THE IMPACT OF OIL PRICE ON MALYSIAN STOCK MARKET DURING THE PERIOD OF 2014 OIL SHOCKS

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the research project.

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Table of Contents

LIST OF TABLE

LIST OF FIGURE

LIST OF ABBREVIATIONS

ADB	Asian Development Bank
ADF	Augmented Dickey-Fuller
ARJI	Autoregressive Conditional Jump Intensity
DCC	Dynamic Conditional Correlation
DCC-GARCH-GJR	Dynamic conditional correlation- generalized autoregressive conditional heterosekdascity – Glosten, Jaganathan and Runkle
ECM	Error Correction Model
FBMT100	FTSE Bursa Malaysia Top 100 index
FTSE	Financial Time Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroscedasticty
GCC	Gulf Cooperation Countries
IRF	Impulse Response Function
ML	Maximum Likelihood
OECD	Organization for Economic Cooperation and Development
OPEC	Organization of Petroleum Exporting Countries
RUB	Russian Ruble
UAE	United Arab Emirates
UK	United Kingdom
US	United States
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model
WTC	World Trade Centre
WTI	West Texas Intermediate

ABSTRACT

This study examines dynamic causality between the Brent crude oil return and Malaysian stock return, and as well as between the West Texas Intermediate (WTI) crude oil return and Malaysian stock return. The sample period of 2014-2015 is separated to become pre and post oil shock period. Granger causality test, impulse responses function and variance decomposition are used. Empirical result provides two findings. First, Brent crude oil price is found to be a tool for inflation hedged as compared to the WTI crude oil price. Second, Granger causality is found to be occurred from Brent crude oil return to stock returns during the pre-oil shocks period. Furthermore, there is a strong respond of stock due to oil price shocks. This study suggests that investors should emphasize on crude oil price movement before the oil shocks in hedging their risk in stock market. This is because they react faster in stock market due to their sensitivity toward changes of crude oil price movement.

CHAPTER 1: INTRODUCTION

1.0 Background of Study

The linkage between oil and stock markets has received great attention among researchers, economists, practitioners and policy makers. This is due to oil acts as an important source for modernization and civilization around the world. Therefore, any price changes of crude oil in the international market always grab the attention of market players such as investors and portfolio managers.

Moreover, the relationship between both markets is associated with oil as a core input production in terms of machineries, transportations, shipping and travelling in the manufacturing sectors. These costs are subsequently taken into account in determining the expected earnings of firms. This suggests that rising oil price contributes to high cost of input productions and subsequently reduces firm's productivity. As a consequence, stock prices will be reduced through low expected earnings of firms. Therefore, changes in oil prices should be presumed to have a negative relationship with changes in stock prices. This presumption corresponds to the study of Bhat, Nain and Kamaiah (2014). They identified significant negative relationship between oil and stock prices in transportations, industrials, and other energy dependent industries.

Furthermore, the negative relationship of oil and stock markets can be explained through the expectation of high inflation. For instance, high oil prices create opportunities of speculative pressure among investors through short-selling activities. This will cause them to transfer or withdraw their investment funds from stock markets to oil markets. These activities will subsequently reduce the performance of stock and equity markets. This is because investors expect that inflated commodity will lead to scarcity of inventory in the short run productions.

In order to earn attractive returns from their investments, investors tend to sell off inflated commodities to producers. Consequently, the inflationary pressure from inflated commodities led banks to raise interest rates as an effort to decrease inflation rate through reducing money supply in the market. Both high inflation and interest rates result in the use of higher discount rates in discounted cash flows, this subsequently decrease stock prices.

On the other hand, oil price fluctuations affect stock prices of oil exporting and importing countries in different directions. This is because falling oil prices benefit oil importing countries at the expense of oil exporting countries. Park and Ratti (2008) found that oil prices negatively impact stock returns in oil-importing United States (US). When oil prices remained low, it reduced inflation rate and increased economic output of importing countries. This is because oil importing countries benefit from lower input costs. In the report of Asian Development Bank (ADB), it highlighted that that falling oil prices helped oil importing countries to reform their fuel subsidy. Besides, the report stated that a 20% decreased in oil price led to an approximately 0.003% growth in Gross Domestic Product (GDP) of Asian emerging countries. Hence, it will foster economic growth and attracts foreign direct investments into the country. Therefore, stock prices and returns are expected to rise.

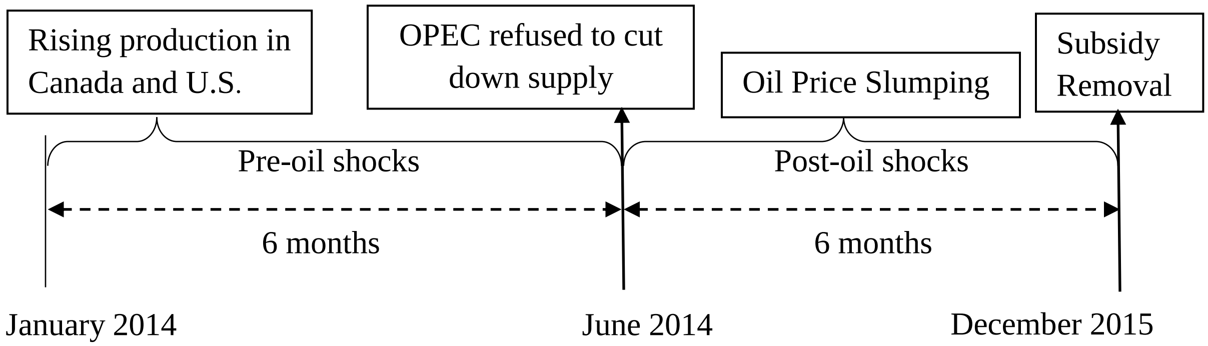
On the other hand, Park and Ratti (2008) found that oil exporting Norway's stock returns responded positively towards oil prices. Falling oil prices decrease oil revenue of oil exporting countries. For instance, slumping oil price led Russia to fall into a deep recession since the last decade. This caused Russian companies experienced difficulties to meet their obligations to repay foreign debt when the Russian Ruble (RUB) depreciated drastically (Eberhardt & Menkiszak, 2015).

