mean square error, compared to 10% for other common models. Therefore, the SETRA has a better accuracy.

Katias, Karya and Herlambang et al. (2019) stated that oil prices play an important role in the world economy. They said that the relationship between the oil market and other markets will influence the oil prices' indices, and the oil price will also be affected by varying conditions. Due to these reasons, the oil price is uncertain, and analysing the volatility of the oil price can help in estimating oil prices. They employed the Kalman Filter (KF) and Ensemble Kalman Filter (EnKF) method to predict the oil price, and found that they are both effectively accurate, although the EnKF is more precise.
There are many factors that can influence oil prices, some of which can also influence the predictability of the oil prices and the accuracy of oil price estimation. Sharma, Phan and Iyke (2019) and Noneiad (2020) found that macro-economic variables have a relationship with oil prices. Sharma et al. (2019) concluded that oil prices can act as predictors to forecast macro-economic variables in Indonesia. They also concluded that various oil prices have different predictability on respective variables' estimation. Therefore, it is important to have an appropriate oil price selected.

Nusair (2019) found that oil price shocks could affect the influences on inflation in Gulf Cooperation Council countries. The paper also found that oil prices have greater influences in the long term.

Nyangarika and Tang (2018) employed the vector autoregressive (VAR) and the Dickey-Fuller test (ADF), and found that the oil price has a positive and significant long-term relationship with Russian GDP dynamics. By analysing the relationship between the oil price and the economy in Russia, they suggested that it would be better to focus on innovation and improvement of the environment, which can attract more foreign investment.

Additionally, the production, the supply, and the demand for oil in the world will also influence the price of oil. It is also necessary to take the supply and demand of oil into consideration. Kim (2018) investigated the supply and demand factors' influence on oil prices during the oil price decline periods from 2008 to 2009 and from 2014 to 2016. The paper used autoregressive models to find that the demand reduction was the main reason for the decrease in the oil prices on the first occasion, while for the second period, US shale oil production and speculative demand factors played the main role.

Zhao, Guo and Zeng (2018) proposed a vector trend forecasting method that predicted the future oil price, based on the vector trend series of historical crude oil prices. To avoid the difficulty of the price trend and stochastic factors in forecasting price trends, they included an econometric model to make the definition of the historical data more reasonable and the prediction more accurate. Their results showed that the forecasting errors are no longer above 5%, which is lower than other methods. Their results indicated that their method is more reliable and more accurate.

In addition, due to the complexity of the oil markets, a combination of different methods can perform well. Sun, Hao and Li (2020) stated that the optimal portfolio of the energy assets was a hot issue, and it was related to the development of national strategy. They concluded that using various prediction methods was better than using a single method. In addition, using the increase of the optimal parameter improved the prediction of the result.

Jianwei, Bao and Ye (2017) combined variational mode decomposition (VMD), independent component analysis (ICA) and an autoregressive integrated moving average (ARIMA), called VMD–ICA–ARIMA. Their aim was to investigate the factors influencing the crude oil price and thus estimate the oil price in the future. They concluded that the WTI crude oil price has periodic declines, and that their modified ARIMA model is better than the basic one.

Yu, Zhang and Wang (2017) combined five feed-forward neural networks (FNN) methods, an auto-regressive integrated moving average (ARIMA) model, a fractional integrated ARIMA (ARFIMA) model, a Markov-switching ARFIMA (MS-ARFIMA) model, and a random walk (RW) into a learning algorithm to test the feasibility and potentiality of a support vector machine (SVM). The findings showed that the SVM outperformed the other five methods in oil prices prediction. The SVM provides forecasts with the lowest RMSE.

To choose an appropriate method to run the test on the prediction of the oil prices is very important, as it can increase the accuracy and reduce the estimation error. Moreover, Ali and Davallou (2018) combined an exponential smoothing model (ESM), an autoregressive integrated moving average model (ARIMA), and a nonlinear autoregressive (NAR) neural network to predict the oil price. The results showed that the combination of different methods can solve the problems that one model on its own cannot – problems like nonlinearity, uncertainty, dynamism and fluctuation. The combination method can make a better prediction of the future oil price time series.

Chai and Xing et al. (2018) investigated the WTI crude oil prediction by using a hybrid-refined method. Due to the complexity of the crude oil price, they employed a new method that proposed a novel solution. This method can catch change points, regime-switching, time-varying determinants, trend decomposition of high-frequency sequences, and the possible nonlinearity of model settings. They also concluded that the oil price had an upward trend in the short-term, but the increase would not be large.

Further, Chai and Wang et al. (2019) found a new prediction model for oil prices that can help a country's long-term development. This model can enable a better understanding of different scales of oil prices and, secondly, it can provide a better prediction of oil prices. The results of this paper showed that the model decreases the seven IMF components into three, which reduce the complexity, and the estimation results are directly integrated into the original data.

Due to the complexity of the oil market, Zhao and Wang et al. (2019) combined the Hodrick-Prescott filter with X12 methods and adjusted the order used. The results showed that their method can be used in predicting the WTI and Brent oil prices, which were accurate. They concluded that the combination of these methods was more stable and accurate, which also provided useful cutting-edge information for Chinese energy development.

Oil price prediction is complex, and to increase the accuracy of the prediction, many researchers and papers employed a modified method to help them predict future oil prices.

Yu, Xu and Tang (2017) used a modified least squares support vector regression (LSSVR) model with uncertain parameters to avoid the drawback of parameter sensitivity and long tuning. They defined this as four steps: 1) define low upper bound estimation; 2) generate random sets of parameters; 3) make each individual set an individual prediction; and 4) use ensemble weighted averaging to combine all individual results. They found that using these steps could help the prediction to be more effective and that this method is more accurate.

Nyangarika, Mikhaylov and Richter (2018) employed a modified auto-regressive integrated moving average model to find the parameters of predictions. They used data from 1991 to 2016 relating to the Brent crude oil price and gas prices. Their tests showed that a modified ARIMA can improve the accuracy of prediction. Additionally, the emissions only occur at the end of the time series and in influence on other data series. Their results showed that it is possible for investors to predict future oil prices.

Duan, Lei and Shao (2018) investigated the estimation of crude oil consumption in China by employing a grey-extended SIGM model, which has high simulation and prediction accuracies in grey theory. However, the raw data of the Chinese crude oil consumption data are not suitable for this method, and they use the least squares estimation for this model. The results showed that it is capable to estimate the crude oil price consumption in China from 2015 to 2020 by using the data from 2002 to 2014.

Wang, Tian and Zhou (2018) introduced a new time series prediction method for data fluctuation. The basic idea of this model is to convert a time series into a data fluctuation network and use the topological structure to collect the time series to make the prediction. By using this model, it can be effective to predict the historical data by its fluctuation features. They also found that the larger the data size, the higher the prediction of the subjects. Their results also indicated that the compound rules' prediction model can predict prices and price fluctuations more accurately.

Huang and Zheng (2020) investigated the changes in the relationship between investor sentiment and the crude oil future price since COVID-19. They selected data from January 2 2019 to May 11 2020. They tested the structural changes in the WTI crude oil future price and the OVX by using the Engle & Granger cointegration method. The results showed that investor sentiment had a significant influence on the oil price. From December 31 2019, the decline in oil demand hit the oil price heavily. The results showed that the elasticity of the price to sentiment increased from -0.295 to -0.678 after COVID-19. This paper provides a topic for future investigation – that investor sentiment could be a consideration when predicting oil prices.

Moreover, there are many papers that use machine learning to help them have a deeper investigation into the prediction of oil prices. Machine learning can handle a larger volume of data, and it is able to make a long-term investigation into prediction, and possibly to provide a better result.

Huang and Wang (2018) employed a new neural network to predict the crude oil price more accurately. They combined the wavelet neural network (WNN) with a random time-effective function. The former network can provide nonlinear approximation and the second function can formulate the influence of past data on the current one. They concluded that the new neural network could improve the accuracy of prediction, which gives it an advantage over others.

By using machine learning, Orojo, Tepper and McGinnity et al. (2019) found that there were some hidden features of the 2008 financial crisis. They employed a multi-recurrent network (MRN), which is more flexible and rigid than the long short-term memory (LSTM). They used out-of-sample data and found that this method could help them to have an early prevention of financial crises.

Similarly, Lu, Li and Chai et al. (2020) employed a new method that they called a dynamic Bayesian structural time series model (DBSTS) to investigate the oil price. They also included the Google trend to reflect the influence on the oil price. They found that the DBSTS had the ability to identify the turning point during the 2008 financial crisis, and they also found that the DBSTS had good predictability in the short term.

However, Gupta and Pandey (2018) employed the long short-term memory (LSTM) based neural network to predict the oil price. They also agreed that artificial neural networks (ANN) can have a better accuracy prediction of the future oil price. The paper also concluded that the increase in the layers was not necessary to improve accuracy. For further investigation, researchers can add other conditions to have a better estimation. In addition, Wu, Wu and Zhu (2019) also used LSTM networks to predict the EEMD-based crude oil price. The results showed that the EEMD-LSTM can solve the problem in which the EEMD cannot handle the number of components when adding new data. Also, the results showed that it had the smallest RMSW and MAPE.

Li, Shang and Wang (2019) used a deep learning machine to help them forecast the crude oil price. They employed a convolutional neural network (CNN) to mine the online media text and used the latent dirichlet allocation (LDA) topic model to group the texts they collected online. Their result stated that the topic-sentiment synthesis forecasting model analysed better than other benchmark models. Moreover, they claimed that the text feature can improve the accuracy of crude oil price forecasts. It is important to have an accurate estimation of the oil price, not only for investors but also for the world economy. Wu, Chen and Zhou et al. (2019) employed machine learning to have an accurate estimation of the oil price, which contains complementary ensemble empirical mode decomposition (CEEMD), an autoregressive integrated moving average (ARIMA) and sparse Bayesian learning (SBL), namely CEEMD-ARIMA&SBL-SBL (CEEMD-A&S-SBL). The result showed that the CEEMD-A&S-SBL can significantly improve the accuracy of oil price prediction. In addition, SBL outperforms in the comparison with other methods on estimating the forecast components.

Oil price changes are also influenced by other factors. Mikhaylov and Molseev (2019) employed the machine learning approach to predict the oil price by investigating the following factors, such as the US key rate, the US dollar index, the S&P 500 index, the volatility index and the US consumer price index. In this article, the machine learning approach is based on the linear regression and the modified linear regression model. By running the test, they found that the oil price would be influenced most by the US Federal Reserve rate and the US dollar index. They also concluded that conflicts in the Middle East will also influence oil prices. Finally, they found that the oil price slightly increased between 2019 and 2022, and then became stable.

Qu, Tang and Lao (2018) employed the combination of the empirical mode decomposition (EMD) and the BP_AdaBoost neural network to estimate the oil price. The comparison of these two methods' advantages is that EMD can separate the data due to their frequencies without losing any information, while BP_AdaBoost has a better generalisation ability and increases the accuracy of prediction compared to the BP network. Their result showed that the combination had a smaller root mean square error (RMSE), a mean absolute error (MAE), a mean absolute percentage error (MAPE), and that it provides a more accurate result.

In addition, Gumus and Kiran (2021) employed gradient boosting machine learning (XGBoost) to estimate the crude oil price for those countries that highly depend on oil imports and have low oil production in their own country. This could help the government and related economies to save money and investment, thereby providing a better economy.

Moreover, using search engines and collection data online can also help the prediction of oil prices. Tang, Zhang and Li et al. (2020) considered the development of search engines and their ability to drive oil prices. They employed a multi-scale forecasting method: first, collecting informative search engines, reducing dimensionality; second, matching the similar timescales of oil prices; and third, to run the oil price prediction. They found that using these methods can significantly improve the original methods and obtain better predictions.

Wu, Wang and Lv et al. (2021) investigated the oil price prediction by using Google trends and online media text mining. They stated that the online-big-data-based method can have a better prediction than other methods. They collected thousands of news headlines and found that the Google trend truly improves crude oil price forecasting.

The above literatures confirm the importance of the oil price prediction. The results showed that oil prices are predictable. Katias, Karya and Herlambang et al. (2019) and Wu, Chen and Zhou et al. (2019) claimed that the oil market plays a crucial role in the world economy. Therefore, it is necessary and important to have an investigation into oil prices.
Based on the literatures listed, Nusair (2019), Sharma, Phan and Iyke (2019) and Noneiad (2020) tested the oil prices with other macro-economic variables and found that the oil price is influenced by other factors. They concluded that the oil price can help to estimate other factors like inflation. Nyangarika and Tang (2018) also found that oil price shocks were more influential on the long-term oil price.

In addition, oil prices’ fluctuations are affected by oil production and its supply and demand (Kim, 2018 & Zhao, Guo and Zeng, 2018). Furthermore, due to the complexity of the oil markets, Sun, Hao and Li (2020) found that a single method may not be enough, and they suggested having various prediction methods. Ali and Davallou (2018) stated that multi-methods can solve the problem that one model cannot, including nonlinearity and uncertainty. Besides this, Duan, Lei and Shao (2018) claimed that multi-methods could handle data suitability to different models. Moreover, Yu, Zhang and Wang (2017) and Zhao and Wang et al. (2019) found that multi-methods could help to increase the accuracy of the oil price estimated.

Apart from these literatures, many literatures have included machine learning in their investigations to predict oil prices. By using machine learning, Orojo, Tepper and McGinnity et al. (2019), and Lu, Li and Chai et al. (2020) found that it enabled better investigation into the 2008 financial crisis, while a former paper also concluded that it could help to prevent financial crises. Li, Shang and Wang (2019), Wu, Chen and Zhou et al. (2019) and Gumus and Kiran (2021) stated that machine learning and neural networks result in better oil prices prediction, which is better than the original methods.

## 2.2 Data and methodology

### *2.2.1 Data description*

In this chapter, I will only include the WIT crude oil price and the Brent oil price to run the oil price prediction tests. The oil price has become one of the economic hotspots in the world, especially the prediction of future prices. The previous chapter concluded that the oil price has a long-term relationship between stock markets. There are many articles proving that the stock markets are predictable, combining with the conclusion found in the previous chapter that oil prices are predictable.

For the oil prices, this chapter will select the WTI and Brent crude oil spot prices. All the data will be collected from the Refinitiv Datastream. All the data will be collected from daily figures from January 1 1990 to December 31 2020, and from monthly figures from January 1990 to December 2020. The reason for choosing this period is that the time series will test three groups of data. The first group will be from

January 1990 to December 31 2019, which contains 30 years data. The second group includes the data from January 1 2010 to December 31 2019. The last group starts from January 1 2020 and runs to December 31 2020. The first two are in a comparison group to try and show which period is better – the longer or the shorter one. The third sample is designed to test during the COVID-19 period – will the prediction be more accurate or less? Doing this can provide a reasonable result with which to predict the appropriate length and period of the data in the future.

There will be two groups of tests in this chapter. The first group of test is aimed to test the predictability of the length of the data. The first and second groups of data will be divided into two parts – the in-sample data and the out-of-sample data. The out-of-sample data is set to last three years, which is from January 2017 to December 2019. The in-sample data is from 1990 and 2010. The two groups of data will be tested by Holt's linear trend and Winters' multiplicative trend in order to do the forecast. After getting the results from the two tests, the forecast errors, such as MAPE, MaxAPE, MAE and MaxAE, will be compared to each other in two tests, and the aim is to choose the smaller one. Basically, the smaller the error, the more accurate will be the forecast. In addition, after getting the estimated data, the chapter will also compare the estimated data with the real data.

Meanwhile, this chapter will run tests to use the 30-year data and the 10-year data in order to forecast the data in 2020. The results of the prediction give an opinion regarding whether the prediction of the tests would still be reliable in 2020. Similar to the previous tests, the in-sample data is the 30 years and 10 years data, and the out-of-sample data is the 2020 data. Similar to the previous tests, two tests are employed in this step, and a comparison made as to which has the smaller forecast error.

Table 20. Summary Statistics for chapter two

| | Min | Mean | Max | Std.err | Number of observation |
|---|---|---|---|---|---|
| Panel A : ten-year data set | | | | | |
| WTI daily | 26.1900 | 72.4996 | 113.3900 | 0.4372 | 2513 |
| Brent daily | 26.0100 | 79.5692 | 128.1400 | 0.5190 | 2536 |
| WTI monthly | 32.7400 | 72.7074 | 113.3900 | 2.0005 | 120 |
| Brent monthly | 33.1400 | 79.6338 | 126.5900 | 2.3845 | 120 |
| Panel B : thirty-year data set | | | | | |
| WTI daily | 10.8200 | 47.7529 | 145.3100 | 0.3370 | 7555 |
| Brent daily | 9.1000 | 49.2099 | 143.9500 | 0.3775 | 7588 |
| WTI monthly | 11.3700 | 47.9986 | 139.9600 | 1.5503 | 360 |
| Brent monthly | 9.9100 | 49.3016 | 138.4000 | 1.7381 | 360 |

## *2.2.2 Methodology*

In this methodology part, I will use the Holt-Winters model and I will also include the ARIMA model to run the prediction in the SPSS. There will be in-sample data and out-of-sample data; the in-sample data is used to do the forecast and then to see the difference between prediction data and real data. By doing the forecast, the errors will be compared in the results part, such as mean absolute percentage error (MAPE), relative absolute error (RAE) and mean square error (MAE). Theoretically, the smaller the value of these errors, the better the estimation. The result will also provide charts to show the movement of the oil price trend directly.

Holt (1957) developed a model of exponential weighted moving averages. This method is mainly for the series data, which has no trend, additive or multiplicative. The paper pointed out that the exponential weighted moving average is designed to have three properties: 1) it declines the weight in older data; 2) it computes easily; and 3) less data are required. This method is mainly desired for industrial data, with larger numbers of data needed to be predicted. In addition, the paper also concluded that this method is flexible and suitable for seasonal factors and trends.

Winters (1960) said that the development of computer systems in managing inventory control and production planning enable a model that can be computed

easily and can be designed for different variables. The paper also extends the traditional weighted moving average model to capture seasonality. The paper concluded that this model: 1) gives a better forecast; 2) needs less information; and 3) can be adjusted quickly when there are sudden changes in time series data.
In addition, apart from the Holt-Winters model, this thesis also includes the ARIMA model. The ARIMA model uses past data to do the regression against itself. In this thesis, this method is used to run oil prices data and to test its accuracy of prediction. Mgale, Yan and Timothy (2021) used the ARIMA and Holt-Winters Exponential Smoothing model to forecast agricultural products in Tanzania and found these two methods to be useful and accurate. Nyangarika and Tang (2018), Ali and Davallou (2018) and Nyangarika, Mikhaylov and Richter (2018) also found that the ARIMA model can help to predict the future oil price. Therefore, this thesis is using the Holt-Winters and ARIMA model to predict future oil prices.

### *2.2.2.1 Simple exponential smoothing*

The initial equation of this method is,

$$Y_t = \alpha X_t + (1-\alpha)Y_{t-1} \tag{32}$$

where $\alpha$ is the smoothing factor, and $0 \leq \alpha \leq 1$, $S_t$ is the weighted average of the $X_t$. The process is as follows:

$$\begin{aligned} Y_2 &= \alpha X_2 + (1-\alpha)Y_1 \\ Y_3 &= \alpha X_3 + (1-\alpha)Y_2 \\ Y_4 &= \alpha X_4 + (1-\alpha)Y_3 \\ &\vdots \\ Y_t &= \alpha X_t + (1-\alpha)Y_{t-1} \end{aligned} \tag{33}$$

Substituting each equation into one equation obtains

$$Y_{t+1} = \sum_{j=0}^{t-1} \alpha\,(1-\alpha)^j Y_{t-j} + (1-\alpha)^t \ell_0 \tag{34}$$

The last term $\ell_0$ becomes very tiny when t goes very large.

### 2.2.2.2 The Holt-Winters method

Holt (1957) stated that it is possible to add a trend to a simple exponential smoothing model with a trend. The equation is as follows:

$$Y_{t+h} = \ell_t + hb_t \tag{35}$$

where this equation is the forecast equation, $\ell_t$ is the estimate of the level of the series at time t, $b_t$ is an estimate of the trend of the series at time t.

$$\ell_t = \alpha Y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{36}$$

where this equation is the level equation, $\alpha$ represents the smoothing parameter of the level and its value is between zero and one.

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{37}$$

where this equation is the trend equation, $\beta$ is the smoothing parameter of trend, $0 \le \beta \le 1$.

### Holt-Winters' additive method

Holt (1957) and Winter (1960) claimed a new model Holt-Winters seasonal method which including the forecast equation and three smoothing equations. Hyndman and Athanasopoulos (2013) stated that the additive one suits the seasonal variations constant through the series. Within the additive method, the seasonal component is using the absolute value and the sum in a year is approximately equal to zero.

$$Y_{t+h} = \ell_t + hb_t + s_{t+h-m(k+1)} \tag{38}$$

$$\ell_t = \alpha(Y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{39}$$

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{40}$$

$$s_t = \gamma(Y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{41}$$

where $\ell_t$ is the level, $b_t$ is the trend, $s_t$ is the seasonal component. k is the integer part of $(h-1)/m$. The level equation is the weighted average between the seasonally adjusted observation $Y_t - s_{t-m}$ and the non-seasonal forecast $(\ell_{t-1} + b_{t-1})$. $(Y_t - \ell_{t-1} - b_{t-1})$ is the current seasonal index.

### Holt-Winters' multiplicative method

The other version of the Holt-Winters model is multiplicative method. Differ from the additive one, it suits for the seasonal variations are changing through the series. The seasonal component is relative value in multiplicative one and the sum of the component is approximately equal to m which is the time frequency (for example, monthly data, m=12)

$$Y_{t+h} = (\ell_t + hb_t)s_{t+h-m(k+1)} \tag{42}$$

$$\ell_t = \alpha\frac{Y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{43}$$

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)b_{t-1} \tag{44}$$

$$s_t = \gamma\frac{Y_t}{\ell_{t-1} + b_{t-1}} + (1-\gamma)s_{t-m} \tag{45}$$

### *2.2.2.3 The ARIMA model*

The autoregressive model uses the past values of the variable to do the regression against itself, therefor, the autoregressive model AR($p$) of order $p$ shown as below:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \tag{46}$$

where $\varepsilon_t$ is the white noise.

Apart from the AR model using the past value, the moving average model uses the past value of error to do the regression, MA($q$) with order of $q$ can be written as:

$$y_t = c + \varepsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{47}$$

where $\varepsilon_t$ is the white noise.

Then, when writing the stationary AR($p$) as an MA(∞) model. Consider a AR(1) model:

$$\begin{aligned} y_t &= \emptyset_1 y_{t-1} + \varepsilon_t \\ &= \emptyset_1(\emptyset_1 y_{t-2} + \varepsilon_{t-1}) + \varepsilon_t \\ &= \emptyset_1^2 y_{t-2} + \emptyset_1 \varepsilon_{t-1} + \varepsilon_t \\ &= \cdots \end{aligned} \tag{48}$$

which finally result as below:

$$y_t = \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \emptyset_1^2 y_{t-2} + \emptyset_1^3 y_{t-3} + \cdots \tag{49}$$

Then, the non-seasonal ARIMA model can be obtain by combine the differencing with AR and MA model, which as follows:

$$y_t' = c + \emptyset_1 y_{t-1}' + \cdots + \emptyset_p y_{t-p}' + \theta_1 \varepsilon_{t-1} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \tag{50}$$

where $y_t'$ is the differenced series and this is called an ARIMA (p,d,q) model, where p presents the number of autoregressive terms, d is the number of nonseasonal differences for stationarity and q is the lagged forecast error.

## 2.3 Results

In this part, two groups of data will be tested to get the forecast result of the Holt and Winters' tests. For the first group of data, 27 years data (in-sample) will be used to check the predictability of three years (out-of-sample) data from 2017 to 2019, and the second set uses seven years data to predict the out-of-sample data. The second group of data will be using 30 years and 10 years data respectively to check the data in 2020.

### *2.3.1 The result of the first group set*

In this part, the WTI and Brent crude oil spot prices are collected from the Datastream from 1990 to 2019 in order to test the forecast ability. The first set of group data is from January 1990 to December 2019, which contains the in-sample data from January 1990 to December 2016 and the out-of-sample data from January 2017 to December 2019. For the second group, the in-sample data is from January 2010 to December 2018, and has the same out-of-sample data as the first group.

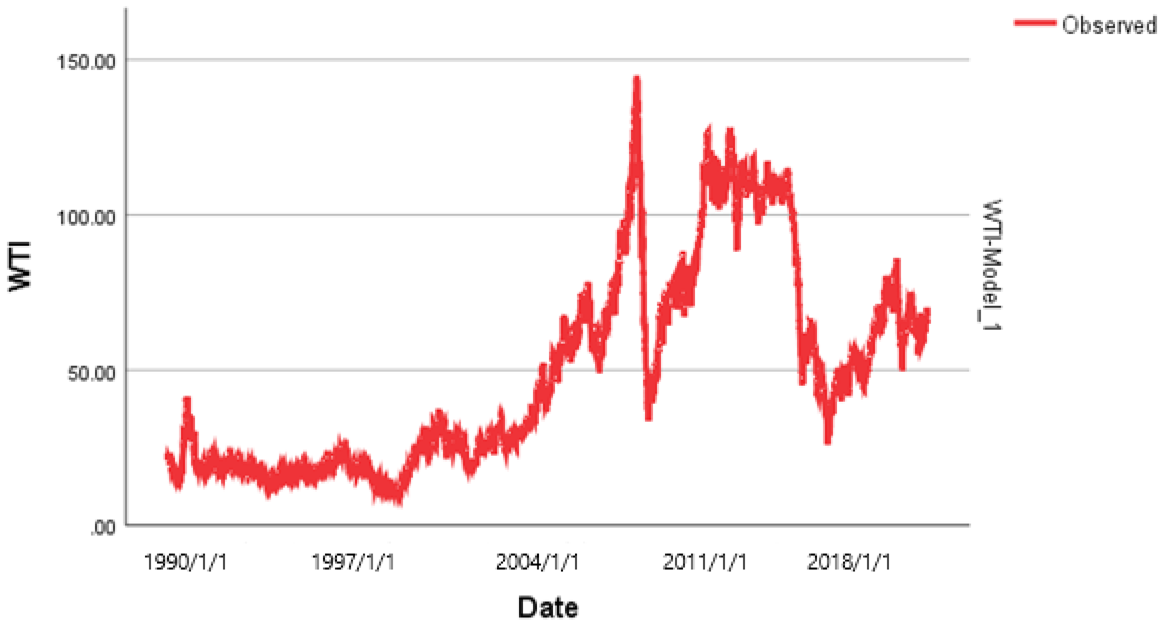
Chart 6 and Chart 7 show the oil price trend of the crude oil price of the WTI and Brent, which presents a similar movement in these 30 years. Tables 20 and 31 show the results obtained from the SPSS after running the Holt-Winters model.
After running the analysis, the result of the forecast of the first group by using Holt's linear trend and Winters' multiplicative trend is shown. To compare the RMSE, MAPE, MAE and MaxAE between Holt and Winters can help to identify the better method for oil price prediction.

In Table 21, the results shown are from the Holt model, to see the linear prediction of the oil prices based on the daily data, which means that there is no consideration of the seasonal changes of the oil prices. It is clear to see that all the RMSW, MAPE, MaxAPE, MAE and MaxAE values of the Brent case are smaller than in the WTI case. This indicates that the Holt linear prediction model is more accurate for Brent oil price prediction. In other words, the prediction ability of the Brent oil price is more reliable than the estimation of the WTI oil price.

In Table 22, the results are from the Winters model, which indicates that monthly data have seasonal changes. Different from the daily cases, the performance of the model is more reliable in WTI cases. There are only a few values of these comparable variables of WTI that are bigger than Brent, such as the 10 years case in MAPE and MaxAE.

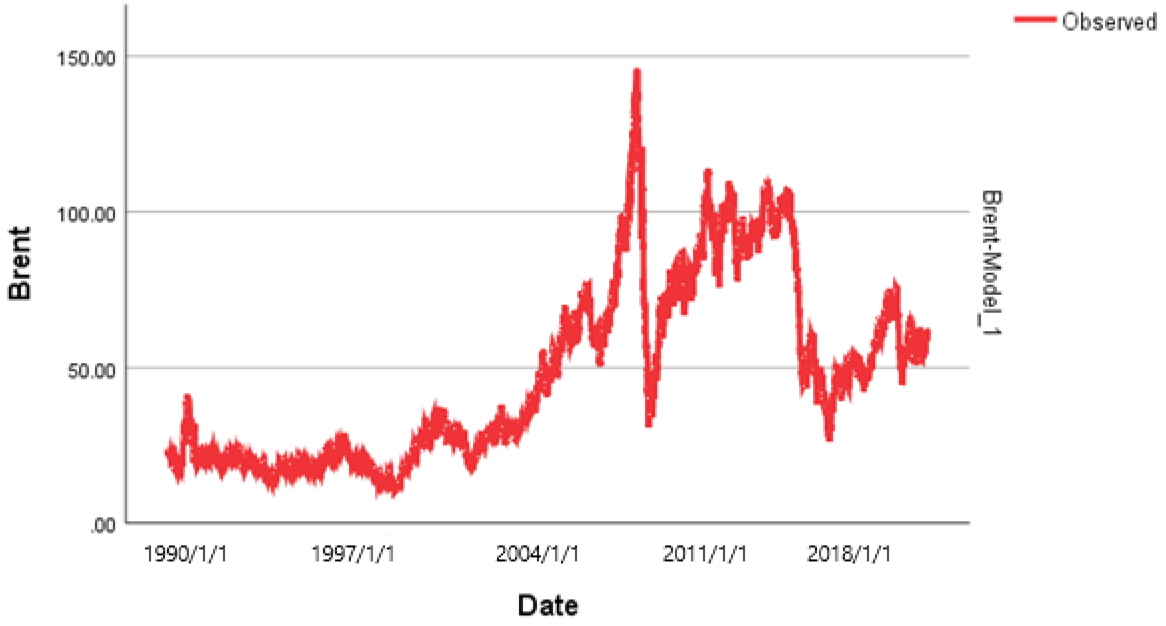
By making a comparison of the results based on tables 29 and 30, it can be seen that the Holt-Winters model has a different performance in regard to the two oil prices. The Holt performs better in Brent with daily data and the Winters has a better estimation in the monthly data of WTI.

Chart 6. The WTI crude oil spot price trend (30 years)




*Self-made*

Chart 7. The Brent crude oil spot price trend (30 years)




*Self-made*

Table 21. The Holt-Winters model with daily WTI and Brent data

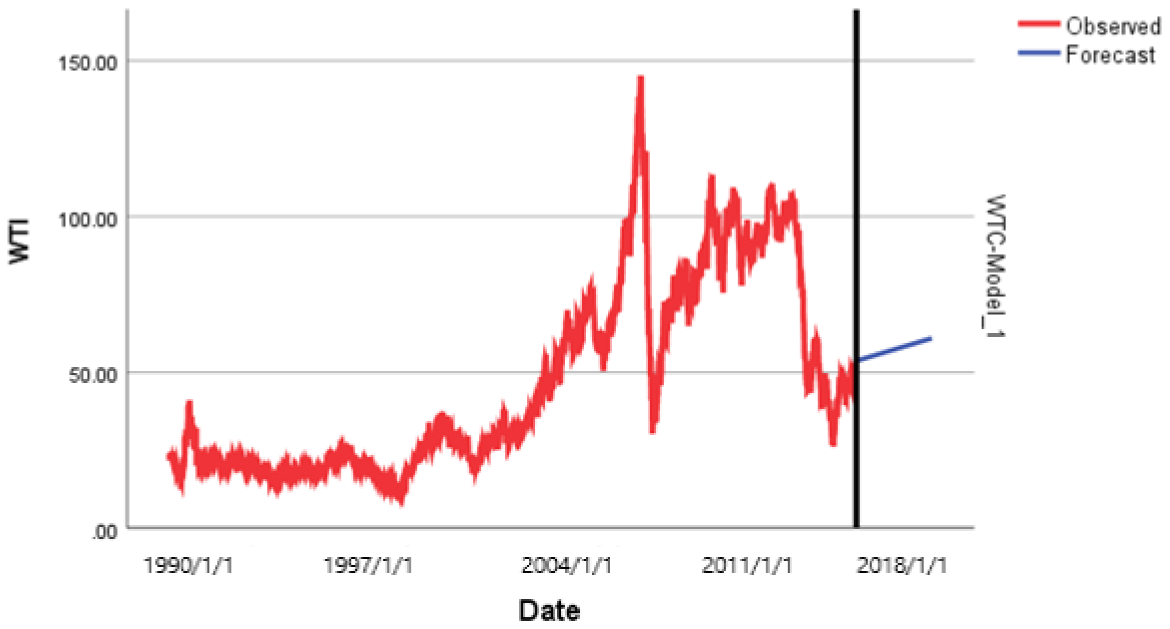
| | R-square | RMSE | MAPE | MaxAPE | MAE | MaxAE |
|---|---|---|---|---|---|---|
| Panel A : WTI | | | | | | |
| Holt (10-1) | 0.9960 | 1.3830 | 1.5050 | 11.7500 | 1.0230 | 8.9310 |
| Holt (10-3) | 0.9960 | 1.4630 | 1.5570 | 11.7960 | 1.0960 | 8.9850 |
| Holt (30-1) | 0.9980 | 1.2070 | 1.7120 | 49.7710 | 0.7680 | 17.1770 |
| Holt (30-3) | 0.9980 | 1.2170 | 1.7400 | 49.7700 | 0.7690 | 17.1790 |
| Panel B : Brent | | | | | | |
| Holt (10-1) | 0.9980 | 1.3430 | 1.3590 | 9.6050 | 0.9980 | 9.6620 |
| Holt (10-3) | 0.9970 | 1.4060 | 1.3740 | 9.6100 | 1.0510 | 9.6600 |
| Holt (30-1) | 0.9990 | 1.1100 | 1.6080 | 43.5460 | 0.7170 | 10.3830 |
| Holt (30-3) | 0.9990 | 1.1110 | 1.6310 | 43.5460 | 0.7100 | 10.3820 |

Table 22. The Holt-Winters model with monthly WTI and Brent data

| | R-square | RMSE | MAPE | MaxAPE | MAE | MaxAE |
|---|---|---|---|---|---|---|
| Panel A : WTI | | | | | | |
| Winter (10-1) | 0.9360 | 5.7520 | 6.8240 | 24.0890 | 4.7250 | 15.6120 |
| Winter (10-3) | 0.9330 | 6.0230 | 6.6690 | 24.3740 | 4.9000 | 15.2380 |
| Winter (30-1) | 0.9720 | 4.9670 | 7.4550 | 45.3820 | 3.4160 | 30.9050 |
| Winter (30-3) | 0.9740 | 4.9950 | 7.5360 | 45.4730 | 3.3860 | 30.9670 |
| Panel B : Brent | | | | | | |
| Winter (10-1) | 0.9530 | 5.8840 | 6.5860 | 26.5860 | 4.8680 | 15.0970 |
| Winter (10-3) | 0.9540 | 6.0650 | 6.5050 | 26.5040 | 4.9900 | 14.6490 |
| Winter (30-1) | 0.9760 | 5.2080 | 8.4450 | 52.8840 | 3.6070 | 31.7300 |
| Winter (30-3) | 0.9770 | 5.2270 | 8.7000 | 52.8580 | 3.5990 | 31.7150 |

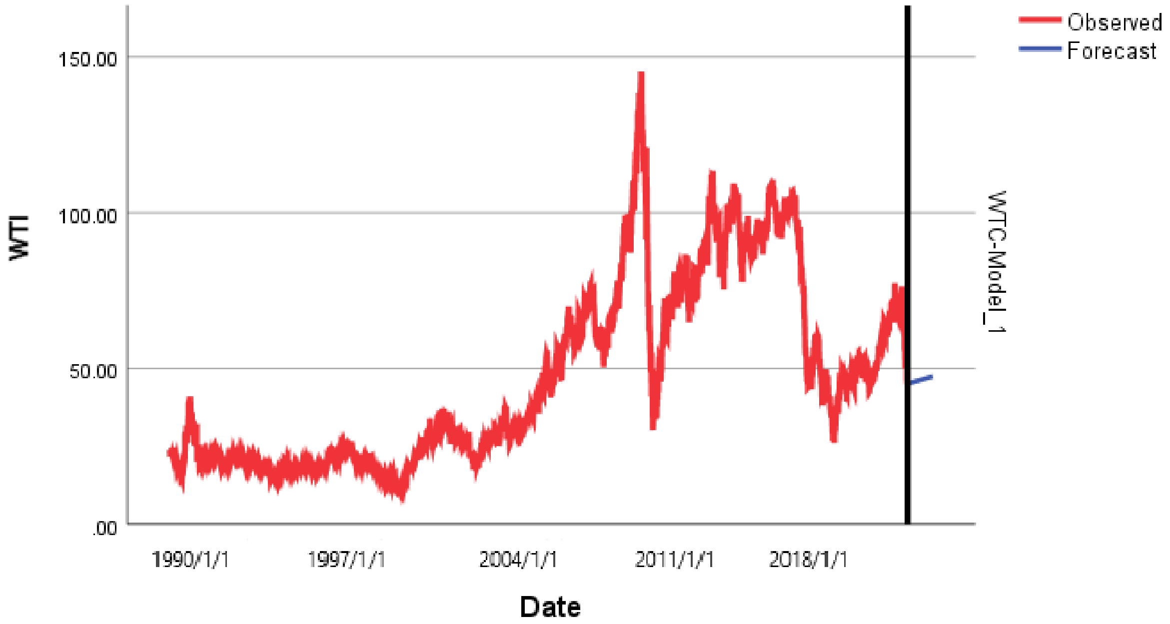
Charts 8 to 15 show the visual prediction values of the WTI and Brent oil prices over a total of 30 years data and predictions. In these charts, the predictions from using the Holt model are all in a straight line, while the Winters one shows seasonal changes of the predictions.

Chart 8. The WTI crude oil price trend (30 years) with a three-year forecast (daily)



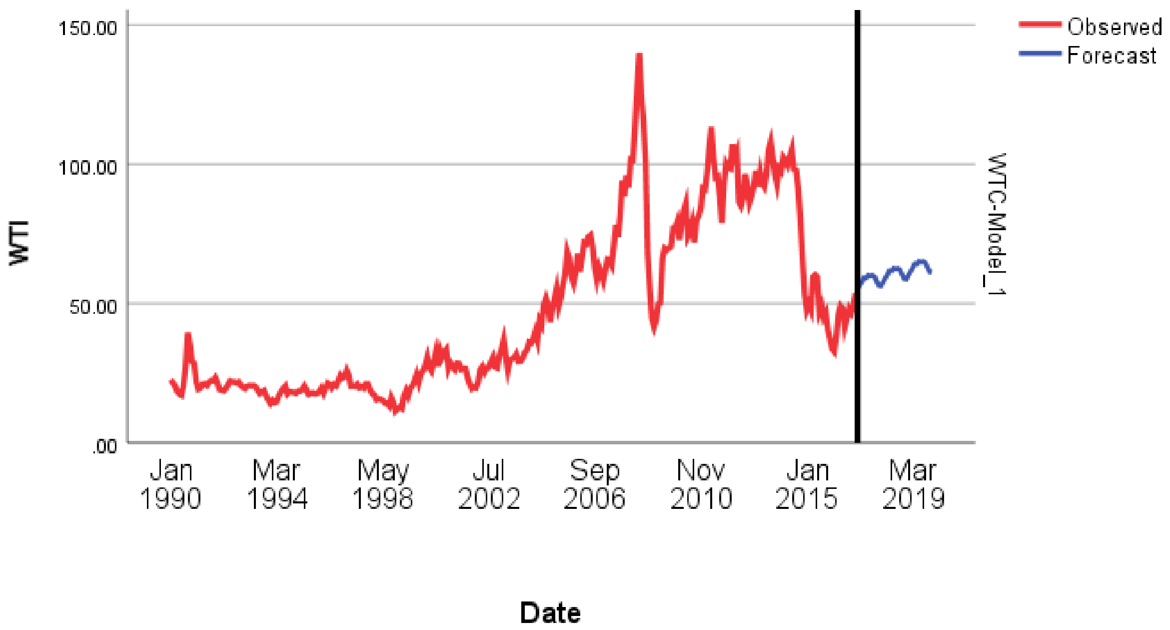

*Self-made*

Chart 9. The WTI crude oil price trend (30 years) with a one-year forecast (daily)




*Self-made*

Chart 10. The WTI crude oil price trend (30 years) with a three-year forecast (monthly)

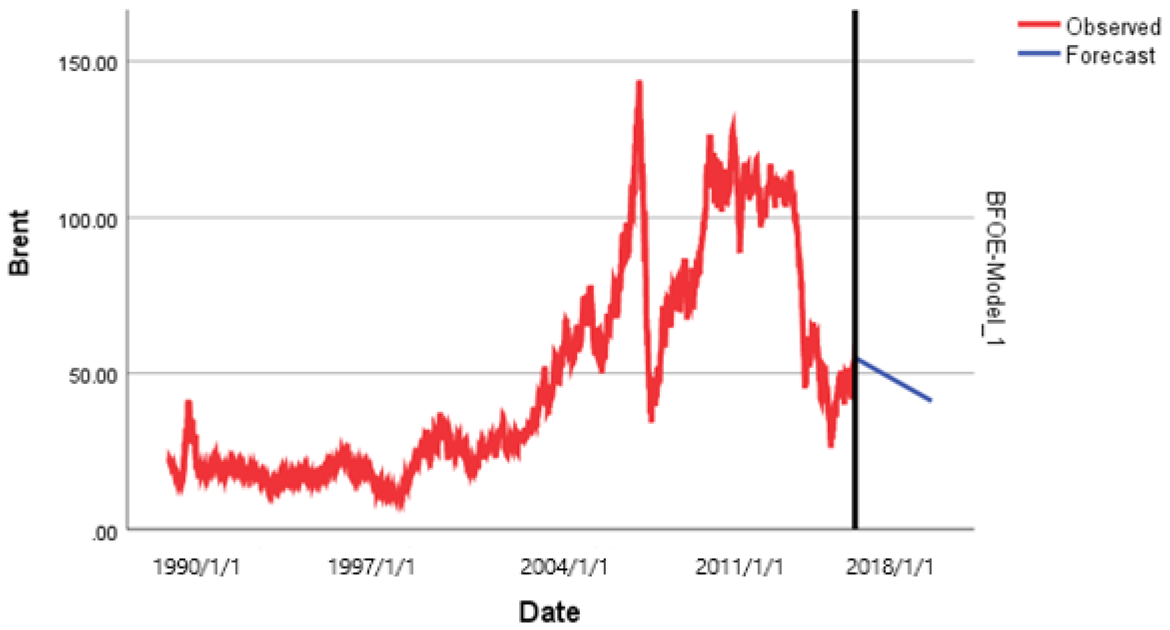



*Self-made*

Chart 11. The WTI crude oil price trend (30 years) with a one-year forecast (monthly)

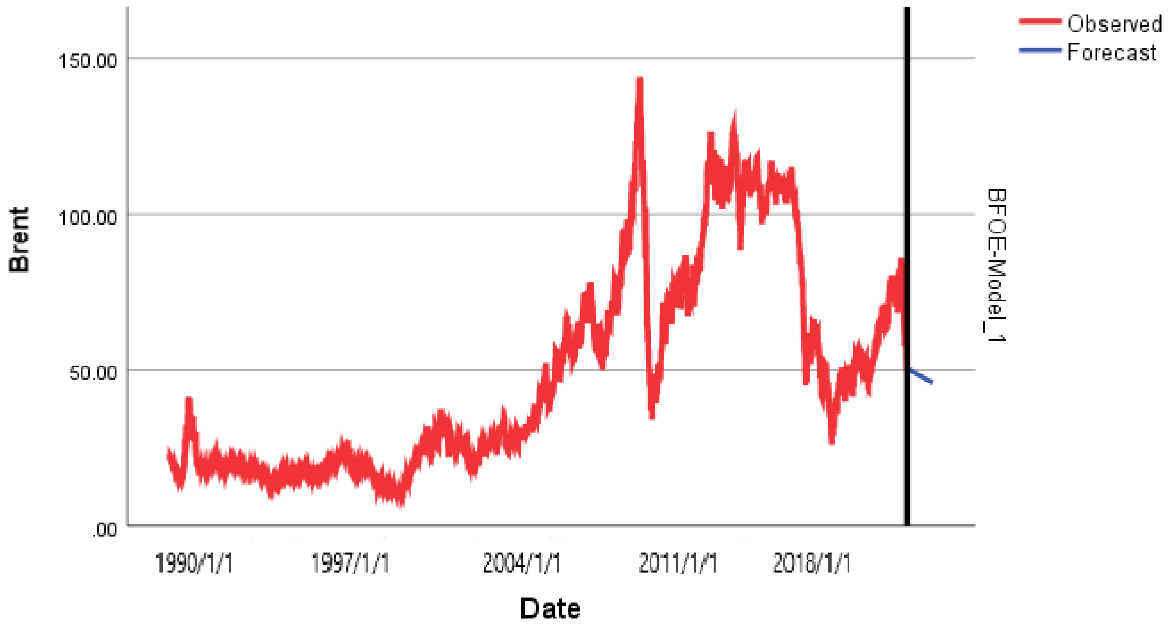

*Self-made*

Chart 12. The Brent crude oil price trend (30 years) with a three-year forecast (daily)



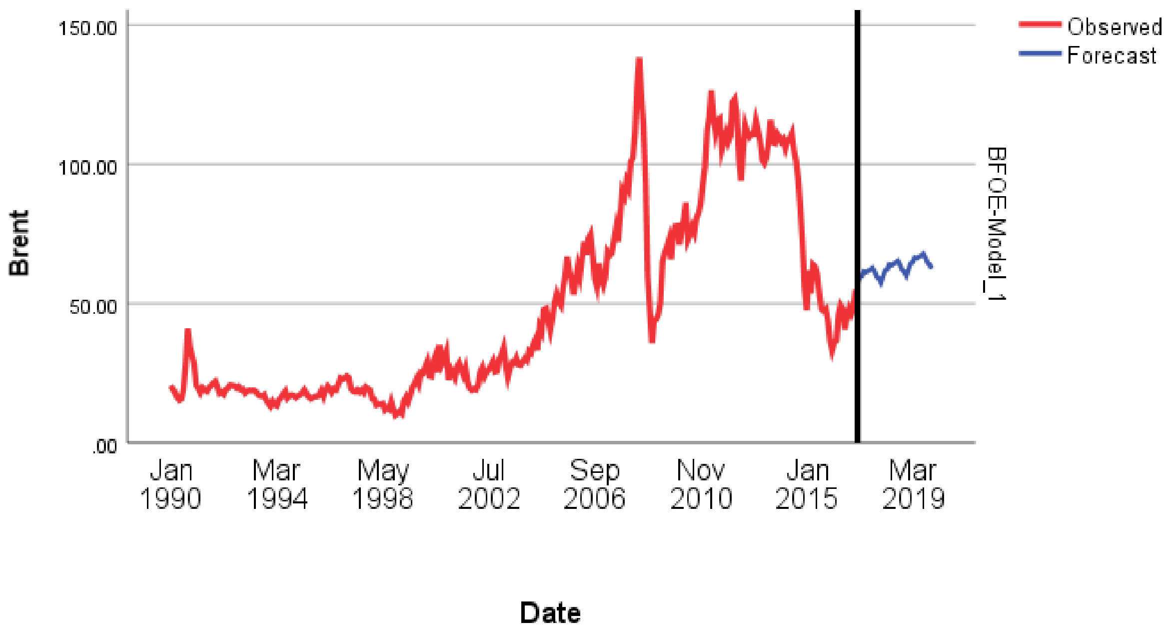

*Self-made*

Chart 13. The Brent crude oil price trend (30 years) with a one-year forecast (daily)




*Self-made*

Chart 14. The Brent crude oil price trend (30 years) with a three-year forecast (monthly)




*Self-made*

Chart 15. The Brent crude oil price trend (30 years) with a three-year forecast (monthly)

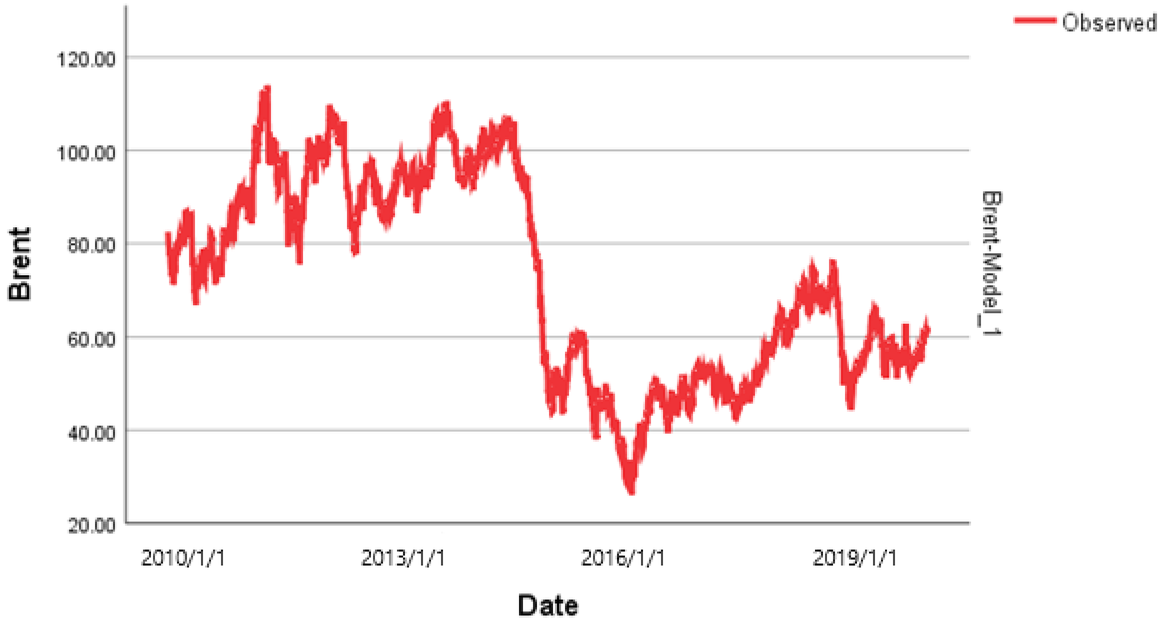

*Self-made*

Charts 15 and 16 show the movement trend of the crude oil price in the past 10 years. It is clear to see that these two oil prices have slightly different movements between them, and visually that these two oil prices have had no seasonal changes during these ten years.