Moreover, when oil price falls below production cost in oil exporting countries, government has to sacrifices infrastructure spending to protect welfare and defense budget. Moreover, this decelerates the economic growth of the country and oil and gas companies will suffer in terms of profitability. Consequently, Investors will lose confident in the oil markets and withdraw their investments to protect their returns. As a result, this will negatively affect the stock market performance in oil exporting countries.

1.1 Problem Statement

By the mid of 2014, rising production of oil in United States and Canada led to over supplied of oil in the international commodity market. Since oil price is determined by expectations and demand and supply forces of market, the overtaken of oil supply forces in the market caused oil prices to decline. In addition, Organization of Petroleum Exporting Countries (OPEC) refused to cut down their oil supply at the expense of their market shares. Consequently, their decision shaped the expectations of investor and this led oil price to slump for more than 50% from July 2014 to December 2014.

On December 2014, Malaysian government has removed the fuel subsidy which allowed domestic oil price to float based on the market's demand and supply forces. Hence, Malaysian's oil price becomes more volatile and firms' cash flow becomes more uncertain. Firm’s uncertainty in cash flows led to a more unpredictable stock price. This increased the difficulty for investors to evaluate firm’s stock prices and they are exposed to a higher risk. Consequently, investors in Malaysia may move their funds to another country to be less exposed to risks related to a firm’s cash flow uncertainty.



Source: Developed for the study.

Given that oil price shocks occurred on July 2014, West Texas Intermediate (WTI) and Brent oil price has fallen to $47.52 and $48.93 by January 2014. In the same period, FTSE Bursa Malaysia Top 100 (FBMT 100) has also declined to 11808.53. The gap between crude oil prices and stock index becomes larger during post-oil shocks period from July 2014 to January 2015. Figure 1 shows WTI and Brent are moving in the same direction with FBMT 100.

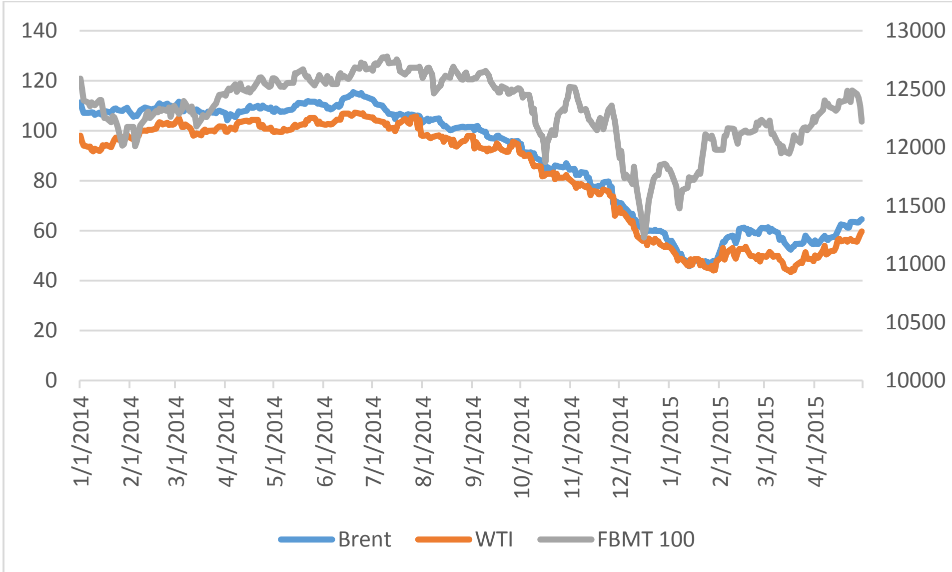


Figure 1: The Movement of WTI, Brent and FBMT 100 from January 2014 to April 2015.

Source: Thompson Reuters Datastream (2015)

During post-oil shocks period, spillover effect of volatility in oil price is expected to impact the stock market performance in Malaysia. According to Janor, Abdul-Rahman, Housseinidoust, and Rahim (2013), negative oil price shocks tend to increase the volatility of stock returns in Malaysia. Moreover, higher oil price volatility will lead to a higher uncertainty in firms' cash flows and stock returns.

This study investigates the impact of West Texas Instrument (WTI) and Brent light sweet crude oil pricing benchmarks on Malaysian stock market. Both crude oil markets are widely used as oil pricing benchmarks around the world. According to Platts (2011), approximately two thirds of the world use Brent oil pricing benchmark while WTI serves as the main oil pricing benchmark in United States. Malaysian government has been using Brent as oil pricing benchmark since June 2011**.** Brent crude oil is higher priced than other benchmarks such as WTI and Tapis, leading to a higher cost and thus presumed to cause a larger impact on Malaysian stock market during oil price shock. On the other hand, WTI is trading at a discount to Brent due to surplus of oil supply in United States.

1.2 Research Questions

i) How causal direction is happened between Brent crude oil and Malaysian stock market and as well as between WTI crude oil and Malaysian stock market during pre and post crisis period?

ii) Which crude oil price can be used as inflation hedged for stock price fluctuation?

1.3 Research Objectives

i) To identify the causal direction between crude oil and Malaysian stock returns.

ii) To identify whether crude oil price that can be used as an inflation hedge for stock price fluctuation.

1.4 Significance of Study

This study investigates the impact of oil price shock on Malaysian stock market index by using WTI and Brent crude oil benchmarks. The findings of causal direction between oil and stock prices can assist Malaysian portfolio managers to create a more efficient investment portfolio. For example, Malaysian portfolio managers can hedge their portfolio risk by entering short position in crude oil futures when oil price falls. Therefore, their loss in stock market can be offset by the gain from crude oil futures market. As a result, their portfolio returns will be protected against oil price changes.

In addition, investors can predict stock price movements based on the movements of crude oil price that has a higher causality effect towards Malaysian stock market. As oil price decrease, stock price will decrease due to the positive relationship between oil and stock prices. Therefore, investors may observe oil price as an aiding tool to predict the stock price movements for their hedging decisions.

1.5 Chapter Layout

Chapter 2 presents the literature review on oil and stock prices relationship. Then, chapter 3 describes the data and methodology employed for this study. Next, chapter 4 presents the empirical results. Lastly, chapter 5 summarizes the overall findings.

CHAPTER 2: LITERATURE REVIEW

2.0 Overview

Empirical studies have been conducted to assess the impact of oil price shocks on stock price in different countries. This chapter consist four sections: (i) positive relationship between oil and stock markets, (ii) negative relationship between oil and stock markets, (iii) volatility transmission between oil and stock markets and (iv) conclusion.

2.1 Positive Relationship between Oil and Stock Market

To the best of our knowledge, there are four factors that established the positive relationship between oil and stock market: (i) oil exporting country, (ii) aggregate oil demand shocks, (iii) increased financial speculation, and (iv) crisis.

Positive Relationship between Oil and Stock Market of Exporting Country

Park and Ratti (2008) used Vector Autoregressive (VAR) and they found that Brent crude oil have significant positive impact on stock returns for oil exporting countries during 1986 - 2005. This relationship can be explained by the recapture of market share from Organizational of Petroleum Exporting Countries (OPEC) during that period. Similarly, Donoso (2009) implemented the same model and they found that Standard and Poor’s 500 (S&P 500) have a positive relationship with West Texas Intermediate (WTI) during 1986 - 2008. This was because US heavily relied on oil as their industrial product and dramatically increased their industrial production during that period.

Furthermore, Arouri, Lahiani and Bellalah (2010) implemented different international multifactor models. They concluded that stock market returns positively responded to Brent Crude oil in Qatar, Oman, Saudi Arabia and United Arab Emirates (UAE) during 2005 - 2008. Their findings suggested that rising oil price increased government and corporate earnings in Gulf Cooperation Countries (GCC). Moreover, Nguyen and Bhatti (2012) used plots and copula method and found positive relationship between WTI and Ho-Chi Minh Stock Exchange (HOSE) during 2000 - 2009. This relationship can be explained by Vietnam being one of the major non OPEC regional crude oil exporters in the world. Therefore, their stock market's performance heavily depended on oil revenues.

Furthermore, Gil-Alana and Yaya (2014) used fractional co-integration model and they found positive relationship between Brent crude oil and Nigerian All Share Index (ASI) during 2007 - 2012. Their findings suggested that increased oil price that positively affected the income of Nigeria. In addition, Louis and Balli (2014) used Granger causality and pairwise correlation test and studied on GCC. They found that stock returns were positively and highly correlated to WTI during 1999 - 2010. Their findings suggested that rising oil price increased oil export revenues and fostered investments in other sectors in their countries.

Positive Relationship between Oil and Stock Market during Aggregate Oil Demand Shocks

Miller and Ratti (2009) used Vector Error Correction Model (VECM) and studied on Organization for Economic Co-operation and Development (OECD) countries. They identified positive relationship between stock markets (Canada, France, Germany, Italy, United Kingdom, United States) and Brent crude oil during 1971 - 1980 and

1988 - 1998. This was because OECD countries relied heavily on oil for economic developments during the two periods. On the other hand, Apergis and Miller (2009) used Granger temporal causality test and they found that oil demand shocks positively affected stock market returns during 1981 - 2007. Furthermore, their findings suggested that oil supply shocks have temporal causality effect on Australian stock market while oil demand shocks have an impact on France.

Filis, Degiannakis and Floros (2011) used dynamic conditional correlation - generalized autoregressive conditional heterosekdascity - Glosten, Jaganathan and Runkle (DCC-GARCH-GJR) model. They found positive relationship between Brent crude oil and stock markets during 1987 - 2009. This relationship was initiated through the high demand for oil caused by the rapid growth in the construction industry and housing markets around the world. They highlighted that aggregate demand oil shock was expected to have a positive impact on stock markets for both oil exporting and importing countries. Similarly, Caporale, Menla Ali and Spagnolo (2015) used bivariate VAR-GARCH-in-mean-model and studied on China. They found that WTI has a positive impact on China's stock market during 1997 - 2014. This relationship can be explained by China's rising demand for oil during its rapid economic growth period.

Positive Relationship between Oil and Stock Market caused by Increased Financial Speculations

Cong, Wei, Jiao and Fan (2008) used multivariate VAR and they concluded that China's stock markets have a positive relationship with Brent Crude oil during 1996 - 2007. Rising oil price volatility increased investors' speculations in mining and petrochemicals index. This eventually increased the companies' stock returns. In addition, Narayan and Narayan (2010) used VAR and identified significant positive relationship between WTI and Vietnam's stock market during 2000 - 2008. The growth of the Vietnamese stock market was accompanied by rising oil prices due to changes in preferences from holding foreign currencies and rising leveraged investment in stocks.

On the other hand, Dagher and El Hariri (2013) implemented VAR and they identified rising Brent oil price positively impacts Lebanon's stock market during 2006 - 2012. This relationship can be explained by the substantial investments for Lebanese stocks from foreign investors from neighbouring oil exporting Arab countries. In addition, Broadstock and Filis (2014) used Scalar Baba, Engle, Kraft and Kroner (BEKK) model and found that NYSE was always positively correlated with Brent crude oil during 1995 - 2012. During that period, increased participation in hedge funds had increased speculation in the oil market. This could justify the positive relationship between stock and oil market.