Chart 16. The WTI crude oil spot price trend (10 years)

Self-made

Chart 17. The Brent crude oil spot price trend (10 years)

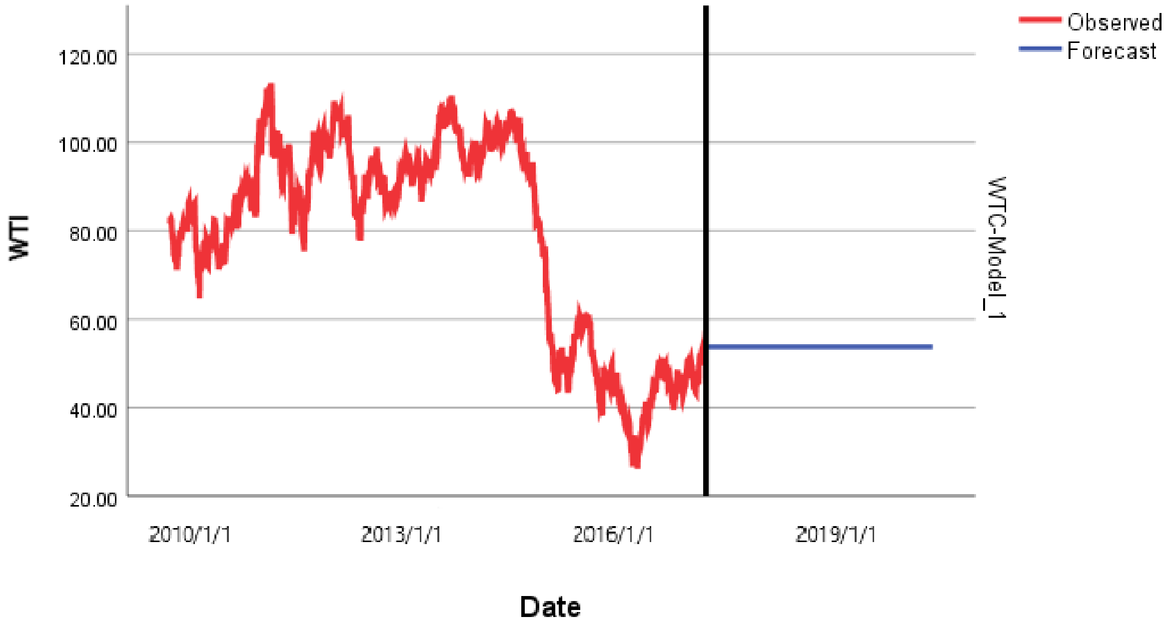



Self-made

Charts 18 to 25 show the prediction values of oil prices over 10 years. It is clear to see that the prediction value of the oil price is a straight line in both cases, and they decrease. The prediction values of the WTI and Brent oil prices both have large differences to the original data. The two prediction values have no fluctuation in the prediction period. In all the monthly data cases, the prediction value shows that they have seasonal changes during the prediction period.

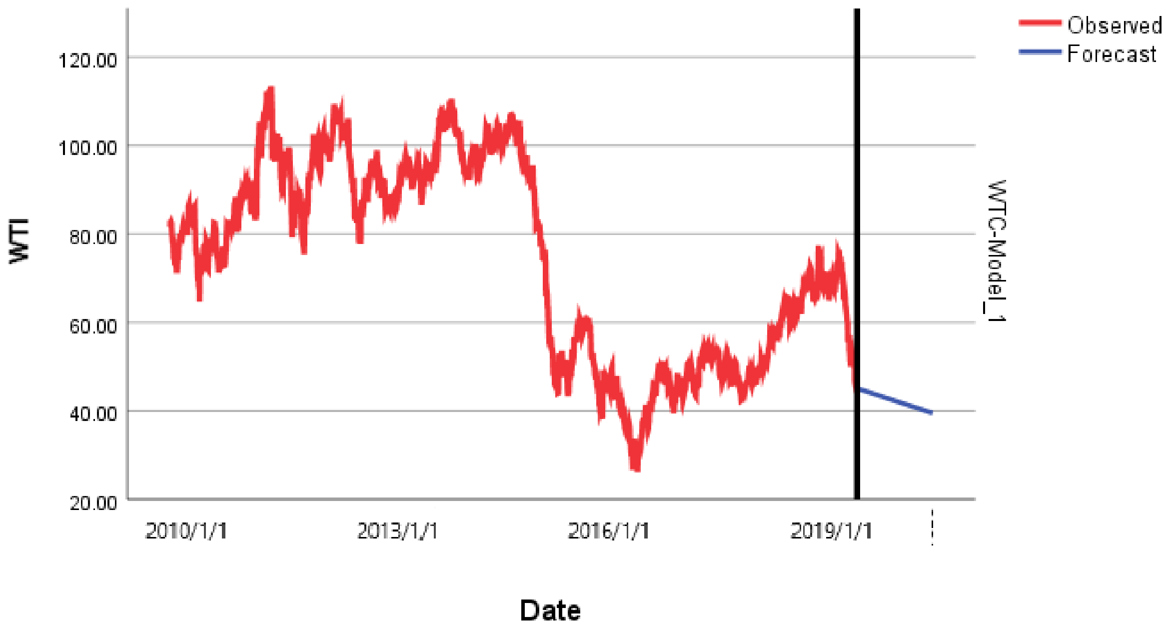
Different to the opinion from Wang, Tian and Zhou (2019), their method states that the oil price fluctuation can effectively predict the historical data. They also found that the larger size of historical data results in a better prediction. However, in this chapter, the 10 years prediction has a better estimation than the 30 years one. This may be due to the model selected. The Holt-Winters model is based on the exponential smoothing model, which is more suitable for short-term estimation. Also, 30 years of data include a few financial crises that hit the oil markets heavily.

Chart 18. The WTI crude oil price trend (10 years) with a three-year forecast (daily)



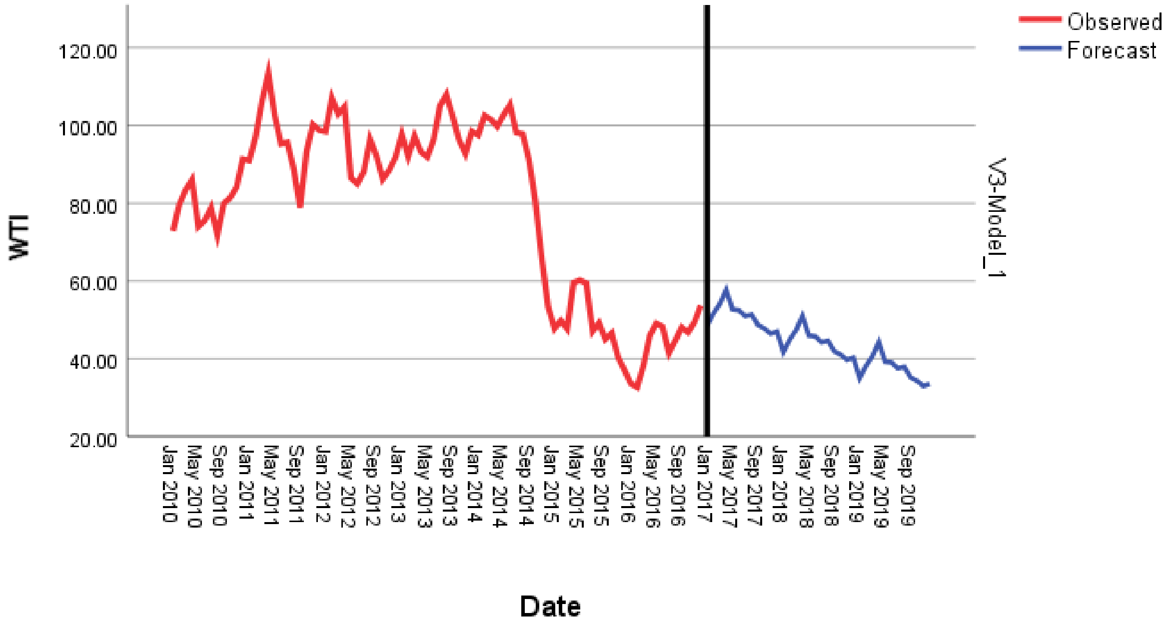

*Self-made*

Chart 19. The WTI crude oil price trend (10 years) with a one-year forecast (daily)



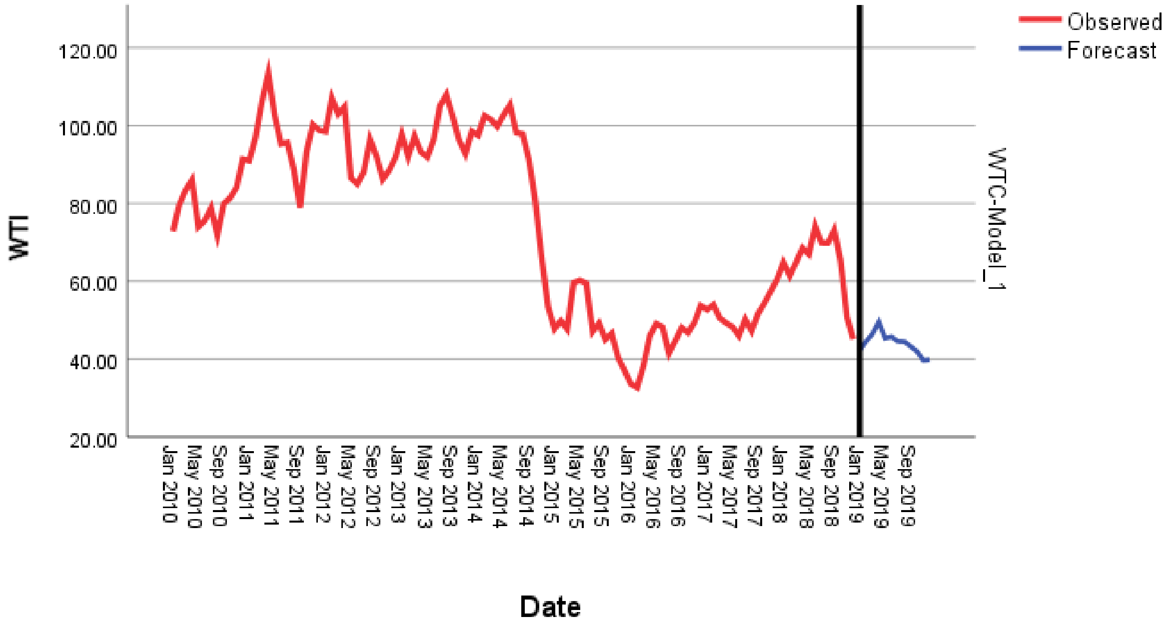

*Self-made*

Chart 20. The WTI crude oil price trend (10 years) with a three-year forecast (monthly)



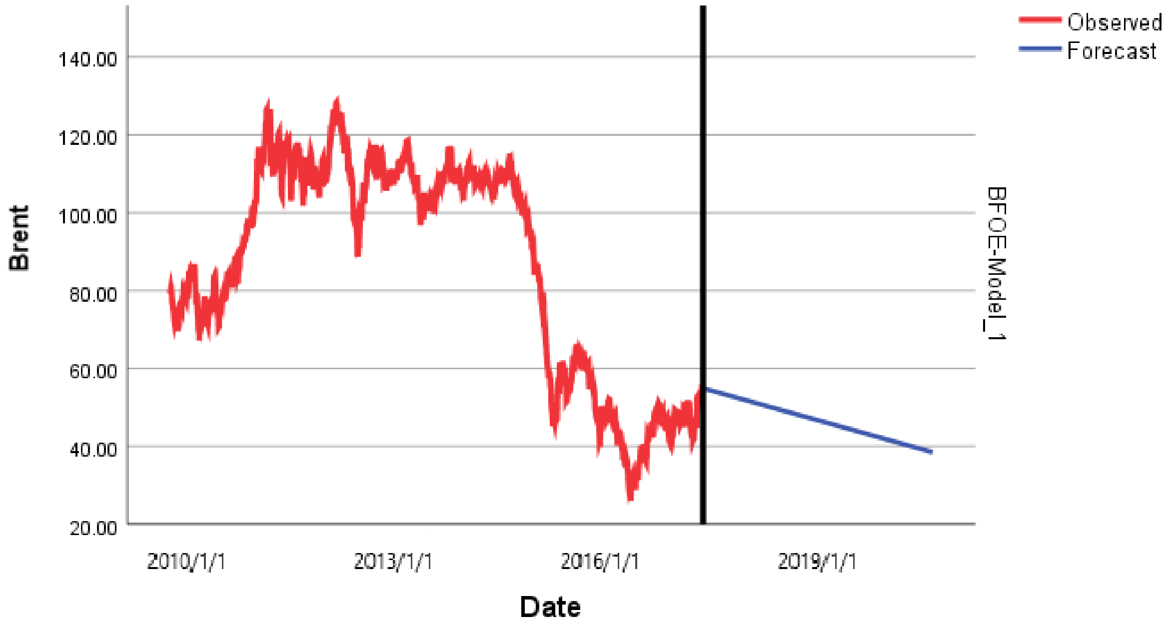

*Self-made*

Chart 21. The WTI crude oil price trend (10 years) with a one-year forecast (monthly)



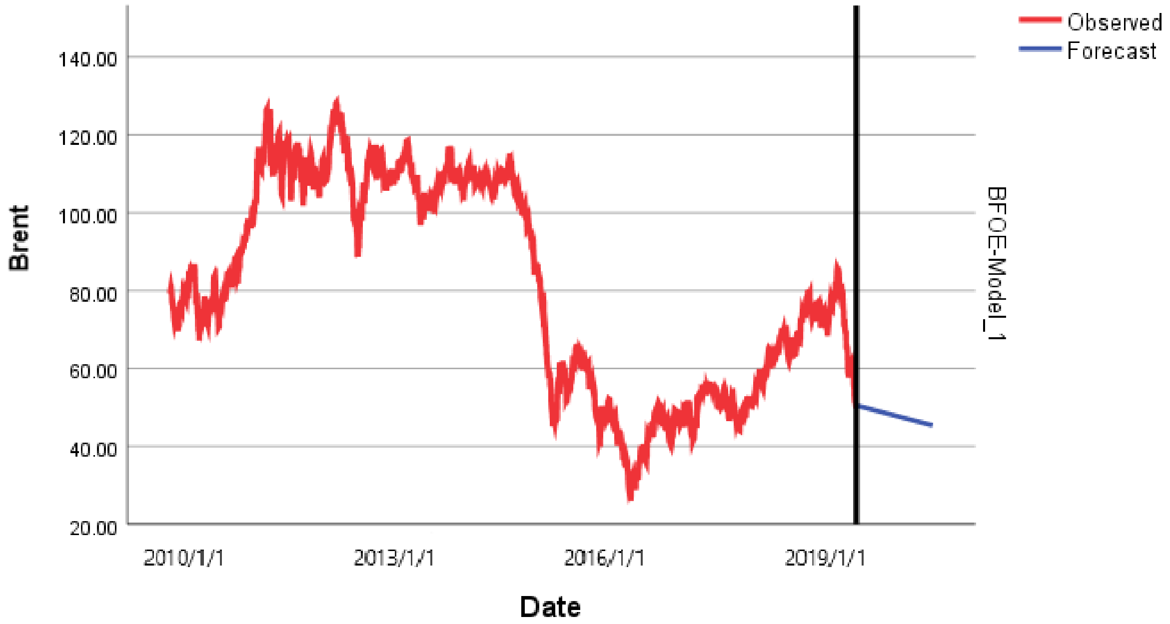

*Self-made*

Chart 22. The Brent crude oil price trend (10 years) with a three-year forecast (daily)



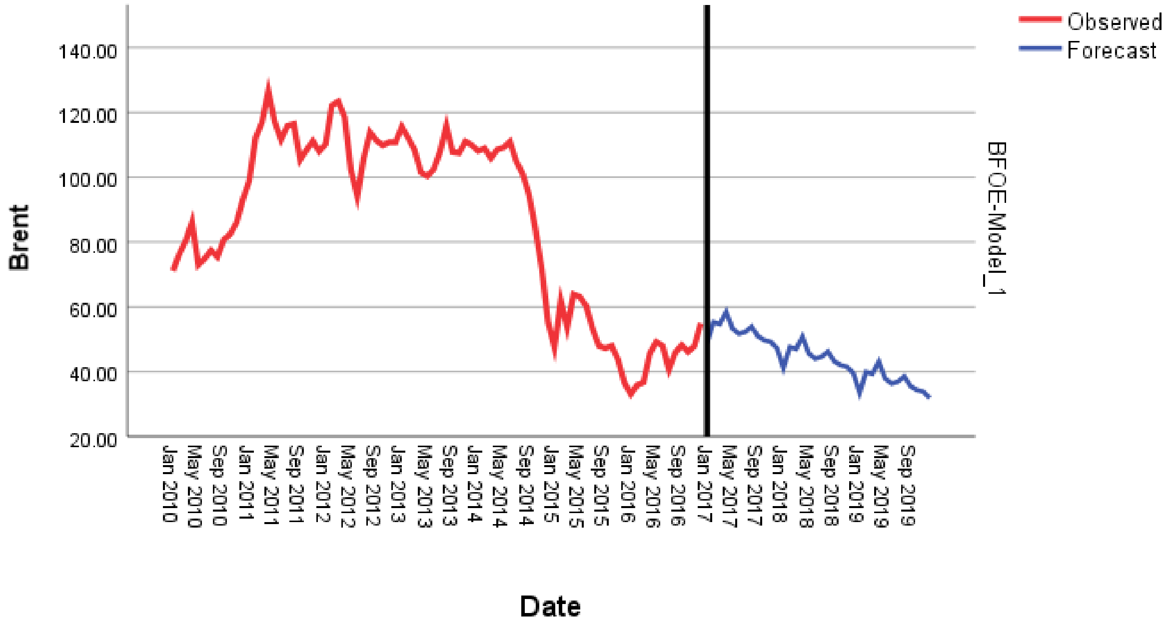

*Self-made*

Chart 23. The Brent crude oil price trend (10 years) with a one-year forecast (daily)



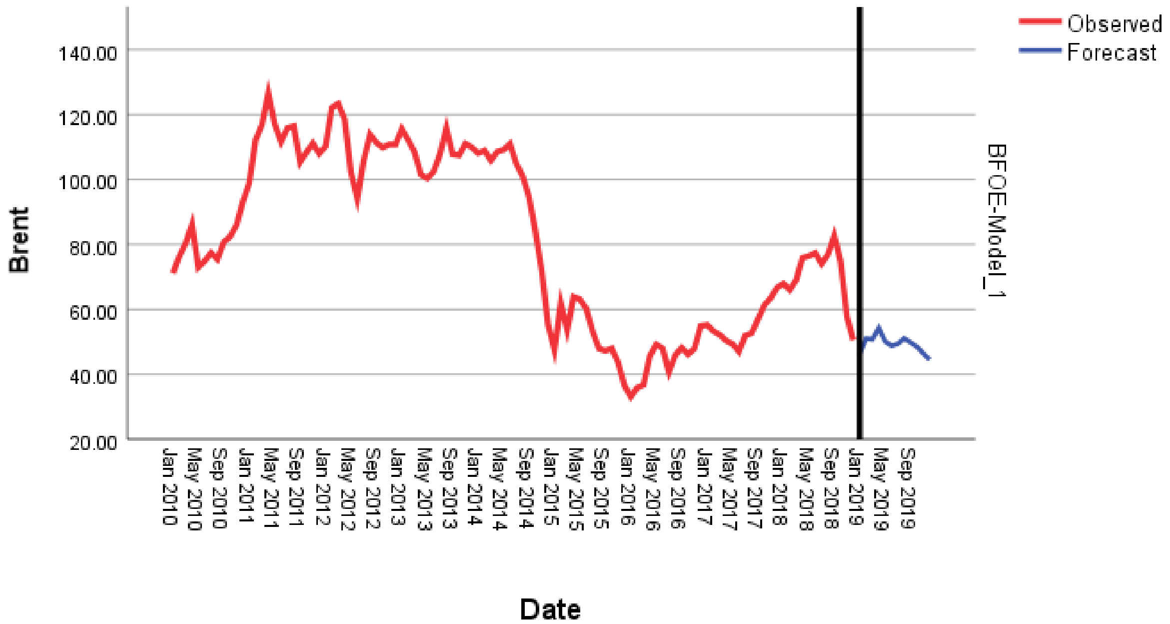

*Self-made*

Chart 24. The Brent crude oil price trend (10 years) with a three-year forecast (monthly)




*Self-made*

Chart 25. The Brent crude oil price trend (10 years) with a one-year forecast (monthly)




*Self-made*

In addition, Ali and Davallou (2018) also used the exponential smoothing model (ESM) to test the predictions of the oil price. They found that the ESM can predict the oil price, but to create a more accurate result they also included the autoregressive integrated moving average model and the nonlinear autoregressive model. They found that the combination of these three models can lead to a better result. This indicates that it could be worthwhile to use more than one method to run the test and get a better estimation.

Qu, Tang and Lao (2018) confirmed that the EMD can divide the data into different frequencies. They combined the EMD with the BP AdaBoost, which can provide an accurate prediction. The results of their tests show that the combination of the method can get smaller RMSE, MAE and MAPE values. Therefore, it would be good to have a combination of models to get a better result. Moreover, Zhao and Wang (2019) stated that the combination of the prediction methods can have more accuracy.

### *2.3.2 The result of the second group set*

In this part, the two groups of data have been used to forecast the data in 2020. The aim of doing this was to see whether the method was still reliable to forecast the oil price in 2020, because in 2020 the oil market experienced a difficult time and unpredictable events happened in 2020.

By looking at Table 23, for RMSE, MAPE, MaxAPE and MAE of Holt on both WTI and Brent crude oil prices, they are all smaller than the Winters model. Apart from the cases in MaxAE, the Holt one is larger than the Winters one. Therefore, in these cases, I will use the Holt one.

Table 23. The Holt-Winters model with WTI and Brent, with 30 and 10 years to one year

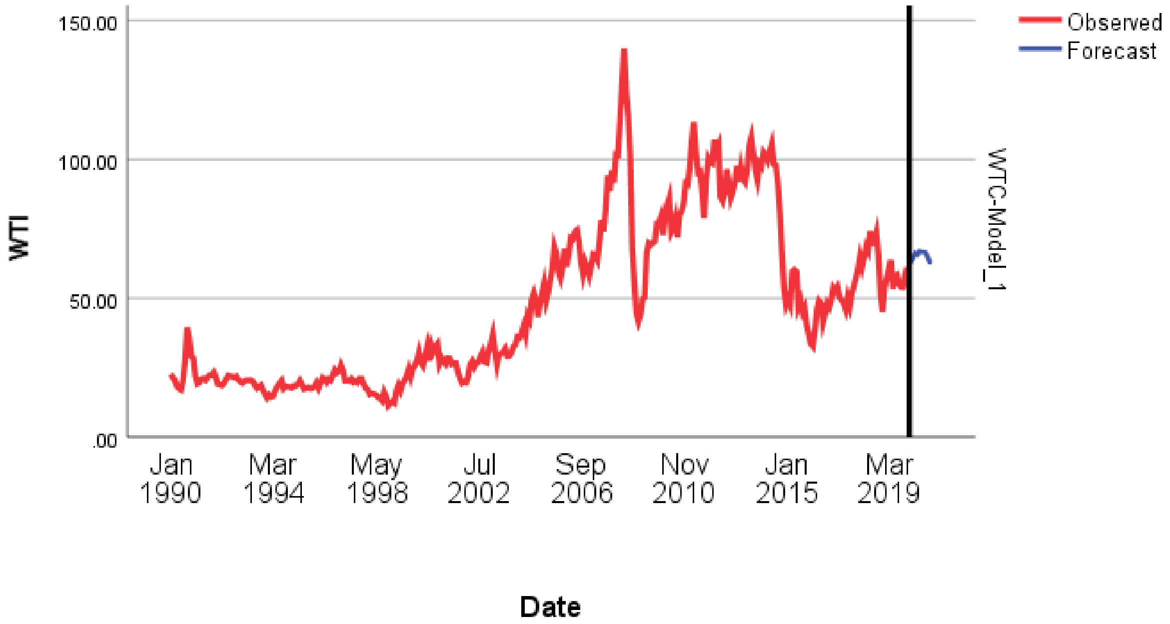
| | R-square | RMSE | MAPE | MaxAPE | MAE | MaxAE |
|---|---|---|---|---|---|---|
| Panel A : WTI | | | | | | |
| Winter (10-1) | 0.9340 | 5.6570 | 6.7690 | 25.3550 | 4.5940 | 15.4840 |
| Winter (30-1) | 0.9720 | 4.9430 | 7.3750 | 45.4840 | 3.4040 | 30.9750 |
| Panel B : Brent | | | | | | |
| Winter (10-1) | 0.9510 | 5.8360 | 6.4550 | 27.6600 | 4.7060 | 15.9630 |
| Winter (30-1) | 0.9760 | 5.1750 | 8.2640 | 52.9000 | 3.5830 | 31.7400 |

Charts 26 to 29 show the WTI and Brent crude oil price forecast and original data. Different from the previous tests, they show that the WTI crude oil price kept at a stable level for the prediction time, while the Brent oil price increased rather than decreased. However, the prediction values are different from the original one.