Furthermore, Sukcharoen, Zohrabyan, Leatham and Wu (2014) implemented copula method and identified positive relationship between Brent crude oil and stock returns of United States and Canada during 1982 - 2007. Furthermore, they identified positive relationship between stock market indices and Brent crude oil for Italy, Germany, France, Spain and Netherlands. Their findings suggested that decreased oil price that negatively affected local investors and companies. Therefore, the stock markets were more sensitive to negative oil price shocks.

Positive Relationship between Oil and Stock Market During Crisis Period

Faff and Brailsford (1999) used two factor model. They found significant positive relationship between oil price Australian stock market during 1983 - 1996. This relationship was initiated by the "Dutch disease" and Gulf War during that period. On the other hand, Filis, Degiannakis and Floros (2011) used DCC-GARCH-GJR model and found positive relationship between Brent Crude oil and stock markets during economic crises during 1987 - 2009. Their empirical results showed that the positive correlation was high during the 911 US World Trade Centre (WTC) terrorist attack and Iraq second war.

2.2 Negative Relationship between Oil and Stock Market

Chiou and Lee (2009) used Auto-regressive Conditional Jump Intensity (ARJI) and studied on US. They found that the WTI have a significant and negative impact on S&P 500 index during 1992 – 2006.This was because rising oil prices had increased the costs of production, reduced corporate earning and caused inflation impacts. Furthermore, Wang, Wu and Yang (2013) employed VAR and they identified negative relationship between WTI stock markets during 1999 - 2011. During that period, rising oil price increased business uncertainty and depressed economic activities of oil importing countries.

In addition, Cunado and Perez de Gracia (2014) used VAR and VECM and studied on European oil importing countries. They found negative relationship between Brent crude oil and stock markets of Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, Netherlands, Portugal, Spain and United Kingdom during 1973 - 2011. Furthermore, their findings highlighted that oil supply shocks contributed to a greater negative impact on stock markets. This was because oil supply shocks decelerated economic activities during the period.

2.3 Volatility Transmissions between Oil and Stock Markets

Arouri, Jouini, and Nguyen (2011) used VAR-GARCH and they concluded that spillover is mostly unidirectional from oil to stock markets in Europe and bi-directional in United States during 1998 - 2009. The bi-directional results were expected, as increasing oil price affected consumers' and investors' sentiment and demand for financial products. Similarly, Masih, Peters and De Mello (2011) used VAR and they found that oil price movements significantly affect the stock market of South Korea during 1988 - 2005. They found that oil price shocks decreased firm's profitability due to increased production cost.

Furthermore, Chang, McAleer, and Tansuchat (2013) used dynamic conditional correlation (DCC) model and studied US and United Kingdom (UK). They identified significant positive correlation between WTI and stock index returns, as well as between Brent crude oil and stock index returns during 1988 - 2009. Their findings emphasized on the dynamic conditional correlation between FTSE 100 and Brent forward returns, which varied dramatically over time. In addition, Awartani and Maghyereh (2013) implemented directional spillover index measure. They identified bi-directional return and volatility transmission between WTI and GCC equities during 2004 - 2012. This was because oil revenue was the main determinant of government budgets, earnings, aggregate demand, and expenditures of GCC. Therefore, positive correlations were expected between GCC stock and oil markets.

Moreover, Kang, Ratti and Yoon (2015) employed structural VAR and found that positive oil shocks negatively affect stock returns and volatility covariance relationships for United States during 1973 - 2013. They highlighted that oil price shocks contain information to forecast contemporaneous relationship between stock return and stock volatility.

2.4 Conclusion

Table 2.1 summarizes the past findings on the relationship between oil and stock price.

Table 2.1 Summary of Literature Review

Author	**Country**	**Period**	**Method**	**Finding**
Gil-Alana and Yaya (2014)	Nigeria	Monthly data, 2007 - 2012	multiple regression	Positive relationship O → S
Apergis and Miller (2009)	Australia, Canada, France, Germany, Italy, Japan, United Kingdom, United States	Monthly data, 1981 – 2007	Granger causality test	Positive relationship O → S
Arouri, Jouini and Nguyen (2011)	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States	Weekly data, 1998-2009	VAR-GARH model	Significant volatility transmission O → S (Europe) O ↔ S (U.S.)
Arouri, Lahiani and Bellalah (2010)	Bahrain, Oman, Kuwait, Qatar, Saudi Arabia and United Arab Emirates (UAE)	Weekly data, 2005 - 2008	international multifactor model	Positive relationship O → S
Awartani and Maghyereh (2013)	Saudi Arabia, Bahrain, Kuwait, Oman, Qatar, Abu Dhabi, and Dubai	Daily data, 2004-2012	spillover directional measure method	Significant volatility transmission O ↔ S
Broadstock and Fillis (2014)	China, United States	Monthly data, 1995 - 2013	scalar- BEKK and structural VAR model	Positive relationship O → S
Caporale, Menla Ali, and Spagnolo (2015)	China	Weekly data, 1997 - 2014	bivariate VAR GARCH-in-mean model	Positive relationship O → S

Chang, McAleer, and Tansuchat (2013)	United Kingdom, United States	Daily data, 1998 – 2009	DCC model	Significant volatility transmission O → S
Chiou and Lee (2009)	United States	Daily data, 1992-2006	ARJI model	Negative relationship O → S
Cong, Wei, Jiao and Fan (2008)	China	Monthly data 1996 – 2007	Multivariate VAR model	Positive relationship O → S
Cunado and Perez de Gracia (2014)	Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, Netherlands, Spain, Portugal and United Kingdom	Monthly data, 1973 - 2011	VAR and VECM model	Negative relationship O → S
Dagher and El Hariri (2013)	Lebanon	Daily data, 2006 – 2012	VAR model	Positive relationship O → S
Donoso (2009)	Japan, United Kingdom, United States	Monthly data, 1986 to 2008	VAR model	Positive relationship O → S
Faff and Brailsford (1999)	Australia	Monthly data, 1983- 1996	two factor model	Positive relationship O → S
Filis, Degiannakis and Floros (2011)	Canada, Mexico, Brazil , Germany, Netherlands, United States	Daily data, 1987 – 2009	DCC-GARCH-GJR model	Positive relationship O → S
Kang, Ratti and Yoon (2015)	United States	Daily data, 1973-2013	structural VAR	Significant volatility transmission O → S
Louis and Balli (2014)	Bahrain, Saudi Arabia, Dubai, Abu Dhabi, Oman, Kuwait, Qatar	Daily data, 1999-2010	Granger causality test and pairwise correlation	Positive relationship O → S
Masih, Peters and De Mello (2011)	South Korea	Monthly data, 1988-2005	VAR model, VECM model, and unit root test	Significant volatility transmission O → S
Narayan and	Vietnam	Daily data,	VAR model	Positive

Narayan (2010)		2000-2008		relationship O → S
Nguyen and Bhatti (2012)	China, Vietnam	Daily data, 2000- 2009	plots and copula method	Positive relationship O → S
Park and Ratti (2008)	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Spain, Sweden, United Kingdom, United States	Monthly data, 1986 – 2005	VAR model	Positive relationship O → S
Sukcharoen, Zohrabyan, Leatham and Wu (2014)	Canada, China, Czech Republic, Finland, France, Germany, Hong Kong, Hungary Italy, Japan, Poland, Russia, Spain Netherlands, Switzerland, United Kingdom, United States, Venezuela,	Daily data, 1982- 2007	copula method	Positive relationship O → S
Wang, Wu and Yang (2013)	Canada, China, France Germany, India, Italy, Japan, Korea, Kuwait, Mexico, Norway, Russia, Saudi Arabia, United Kingdom, United States, Venezuela	Monthly data, 1999 - 2011	VAR model	Negative relationship O → S

Notes: (1) → unidirectional, ↔ bidirectional. (2)S represents stock market and O represents oil price.

CHAPTER 3: DATA AND METHODOLOGY

3.0 Overview

This chapter outlines the data source and research methodology employed to achieve the research objectives of this study.

3.1 Data

In this study, the data for FTSE Bursa Malaysia Top 100 (FBMT100), West Texas Intermediate (WTI) and Brent crude oil price are collected on a daily basis from January 1, 2014 to April 30, 2015, a total of 354 observations. This period is chosen to study the oil shocks of 2014. Moreover, the data are retrieved from Thomson Reuters DataStream.

On the other hand, the sample period of all three series was separated into pre and post-oil shocks. For the data series of WTI, the sample period was separated into pre-oil shocks (January 1, 2014- January 23, 2015) and post-oil shocks (January 23, 2015- April 30, 2015). Furthermore, Brent data series was separated into pre-oil shocks (January 1, 2014-January 13, 2015) and post-oil shocks (January 13, 2015-April 30, 2015). The detail of data sourcing is shown in table 3.1 and 3.2.

Table 3.1: Descriptive of Data

Variable	**Proxy**	**Explanations**	**Units**	**Sources**
Stock Market Index	FBMT 100	100 public listed companies for Malaysia stock market	Index	Thomson Reuter DataStream
Brent light sweet crude oil	Brent	International crude oil benchmark	Per Barrel	Thomson Reuter DataStream
WTI light sweet crude oil	WTI	International crude oil benchmark	Per Barrel	Thomson Reuter DataStream

Table 3.2: Sample period of WTI and Brent during Pre and Post-oil shocks

Crude Oil	Pre-oil shocks	Observations	Post-oil shocks	Observations
WTI	January 1, 2014- January 23, 2015	278	January 23, 2015- April 30, 2015	69
Brent	January 1, 2014- January 13, 2015	269	January 13, 2015- April 30, 2015	78

3.2 Methodology

Augmented Dickey-Fuller (ADF) Unit Root Test

ADF test is used to determine whether if the series is stationary or non-stationary. In addition, it is also used to determine the number of integrated order. These are tested by using following models:

$$\Delta \ln P_t = \mu + \gamma \, lnP_{t-1} + \sum_{i=1}^{k} \alpha_i \, \Delta lnP_{t-1} + \varepsilon_t (1)$$

$$\Delta \ln P_t = \mu + \theta_t + \gamma \, lnP_{t-1} + \sum_{i=1}^{k} \alpha_i \, \Delta lnP_{t-1} + \varepsilon_t (2)$$

Where:

$\Delta \ln P_t$ = First difference for daily prices in natural logarithmic form at a particular time

$\Delta \ln P_{t-1}$ = First difference for daily prices in natural logarithmic form at a preceding time

μ= intercept

t= intercept and trend

ε_t= error term

According to Gujarati and Dawn (2009), if the time series data is stationary, autocorrelation depends only on the time, with the mean and variance constant over time. Besides, Al-Sharkas and Al-Zoubi (2014) stated that this test was conducted through certain procedure which consists of a regression of the first difference series against the lagged one series, lagged difference terms, a constant and a time trend. The time series data is trended, therefore unit root test is needed to determine the consistency of the series with I(0) and I(1) process. If the series is consistent with an I(1) process, then the series has a stochastic trend. On the other hand, if the series is consistent with an I(0) process, then it is stationary with a deterministic trend. The test statistic of ADF is to follow a non-standard distribution under null hypothesis.

Furthermore, one of the major concerns of the test is to determine the optimal lag length for the dependent variable. There are two methods suggested to determine the optimal lag length. Firstly, optimal lag length can be determined by using the frequency of data. For example, if monthly data was collected, then twelve lags should be used (Brooks, 2008).