For the 10 years data to run the one-year forecast, this shows that apart from the MaxAPE and MaxAE, which is larger with the Holt test, the other variables are smaller than the Winters tests. Similar to the previous tests, the oil prices have had no seasonal changes during the last 10 years.

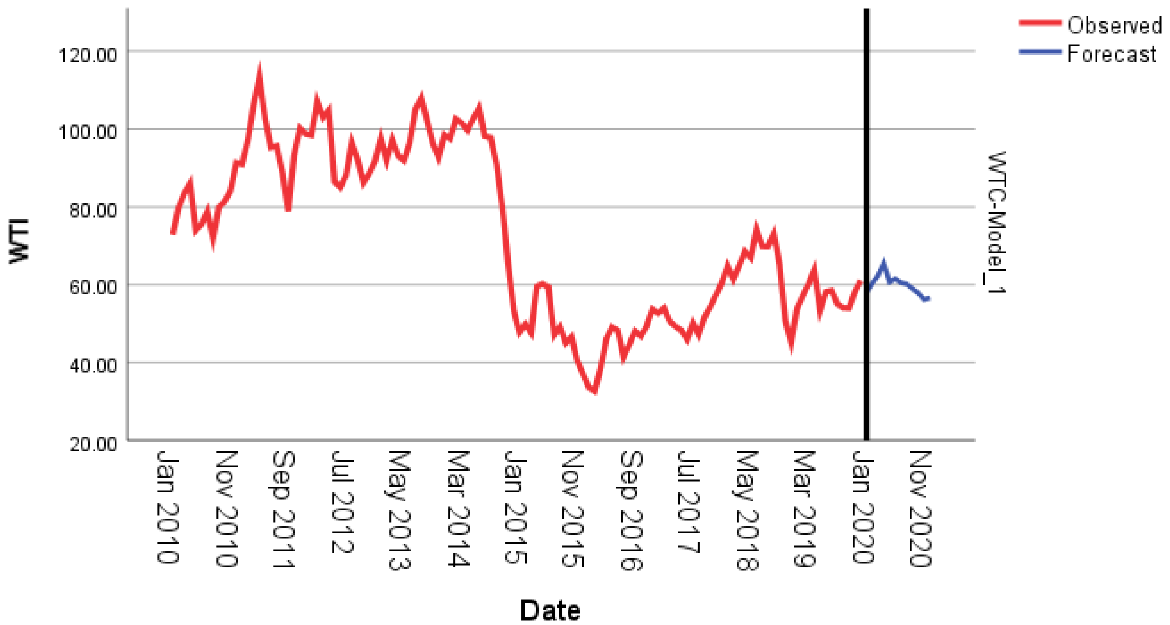
For these two cases, it shows that the WTI and Brent oil price decrease in the forecast period is similar to the previous tests. Like the previous analysis result, the prediction value is a straight line without fluctuation.

Chart 26. The WTI crude oil price trend (30 years) with a one-year forecast (monthly)




*Self-made*

Chart 27. The WTI crude oil price trend (10 years) with a one-year forecast (monthly)

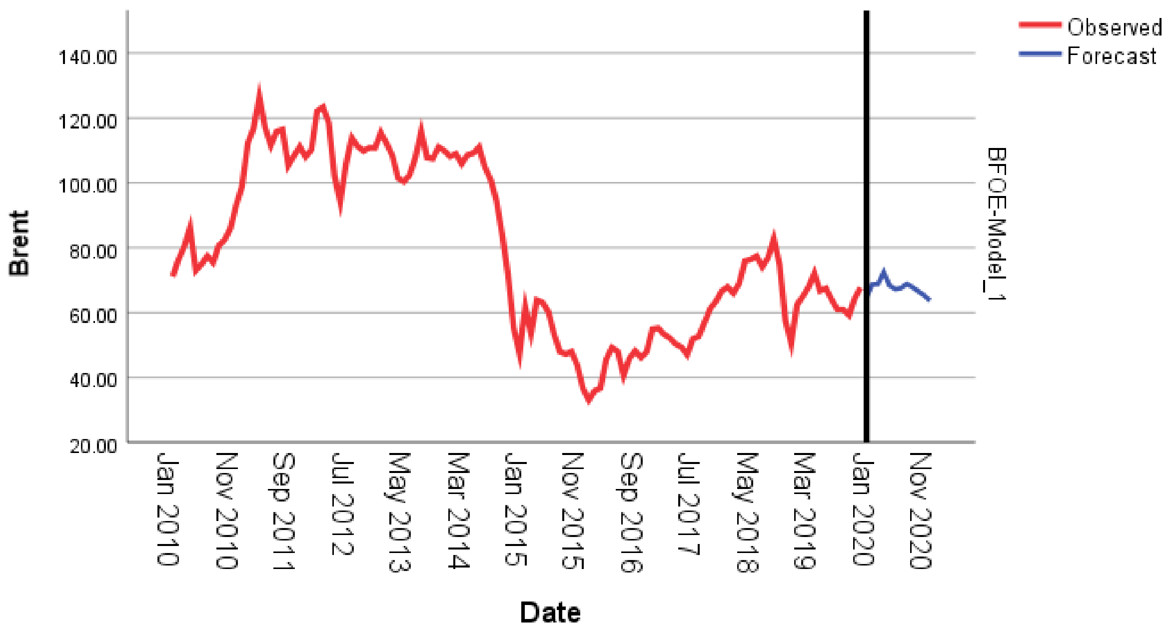



*Self-made*

Chart 28. The Brent crude oil price trend (30 years) with a one-year forecast (monthly)


*Self-made*

Chart 29. The WTI crude oil price trend (10 years) with a one-year forecast (monthly)




*Self-made*

Zhao and Wang et al. (2019) stated that the combination of methods can improve the accuracy of prediction of oil prices. They combined the Hodrick-Prescott filter with X12 methods to improve the stability and accuracy of the estimation of the oil prices.

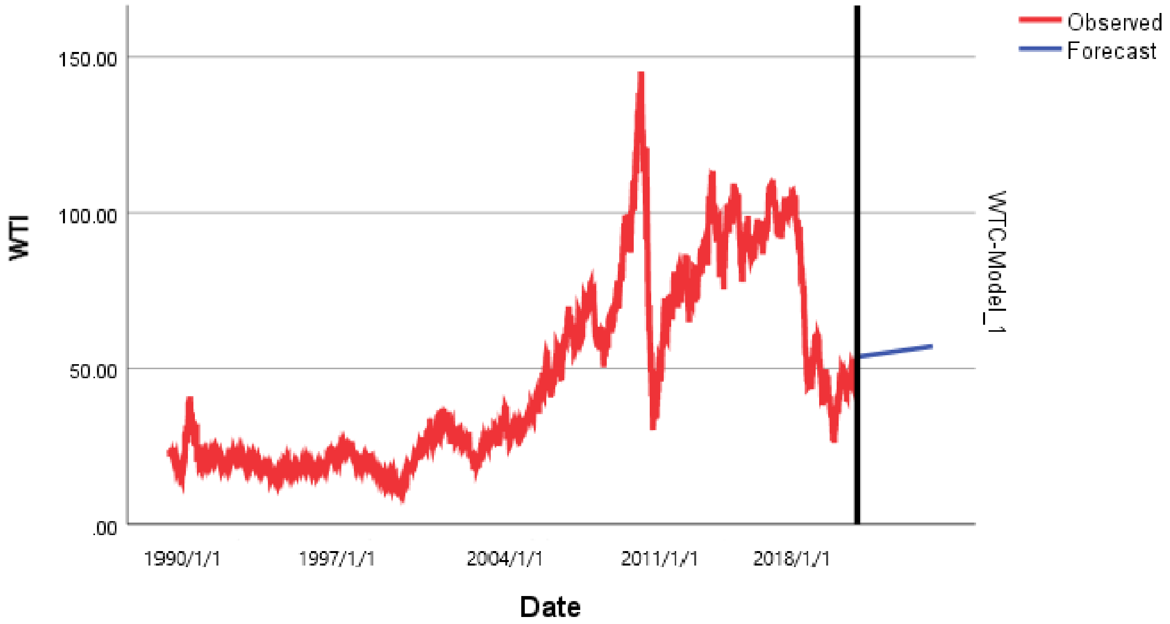
Wu and Chen et al. (2019) also combined some methods together that significantly improved the accuracy of the oil price prediction. These indicate that the combination of different methods can improve the prediction of the oil price.

In addition, Huang and Zheng (2020) found that due to COVID-19, investor sentiment had a significant influence on oil prices. Also, due to the unexpected situation that happened in 2020, the heavy hit on transportation also influenced oil prices. Therefore, only considering the oil prices themselves and running tests based on the oil price may be not enough. There are a lot of other factors that can influence oil prices.

Su, Qin and Tao et al. (2020) stated that US factors plays an important role in the oil markets. They especially made reference to the Partisan conflicts and the value of the dollar. They also suggested that it is necessary to understand the influence of the US factors, which can help others to make better decisions on the oil market.
Lu, Li and Chai et al. (2020) also pointed out that the oil supply and demand and the financial markets are the main influences on oil prices. The changes to the supply of oil and the hit on the transportation due to COVID-19 in 2020 influenced the oil price, which may cause the result that the prediction of the oil price in 2020 was not as accurate as the estimation from 2017 to 2019.

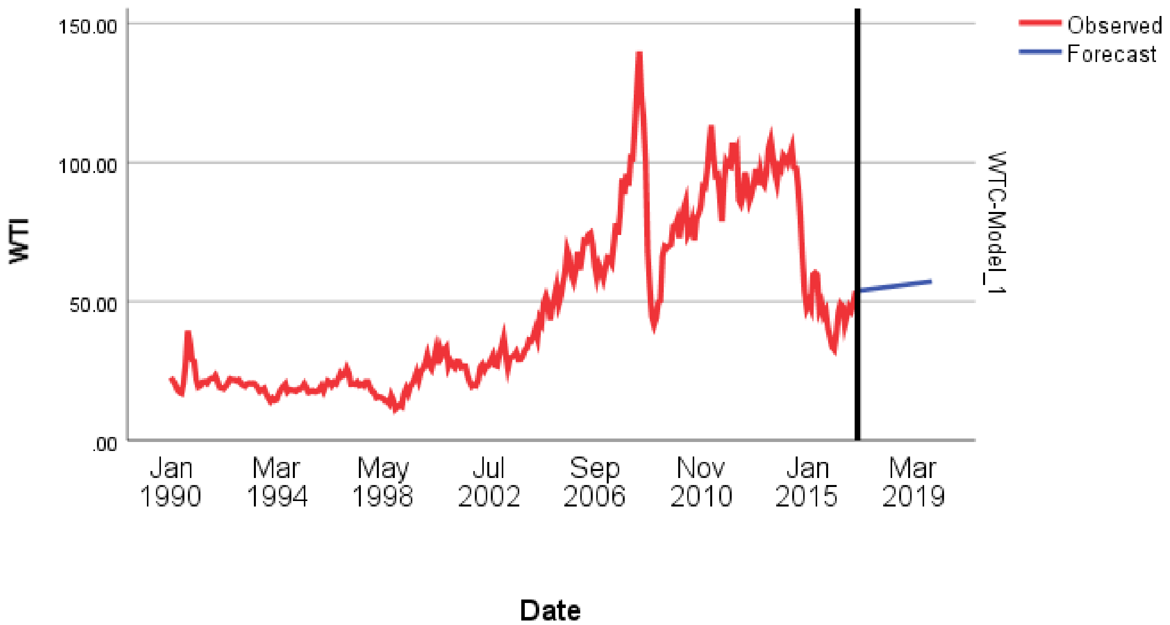
Chart 30 to Chart 37 show the results of the ARIMA model to predict oil prices. These also have the same period of data as previous tests. It is clear from going through these charts that using the ARIMA data provides the estimation period as a straight line, which denotes that the oil price is stable in both cases. Different from the previous case, the monthly case in the ARIMA model also shows a straight line, which has no seasonal changes.

Chart 30. The WTI crude oil price trend (30 years) with a three-year forecast (daily)



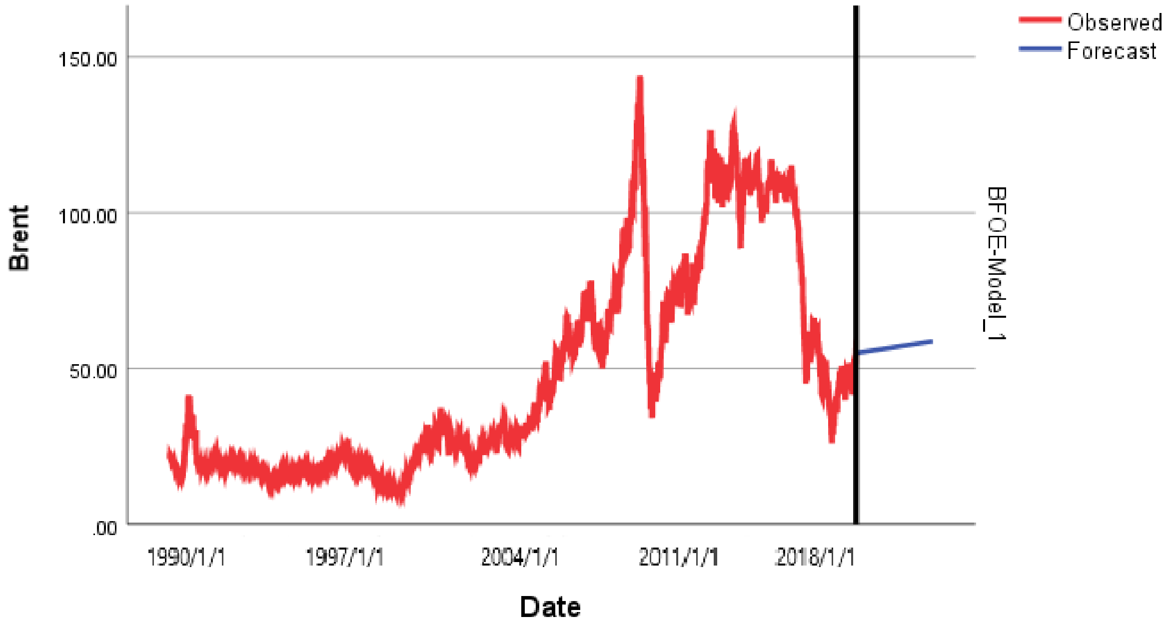

*Self-made*

Chart 31. The WTI crude oil price trend (30 years) with a three-year forecast (monthly)



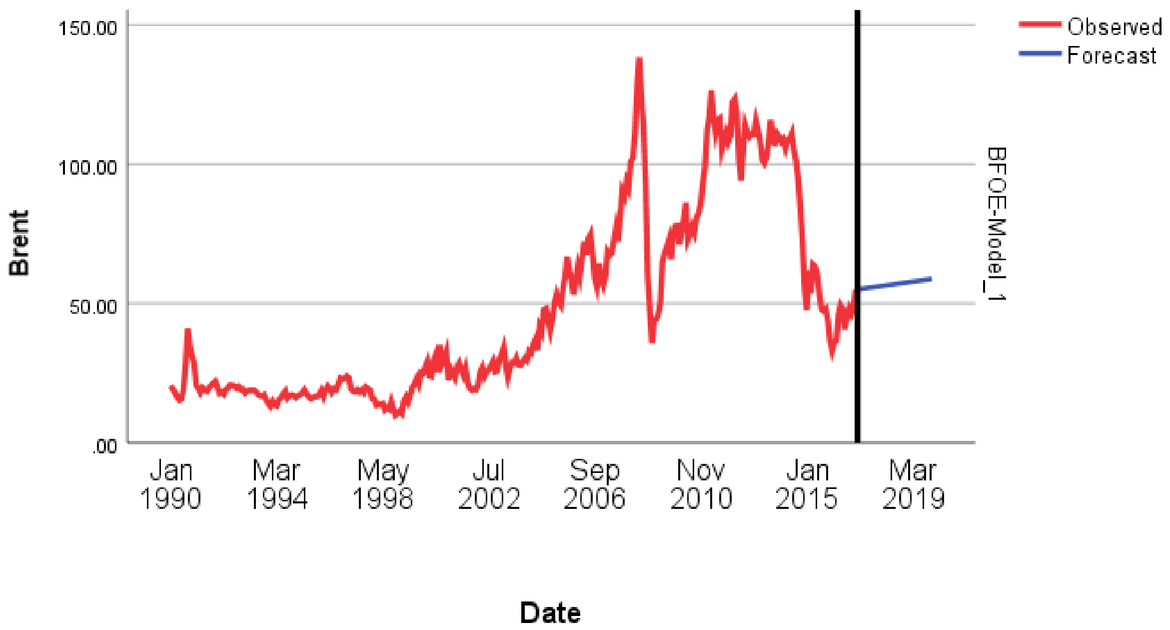

*Self-made*

Chart 32. The Brent crude oil price trend (30 years) with a three-year forecast (daily)




*Self-made*

Chart 33. The Brent crude oil price trend (30 years) with a three-year forecast (monthly)

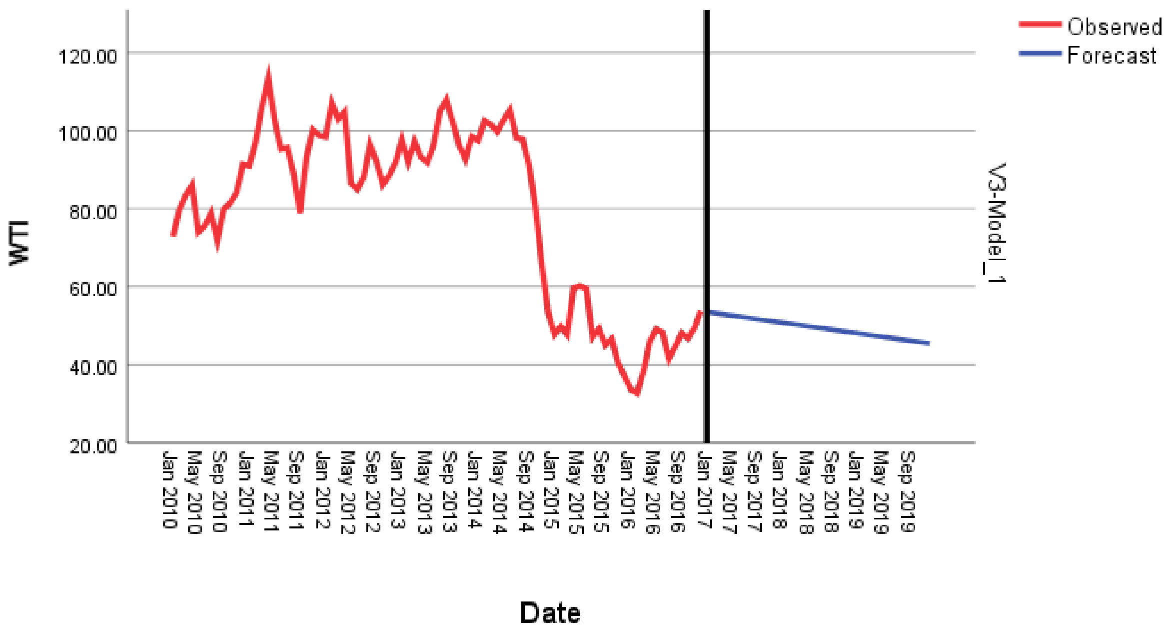



*Self-made*

Chart 34. The WTI crude oil price trend (10 years) with a three-year forecast (daily)

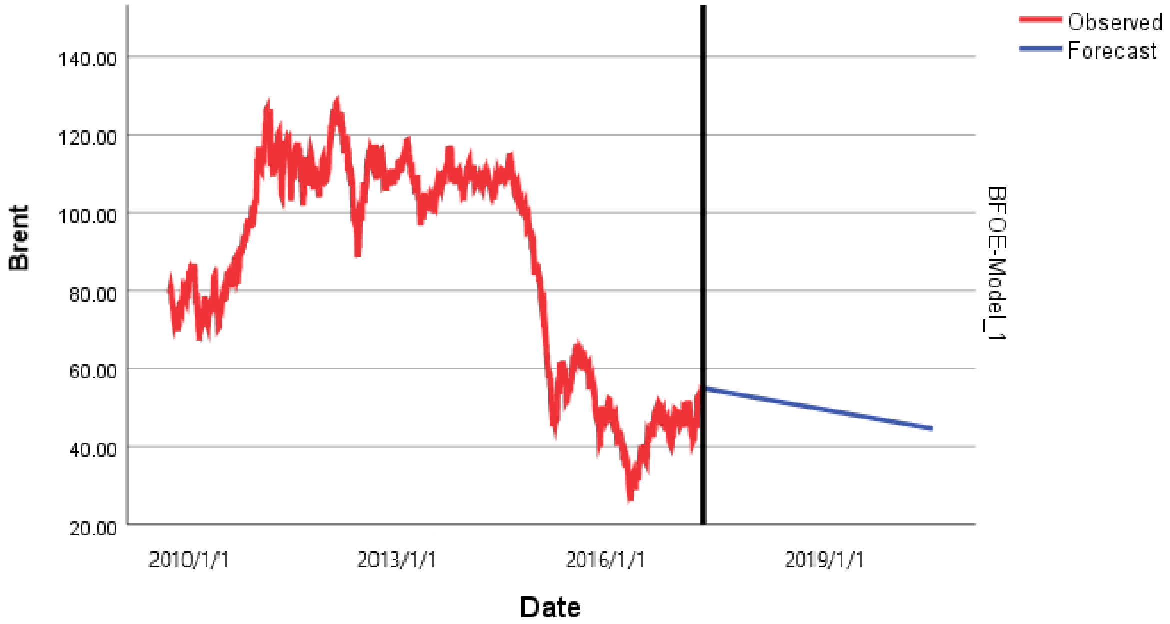

*Self-made*

Chart 35. The WTI crude oil price trend (10 years) with a three-year forecast (monthly)



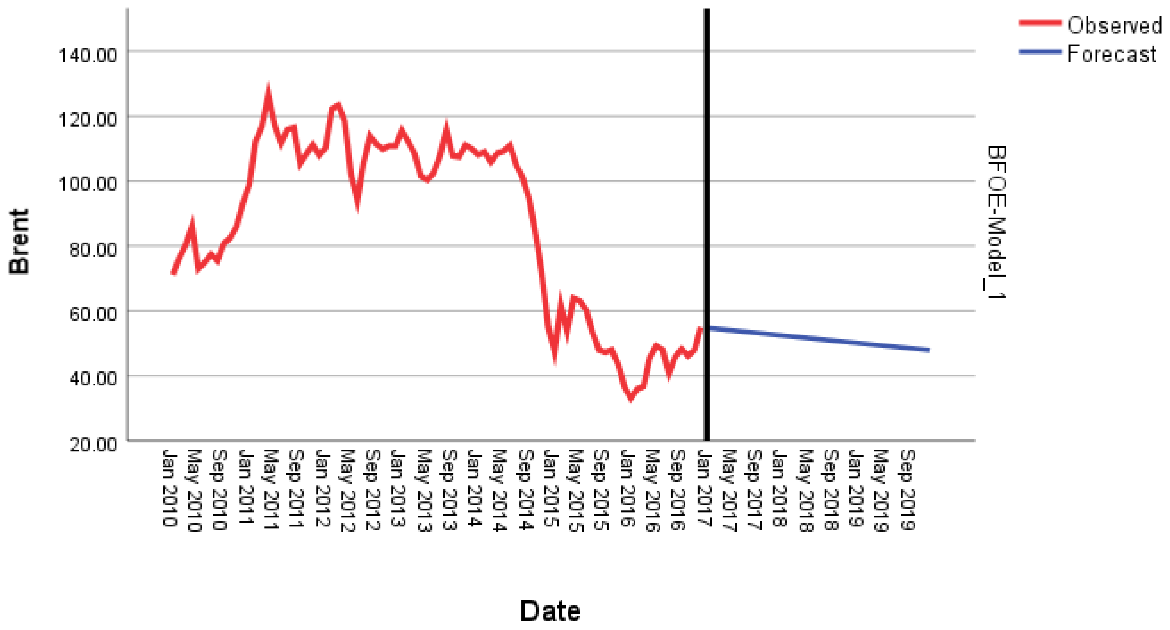

*Self-made*

Chart 36. The Brent crude oil price trend (10 years) with a three-year forecast (daily)




*Self-made*

Chart 37. The Brent crude oil price trend (10 years) with a three-year forecast (monthly)




*Self-made*

Table 24. The ARIMA model with daily WTI and Brent crude oil prices

| | R-square | RMSE | MAPE | MaxAPE | MAE | MaxAE |
|---|---|---|---|---|---|---|
| Panel A : WTI | | | | | | |
| ARIMA (10-1) | 0.9960 | 1.3840 | 1.5070 | 11.7440 | 1.0240 | 8.8840 |
| ARIMA (10-3) | 0.9960 | 1.4640 | 1.5570 | 11.7440 | 1.0970 | 8.8840 |
| ARIMA (30-1) | 0.9980 | 1.2080 | 1.7120 | 50.1540 | 0.7690 | 16.8770 |
| ARIMA (30-3) | 0.9980 | 1.2190 | 1.7400 | 50.1610 | 0.7690 | 16.8750 |
| Panel B : Brent | | | | | | |
| ARIMA (10-1) | 0.9980 | 1.3430 | 1.3610 | 9.4630 | 0.9990 | 9.6080 |
| ARIMA (10-3) | 0.9970 | 1.4050 | 1.3770 | 9.4670 | 1.0520 | 9.6060 |
| ARIMA (30-1) | 0.9990 | 1.1100 | 1.6090 | 43.5260 | 0.7170 | 10.4460 |
| ARIMA (30-3) | 0.9990 | 1.1110 | 1.6320 | 43.5310 | 0.7100 | 10.4450 |

Table 25. The ARIMA model with monthly WTI and Brent crude oil prices

| | R-square | RMSE | MAPE | MaxAPE | MAE | MaxAE |
|---|---|---|---|---|---|---|
| Panel A : WTI | | | | | | |
| ARIMA (10-1) | 0.9290 | 6.0090 | 6.8690 | 28.1040 | 4.7710 | 18.1110 |
| ARIMA (10-3) | 0.9250 | 6.3370 | 6.9670 | 25.7690 | 5.0700 | 18.1400 |
| ARIMA (30-1) | 0.9720 | 5.0380 | 7.1870 | 47.9660 | 3.3930 | 32.6650 |
| ARIMA (30-3) | 0.9730 | 5.0600 | 7.2350 | 48.0120 | 3.3650 | 32.6960 |
| Panel B : Brent | | | | | | |
| ARIMA (10-1) | 0.9480 | 6.2030 | 6.5710 | 29.7220 | 4.8000 | 16.9370 |
| ARIMA (10-3) | 0.9460 | 6.5020 | 6.7790 | 29.7170 | 5.1350 | 16.4240 |
| ARIMA (30-1) | 0.9750 | 5.2970 | 7.9640 | 56.0110 | 3.5710 | 33.6070 |
| ARIMA (30-3) | 0.9760 | 5.3140 | 8.1240 | 56.0440 | 3.5690 | 33.6270 |

The result from this paper does not show strong evidence to prove that the ARIMA model has significant and accurate predictions of the oil price. The ARIMA model does not perform well with the selected time series. The value of the prediction period is level, and jumps to a higher value in some cases. However, Wu and Chen et al. (2019) stated that the modified ARIMA model has a better estimation ability compared to other methods. They combined the ARIMA model with two other models – complementary ensemble empirical mode decomposition (CEEMD) and sparse Bayesian learning (SBL).