Secondly, the Schwarz information criterion (SIC) and Akaike information criterion (AIC) can also be used to determine the optimal lag length. We can choose the determined lag length by using the minimum value of information criterion. Nevertheless, including too many lags length in a model will increases the standard error and lowers the test statistic value. The null hypothesis of ADF states that the time series is non-stationary while the alternative states that the time series is stationary. The null hypothesis will be rejected if the p-value is lesser than 5%, otherwise do not reject.

Johansen co-integration Test

Johansen co-integration test is used to determine the number of co-integrating vectors between variables in the long run when the exogenous and endogenous variables have the same order of integration. Maximum Likelihood (ML) approach can be carried out for this test. This approach is also known as "multivariate approach to co-integration" due to the probability of having more than one co-integrating relationship. Besides, Maximum Eigen value test (Equation 3) and Trace test (Equation 4) can be used to determine the co-integration ranking in Johansen co-integration test (Gujarati & Porter, 2009). According to Brooks (2008), when the error correction terms is included into the model, Vector Autoregressive Model (VAR) will convert into Vector Error Correction Model (VECM). If the variables are co-integrated, this means there is a long term equilibrium relationship between the variables.

Ranking of the co-integrating vectors in VECM is used to determine the number of co-integrating vectors. For example, when the ranking of co-integrating vectors equals two, the two linear combinations of non-stationary variables will become stationary. In addition, when there is a short term fluctuation among variables and a negative significant coefficient of Error Correction Model (ECM), it reveals that a long run relationship exists between the endogenous and exogenous variables (Asari, Baharuddin, Jusoh, Mohamad, Shamsudin & Jusoff, 2011).

$$\gamma_{nax\,(r)} = -T \ln\left(1 - \hat{\gamma}_{r+1}\right) \qquad (3)$$

$$\gamma_{trace\,(r)} = -T \sum_{i=r+1}^{m} \ln\left(1 - \hat{\gamma}_i\right) \quad (4)$$

Vector Autoregressive Model (VAR)

VAR is formed when there is a short-run relationship without any long-run relationship between stock and oil price during pre and post-oil shocks. In addition, VAR model was employed to capture the dynamics effect in multiple time series. While employing a VAR model, we have to ensure that the VAR form uses stationary series and all series are treated as endogenous in the equations. Based on the results, it stated that each variable in the model depends on its own and other variables' lag length. Besides, VAR is a simultaneous model allowing the two series in this study to be treated as the dependent variable to explain the dynamics effect. The order (p) of VAR is identified by using SIC in this study. The estimated VAR model for this study is written as follow in which all variables used are stationary:

$$\Delta SP_t = \alpha_1 + \sum_{i=1}^{q} \beta i \, \Delta WP_{t-i} + \sum_{i=1}^{p} \gamma i \, \Delta SP_{t-i} + V_{1t} \qquad (5)$$

$$\Delta WP_t = \alpha_2 + \sum_{i=1}^{q} \beta i \, \Delta WP_{t-i} + \sum_{i=1}^{p} \gamma i \, \Delta SP_{t-i} + V_{2t} \qquad (6)$$

$$\Delta SP_t = \alpha_3 + \sum_{i=1}^{d} \delta i \, \Delta BP_{t-i} + \sum_{i=1}^{p} \gamma i \, \Delta SP_{t-i} + V_{3t} \qquad (7)$$

$$\Delta BP_t = \alpha_4 + \sum_{i=1}^{d} \delta i \, \Delta BP_{t-i} + \sum_{i=1}^{p} \gamma i \, \Delta SP_{t-i} + V_{4t} \qquad (8)$$

Where,

Δ = First difference

$\Delta \, SP_t$ = stock price (FBMT 100)

$\Delta \, SP_{t-i}$ = lag term of stock price

$\Delta \, WP_t$ = WTI price

$\Delta \, WP_{t-i}$ = lag term of WTI

$\Delta \, BP_t$ = Brent price

$\Delta \, BP_{t-i}$ = lag term of Brent

V_{1t},V_{2t},V_{3t},V_{4t} = residual

α_1,α_2,α_3,α_4=intercept

βi = estimated parameter for WP, i = 1, 2…, q

γi = estimated parameter for SP, i = 1, 2… p

δi = estimated parameter for BP, i = 1, 2 …d

Granger Causality Test

Granger causality test is used to determine the short run directional relationship between variables (Asari, Baharuddin, Jusoh, Mohamad, Shamsudin & Jusoff, 2011). Granger causality test is superior to co-integration test in the way that it can be used to examine the effects of non-stationary data. Furthermore, relevancy of causality test between dependent and independent variables is strengthened with the presence of lags in the time series data (Gujarati & Porter, 2009). However, durations and expectation sign will not show for the causal effect.

The null hypothesis of F-test states that the overall model is insignificant and the alternative hypothesis states that the overall model is significant. The decision rule states that if the Wald-F test statistic is greater than the critical value, then the null hypothesis will be rejected. Otherwise, do not reject. (Gujarati & Porter, 2009). The Wald-F test formula is as follow:

$$F = \frac{[RSS_R - RSS_U]/[k_U - k_R]}{RSS_U/[n - k - 1]}$$

Where:

RSS_R = sum square of residuals for restricted model

RSS_U = sum square of residuals for unrestricted model

k_R = number of independent variables in restricted model

k_U = number of independent variables in unrestricted model

n = number of observations

Impulse Response Function (IRF)

IRF states the effect of standard deviation shock to the innovations on current or future time values of endogenous variables. Besides, IRF also provides the magnitude and direction of the effect between endogenous variable. Furthermore, the endogenous variable is directly influenced by a shock from itself. This further influences other endogenous variables through VEC and VAR dynamic structure. Any shocks occurred in a variable will influences itself and other variables when there are addition of new information.