Moreover, Yu, Zhang and Wang (2017) combined five methods together, including the ARIMA model, to predict the oil price; they found that the combination of the different model performed well, resulting in a low estimation error. Ali and Davallou

(2018) combined the exponential smoothing model (ESM), the autoregressive integrated moving average model (ARIMA), and the nonlinear autoregressive (NAR) neural network to predict the oil price, which could provide accurate and outperformance results.

Nyangarika, Mikhaylov and Richter (2018) also used a modified ARIMA model to predict oil prices and concluded that the oil price is predictable. Jianwei, Bao and Ye (2017) stated that their modified ARIMA model is better than the basic one, and found that oil price changes could influence the level of inflation.

Mohammadi and Su (2010) tested some ARIMA-GARCH models in crude oil price forecasting. They found that among GARCH, EGARCH, APARCH and FIGARCH, the APARCH model performed better in most cases. They also found that the conditional standard deviation captures the volatility better than the original one.

Besides this, Dritsaki (2018) pointed out that the basic ARIMA model can provide accurate forecasting in the short term, but it cannot handle the volatility and nonlinearity of the time series. Therefore, the paper employed an ARIMA-GARCH model and found that the static procedure performs better than the dynamic one.

These literatures suggested that modified methods of the ARIMA model, or combining the ARIMA with other models to do the oil price forecasts and the results, show that the modified model and the combination perform better than the original one. Moreover, using the combination of the ARIMA model can solve the problem that the basic ARIMA model has.

Aamir and Shabri (2016) compared three models – the ARIMA, GARCH and ARIMA Kalman models – to see their predictability in forecasting the monthly crude oil price in Pakistan. They found that the ARIMA Kalman performed better than the other two, resulting in lower MAE and RMSE.

Wang, Song and Li (2018) employed the nonlinear metabolism grey model (NMGM) and ARIMA models to predict the US shale oil price. The combination method can help them solve linear and nonlinear problems. They found that the NMGM-ARIMA significantly increases the predictability of the oil price.

Moreover, the ARIMA model is highly reliant on past data of its own. Therefore, the predictability of the ARIMA model in the long term is limited. The ARIMA performs better in the short term than in the long term. Besides this, due to predictions based on historical data, the influential events that happened in the past will also influence the accuracy of the ARIMA model.

These papers showed that the ARIMA model is capable of predicting the oil price. However, it may need to be modified or combined with another method to investigate the prediction of the oil price. In addition, for future investigation, the prediction of future crude oil prices should also consider using a neural network or machine learning to increase accuracy. Based on the discussion of the above literature and their results, it can be considered that adding other methods to combine with the ARIMA model can offset the drawbacks, leading to more accuracy and better predictions.

## 2.4 Summary

In this chapter, the WTI and Brent oil price data have been collected from Datastream to run prediction tests. The data have been collected from January 1990 to October 2020. These data are divided into two groups. The first set of group data is from January 1990 to December 2019 and the second set of group data is from January 2010 to December 2019. For the first set, the data from January 2016 to December 2019 were chosen as the out-of-sample data and the remaining period of data in both groups as in-sample data to run the forecast. For the second group set, the data in 2020 have been considered as the out-of-sample data and the whole period of both groups as the in-sample data.

For the first group set, the aim of doing this was to identify the predictability of the length of in-sample data. The results given by the holt-winter mode shows that the data collected did not have the seasonal changes. In addition, after choosing the

specific results, the result given by the analysis of variance shows that the 10 years data have a better prediction ability of oil prices. Moreover, the results indicate that using a combined method can lead to better prediction.
For the second group, the ARIMA model can also predict the future oil price to some extent. The results show that the out-of-sample data is a level in the whole prediction period that has no trend. Similar to the first group, the 10 years data prediction performs better than the 30 years data prediction.

For both methods, the Holt-Winters model and the ARIMA model, the results seem to be unacceptable, and are different from the original data. The prediction values keep a straight line in all cases, without any fluctuations. The results cannot reflect the oil price movement appropriately. This may be due to the fact that the analysis only takes the oil price into consideration. There are many other factors that influence the oil price, and it might be better to have more than one variable taken into consideration.

There are some reasons that may explain why ten-year data predictions are better than the results of thirty-year data prediction. Firstly, the exponential smoothing model is more suitable for short-term prediction, which is consistent with results obtained from this thesis. Secondly, the results obtained from these methods probably have a similar trend to the previous data. The thirty-year data trend contains some financial crises. The sudden decrease and increase that happened during the financial crisis period influenced the prediction for the results. Thirdly, these methods only consider the one variable – the oil price. They only use previous oil prices to predict out-of-sample data, which ignores other influential factors. The thirty-year data is influenced largely by these factors, and they may make prediction harder.

## 2.5 Limitations

The Holt-Winters and ARIMA models are suitable for time series data prediction. However, they still have their drawbacks in terms of prediction. For the exponential smoothing method, they provide results that have a smooth curve, even for seasonal ones. They may ignore some potential or unexpected changes in the future. For instance, if large changes or shocks have happened in the past, a similar external change will also be estimated in the prediction period. In addition, the Holt-Winters method is more suitable for short-term prediction. The results of the exponential smoothing predict that the future is similar to the present value, which may look reasonable in the short term, but it may not be that accurate in the long term. Moreover, the method only considers the oil price as the parameter, which may result in ignoring other factors' influence on oil prices. This led to a result that may not have been as accurate as expected.

## 2.6 Efficient market hypothesis

In this chapter, the efficient market hypothesis (EMH) is also taken into consideration to see if the oil market is efficient or not. The theory of the efficient market is that the prices in these markets can fully reflect all the available information in the markets (Fama 1970). Fama also pointed out that the efficient market can be divided into three categories – weak form, semi-strong form and strong form.

1. Weak Form EHM: Weak Form EHM suggests that the prices reflect all the past information. This suggests that investors can use past information to do the analysis in the market and gain benefits above the market average in the short term. The above is available in the short term but not the long term.
2. Semi-strong Form EMH: Semi-strong Form EMH not only reflects past information in the prices, but new information will also be counted in the prices. In addition, by using fundamental and technical analysis, investors can still gain benefits above the market average.
3. Strong Form EMH: Under Strong Form EMH, the prices reflect all the information in the public and private spheres. Therefore, it is almost impossible for investors to gain benefits above the market average, unless they are lucky.

Lawal (2018) investigated the validity of EMH in oil price indices. The paper found that the oil price indices have structural shift and nonlinearity, which led to them being inefficient when there was a structural break. Besides this, the paper also pointed out that not all the public information will be reflected in the price, which provides the opportunity for some investors to gain excess returns compared to the market average. It suggested that market regulators should provide quality information for the public, which could avoid mispricing and bubbles.

Ghazani and Ebrahimi (2019) employed an adaptive market hypothesis (AMH) as an alternative to the EMH, by analysing daily returns on three benchmark crude oils. They concluded that the Brent and WTI crude oil markets have a high efficiency level. They also found that the longer the time they estimated, the less AMH they would achieve.

Kristoufek (2019) found that oil markets were inefficient during the 2008 financial crisis. During the inefficient market period, the Brent oil market showed stronger evidence of inefficiency than the WTI oil market. They also confirmed that the oil market stayed efficient from 1994 until the 2008 financial crisis. After 2012, the oil market efficiency increased.

Mensi, Sensoy and Kang (2020) concluded that COVID-19 influenced the multifractality of gold and oil prices, based on upward and downward trends. They found that COVID-19 decreased the efficiency of oil markets. The efficiency of the oil market is sensitive to scales.

Arshad, Rizvi and Haroon et al. (2021) tested the oil prices from 1996 to 2018 and found that the oil market always increases its efficiency after a previous recession. However, they still did not find that efficiency increases in the long term. They concluded that during the selected period, the Brent oil market performed as a low-efficiency market, which is largely unpredictable.

Gil-Alana and Monge (2020) investigated the influence of COVID-19 on crude oil prices. They found that before the COVID-19 period, the oil prices presented a higher integration of 0.84, which confirmed that they have reversion. Then, they only tested the COVID-19 period, which showed that the oil price is efficient. However, they found that when combining these two periods, the result showed that the oil markets are inefficient. The paper concluded that the shock is temporary in the short term.

Based on the results obtained for this thesis, the oil prices can be predicted at some level, but not to a high level. Similar to other researchers, the oil prices can be predicted based on the previous data, but the results showed that out-of-sample data is a bit different to real data.

This chapter also concluded that the ten-year data has a better predictability compared to thirty-year data, even the thirty-year data including the ten-year data. Ghazani and Ebrahimi (2019) stated that the longer the estimation period, the less the efficiency. In addition, due to the limitation of the exponential smoothing method, the thirty-year data contain few financial crises like the 2008 financial crisis, which would influence the out-of-sample prediction because the exponential smoothing method would generate results that have similar trends to past data.

The results stated that the oil market is efficient to some extent. Oil prices cannot reflect all the influential factors. The investors can consider the exponential smoothing method's result as a reference, but they should not rely on these results. The oil market is efficient, and they should consider more influential factors to help them have a better assets allocation.

In this thesis, I conclude that the oil markets both under WTI and Brent crude oil are weak form. In these cases, the prediction model only considers the historical data of its own in order to run the analysis. In this thesis, I assume that the oil market is weak form from the original. Advice should be given for investors who want to gain short-term benefits in the oil market. However, the results obtained from this thesis do not provide an appropriate investment strategy for investors.

Further research could consider combining other macro-economic variables with oil prices in order to predict oil prices, which may lead to better prediction and more accuracy.

## 2.7 Adaptive Market Hypothesis

Adaptive market hypothesis (AMH) first claimed by Lo (2004), which is a new theory that combines the efficient market hypothesis with behavioral finance. Under the EMH, there is a condition that the market is efficient which indicates that the investors cannot beat the market because all the trades are traded at their fair value and there is no chance to buy undervalued stocks and sell at a higher price. Lo's theory points out that investors are not always rational and for the stock market during financial crisis and bubbles may not trade at their fair value.

Lo (2004) also gives some practical implications. First, there is a fluctuation between risk and reward which will not keep stable over time. The influential factors can be the populations in the market and as the factors changes over time, thus the relation between risk and reward changes. Second, arbitrage opportunities are possible under the AMH. Third, the same investment strategy performs differently under different environment. It may perform well during this time but decline the profit when specific condition occurs. Finally, innovation and survival matters. Different from EMH, taking certain risk can achieve expected level of return. However, AMH supports that the risk/reward changes over time which claims that the investment strategy needs to adapt the changes in market.

Neely, Weller and Ulrich (2009) proved the AMH in foreign exchange market. They found that the excess returns in 1970s and 1980s are true. When the filter and moving average occurred in 1990s, the excess return disappeared.

Kim, Shamsuddin and Lim (2011) claimed that the time-varying return predictability of the Dow Jones Industrial Average index consistent with the adaptive markets hypothesis. Their results find that the during different time period, the predictability of return is different. During the economic or political crises, stock returns are highly predictable while the predictability become less during the economic bubbles.
Noda (2016) find that the AMH is apply to the Japanese stock markets (TOPIX and TSE2) Their results showed that the degree of market efficiency change over time and the degree of market efficiency is different in two stock markets. Urquhart (2015) claimed that the return predictability of three precious metals is time-varying, not stable. The finding indicated that the whole period is unpredictable but for some period in the sample is become significant predicable.

Within this chapter, the oil price prediction under the EMH indicates a weak form of the market efficient. In addition, the results show that the prediction of ten-year data is better than prediction of thirty-year data, which indicates that the market efficiency change over time. This also fits the model that it is more suitable for short-term prediction. The reduction of the predictability of the thirty-year data may also be due to the thirty-year data contains some financial crisis which influence the predictability of oil prices.

For investors, based on the prediction result found in this chapter, it suggests them to avoid invest in the oil market during the financial crisis period and it is preferable for them to invest in a relative short time. This can help the investors to have a better control for their assets in oil market. Furthermore, the predictability of the oil market or oil price is time-varying. Different period may have different predictability and uncertainty of the oil price. Therefore, they are recommended to have different investment strategies in different period to adapt the changes in the market.

# 3. Chapter Three: The potential influence between macroeconomic factors (exchange rates, inflation, interest rates) and oil prices (WTI, Brent)

## 3.1 Introduction

Oil is one of the main fossil fuel sources of energy in the world. Its price moves and fluctuation is crucial to the world economy.

In the first chapter of this thesis – an investigation into the relationship between oil prices and OPEC countries' stock indices, the results show that oil price changes have some influence on the relationship between different stock markets. The single regression model indicates that all the coefficients are positive and significant. Also, the financial crisis enhanced the relationship between oil price changes and stock markets' indices. The VAR model results show that the oil prices and the stock indices are cointegrated and have a long-term relationship. In addition, the oil price changes have some influence on the relationships between different stock markets.

In the second chapter of this thesis – the prediction of the oil price under Holt-Winters and ARIMA models which is suitable for time series data prediction – I tested the predictability of oil prices. This model is to do the forecasting based on the historical data. Including the Holt-Winters and ARIMA model is because the former one gives a more accurate forecast the later one fits the training data better. The data used in this chapter is thirty-year oil price from 1990 to 2019 and ten-year oil price from 2010 to 2019 both WTI and Brent. The results show that the oil price is predicable to some extent and the ten-year data is more accurate than thirty-year data. This chapter also includes the Efficient Market Hypothesis (EMH) and Adaptive Market Hypothesis (AMH). As the prediction is based only on the historical variables, this indicates a weak form in EMH. The prediction fit the AMH where the prediction is time varying. This suggests that investors need to have different investment strategy in different period and avoid invest into oil market during financial crisis..

In this chapter, some macro-economic factors (such as inflation, the interest rates and the exchange rates) are taken into consideration to see the potential relationship with oil prices (WTI and Brent). The OPEC countries and economical top-performing countries are selected. This is the first investigation to take these two group into consideration and comparing at the same time. The the Phillips-Perron (PP) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, Johansen cointegration test, VAR and VECM are employed in this chapter. The exchange rate, inflation, interest rate (select one-year treasury bill) and two oil prices (WTI and Brent) are collected from Refinitiv Datastream. The result shows that oil prices have explanation power to interest rate and inflation and the explanation power is from each other between oil prices and exchange rate. The findings help investors to have better management for their saving and investment in foreign exchange market. For policy makers, these help them to set the appropriate monetary policy to against the influence of oil price changes.

## 3.2 Relevant literature

This part includes some relevant literature that has investigated the relationship between macro-economic factors such as interest rates, exchange rates, and inflation and oil prices. Based on the results from the previous two chapters, the macro-economic factors may also have some influence on the oil price. By taking these factors into account, the analysis can help us to have a better understanding of the oil price movement, and can enable a better estimation of oil prices in the future.

### *3.2.1 Inflation*

Inflation implies the reduction of the purchasing power of a currency in a nation. It also means that the same amount of currency can buy fewer of the same products over time. The oil price changes may lead to a higher production cost and a higher cost of importing and exporting.

High and low oil dependent countries may be influenced differently by oil price changes. Alvarez, Hurtado and Sanchez et al. (2011) found that oil prices become less influential to the Spanish and Eurozone area's inflation level, because of less dependence on oil.

Sek, Teo and Wong (2015) used the autoregressive distributed lag (ARDL), which found that in countries with a low dependence on oil, the influence on inflation is direct. But for a highly dependent group, the influence is on the exporter's production costs, and this leads to inflation. Based on the different influences on inflation, different countries can have various and appropriate monetary policies to handle oil price changes. For oil-importing countries, such as Turkey, Gokmenoglu, Azin and Taspinar (2015) found that inflation has a long-term relationship between industrial production, oil prices, inflation and GDP.

Also, oil-importing and oil-exporting can be influenced by oil prices differently. Oil prices are more influential on inflation levels in net oil importing countries than exporting ones (Salisu, Isah and Oyewole et al., 2017). Salisu et al. (2017) also claimed that oil prices have a significant long-term relationship with inflation in both types of countries. Nusair (2019) analysed the Gulf Cooperation Council (GCC) countries and found that all the countries in the GCC have a cointegration relationship and long-term asymmetry with oil prices.

In addition, oil price changes may not directly influence a local economy by impacting on the political decisions made by local government. Zhao, Zhang and Wang et al. (2016) found that oil price shocks to China are mainly from OPEC countries. They also confirmed that oil price shocks would lead China to take action, which would then lead to inflation in China. Also, for the Chinese case, Chen, Zhu and Li (2020) found that the influence of oil prices shocks become less during a financial crisis; they suggested that the Chinese government should create a policy to guard against oil price shocks. A similar situation prevails in five Asian countries

(Thailand, Malaysia, Singapore, the Philippines, and Indonesia), but Basnet and Upadhyaya (2015) found that these countries have built a defence system to combat the negative influence caused by oil price shocks.

Apart from these cases, Hammoudeh and Reboredo (2018) found that the US central bank helps the US to handle the influence of oil price changes on inflation by employing a monetary policy. They also concluded that the oil price has significant and positive nonlinear impacts on the inflation risk premium. Bala and Chin (2018) also suggested that the contractionary monetary policy can help to guard against the inflation rise caused by oil price declines in Algeria, Angola, Libya, and Nigeria. It is also good for the government to provide financial support to small firms and improve agricultural production to help increase commercial revenue.

Furthermore, different kinds of oil price shocks lead to distinct results on inflation. Oil prices can influence production costs and resources allocation on the supply side, while for the demand side, they can affect income and uncertainties (Schneider, 2004). Alvarez et al. (2010) similarly concluded that technological innovation (efficiency of oil usage, less dependence on oil) reduces the influence of oil prices. There occurs an asymmetric phenomenon due to different oil price movements. Schneider (2004) and Lacheheb and Sirag (2019) found that oil price rises have a larger influence than oil price decreases. However, Davari and Kamalian (2018) found that oil price decreases have a significant influence on the oil price and that rises in oil prices are insignificant.

Bala and Chin (2018) found that both positive and negative oil price changes have a positive influence on inflation in Algeria, Angola, Libya, and Nigeria. In addition, the effects are larger when oil prices decline. Differently, Bala and Nusair (2019) concluded that oil price rises had a positive influence on inflation, while the decline of the oil price had an insignificant and negative influence.

Moreover, Raheem, Ibrahim and Bello et al. (2020) employed a multiple threshold nonlinear autoregressive distributed lag (NARDL) to analyse the asymmetry between these two variables. The results show that asymmetry appeared in both the long term and the short term. For oil-exporting countries, a higher oil price led to an increase in inflation and a lower price of oil led to a decrease in inflation. They also confirmed that governments can help their national economy to handle the impact of oil price shocks on inflation.

Besides this, Adebayo (2020) investigated the co-movement and causality between oil price and inflation. The paper employed a wavelet coherence method, which can test co-movement and causality at the same time. The analysis showed that oil price and inflation have positive co-movement in the short term. Furthermore, the results stated that there is evidence of causality from oil price to inflation. It is also confirmed that the causality is unidirectional. The study also suggested that Nigeria should diversify its revenue streams to guard against the influence of uncertainty in oil price changes.

These literatures confirm that the oil price has a long-term relationship or a short-term relationship with inflation. They also found that there appears to be an asymmetric relationship between oil price and inflation. Some of them said that oil price rises have a significant influence on inflation. Some others state that the decline in oil prices has a significant influence on inflation. Oil prices could have discrete effects on different types of countries in terms of oil (like oil-importing and oil-exporting countries). In addition, it is necessary for governments to make appropriate policies to guard against the influence of the oil price. As well as the countries' type, the oil price shocks type could result in different results. Not only has inflation got a relationship with the oil price, but so do other macro-economic factors, like exchange rates.

### 3.2.2 *Exchange rates*

The exchange rate is one currency's value against anther currency's value. In 2.2, Cunado and Gracia (2005) confirmed that using local currency would enhance the effects of oil price changes. This suggested that using a different currency may enhance the same effect. Thus, it is necessary to have an investigation into the relationship between oil prices and exchange rates.

A novel empirical approach has been used to examine the influence of the exchange rate of US dollars against other major currencies on the crude oil price in OPEC countries (Yousefi and Wirjanto, 2004). Yousefi and Wirjanto (2004) confirmed that OPEC countries have different oil prices in their own countries. The main reasons why they have different oil prices is that they all want to have their own strength in terms of market power. They also pointed out that Saudi Arabia seems to have larger oil stocks and a greater exporting function than other member states, which gives them more power over the oil price setting.

Huang and Guo (2007) stated that as China becomes the main player in international energy and foreign exchange markets, it is necessary to examine the relationship between the oil price and exchange rates, which could help China to have a better understanding of this relationship, and improved solutions to handle oil price changes. The analysis shows that oil price shocks could make the real exchange rate have a minor increase in the long term. Moreover, they found that positive real oil supply shocks depreciate China’s real exchange rate, while appreciating the rate when positive real demand shocks happen. In addition, specific tight control measures limit monetary shocks in China.

Aliyu (2009) examined the influence of oil price shocks and exchange rate volatility on economic growth in Nigeria. This author found that oil price shocks and exchange rates both have a positive influence on the economy in Nigeria. Furthermore, economic growth is mainly because of oil prices shocks. Moreover, Muhammad, Suleiman and Kouhy (2012) investigated the relationship between oil prices and the exchange rate from 2007 to 2010 in Nigeria. They found that during the analysis period, the increase in oil prices led to a depreciation of the Nigerian dollar against the US dollar.

In addition, investors can invest their assets into items like metals, oil and the Euro to diversify risk in their investment portfolio (Sari, Hammoudeh and Soytas, 2010). Sari et al. investigated the relationship between spot prices of metal and oil with the US dollar/Euro exchange rate. Choosing the US dollar/Euro exchange rate is due to the fact that the Euro may become the linkage of these commodities. For mineral trading, the influence between metals and oil markets is small. On the monetary side, there is no evidence to prove that the oil price has an influence on the exchange rate.