Moreover, IRF is superior to granger-causality test in the way that it is able to interpret the complete information on the interaction between variables. In most cases, researchers are interested to examine the response of one variable to the impulse of another variable which involves several other variables.

Variance Decomposition

Variance decomposition is used to explain how much a variable is changed by the shock from itself and other variables. The relative importance of each random innovation in affecting the variables in VAR is defined as variance decomposition. Variance decomposition can be used to predict the variance percentage contribution of each variable in VAR.

CHAPTER 4: EMPIRICAL RESULTS

4.0 Overview

In this chapter, methodologies will be employed to conduct the empirical analysis. This chapter consists of: relationship between West Texas Intermediate (WTI) crude oil and FTSE Bursa Malaysia Top 100 (FBMT 100), relationship between Brent crude oil and FBMT 100 and the comparison of causal direction between crude oil and FBMT 100 during pre and post-oil shocks.

4.1 The Relationship between the WTI Crude Oil and FBMT 100

Table 4.1: Result of the Augmented Dickey-Fuller Unit Root Test for WTI Crude oil price

	FBMT 100		Oil price	
WTI	Level	First Difference	Level	First Difference
Pre-oil shocks				
Intercept	-1.8796	-13.8061***	3.4389	-22.9070***
	(1)	(0)	(1)	(0)
Intercept and trend	-2.1303	-13.7812***	0.4270	-23.9164***
	(1)	(0)	(1)	(0)
Post-oil shocks				
Intercept	-1.5442	-7.6678***	-1.9092	-9.6460***
	(0)	(0)	(0)	(0)
Intercept and trend	-1.9831	-7.6009***	-2.5155	-9.5782***
	(0)	(0)	(0)	(0)

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.

Table 4.1 shows that the null hypothesis of unit root test for level form of a series was not rejected at the significant level of 10 percent, 5 percent and 1 percent for the FBMT 100 and WTI crude oil price. After going through the first difference in the two series, the null hypothesis of non-stationary of FBMT 100 and WTI crude oil was rejected at the significant level at 10 percent, 5 percent and 1 percent. Therefore, we can conclude that FBMT 100 and WTI crude oil price follow the integrated at order one.

Table 4.2.: Result of the Johansen Co-integration Test for WTI and FBMT 100

	Test Statistic		Critical value (5%)	
	Trace	Max-Eigen	Trace	Max-Eigen
Pre-oil shocks				
r = 0	23.6170***	16.8232**	15.4947***	14.2646**
r = 1	6.7939***	6.7939***	3.8415***	3.8415***
Post-oil shocks				
r = 0	22.2022***	18.0487**	15.4947***	14.2646**
r = 1	4.1535**	4.1535**	3.8415**	3.8415**

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.

Table 4.2 show the results of Johansen Co-integration test based on Trace and Maximum Eigen value test statistic. The result was consistent for WTI pre-oil shocks from both tests. The results indicates that FBMT 100 and oil price are not co-integrated because the null hypothesis of the co-integration vectors (r) equal to zero and one are rejected in WTI pre-oil shocks. Therefore, we can conclude that there are two co-integration vectors that exist in the model, indicating that there is no long run relationship between FBMT 100 and oil prices during pre-oil shocks.

On the other hand, the results of FBMT 100 and WTI crude oil are consistent based on Trace and Maximum Eigen value test statistic during the post-oil shocks period. Results in Table 4.2 show that there is short run relationship between WTI crude oil price and FBMT 100 because the null hypothesis of co-integration vectors (r) equal to zero and one was rejected. Therefore, we can conclude that there is a short run relationship between the variables at the significant level of 10 percent, 5 percent and 1 percent.

Vector Autoregressive (VAR) Model Analysis

Since the long run relationship between the FBMT 100 and WTI crude oil price has been rejected, the short-run dynamics effect that exists between the FBMT 100 and WTI crude oil return during pre and post-oil shocks has become a problem. In order to overcome the problem, VAR model is formed using the first difference of the FBMT 100 and WTI crude oil price, which are stock return and WTI crude oil return. Lag length one is the appropriate lag length selected based on Schwartz (SIC) and Akaike (AIC) information criteria. Afterwards, to conduct the VAR analysis, Granger Causality, impulse response functions and variance decomposition are employed to identify the causality linkage between the stock return and WTI crude oil return.

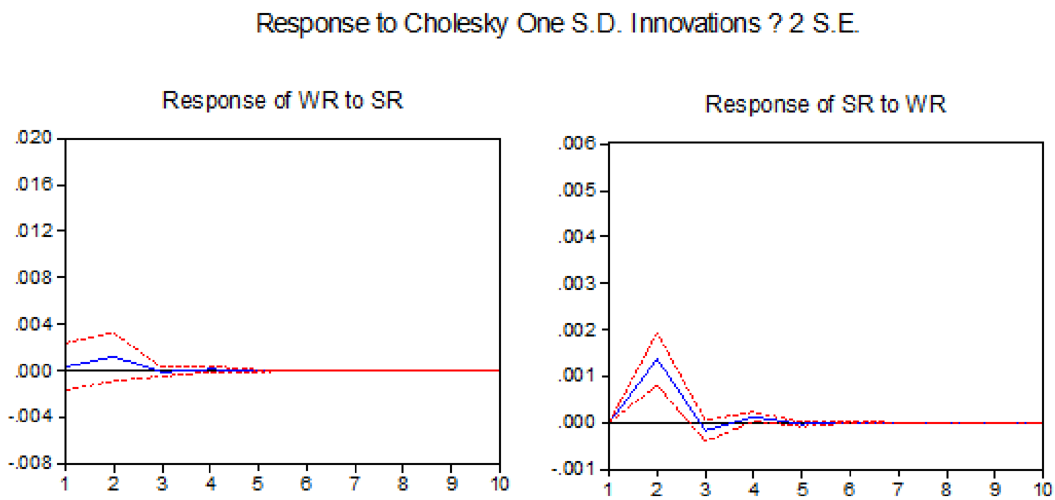
Table 4.3: Result of the Granger Causality Test for WTI and FBMT100

	WTI
	F-statistic
Pre-oil shocks	
O➔S	24.9072***
S➔O	1.7887
Post-oil shocks	
O➔S	3.4036**
S➔O	0.0393

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.(2)S represents FBMT 100 and O represents oil return.