The US dollar is the main currency of the oil price in international crude trading, so its changes may lead to some influences on oil prices. Lizardo and Mollick (2010) claimed that since 2001, the US dollar has depreciated against other key currencies. They found that in the long term, the oil price has a large contribution to the fluctuation of the exchange rate. The results show that the real oil price rise leads to a depreciation of the US dollar against net oil-exporting countries' currencies, such as Canada, Mexico and Russia. However, for oil-importing countries like Japan, there is an appreciation of the US dollar. In the international oil market, the oil price is denominated in US dollars, which leads to a reduction value of the US dollar when the US significantly increases their purchasing of oil in the market.

Furthermore, Wu, Chung and Chang (2012) investigated the co-movement of the oil price and the US dollar exchange rate by using copula-based GARCH models. This model can help describe and explore the relationship between the oil price and the exchange rate return. The analysis shows that crude oil futures have larger volatility in the short term than in the long term. Wu et al. (2012) also concluded that the crude oil and exchange rate dependency became negative after 2003.
In the international oil market, the US dollar is used as the invoicing currency for crude oil. Therefore, the US dollar can be seen as a good predictor of the oil price. Zhang, Fan and Tsai et al. (2008) examined the spillover effect of the US dollar exchange rate on oil prices by using cointegration, a VAR model and ARCH models. The results showed that the depreciation of the US dollar led to an increase in the oil price. In the long term, US dollar fluctuation does not have the driving force to lead a move in the oil price. Narayan, Narayan and Prasad (2008) employed generalised autoregressive conditional heteroskedasticity (GARCH) and exponential GARCH (EGARCH) models to test the relationship between the oil price and the exchange rate on the island of Fiji. The result showed that a rise in oil prices leads to an appreciation of the Fijian dollar against the US dollar.

Moreover, Reboredo (2012) also investigated the co-movement between oil prices and the exchange rate. They found that the oil price and exchange rate dependency relationship is weak, and even became enhanced after the financial crisis. However, they also found that after the financial crisis, some currencies' tail dependence increased, which limits diversification in portfolio management. Their findings can help policy makers to have a better management of oil price exporting and controls on inflation.

During the financial crisis, the relationship between the oil price and the exchange rate could have changed. Reboredo and Rivera-Castro (2013) employed a wavelet decomposition approach to investigate the potential spread and dependency effect between them. The analysis showed that the oil price changes had no influence on the exchange rate before the financial crisis. In addition, since the 2008 financial crisis, there appears to have been spread effects and negative dependency between them. Moreover, in the financial crisis, oil prices led exchange rate policy, which was not the case before the financial crisis.

Ghosh (2011) examined the relationship between the oil price and the exchange rate by using India's extreme oil price volatility. A rise in the oil price return will depreciate the Indian currency against the US dollar. The reason is that India needs to buy more US dollars to pay off higher oil importing costs. The analysis reveals that oil price changes and the exchange rate have symmetric effects. Last but not least, the oil price shocks' impact on the exchange rate volatility is permanent.

There is no causal relationship between the oil price and the exchange rate in India, either in the short or the long term (Tiwari, Dar and Bhanja, 2013). Therefore, they employed a wavelets method. By using this method, they found that causality between these two variables is frequency dependent. In addition, they found that for time horizons of 32 months and over, the oil price and the real exchange rate have strong causality between them. Moreover, as India is an oil-dependent country, oil price shocks lead to a reduction in production, a rise in inflation, and a depreciation of the real exchange rate.

Bal and Rath (2015) examined the nonlinear causality between the crude oil price and the exchange rate in China and India. By using the nonlinear Granger causality test, they found a significant bi-directional relationship between oil prices and exchange rates. The analysis also shows that the nonlinearity of the oil price affects the exchange rate in different regimes. In addition, the results from the robustness checking differ from previous studies. For China, the causality is unidirectional from oil prices to the exchange rate, while for India, there is directional causality from oil prices to the exchange rate.

By using a detrended cross-correlation approach (DCCA), Hussain, Zebende and Bashir et al. (2017) overcame the difficulty of analysing different time scales of these variables. Their results support that there is a weak and negative relationship between the oil price and the exchange rate in most Asian countries. For Malaysia, the Philippines, Singapore and Taiwan, the cross-correlation is strong and negative in the long term. However, for Hong Kong and Japan, the cross-correlation is positive in the long term. Distinguishing the difference between the oil price changes and the exchange rate can help these countries to have better monetary policies and trade policies.

Wang, Nie and Liu et al. (2020) examined the influence of the international benchmark oil price on the Chinese real exchange rate. They predicted the real exchange rate based on the theory of exchange rate determination. In addition, they used three international crude oil prices to determine their influence on the real exchange rate. They found that the Brent oil price has the largest degree of influence on China’s exchange rate. Furthermore, their paper claimed that a change in international oil prices has a large influence on the real exchange rate estimation, and considering the oil price information can help to get a better prediction of the real exchange rate.

Volkov and Yuhn (2016) investigated the oil price shocks’ effects on the exchange rate in five major oil-exporting countries (Russia, Brazil, Mexico, Canada, and Norway). They found that oil price shocks have the same influence level on these countries’ exchange rates, and that the influence is significant. Additionally, they found that the asymmetry of the exchange rate movement is mainly due to the efficiency of the financial market, not the oil revenues.

Salisu, Cuñado and Isah et al. (2021) examined the predictability of the exchange rate of the BRICS (Brazil, Russia, India, China, and South Africa) countries in relation to the global oil price. They found that the oil price is a good predictor of the exchange rate for net oil exporting countries (Brazil and Russia) and net oil importing countries (South Africa and China). They also concluded that including asymmetry in the model can improve the predictability of the exchange rate, while ignoring it may lead to a wrong conclusion. Furthermore, the study including the Covid-19 period improves the estimation.

In addition, governments can help to set monetary policy to help nations guard against the influence of oil price shocks on exchange rates. Wesseh and Lin (2018) employed an unrestricted VAR model to test the relationship between oil prices, exchange rates and growth in Liberia. To avoid the limitation of using most of their resources to hedge against oil price shocks and the movement of the exchange rate, they examined the relationship based on the theory. A rise in the oil price appears to increase the GDP in Liberia. Besides this, depreciation in the Liberia dollar causes a real GDP reduction, while the appreciation has no influence on GDP. Moreover, they suggested that the Liberian government should boost national consumption to make the economy grow.

This section has explored those literatures that have investigated the relationship between oil prices and exchange rates. Some of them found that there was not enough evidence to prove that there is a relationship between exchange rates and oil prices. Some confirmed that the relationship between them is negative. In addition, the financial crisis may matter, which can enhance the relationship between oil prices and exchange rates. Additionally, not only may inflation and the exchange rate matter, but the interest rate may also matter.

### *3.2.3 Interest rate*

The interest rate is the percentage rate at which money may be borrowed, or it may express the percentage gain from savings. In 2.2, the exchange rate has a relationship with oil price changes. In this part, the cited literatures analyse the relationship between the oil price changes and the interest rate in different countries.

Lee, Lee and Ratti (2001) investigated the influence of oil price shocks on monetary policy changes in Japan. They claimed that the oil price shocks in the 1970s led to an increase in the call money rate. In addition, the increase of the call money rate enhanced the contractionary effect. In addition, they also confirmed that the negative influence of the oil price shocks was caused by the contractionary position that the Japanese government took.

Cologni and Manera (2008) employed a structural vector autoregressive model for G7 countries to examine the influence of the oil price changes on the monetary policy in these countries. They tested the short- and long-term relationship between money demand, oil prices, inflation, exchange rates and interest rates. They found that oil price changes' effects on inflation in these countries, except the UK and Japan, would be transmitted to the real economy by a rise in the interest rate. Additionally, the influence of the oil price changes is temporary for most countries. They also confirmed that the oil price shocks were eased by monetary policy to some extent.

ThankGod and Maxwell (2013) investigated the influence of oil price and volatility on macro-economic variables in Nigeria. They used the EGARCH and VAR models, and found that interest rates, exchange rates and oil prices have a unidirectional relationship among them. The direction is from oil prices to both variables. Also, they did not find any evidence to prove a significant relationship between oil prices and real GPD. Finally, the analysis reveals that real oil prices may assume an important role in oil price prediction.

To handle the uncertainty of oil price shocks, it was found that the Canadian Central Bank uses an expansionary monetary policy (Bashar, Wadud and Ahmed, 2013). In Canada, which is a net exporting country, oil price shocks have a large influence on the local economy. The analysis showed that the uncertainty of oil price shocks would significantly decrease output and price levels. Therefore, it is important for governments to have the correct monetary policy to guard against uncertain oil price shocks.

Different kinds of oil-related countries may have distinct relationships between oil prices and interest rates. Sotoudeh and Worthington (2015) investigated the global oil price changes' influence on interest rates. They found that the relationship between them is asymmetric and nonlinear in net oil producing countries, while they found no evidence to prove the same result in oil consuming nations.

Kim. Hammoudeh and Hyun et al. (2017) employed the VAR model to investigate the reaction of the monetary policy in China after oil price shocks. They found that China's interest rate has a different reaction to oil price shocks, and the interest rate changes over time. In the early time of the sample (1992-2001), the oil price had a negative influence on the interest rate, while in the later time (2001-2014), the relationship became positive. They stated that the early negative influence on the interest rate seems to have been a negative supply shock or a potential protective demand shock. However, the oil price shocks can be regarded as a boost to the economy.

In addition, Wen, Min and Zhang et al. (2019) claimed that during the 2008 financial crisis, the oil price shocks had a greater negative influence on China's economic growth, and the monetary policy become weak during this period. Also, China's monetary policy had a positive influence on economic growth and influence, and a rise in monetary policy can guard against the negative effects of oil price shocks.

Moreover, different oil price shocks lead to various influences on the national economy of a nation. Lorusso and Pireoni (2018) found that a specific oil demand increase will not depress the economy in the UK, but a shortfall in the crude oil supply can cause a decline in GDP growth immediately. The analysis also pointed out that oil price shocks cannot be ignored, as they have a significant influence on the UK economy. Moreover, the results showed that an unexpected increase in oil stocks and specific oil demand leads to an increase in interest rates, and a sudden oil supply interruption leads to economic decline.

This section demonstrates that oil price changes have a relationship with interest rates under some conditions, such as the types of oil price shocks, while different kinds of oil-related countries may have different reactions to oil price shocks.

## 3.3 Hypotheses

*Hypothesis 1:*

$H_0$: *There is no cointegration relationship between the oil price and exchange rates.*

$H_1$: *There exists cointegration relationship between the oil price and exchange rates.*

*Hypothesis 2:*

$H_0$: *There is no cointegration relationship between the oil price and inflation.*

$H_1$: *There exists cointegration relationship between the oil price and inflation.*

*Hypothesis 3:*

$H_0$: *There is no cointegration relationship between the oil price and interest rates*.

$H_1$: *There exists cointegration relationship between the oil price and interest rates*.

In regard to the first three hypotheses, this chapter is going to investigate the cointegration relationship between oil prices (WTI and Brent) and macro-economic variables (exchange rates, inflation and interest rates). In this chapter, it is believed that oil prices have a cointegration relationship with macro-economic variables. These three included macro-economic variables are the variables that reflect a local or national economy, in which it is believed that the changes in oil prices would lead to an influence on the local economy, Filis (2010) stated that oil price changes have a significant influence on the consumer price index (CPI). Thus, these variables would be influenced by oil price changes. Either in a short-term relationship or in a long-term relationship, or in both a short-term and a long-term relationship, there should exist a relationship between oil prices and macro-economic variables.

Changes in the oil prices will influence macro-economic variables, such as inflation and interest rates (Papapetrou, 2001, Chittedi, 2012). In addition, Narayan and Narayan (2010) found that the oil price and exchange rates have a long-term relationship, which indicates that they are cointegrated.

Therefore, it is important to have an investigation into the cointegration relationship between oil prices and macro-economic variables. In this chapter, I expected to see that all three macro-economic variables have a cointegration relationship with oil prices. Oil price changes have influence on the national economy of a country, either directly or indirectly, through the spread of their influence on the variables.

*Hypothesis 4:*
$H_0$: *There is no bilateral explanation relationship between the oil price and exchange rates.*
$H_1$: *There exists bilateral explanation relationship between the oil price and exchange rates.*

*Hypothesis 5:*
$H_0$: *There is no explanation relationship from the oil price to inflation.*
$H_1$: *There exists explanation relationship from the oil price to inflation.*

*Hypothesis 6:*
$H_0$: *There is no explanation relationship from the oil price to interest rates.*
$H_1$: *There exists explanation relationship from the oil price to interest rates.*

OPEC countries are highly reliant on oil exporting, therefore changes in the oil price would lead to an adjustment of the local economy (Salisu, Cuñado and Isah et al., 2021). Changes in the oil price would lead to a change in the exchange rate and inflation, causing a fluctuation of the production costs and exporting costs, which leads oil-importing countries to make adjustments to oil prices (Thoresen, 1982, Ghosh, 2011, Zhao, Zhang and Wang et al., 2016). In addition, most literatures have found that the oil prices have influence on macro-economic variables, while only a few literatures have confirmed that the relationship is bilateral (Bal and Rath, 2015). Sadorsky (1999) found that oil price changes have large effects on economic activities and a positive influence on the interest rate and industrial production.

Lardic and Mignon (2008) found that there are several ways in which oil price changes are transferred to local economies. They found that an increase in the oil price reduces inputs and enhances the purchasing power of oil-exporting countries compared to oil-importing ones. An increase in the oil price also leads to an increase in inflation, which raises the interest rate as well. In addition, Chittedi (2012) found that an increase in the oil price leads to a rise in the national price level, which results in an elevation of the interest rate.

Delgado (2018) et al. indicated that an increase in the oil price has a significant negative influence on the exchange rate in Mexico. Furthermore, Singhal, Choudhary and Biswal (2019) claimed that oil price changes have a negative influence on the exchange rate in Mexico. Additionally, for BRICS (Brazil, Russia, India, China, and South Africa) countries, the oil price is a good predictor of the exchange rate (Salisu, 2021).

Therefore, this chapter is going to further investigate the bilateral and unilateral relationship between oil prices and macro-economic variables. For inflation and interest rates, this chapter is going to test the unilateral relationship, in which it is believed that the influence is from the oil prices to them.

Inflation represents the declination of one currency’s purchasing power over time. Interest rates represents the percentage of the cost of borrowing money or the percentage gains from saving money. Thus, oil price changes would influence a local economy, which should influence the importing and exporting of a country, and thus influence the purchasing power of the local economy. The exchange rate reflects the value of one currency against another currency. In this chapter, all the currencies are compared against the US dollar, while the two oil prices are in US dollars. An increase or a decrease in the exchange rate could directly influence purchasing costs, or gains from exports. Therefore, oil-exporting and oil-importing countries could make policy adjustments to the oil demand and oil support in order to influence oil prices. In addition, the influence of oil prices could also impact on the local economy and thus lead to a rise or reduction in the value of the currency. Therefore, in this chapter, as regards inflation and interest rates, there is going to be an investigation of the unilateral relationship between them and oil prices. For exchange rates, there is going to be an examination of the bilateral relationship between exchange rates and oil prices.

## 3.4 Data and methodology

### *3.4.1 Data*

In this chapter, the data have been collected from the Refinitiv Datastream. For oil prices, both the WTI and the Brent crude oil price have been collected from January 2002 to December 2021. Oil is one of the main fossil fuels in the world, and its price is sensitive to the world economy and big events. For instance, due to the 2008 financial crisis, the oil price experienced a large fluctuation and it took a long time to recover. Thus, it is crucial to investigate the price of oil to see what other variables can influence it, and to figure out the relationship between them. The previous two chapters have examined the relationship between oil prices and stock market indices, and tried to use the historical price to predict the future oil price.

The exchange rate has been collected as monthly data from January 2002 to December 2021. All the exchange rates are compared to the US dollar (USD). For this data set, all the variables are examined as their log form. Inflation figures have been collected as monthly data from August 2013 to October 2021. In this case, all the variables are not analysed as their log form, because the value of inflation is zero. For interest rates, the short-term interest rate was collected from September 2007 to December 2021. The interest rate in this chapter is a one-year treasury bill (T-bill) in each country. The reason for choosing the treasury bill is that the treasury bill is considered as a risk-free asset issued by the government. To have an investigation on the influence of the oil price changes on the interest rate, it is good to choose T-bills, which are backed by the local government. This also shows how the government or the nation reacts to oil price changes. Interest rates are also examined, because some interest rates are negative. As oil prices were collected from January 2002 to December 2021, the period of the oil price will fit the time of these macroeconomic variables. For the time period of the data, the original aim was to have a longer period of data, but due to limited availability of the macro-economic variables collected from the OPEC countries, all the available data were collected.

Furthermore, in this chapter, the relationship between oil prices and three macroeconomic variables are examined. The reason for this is that two former chapters both mention the probability that macroeconomic variables could influence the oil price to some extent. Similar to the previous two chapters, OPEC countries' data are taken into consideration.

The process of the analysis is that each oil price is going to have a group bond with each macroeconomic variable in each OPEC country selected (Nigeria-NGA, Saudi Arabia-SAU and United Arab Emirates-ARE) and the top three economically high-performing countries selected (United States of America - USA, The United Kingdom - GBR and Japan - JPN). In the first step, the two variables (one oil price and one macroeconomic variable) are run through the cointegration test to see if they are cointegrated or not. Next, they are examined by the VAR or VECM to determine whether these two variables have linear causality. The cointegrated variables will be tested by the VECM to investigate the long-term and short-term causality. VAR is employed to examine the short-term causality for the variables that are not cointegrated.

Table 26. Summary Statistic for chapter three

| | Min | Mean | Max | Std.err | Number of observation |
|---|---|---|---|---|---|
| Panel A : exchange rate | | | | | |
| GBP | 0.4805 | 0.6475 | 0.8226 | 0.0058 | 240 |
| JYP | 76.1900 | 105.8940 | 134.5600 | 0.8281 | 240 |
| AED | 3.6552 | 3.6726 | 3.6730 | 0.0001 | 240 |
| NGN | 114.2000 | 198.2524 | 411.0000 | 5.7146 | 240 |
| SAR | 3.7051 | 3.7501 | 3.7630 | 0.0002 | 240 |
| WTI | 18.8400 | 64.7383 | 140.0000 | 1.5800 | 240 |
| Brent | 14.8500 | 67.7258 | 138.4000 | 1.8117 | 240 |
| Panel B : inflation | | | | | |
| US | -0.0020 | 0.0178 | 0.0620 | 0.0012 | 99 |
| UK | -0.0010 | 0.0153 | 0.0420 | 0.0010 | 99 |
| Japan | -0.0120 | 0.0069 | 0.0370 | 0.0010 | 99 |
| United arab emirates | -0.0271 | 0.0369 | 0.2530 | 0.0077 | 99 |
| Nigeria | 0.0769 | 0.1257 | 0.1870 | 0.0035 | 99 |
| Saudi aribia | -0.0220 | 0.0206 | 0.0620 | 0.0021 | 99 |
| WTI | 18.8400 | 60.0007 | 107.6500 | 1.9808 | 99 |
| Brent | 14.8500 | 64.2290 | 115.9700 | 2.2170 | 99 |
| Pandel C : interest rate | | | | | |
| US | 0.0004 | 0.0078 | 0.0405 | 0.0007 | 172 |
| UK | -0.0013 | 0.0077 | 0.0562 | 0.0009 | 172 |
| Japan | -0.0032 | 0.0004 | 0.0077 | 0.0002 | 172 |
| Nigeria | 0.0013 | 0.1153 | 0.2231 | 0.0041 | 172 |
| WTI | 18.8400 | 71.6269 | 140.0000 | 1.7958 | 172 |
| Brent | 14.8500 | 76.4763 | 138.4000 | 2.0334 | 172 |

### *3.4.2 Methodology*

In this chapter, to empirically solve the relationship between oil prices and macroeconomic variables (exchange rates, inflation and interest rates), there are two models included to test the linear and nonlinear relationship between them, both of which are based on the VAR model. The first model used in this chapter is designed to test the linear relationship between macroeconomic variables and oil prices. The second model is used to test the nonlinear relationship between them. The aim of including these two methods is to help in understanding whether the relationship between them is linear or nonlinear, and these two models can conclude whether the influences of these variables are unidirectional or bilateral.

*The VAR model:*

In this method, the first is going to use the Johansen cointegration test to examine the cointegration relationship between oil prices and the other three macroeconomic variables (exchange rates, inflation and interest rates). This test is mainly to test the long-term relationship between these variables. Then, in the second step, the error correction model (ECM) will examine the direction of the causality among these variables.

At the beginning of this method, it is important to select the lag length of the variables and to do the unit root test. In the cointegration tests and VAR model, the lag value of the variables is used to do the autoregression. Liew (2004) claimed that the lag length selection is crucial for the autoregression, and the author found that the Akaike information criterion (AIC) was good to estimate the autoregression lag length. Emerson (2007) clarified that the different lag length in the long-term cointegration relationship will influence the Johansen estimation procedure. Thus, it is crucial and important to select the lag length. In this chapter, two criteria will be used, which are the AIC and the Bayes information criterion (BIC).

Then, the unit root test is used to figure out the stationarity of the series selected. In this step, the Phillips-Perron (PP) test (Phillips and Perron, 1988) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) are employed. These two unit root tests include a fitted drift and a time trend, which can determine the unit root stationarity of the time series data. Simply put, the unit root can help to tell whether time series data are stationary or non-stationary. To have accurate stationary or non-stationary levels of a time series data is necessary to do the VAR and VECM tests. After confirming the lag length and the unit root, it is time to conduct the cointegration test.

The explanation of the Johansen method of cointegration (Johansen 1991) defines a k-vector of non-stationary I(1) variables $X_t$ and assumes the vector has a VAR representation of the form:

$$X_t = A_1 X_{t-1} + \cdots + A_p X_{t-p} + \varepsilon_t \tag{51}$$

where $\varepsilon_t$ is a vector of innovations. The above equation can be reparameterised as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta X_{t-1} + \varepsilon_t \tag{52}$$

The rank of $\Pi$, taken from Equation 52, provides the number of cointegrating relationships that exist between variables. Based on the different types of rankings, it can generate conclusions on different long-term relationships. Firstly, if $\Pi$ has a rank of zero, this implies that the variables have no long-term cointegration between them. Secondly, if $\Pi$ is fully ranked, all the variables still cannot be regarded as cointegrated, because the full rank stands for variables that are not integrated. Thirdly, if $\Pi$ is between full rank and zero, this means that the variables are cointegrated.

Using the cointegration test can help to discover the cointegrating relationship between them, although this does not imply the influence direction among the variables. It is also crucial to have an investigation into the influence direction from the oil price to others, or others that also have impacts on oil prices. Thus, ECM is used to distinguish the direction between these variables.

At the start of the ECM, the model of the long-run equilibrium relationship is set between two variables:

$$Y_t = K X_t \tag{53}$$

where $Y_t$ stands for the value of the exchange rate and $X_t$ implies the oil price. Then, taking the lag version of Equation 3, this can be written as:

$$y_t = k + x_t \tag{54}$$

where the lower-case $y_t$ and $x_t$ stand for the lag version of the variables.

Within the ECM, the basic model is as follows:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \alpha_1 y_{t-1} + u_t \tag{55}$$

In Equation 55, $y_{t-1}$ and $x_{t-1}$ are the lag value of the oil price lag and different rates' lag at time t-1, $u_t$ is the error term and $\beta_0$, $\beta_1$, $\beta_2$ and $\alpha_1$ are the coefficients. The equation can also be written as:

$$\Delta y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t \tag{56}$$

The left-hand side $\Delta y_t$ is the change of $y_t$. To complete the ECM, changes in the $x_t$ need to be inserted into the right-hand side, which becomes:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + (\beta_1 + \beta_2) x_{t-1} - (1 - \alpha_1) y_{t-1} + u_t \tag{57}$$

It can also be written as:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t - (1 - \alpha_1)(y_{t-1} - \frac{\beta_1 + \beta_2}{1 - \alpha_1} x_{t-1}) + u_t \tag{58}$$

Equation 58 shows the ECM models that contain both long-term and short-term equilibrium within one equation. For the long-term part, the $1 - \alpha_1$ and $\frac{\beta_1+\beta_2}{1-\alpha_1}$ can be regarded as $\gamma_1$ and $\gamma_2$, which lead to the equation as $\gamma_1(y_{t-1} - \gamma_2 x_{t-1})$, the error correction term. In this equation, the variables suggest that they are cointegrated, which assumes that they have a long-term relationship. Thus, $\beta_0 + \beta_1 \Delta x_t$ is the short-run equilibrium plus the error correction term achieving the long-run equilibrium. Furthermore, Equation 8 can be written as:

$$\Delta y_t = \beta_0' + \beta_1 \Delta x_t - (1 - \alpha_1)(y_{t-1} - \beta_2' x_{t-1} - \varepsilon_{t-1}) + u_t \tag{59}$$

where $y_{t-1} - \beta_2' x_{t-1} - \varepsilon_{t-1}$ is the error correction term.

## 3.5 Results

Table 27 and Table 28 show the results of the Philips-Perron (PP) unit root test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root test. In the PP test, it shows the results of the original value or the log level and the first difference under the constant or constant and trend condition if these variables have a unit root. The KPSS test shows the results with lag-truncation parameters of one and four.

These two tests are both to test a time series data is stationary or non-stationary, but they have different hypothesis. For PP unit root test, the null hypothesis is the time series data have a unit root equivalent to non-stationary. However, the null hypothesis is the time series data is stationary for KPSS test.

For exchange rates, all the variables are calculated as the log form and test their first log difference. For inflation and interest rates, all the original values are examined, as are their first difference, except oil prices. In both tests, the null hypothesis is the series data that have a unit root.

In Table 27, the PP test shows all three macroeconomic variables and two crude oil prices under the hypothesis that the time series data have a unit root. For the exchange rate case, JPN, GBR and NGA cannot reject the null hypothesis at the log level and reject the null hypothesis at 5% significance level when using first log difference, which indicates that the exchange rate has the unit root at log level. The exchanges of SAU and ARE both reject the 5% significance at the log level and at the first log difference level. In addition, for oil prices, they reject the 5% significance at log level and at the first log difference level, while they cannot reject the null hypotheses at a 1% level under log level. In Table 28, the result shows that the exchange rate in JPN, GBR, NGA and SAU rejects the null hypothesis that variables at the log level are level and the trend stationary, but cannot reject the null hypothesis at the first log difference level at 5% significance. Moreover, two crude oils reject the null hypothesis at log level and cannot reject it at first log difference level at 5% level. Only the ARE exchange rate cannot reject at both levels. Therefore, the exchange rates of JPN, GBR and NGA and the two oil prices are the

*I*(1) process, and the exchange rate of JPN, GBR, NGA and SAU and the two oil prices are the *I*(0) process at first log difference level.

For inflation, the PP test indicates that all countries' inflation and two oil prices cannot reject the hypothesis that time series data has a unit root at their original data value level or a log level for oil prices at 5% significance. This represents that all the variables at their value level or log level are the *I*(1) process. In Table 28, at their value and log level, they reject the null hypothesis that variables are level and trend stationary in 24 out of 32 cases. At the first difference level, these variables cannot reject the null hypothesis in 29 out of 32 cases. Thus, these variables in the case of inflation are *I*(0) at their first difference level. For interest rates, due to the availability and the negative value of the interest rate, only four countries (JPN, GBR, USA and NGA) are included. The NGA exchange rate and two oil prices are the *I*(1) process at their log level and *I*(0) at first difference level. Then, the cointegration test is employed to examine whether they are cointegrated or not cointegrated.

Table 27. Result of the PP test

| | Log level | | First log difference | |
|---|---|---|---|---|
| Panel A : Exchange rate | | | | |
| Country | C | C&T | C | C&T |
| JPN | -2.177 | -2.048 | -14.503*** | -14.586*** |
| GBR | -1.508 | -3.381* | -14.763*** | -14.795*** |
| USA | none | none | none | none |
| NGA | 0.374 | -1.651 | -12.710*** | -12.753*** |
| SAU | -12.148*** | -12.306*** | -32.290*** | -32.220*** |
| ARE | -14.209*** | -14.232*** | -38.135*** | -38.135*** |
| | Log level | | First log difference | |
| Oil price | C | C&T | C | C&T |
| WTI | -3.132** | -3.022 | -12.737*** | -12.727*** |
| Brent | -3.047** | -2.935 | -13.341*** | -12.335*** |
| | Level | | First difference | |
| Panel B : Inflation | | | | |
| Country | C | C&T | C | C&T |
| JPN | -1.910 | -2.523 | -8.418*** | -8.372*** |
| GBR | -0.968 | -1.236 | -9.668*** | -10.046*** |
| USA | -0.261 | -1.166 | -5.496*** | -5.626*** |
| NGA | -1.288 | -0.143 | -3.766*** | -3.751** |
| SAU | -2.673* | -2.614 | -9.603*** | -9.550*** |
| ARE | -2.624* | -3.133 | -13.063*** | -13.002*** |
| | Log level | | First log difference | |
| Oil price | C | C&T | C | C&T |
| WTI | -2.563 | -2.225 | -7.952*** | -8.023*** |
| Brent | -2.742* | -2.534 | -8.718*** | -8.747*** |
| | Level | | First difference | |
| Panel C : Interest rate | | | | |
| Country | C | C&T | C | C&T |
| JPN | -3.306** | -2.772 | -14.016*** | -14.293*** |
| GBR | -4.101*** | -3.507** | -9.408*** | -9.729*** |
| USA | -3.682*** | -3.758** | -9.985*** | -10.189*** |
| NGA | -2.505 | -2.494 | -14.795*** | -14.779*** |
| | Log level | | First log difference | |
| Oil price | C | C&T | C | C&T |
| WTI | -2.588* | -2.982 | -10.533*** | -10.510*** |
| Brent | -2.682* | -3.002 | -11.016*** | -10.983*** |

Notes: C is constant, and T is trend. The superscripts ***, ** and * stand for the rejection of the null hypothesis at 1%, 5% and 10%.

Table 28. Result of the KPSS test

| | Log level | | | | First log difference | | | |
|---|---|---|---|---|---|---|---|---|
| Panel A : Exchange Rate | | | | | | | | |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Country | L | T | L | T | L | T | L | T |
| JPN | 1.720*** | 1.690*** | 0.712** | 0.700*** | 0.284 | 0.077 | 0.251 | 0.069 |
| GBR | 7.830*** | 0.879*** | 3.210*** | 0.378*** | 0.201 | 0.097 | 0.166 | 0.081 |
| USA | none | none | none | none | none | none | none | none |
| NGA | 10.600*** | 2.270*** | 4.310*** | 0.940*** | 0.187 | 0.038 | 0.191 | 0.390 |
| SAU | 0.531** | 0.098 | 0.359* | 0.067 | 0.010 | 0.007 | 0.019 | 0.013 |
| ARE | 0.285 | 0.143 | 0.217 | 0.110 | 0.005 | 0.005 | 0.011 | 0.011 |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Oil price | L | T | L | T | L | T | L | T |
| WTI | 2.010*** | 1.82*** | 0.864*** | 0.780*** | 0.125 | 0.053 | 0.136 | 0.058 |
| Brent | 2.350*** | 1.810*** | 1.010*** | 0.778*** | 0.101 | 0.039 | 0.123 | 0.047 |
| | Level | | | | First difference | | | |
| Panel B : Inflation | | | | | | | | |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Country | L | T | L | T | L | T | L | T |
| JPN | 1.830*** | 0.324*** | 0.804*** | 0.150* | 0.058 | 0.058 | 0.062 | 0.062 |
| GBR | 0.655** | 0.383*** | 0.286 | 0.168* | 0.501* | 0.215** | 0.347 | 0.154** |
| USA | 1.490*** | 0.207** | 0.697** | 0.099 | 0.309 | 0.108 | 0.255 | 0.093 |
| NGA | 1.830*** | 0.563*** | 0.764*** | 0.234*** | 0.219 | 0.205** | 0.111 | 0.104 |
| SAU | 0.403* | 0.370*** | 0.189 | 0.173** | 0.045 | 0.044 | 0.050 | 0.050 |
| ARE | 1.470*** | 0.335*** | 0.667** | 0.158* | 0.049 | 0.044 | 0.061 | 0.054 |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Oil price | L | T | L | T | L | T | L | T |
| WTI | 0.935*** | 0.407*** | 0.436* | 0.194** | 0.162 | 0.037 | 0.208 | 0.050 |
| Brent | 0.803*** | 0.388*** | 0.381* | 0.188** | 0.110 | 0.031 | 0.160 | 0.048 |
| | Level | | | | First difference | | | |
| Panel C : Interest rate | | | | | | | | |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Country | L | T | L | T | L | T | L | T |
| JPN | 6.490*** | 0.948*** | 2.700*** | 0.410*** | 0.464** | 0.059 | 0.436* | 0.059 |
| GBR | 2.710*** | 0.900*** | 1.180*** | 0.395*** | 0.563** | 0.134* | 0.404* | 0.101 |
| USA | 0.877*** | 0.858*** | 0.378* | 0.371*** | 0.600** | 0.327*** | 0.425* | 0.236*** |
| NGA | 1.160*** | 1.020*** | 0.502** | 0.443*** | 0.057 | 0.049 | 0.066 | 0.056 |
| | Lag=1 | | Lag=4 | | Lag=1 | | Lag=4 | |
| Oil price | L | T | L | T | L | T | L | T |
| WTI | 3.330*** | 0.361*** | 1.460*** | 0.167** | 0.045 | 0.039 | 0.048 | 0.041 |
| Brent | 2.610*** | 0.427*** | 1.160*** | 0.196** | 0.036 | 0.034 | 0.042 | 0.041 |

Notes: L is level stationarity and T is trend stationarity. The superscripts ***, ** and * stand for the rejection of the null hypothesis at 1%, 5% and 10%.

Table 29 contains the results of the cointegration test of exchange rates, inflation, and interest rates with the two oil prices. Cointegration also means that they have a long-term relationship and that they are not cointegrated, which means that they have no long-term relationship. In the exchange rate case, with the examination of WTI, Table 26 shows that GBR and NGA cannot reject the null hypotheses that they have no cointegration. In the inflation case, JPN and NGA reject the null hypotheses at 5% level, which indicates that JPN and NGA inflation have a long-term relationship with the WTI crude oil price. In the interest rate case, only NGA cannot reject the null hypothesis, while others reject the null hypothesis that they have no cointegration at the 5% level. Table 26 also presents the results when considering the Brent crude oil price. For the exchange rates, similar to the WTI case, GBR and NGA are cointegrated with oil prices. Similar to the WTI crude oil price, the Brent crude oil price is cointegrated with JPN and both inflation and the interest rates of NGA.

According to the results of Table 29, conclusions can be made on the hypotheses 1-3 in this chapter. For exchange rates, GBR and NGA cannot reject Hypothesis 1 – that there is no cointegration relationship between the oil price and the exchange rate. Other countries' exchange rates indicate that they are cointegrated with both oil prices. For inflation, JPN and NGA reject Hypothesis 2 – that there is no cointegration relationship between oil prices and inflation. Moreover, only NGA's interest rate cannot reject the hypothesis in this chapter – that there is no cointegration relationship between oil prices and interest rates.

Aziz and Bakar (2009) found that there is no cointegration relationship between exchange rates and oil prices under the Pedroni test, while they suggest that there is a long-term equilibrium relationship between them. Chen, Lee and Goh (2013) found that the exchange rates and oil prices are not cointegrated under the threshold autoregressive (TAR) model. Mensah, Obi and Bokpin (2017) found that there is a long-term equilibrium relationship between oil prices and exchange rates in oil-dependent economies, especially for oil-exporting countries. Butt et al. (2020) found that the exchange rate has a short-term equilibrium asymmetric position in the short term. In this chapter, the results show that JPN, SAU and ARE's exchange rates are cointegrated with oil prices, where these three countries are oil-related countries. Similar to other papers, in oil-exporting countries like SAU and ARE and oil-importing countries like JPN, their exchange rates have long-term relationships with oil prices. This enhances the view that the oil price changes have significant influence on these countries. The influence of the oil price will spread into the local economy and cause the exchange rate to have a corresponding change to adapt the effects of oil price changes.

Nusair (2019) found that the oil price is cointegrated with inflation in Gulf

Cooperation Council (GCC) countries, which also indicates that the oil price leads a co-movement on inflation in these countries. Oloko et al. (2021) found that inflation in oil-exporting and oil-importing countries does not necessarily change due to oil price shocks. In this chapter, JPN and NGA's inflation have a cointegration relationship with oil prices, while other countries cannot reject the null hypothesis that they have no cointegration. Within expectations, the JPN and NGA inflation levels have long-term relationships with oil prices, while GBR, USA, SAU and ARE have no cointegration relationship with oil prices. This differs from the opinion from Nusair (2019) – that the oil price has co-movement with GCC countries (which contain SAU and ARE). It indicates that the oil prices may have another relationship with inflation in SAU and ARE. This also may be due to the different change intervals in oil prices and inflation. The changes in the oil prices lead to uncertainty and changes in inflation levels. In this comparison, the variables included in the model are only two (the oil price and inflation). To deal with the shocks or the influence of the oil price changes, local governments take different policy decisions to handle the uncertainty caused by oil price changes, which could also ease the effects caused by the oil price.

For interest rates, only NGA cannot reject the null hypothesis that there is no cointegration between interest rates and oil prices. This indicates that interest rates have a long-term relationship with oil prices in JPN, GBR and the USA. For the interest rates, the one-year treasury bill in JPN, GBR and USA in the long term are adjustments to the changes in the oil price. They are cointegrated, and the adjustment of the interest rate fluctuates with the movement in the oil price.
After doing the cointegration test, the VAR model is employed for the variables that are not cointegrated and the VECM examines the variables that are cointegrated.

Table 29. Cointegration result

| | | Exchange rate | | inflation | | Interest rate | |
|---|---|---|---|---|---|---|---|
| Panel A : With WTI Crude oil price | | | | | | | |
| Country | hypothesis | r=0 | r≤1 | r=0 | r≤1 | r=0 | r≤1 |
| JPN | Trace test | 19.542** | 4.901** | 22.987*** | 5.700** | 25.091*** | 4.604** |
| | λ max test | 15.451** | 4.901** | 17.287** | 5.700** | 20.487*** | 4.604** |
| GBR | Trace test | 12.873 | 1.547 | 8.114 | 0.479 | 28.893*** | 5.516** |
| | λ max test | 11.326 | 1.547 | 7.635 | 0.479 | 23.377*** | 5.516** |
| USA | Trace test | none | none | 9.874 | 0.249 | 21.123*** | 4.898** |
| | λ max test | none | none | 9.625 | 0.249 | 16.225** | 4.898** |
| NGA | Trace test | 14.423 | 0.097 | 25.879*** | 4.783** | 12.365 | 5.598** |
| | λ max test | 14.326** | 0.097 | 21.962*** | 4.783** | 6.767 | 5.598** |
| SAU | Trace test | 128.338*** | 9.322*** | 13.320 | 6.232** | | |
| | λ max test | 119.015*** | 9.322*** | 7.088 | 6.232** | | |
| ARE | Trace test | 155.415*** | 9.150*** | 14.567 | 5.745** | | |
| | λ max test | 146.265*** | 9.150*** | 8.822 | 5.745** | | |
| Panel B : With Brent Crude oil price | | | | | | | |
| Country | hypothesis | r=0 | r≤1 | r=0 | r≤1 | r=0 | r≤1 |
| JPN | Trace test | 22.257*** | 4.230** | 22.987*** | 4.880** | 25.172*** | 4.936** |
| | λ max test | 18.026** | 4.230** | 17.635** | 4.880** | 20.235*** | 4.936** |
| GBR | Trace test | 12.245 | 1.442 | 9.681 | 0.480 | 31.155*** | 6.655*** |
| | λ max test | 10.803 | 1.442 | 9.201 | 0.480 | 24.500*** | 6.655*** |
| USA | Trace test | none | none | 11.422 | 0.163 | 22.365*** | 6.645** |
| | λ max test | none | none | 11.260 | 0.163 | 15.720** | 6.645** |
| NGA | Trace test | 14.567 | 0.092 | 26.741*** | 3.566 | 13.525 | 5.926** |
| | λ max test | 14.475 | 0.092 | 23.175*** | 3.566 | 7.599 | 5.926** |
| SAU | Trace test | 125.653*** | 9.203*** | 14.377 | 6.297** | | |
| | λ max test | 116.450*** | 9.203*** | 8.081 | 6.297** | | |
| ARE | Trace test | 154.649*** | 9.130*** | 16.064** | 6.591** | | |
| | λ max test | 145.519*** | 9.130*** | 9.473 | 6.591** | | |

Note: r is the number of the cointegration between oil price and macroeconomic variables. The superscripts *** and ** stand for the rejection of the null hypothesis at 1% and 5%.

Tables 30 to 32 are the results of the VAR or the VECM being applied to macroeconomic variables (exchange rates, inflation, and interest rates) and the two oil prices. According to the cointegration tests, the cointegrated variables are examined by the VECM and the others are analysed by the VAR. For the cointegrated variables, the VECM model tests the long-term and short-term causality. For the rest of the variables, the VAR model investigates the short-term causality, as they do not have a long-term relationship.

In Table 30, in the case of WTI with exchange rate, the long-term causality test shows that there is a long-term causality running from JPN to WTI, as the ECT is negative and significant. For the cases of SAU and ARE, there is long-term causality running from WTI to SAU and ARE, as the ECT is negative and significant. There is no bilateral causality in the long term. The null hypothesis for the short-term causality is that the lagged value of one variable has no explanation to another variable in the short term. The results in Table 28 show that the null hypotheses are rejected for SAU (running from WTI to SAU), GBR (running from WTI to GBR) and NGA (running from NGA to WTI). The results claim that there is no bilateral influence in the short term for all cases.

In the case of the Brent oil price with exchange rates, there have been instances of long-term causality running from JPN to WTI, WTI to SAU, and WTI to ARE, as the ECT is negative and significant. Differently from the WTI case, there is only a case rejecting the null hypothesis that there is no explanation from lagged value to dependent variable, which runs from Brent to GBR. Therefore, there is no bilateral relationship for all cases in the short term. The results of Table 27 cannot reject Hypothesis 4 – that there is no bilateral relationship between oil prices and exchange rates for all the cases selected in the short term and the long term.

Differently from Bal and Rath (2015), who found that there is a bilateral relationship between oil prices and exchange rates, in this chapter it is found that there is no bilateral relationship between oil prices and exchange rates. This is similar to the results from Butt et al. (2020), who found evidence of a unidirectional causal relationship running from the exchange rate to the oil price, while they found that the exchange rate has bidirectional causality with other commodity prices.

This agrees with the results of Muhammad et al. (2012), who found that oil price changes led to a change in the exchange rate in Nigeria; in this chapter, the evidence shows that there is a long-run causality running from oil prices to Nigeria's exchange rate. Sari et al. (2010) found that there are no findings of oil price changes' influences on the exchange rate of the US dollar/Euro. In this chapter, the evidence shows that oil prices have short-term causality to GBR. Volkov and Yuhn (2016) indicated that oil price shocks significantly influence the exchange rate in oil-exporting countries, which are different in that in this chapter, the JPN exchange rate has long-term causality to both oil prices.

In addition, Salisu et al. found that the oil price is a good predictor of exchange rates in BRICS (Brazil, Russia, India, China, and South Africa) countries. This also indicates that consideration of the prediction of the exchange rate should result in an examination into the oil prices' influence on the exchange rate, such as the factor that the oil price has long-run causality to SAU and ARE, which are the main oil-exporting countries.

In this chapter, the result shows that there is no bilateral relationship between exchange rates and oil prices, which is out of expectation. In the short-term causality, SAU's and ARE's exchange rate influences the oil price, while in the long term it reverses, and the oil price has influence on the exchange rate. This circumstance may be due to the conditions in oil-exporting countries. In the short term, the changes in the exchange rate could influence the oil price to balance the local economy. However, in the long term, with world level trading, not only could inflation influence the oil price, but it could also limit the effects from the exchange rate on oil prices. Consequently, the oil price changes spread their influence to local economies, and also influence the world economy, which then leads to changes in the exchange rate.

In Table 31, there is a long-run causality running from WTI to JPN and NGA, as the ECT is negative and significant. Similar to the WTI, in the Brent case, there is a long-run causality running from Brent to JPN and NGA. In the short term, the cases of WTI, GBR, USA and SAU reject the null hypothesis that there is no explanation from WTI to inflation in the short term. In addition, GBR, USA and SAU reject the null hypotheses in the cases with Brent. Thus, GBR, USA and SAU cases reject Hypothesis 5 – that there is no unilateral relationship running from oil prices to inflation in the short term. In the long term, there is causality running from WTI and Brent crude oil to JPN and NGA, which rejects Hypothesis 5.

Oil price increases in oil importing countries lead to a reduction in standards of living (Thoresen, 1982). Alvarez et al. (2010) concluded that the oil price becomes less influential, due to the decline of oil dependence. Agreeing with Gokmenoglu et al. (2015), they found that the oil price and inflation have a long-term relationship in Turkey. Salisu et al. (2017) stated that oil-importing and oil-exporting countries have significant long-term relationships between oil prices and inflation. The idea is thus approved in this chapter that JPN (an oil-importing country) and NGA (an oil-exporting country) both have significant long-run causality running from oil prices to inflation.

Raheem et al. (2020) found long-run and short-run asymmetry between oil prices and inflation, whereas in this chapter, it is only found that the short-term causality runs from oil prices to GBR, USA and SAU's inflation, as they are not cointegrated, which means they have no long-run relationship. Adebayo (2020) found that oil price has co-movement with inflation in the short term, and they also found that the causality between them is unidirectional, which proves the findings in this chapter. Differing from others, GBR, USA and SAU are tested, but they have no long-term relationship and they are not cointegrated. The inflation of these countries only has short-term causality running from both of the two oil prices. This indicates that the oil price changes can only have a short-term influence on inflation, and the effects of oil price fluctuation can be absorbed by local markets. In the long term, these countries' governments will employ appropriate policies and methods to ease the influence of the oil price and to make the markets stable, and will not be hurt by any uncertainty and fluctuation in oil prices.

Cunado and Gracia (2005) only found short-term effects of oil prices on inflation in their cases. In this chapter, only JPN and NGA found that the oil prices have long-term causality to inflation. Basnet and Upadhyaya (2015) also indicate that the influence of the oil price shocks is in the short term, and the influence will be absorbed by the market.

In Table 32, due to the cointegration between interest rates and oil prices, GBR, USA and JPN are run through the VECM, and the VAR is employed to NGA. In the long term, there occurs a long-run causality running from the WTI and Brent crude oil prices to GBR, USA and JPN, as the ECT is negative and significant. There is no explanation power of the lagged value of oil prices to interest rates in the short term. Furthermore, Table 6 indicates that GBR, USA and JPN reject Hypothesis 6 – that there is no unidirectional relationship running from oil prices to interest rates in the long term for all tested interest rates – but cannot reject Hypothesis 6 in the short term for all cases.

In this chapter, the oil price has long-run causality to the interest rate in Japan, where Lee et al. (2001) found that the Japanese government used their monetary policy to guard against the influence of oil price shocks. Differently from Cologni (2008), they concluded that oil prices have no relationship with interest rates in the UK and Japan, while in this chapter, there is long-run causality running from the oil price to GBR and JPN's interest rate in the long term, and there is no short-run causality.

ThankGod and Maxwell (2013) found that there exists a unidirectional relationship from oil prices to interest rates in Nigeria, but in our cases, the oil price has no long-term and short-term causality to Nigeria's interest rate. It is necessary for governments to take the appropriate monetary policy to guard against oil price shocks in local economies (Bashar, Wadud and Ahmed, 2013; Kim Hammoudeh and Hyun et al., 2017; Wen, Min and Zhang et al., 2019).
In all cases, I concluded that the oil prices have a long-term causality cause to interest rates in GBR, USA and JPN. This indicates that the local government will amend their interest rates (like monetary policy) based on the changes in the oil prices in order to guard against the effects of oil price changes. This indicates that oil prices can be a good predictor to estimate one-year treasury bills in GBR, USA and JPN. However, in the case of NGA, this may be due to local government policy and other factors influencing where the oil prices cannot be considered as the predictor of local interest rates.

Table 30. VAR and VECM result of the exchange rate with oil prices

| | Short-run causality | | Long-run causality | | | |
|---|---|---|---|---|---|---|
| Panel A : With WTI | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| WTI(JPN) | 0.5300 | 0.9130 | -0.0857 | 0.0236 | -3.6400 | 0.0000 |
| JPN(WTI) | 0.3900 | 0.9432 | -0.0011 | 0.0104 | -0.1000 | 0.9190 |
| WTI(SAU) | 2.4100 | 0.4913 | -0.0030 | 0.0038 | -0.8100 | 0.4190 |
| SAU(WTI) | 8.7400 | 0.0329 | -0.6093 | 0.0997 | -6.1100 | 0.0000 |
| WTI(ARE) | 2.0100 | 0.5712 | -0.0064 | 0.0038 | -1.6600 | 0.0980 |
| ARE(WTI) | 1.7200 | 0.6330 | -0.7382 | 0.1123 | -6.5700 | 0.0000 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| WTI(GBR) | 4.3800 | 0.2233 | | | | |
| GBR(WTI) | 8.0800 | 0.0445 | | | | |
| WTI(NGA) | 9.8800 | 0.0196 | | | | |
| NGA(WTI) | 2.5700 | 0.4634 | | | | |
| Panel B : With Brent | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| Brent(JPN) | 0.8600 | 0.8361 | -0.0958 | 0.0255 | -3.7600 | 0.0000 |
| JPN(Brent) | 1.0200 | 0.7957 | 0.0012 | 0.0115 | 0.1100 | 0.9150 |
| Brent(SAU) | 0.7900 | 0.8512 | -0.0013 | 0.0030 | -0.4400 | 0.6600 |
| SAU(Brent) | 6.7000 | 0.0821 | -0.6018 | 0.0989 | -6.0900 | 0.0000 |
| Brent(ARE) | 1.1700 | 0.7603 | -0.0041 | 0.0030 | -1.3900 | 0.1650 |
| ARE(Brent) | 0.7400 | 0.8627 | -0.7318 | 0.1121 | -6.5300 | 0.0000 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| Brent(GBR) | 4.4700 | 0.2149 | | | | |
| GBR(Brent) | 7.1800 | 0.0665 | | | | |
| Brent(NGA) | 2.7000 | 0.4398 | | | | |
| NGA(Brent) | 2.2600 | 0.5208 | | | | |

Notes: ECT stands for the error correction term. For the name of the ECT or the VAR, for example, WTI(JPN) is where the WTI is the dependent variable and JPN is the independent variable.

Table 31. VAR result of inflation with oil prices

| | Short-run causality | | Long-run causality | | | |
|---|---|---|---|---|---|---|
| Panel A : With WTI | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| JPN(WTI) | 3.5000 | 0.3209 | -0.1793 | 0.0465 | -3.8500 | 0.0000 |
| NGA(WTI) | 6.3600 | 0.0952 | -0.0495 | 0.0103 | -4.8100 | 0.0000 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| GBR(WTI) | 22.3000 | 0.0002 | | | | |
| USA(WTI) | 19.3200 | 0.0007 | | | | |
| SAU(WTI) | 19.3300 | 0.0007 | | | | |
| ARE(WTI) | 1.2500 | 0.8694 | | | | |
| Panel B : With Brent | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| JPN(Brent) | 2.4800 | 0.4797 | -0.1398 | 0.0419 | -3.3300 | 0.0010 |
| NGA(Brent) | 6.3600 | 0.0952 | -0.0484 | 0.0100 | -4.8200 | 0.0000 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| GBR(Brent) | 21.9300 | 0.0002 | | | | |
| USA(Brent) | 18.0000 | 0.0012 | | | | |
| SAU(Brent) | 16.1200 | 0.0029 | | | | |
| ARE(Brent) | 0.3000 | 0.9896 | | | | |

Table 32. VAR and VECM result of interest rates with oil prices

| | Short-run causality | | Long-run causality | | | |
|---|---|---|---|---|---|---|
| With WTI | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| GBR(WTI) | 1.5600 | 0.6685 | -0.5156 | 0.0143 | -3.6000 | 0.0000 |
| USA(WTI) | 0.4500 | 0.9287 | -0.0398 | 0.0116 | -3.4400 | 0.0001 |
| JPN(WTI) | 0.2900 | 0.9623 | -0.0536 | 0.0159 | -3.3700 | 0.0010 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| NGA(WTI) | 0.9200 | 0.8213 | | | | |
| With Brent | | | | | | |
| VECM | | | | | | |
| | chi2(2) | Prob | ECT | Std,err | z | P |
| GBR(Brent) | 1.0300 | 0.7932 | -0.0511 | 0.0153 | -3.5800 | 0.0000 |
| USA(Brent) | 0.2600 | 0.9678 | -0.0416 | 0.0120 | -3.4700 | 0.0000 |
| JPN(Brent) | 0.4200 | 0.9361 | -0.0487 | 0.0143 | -3.4200 | 0.0010 |
| VAR | | | | | | |
| | chi2(2) | Prob | | | | |
| NGA(Brent) | 0.2000 | 0.9771 | | | | |

## 3.6 Summary

The previous two chapters focus on the relationship between oil prices and stock market indices, and the predictability of future oil prices, by using the Holt-Winters model. This chapter investigates and analyses the relationship of macroeconomic variables (exchange rates, inflation and interest rates) with oil prices (WTI and Brent crude oil prices) over January 2002 and December 2021 in different data sets, using cointegration tests, VAR and VECM analysis.

This chapter finds that the JPN, SAU and ARE exchange rates are cointegrated with both crude oil prices (WTI and Brent), while GBR and NGA cannot reject the null hypothesis that there is no cointegration between exchange rates and oil prices. Differently from the exchange rate cases, the inflation of JPN and NGA are cointegrated with oil prices, and other factors cannot reject the null hypotheses. For the interest rate, only NGA has no cointegration with oil prices. Thus, the results of the JPN, SAU and ARE exchange rates reject Hypothesis 1 – that there is no cointegration relationship between oil prices and exchange rates. For inflation, JPN and NGA reject Hypothesis 2. Additionally, all interest rates reject Hypothesis 3, apart from the NGA ones.

The original expectation was that I regarded all the exchange rates as being cointegrated with both oil prices. However, only JPN, SAU and ARE's exchange rate are cointegrated with oil prices. All these three countries are oil-related countries. In this case, I conclude that the oil price and the exchange rate have an equilibrium relationship. As they are non-stationary as a single term, when considered as a pair, the error correction mechanism will bring these two variables back to the equilibrium. This indicates that when considering the exchange rate in these three countries, oil price can be seen as one of the predictors. Without expectation, the GBR and NGA's exchange rate has no long-term relationship with oil prices. For GBR, this may be due to the fact that other factors that influence the exchange rate and the oil price are not significant. For NGA, as an oil-exporting country and a member of OPEC, this may be due to its local government policy and monetary policy, which cause differences with SAU and ARE.

For inflation, JPN and NGA's inflation are cointegrated with oil prices, which claims that the inflation in these two countries can be estimated by the oil price, based on the cointegration model. This also indicates that oil prices will influence the local economy, causing inflation. For other countries, their inflation has no long-term relationship with the oil price, and this may be due to their monetary policy and local control to stabilise the local economy. In addition, all the countries' interest rates are cointegrated with the oil price except NGA, which shows that these countries react to the changes of oil prices over time, and make the appropriate changes in their interest rates, or create a monetary policy to respond to changes in the oil price.

The results of the VAR and the VECM vary between exchange rates, inflation and interest rates. For the exchange rates, there is long-run causality running from JPN to oil prices, and from oil prices to SAU and ARE. In the short term, the lagged value of WTI has the explanation power to SAU's, GBR's and WTI's exchange rates in the short term, while only Brent can explain the GBR inflation in the short term. There is no bilateral relationship between exchange rates and oil prices. Unlike the expectation, there is no bilateral relationship between exchange rates and oil prices in all cases. In addition, in the long-term causality, oil prices offer an explanation to SAU and ARE, the two oil-exporting countries. This enhances the opinion that the oil-exporting countries' economies have a strong relationship with oil prices. For GBR, the fluctuation of the exchange rates is not mainly caused by oil price, and may also be influenced by other economic factors. As in the short term, the WTI crude oil price affects the exchange rate in SAU and GBR, which indicates that the WTI crude oil influences them temperately, and the influences are absorbed by the markets. However, there is no evidence to support the influence of the oil price on the exchange rate. This may be because the influence is weak or the oil price is one of the influential factors, and cannot explain the changes of exchange rate by itself.

For inflation, there is a long-run causality running from oil prices to JPN and NGA. For the short term, oil prices have explanation power to GBR, USA and SAU. There is a uniliteral relationship between inflation and oil prices. The oil price has a short-term influence on GBR, USA and SAU, which indicates that oil price fluctuations cause inflation, and as time passes, the influence on inflation will be eased by the policy made or absorbed by the market. However, JPN and NGA have no short-term causality, which may be due to the oil price changes having no immediate influence in these two countries, and there is a time lag for the nation to react to the changes. Thus, for short-term estimation of inflation, oil price is a good predictor in GBR, USA and SAU, while it is good to predict long-term inflation in JPN and NGA.

In addition, there is long-run causality running from oil prices to GBR, USA and JPN interest rates, while in the short term, oil prices have no explanation power. In the interest rate case, oil prices have a long-term influence on the economy and local governments amend their interest rate to get rid of the influence of the oil price. This concludes that the oil price can be seen as a good predictor for the long-term estimation of the treasury bill in these countries.

Therefore, this chapter cannot reject Hypothesis 4 – that there is no bilateral relationship between exchange rates and oil prices. The GBR, USA and SAU's inflation in the short-term and JPN and NGA's inflation in the long-term reject

Hypothesis 5. The interest rates reject the hypothesis in the long term for all cases but cannot reject the hypothesis in the short term for all cases.

In this chapter, the analysis results show that a causality relationship occurs between oil prices and macroeconomic variables. The results show that oil prices have significant influence on the SAU and ARE’s exchange rates in the long term, while others show that there is no causality in the long term. This indicates that the fluctuation of the oil prices will influence the exchange rate of some OPEC countries. The result from inflation indicates that we should pay attention to JPN and NGA’s inflation when the oil price changes in the long term, and for GBR, USA and SAU’s inflation in the short term. Finally, oil price changes have significant influence on the interest rates of GBR, USA and JPN. For further investigation of the relationship between oil prices and macroeconomic variables, there should be an investigation into the nonlinearity between them.

# 4. Conclusion

This thesis investigates into the oil price and oil market as the main target, combining with the stock market, oil price prediction and the macro-economic variables. The results of this thesis can help readers and investors to have a better understanding of the oil price and other related factors. In this thesis, I examine three things: the relationship between oil prices and OPEC stock indices and how the oil prices influence the relationship between different stock indices (Chapter 1); oil price prediction under the Holt-Winters and ARIMA models (Chapter 2); and the relationship between oil prices and macro-economic variables (Chapter 3).
In the first chapter, I employ the single regression model, the cointegration test and the VAR model to test the collected data. Four OPEC countries' indices (Ecuador, Nigeria, Saudi Arabia and the United Arab Emirates) are collected, and three economically high-performing countries' (the US, the UK and Japan) indices are collected. The period of the data collected varies from 1998 to 2019, due to availability.

In the single regression model, I conclude that oil prices are correlated positively with all the indices. In addition, the period of data includes the 2008 financial crisis, and the results show that the crisis had a significant influence on the relationship between oil prices and indices, which enhanced the relationship. The crisis made the coefficient become bigger, which means the same – that the oil price causes a larger amendment to the indices. In the cointegration test, the result shows that all the indices are cointegrated with both oil prices, which indicates that they have a long-term relationship. This is a sign that the oil prices can be seen as a considerable variable when estimating the selected indices. The VAR model test shows that the oil price has influence on the relationship between different indices. However, the influence is limited. When considering the oil price as the condition in the VAR model, this can remove the explanation power of the US stock market (S&P 500) and the UK stock market (FTSE 100) to the Nigerian stock exchange (NSE). The results shows that when taking the oil price into consideration in the relationship between different indices, it can help to have better understanding. This chapter concludes that oil prices are cointegrated with all the selected OPEC countries' indices, and considering the oil price as a condition can remove or enhance the explanation power of one index to another.

In the second chapter, I employ the Holt-Winters and ARIMA prediction to the oil prices (WTI and Brent). I aim to have an investigation on the predictability of the oil prices on themselves. Oil prices are collected from 1990 to 2020. The data are divided into groups: one contains thirty-year data and one includes ten-year data. The model included in this chapter seeks to compare the prediction errors, such as MAPE, MaxAPE, MAE and MaxAE. The smaller the error, the better the predictability.

The result from both the Holt-Winters and ARIMA prediction models shows that oil prices can be predicted to some extent but not perfectly. The prediction of the oil price in the respective cases is the stable or upward or downward straight line. Comparing the prediction data with the true selected data shows that the ten-year data have a better predictability than the thirty-year data. The reason for this may be due to the thirty-year data, which encompasses the 2008 financial crisis, which influenced the oil price heavily. In addition, this analysis only fits the weak form hypothesis on the historical information itself. The inaccuracy of the model may be due to the limitation of other influential factors that are not included.

In the third chapter, I employ the cointegration test and VAR/VECM to test the relationship between oil prices (WTI and Brent) and macro-economic variables (exchange rates, inflation and interest rates). The previous two chapters all have some limit on analysing the relationship between oil prices with other factors and the predictability of the oil prices. Thus, the third chapter is going to have an analysis to see how these variables would influence or be influenced by oil prices.

The data have been collected from 2002 to 2021 in OPEC countries (Nigeria-NGA, Saudi Arabia-SAU and United Arab Emirates-ARE) and three economically high-performing countries (United States of America - USA, The United Kingdom - GBR and Japan - JPN) for exchange rates, inflation and interest rates. In the cointegration test, not all the macro-economic variables are cointegrated with oil prices. For exchange rates, only JPN, SAU and ARE's exchange rates are cointegrated with both oil prices. For inflation, only JPN and NGA are cointegrated with oil prices. Differing from exchange rates and inflation, all the interest rates have a cointegration relationship with oil prices, except NGA.

In the VAR and VECM results, no bilateral relationship occurs in the exchange rate. In the long term, JPN has explanation power to oil prices and oil prices have explanation power to SAU and ARE. This indicates that oil-related countries are easier to be influenced compared to other countries. In the short term, the WTI crude oil price has explanation power to SAU.

For inflation, there is long-term causality running from oil prices to JPN and NGA. There is short-term causality running from oil prices to GBR, USA and SAU. This indicates that oil prices are a good predictor for inflation in JPN and NGA in the long term and for GBR, USA and SAU in the short term. This also concludes that the GBR, USA and SAU's governments can guard against the influence caused by oil prices in the long term. For the interest rates, there is long-term causality running from oil prices to GBR, USA and JPN. Thus, oil prices can be seen as a good predictor to estimate the interest rates in these countries.

The findings suggest that oil prices play an important role in the world economy. By only using the oil prices it could be difficult to have an accurate estimation for future oil prices. Other information or other variables should be compared to increase accuracy and help to have better asset allocation in oil markets. When considering oil prices, it can help to have a better understanding of investing in different stocks. I also conclude that oil prices have relationships with macro-economic variables, such as exchange rates, inflation and interest rates. The findings could help readers and investors to have better asset allocation when considering oil prices.

The main finding of the whole thesis is that the oil price changes play an important role in the world economy by influence the relationship between different stock markets and other economic variables, such as exchange rate, inflation and interest rate. First, this thesis find that oil price changes can influence the relationship between OPEC countries and economical top-performing countries' stock markets.

This gives a guide to the investors that when have an international portfolio including OPEC stock markets and three top countries' stock markets, they need to pay attention to the oil price changes which can help them to manage their portfolio effectively. In addition, when oil price changes, there might be change of the local economy by the changes of internal and external investment into the stock markets where the policy makers need to make the appropriate actions to handle the suddenly changes on the large amount of the investment flow to stable the local economy. From the economic interpretation, the oil price changes have different influence on these two groups of stock markets. Normally, an increase in the oil price will hit the economy in developed countries where benefits the OPEC countries as oil-exporting countries. Therefore, for investor, it can generate an opportunity of diversification and for policy maker, they can have the appropriate changes on policy in time to against the influence on local economy.

Second, this thesis claims that the oil price changes have influence on the macro-economic variables approved in OPEC countries. From the economic interpretation, the increase of the oil prices will increase the oil revenue of local economy in the selected OPEC countries, which eventually increase the local GDP. At the same time, the oil price increase also increases the expense of transportation, manufacturing and heating. Thus, these influences will increase the cost of living. Therefore, an increase in the oil prices is not always a good sign for the oil-exporting counties. As the results get from in chapter three, the oil price changes can be a good predictor for macro-economic variables in the selected OPEC countries. Therefore, for investors who invest their asset into the foreign exchange market or whether decide to save the money in the bank or buying assets during the changes of inflation and interest rate, the oil prices change can be sign for them to make decisions. For policy makers, they should set the monetary policy (like change interest rate) to the reasonable amount to against the influence of oil price changes, protecting the local economy.

Last but not least, the oil price prediction is difficult, and the oil market fit the AMH, which indicates that the oil price prediction is time-varying. The results in this thesis suggest investor to avoid invest the oil market during the financial crisis period. It is also suggestable to invest into the oil market in relatively short period.

In addition, there are some limitations to this thesis. For Chapter 1, there was not full availability of data access. Full access to the data could increase the accuracy of the analysis. Other variables should also be considered in the relationship between different indices. Chapter 2 could include a modified or alternative analysis method to predict the oil price. Chapter 3 only looks at the cointegration relationship and the VAR or the VECM, which is only based on the linear relationship.

For researchers, this thesis provides an idea of considering the oil price as a condition when investigate the relationship between different markets, not only investigate the relationship between oil price and the target markets. Furthermore, the research can combine the oil price changes with other variable together like macro-economic variables to as the condition, to see how this combination will influence the relationship between different financial markets. Moreover, the research investigates into the influence substitution of oil (like green energy) and compare with influence of oil. Finally, it is possible to involve the machine learning or deep learning to help with the prediction of oil price.

# Appendices

Table 33. Regression model of DJT and MSCIWE with WTI and Brent

| | DJT | MSCIWE |
|---|---|---|
| Panel A : With WTI | | |
| Coefficient | 0.0842 | 0.3118 |
| Standard error | 0.0104 | 0.0086 |
| R-square | 0.0168 | 0.2550 |
| p-value | 0.0000 | 0.0000 |
| Panel B : With Brent | | |
| Coefficient | 0.0721 | 0.3006 |
| Standard error | 0.0114 | 0.0098 |
| R-square | 0.0103 | 0.1971 |
| p-value | 0.0000 | 0.0000 |

Table 34. Regression model of DJT and MSCIWE with WTI and Brent (pre-, during and post-financial crisis)

| | DJT(pre) | DJT(during) | DJT(post) | MSCIWE(pre) | MSCIWE(during) | MSCIWE(post) |
|---|---|---|---|---|---|---|
| Panel A : With WTI | | | | | | |
| Coefficient | -0.0508 | 0.1304 | 0.1929 | 0.1818 | 0.3838 | 0.3918 |
| Standard error | 0.0155 | 0.0329 | 0.0141 | 0.0122 | 0.0286 | 0.0115 |
| R-square | 0.0064 | 0.0348 | 0.0968 | 0.1173 | 0.2923 | 0.4009 |
| p-value | 0.0010 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Panel B : With Brent | | | | | | |
| Coefficient | -0.0453 | 0.1357 | 0.1878 | 0.1643 | 0.4145 | 0.4015 |
| Standard error | 0.0156 | 0.0393 | 0.0164 | 0.0124 | 0.0352 | 0.0139 |
| R-square | 0.0050 | 0.0267 | 0.0703 | 0.0945 | 0.2415 | 0.3230 |
| p-value | 0.0037 | 0.0006 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Table 35. VAR results of ADX and DJT with WTI and Brent

| VAR | ADX(-1) | ADX(-2) | DJT(-1) | DJT(-2) | Constent |
|---|---|---|---|---|---|
| ADX | 0.0171* | 0.0430** | 0.0979 | 0.0475** | 0.0296 |
| DJT | 0.0671*** | -0.0606*** | -0.0123* | -0.0133* | 0.0353 |
| ADX(WTI) | 0.0070* | 0.0423** | 0.0800 | 0.0435*** | 0.0328 |
| DJT(WTI) | 0.0613*** | -0.0612*** | -0.2200* | -0.0160* | 0.0371 |
| ADX(Brent) | 0.0117* | 0.0421** | 0.0837 | 0.0470*** | 0.0314 |
| DJT(Brent) | 0.0678*** | -0.0613*** | -0.0079* | -0.0155* | 0.0351 |

Table 36. VAR results of ADX and MSCIWE with WTI and Brent

| VAR | ADX(-1) | ADX(-2) | MSCIWE(-1) | MSCIWE(-2) | Constent |
|---|---|---|---|---|---|
| ADX | 0.0201* | 0.0471*** | 0.2165 | -0.0208* | 0.0257 |
| MSCIWE | 0.0516*** | 0.0054* | -0.0179* | -0.0448** | 0.0383 |
| ADX(WTI) | 0.0121* | 0.0519*** | 0.1905 | -0.0394* | 0.0306 |
| MSCIWE(WTI) | 0.0463*** | 0.0090* | -0.0208* | -0.0597*** | 0.0393 |
| ADX(Brent) | 0.0139* | | 0.2045 | | 0.0289 |
| MSCIWE(Brent) | 0.0414*** | | -0.0171* | | 0.0368 |

Table 37. VAR results of ECU and DJT with WTI and Brent

| VAR | ECU(-1) | ECU(-2) | DJT(-1) | DJT(-2) | Constent |
|---|---|---|---|---|---|
| ECU | -0.1250 | -0.0517*** | 0.0121* | -0.0138* | 0.0213 |
| DJT | 0.0068* | -0.0417* | -0.0031* | -0.0169* | 0.0391 |
| ECU(WTI) | -0.1219 | -0.0480*** | 0.0100* | -0.0136* | 0.0203 |
| DJT(WTI) | 0.0103* | -0.0372* | -0.0164* | -0.0189* | 0.0375 |
| ECU(Brent) | -0.1174 | | 0.0081* | | 0.0192 |
| DJT(Brent) | 0.0111* | | -0.0014* | | 0.0341 |

Table 38. VAR results of ECU and MSCIWE with WTI and Brent

| VAR | ECU(-1) | ECU(-2) | MSCIWE(-1) | MSCIWE(-2) | Constent |
|---|---|---|---|---|---|
| ECU | -0.1239 | -0.500*** | 0.0243** | -0.0053* | 0.0192 |
| MSCIWE | 0.0418* | -0.0381* | -0105* | -0.0350* | 0.0394 |
| ECU(WTI) | -0.1229 | -0.0509*** | 0.0195* | -0.0047* | 0.0196 |
| MSCIWE(WTI) | 0.0406* | -0.0359* | -0.0137* | -0.0490** | 0.0407 |
| ECU(Brent) | -0.1178 | | 0.0186* | | 0.0188 |
| MSCIWE(Brent) | 0.0445* | | -0.0120* | | 0.0374 |

Table 39. VAR results of NSE and DJT with WTI and Brent

| VAR | NSE(-1) | NSE(-2) | DJT(-1) | DJT(-2) | Constent |
|---|---|---|---|---|---|
| NSE | 0.3118 | | 0.0492*** | | 0.0083 |
| DJT | -0.0506*** | | -0.0022* | | 0.0353 |
| NSE(WTI) | 0.3094 | -0.0178* | 0.0340** | 0.0156* | 0.0105 |
| DJT(WTI) | -0.0648*** | 0.0381* | -0.0121* | -0.0174* | 0.0373 |
| NSE(Brent) | 0.3106 | | 0.0358** | | 0.0096 |
| DJT(Brent) | -0.0503*** | | 0.0008* | | 0.0350 |

Table 40. VAR results of NSE and MSCIWE with WTI and Brent

| VAR | NSE(-1) | NSE(-2) | MSCIWE(-1) | MSCIWE(-2) | Constent |
|---|---|---|---|---|---|
| NSE | 0.3149 | -0.0176* | 0.0712 | 0.0429* | 0.0032 |
| MSCIWE | -0.0528 | 0.0187* | -0.0075* | -0.0293* | 0.0382 |
| NSE(WTI) | 0.3111 | -0.0173* | 0.0475** | 0.0160* | 0.0097 |
| MSCIWE(WTI) | -0.0545 | 0.0264* | -0.0112* | -0.0464*** | 0.0410 |
| NSE(Brent) | 0.3121 | | 0.0535*** | | 0.0087 |
| MSCIWE(Brent) | -0.0452** | | -0.0109* | | 0.0388 |

Table 41. VAR results of TASI and DJT with WTI and Brent

| VAR | TASI(-1) | TASI(-2) | DJT(-1) | DJT(-2) | Constent |
|---|---|---|---|---|---|
| TASI | 0.1298 | | 0.0528*** | | 0.0080 |
| DJT | 0.0437*** | | -0.0150* | | 0.0345 |
| TASI(WTI) | 0.1176 | -0.0327*** | 0.0301* | 0.0285* | 0.0103 |
| DJT(WTI) | 0.0435** | -0.0435** | -0.0239* | -0.0121* | 0.0370 |
| TASI(Brent) | 0.1207 | | 0.0406** | | 0.0094 |
| DJT(Brent) | 0.0470** | | -0.0106* | | 0.0340 |

Table 42. VAR results of TASI and MSCIWE with WTI and Brent

| VAR | TASI(-1) | TASI(-2) | MSCIWE(-1) | MSCIWE(-2) | Constent |
|---|---|---|---|---|---|
| TASI | 0.1224 | -0.0543*** | 0.2047 | -0.0034* | -0.0001 |
| MSCIWE | 0.0866 | -0.0179* | -0.0288* | -0.0462*** | 0.0387 |
| TASI(WTI) | 0.1095 | -0.0580*** | 0.1649 | -0.0095* | 0.0049 |
| MSCIWE(WTI) | 0.0840 | -0.0193* | -0.0265* | -0.0555*** | 0.0391 |
| TASI(Brent) | 0.1144 | -0.0599 | 0.1959 | -0.0153* | 0.0026 |
| MSCIWE(Brent) | 0.0883 | -0.0215* | -0.0247* | -0.0514*** | 0.0385 |

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