Tables 4.3 report the result of the Granger Causality Test. According to the result, it shows that FBMT 100 has a unidirectional causality relationship with WTI during pre and post-oil shocks. In other words, WTI pre-oil shocks granger cause FBMT 100 at the significant level of 10 percent, 5 percent and 1 percent and WTI post-oil price shocks granger cause FBMT 100 only at the significant level of 10 percent and 5 percent but no vice versa. This result was consistent with previous studies from Louis and Balli (2014), whom found that the relationship granger causality between stock market and crude oil are unidirectional.

Pre-oil price shock

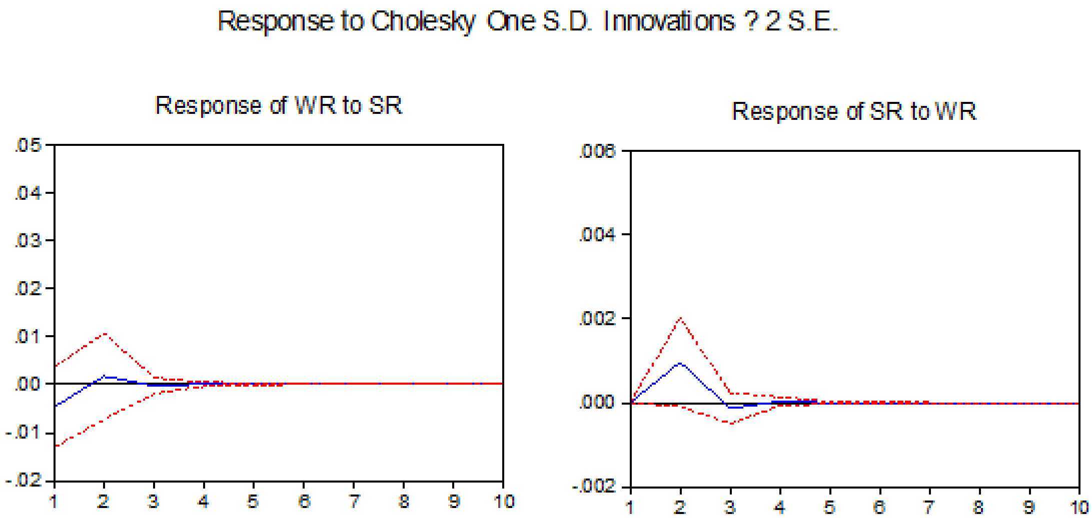


(a) The response of the WTI crude oil return due to shocks of FBMT 100 return.

(b) The response of the FBMT 100 return due to shocks of WTI crude oil return.

Figure 2: Impulse response function for WTI and FBMT00 during pre (January 1, 2014 - January 23, 2015) and post-oil shocks (January 23, 2015 - April 30, 2015

Post-oil price shock



(c) The response of the WTI crude oil return due to shocks of FBMT 100 return.

(d) The response of the FBMT 100 return due to shocks of WTI crude oil return.

Figure 2: continue.

Figure 2 shows the impulse response function of FBMT 100 to WTI crude oil during pre and post-oil shocks. Based on the results, there is only response on WTI crude oil return instead of response on the FBMT 100 return. These results support the Granger Causality test of WTI crude oil and FBMT 100 which indicates that there is a unidirectional causality between the two variables. Furthermore, during pre-oil shocks period, the response of WTI crude oil return due to shocks of FBMT 100 return is positive impact compare to the other direction. On the other hands, during the post-oil shocks there is indicate that negative impact response of the WTI crude oil return due to shocks of FBMT 100 return.

Table 4.4: Results of the Variance Decomposition of Stock Return and WTI during Pre and Post-oil price shocks

Market explained	Horizon (in day)	By innovations in	
		FBMT 100	WTI
Pre-oil shocks			
FBMT 100	2	92.7026	7.2974
	4	92.5625	7.4375
	6	92.5588	7.4412
	8	92.5588	7.4413
	10	92.5587	7.4413
WTI	2	0.4892	99.5108
	4	0.4905	99.5095
	6	0.4906	99.5094
	8	0.4906	99.5094
	10	0.4906	99.5094
Post-oil shocks			
FBMT 100	2	95.0727	4.9273
	4	94.9777	5.0223
	6	94.9776	5.0224
	8	94.9776	5.0224
	10	94.9776	5.0224
WTI	2	1.9467	98.0533
	4	1.9512	98.0488
	6	1.9512	98.0488
	8	1.9512	98.0488
	10	1.9512	98.0488

Table 4.4 shows the Variance decomposition results of the 2-day, 4-day, 6-day, 8-day and 10-day onward forecasted error for each variable based on the VAR model. Table 4.4 shows that the error variance of the market explained their innovation with the large percentage of proportion which are around 90-99 percentages.

In addition, the results indicate that during pre-oil shocks, percentage for proportion of forecast error variance in WTI crude oil explained by innovations in stock market indicates that there is nearly 0 percent. However, the percentage for proportion of forecast error variance in stock market explained by innovation in WTI indicates 8 percent.

On the other hand, during post-oil shocks period, percentage for proportion of forecast error variance in WTI crude oil explained by innovations in stock market indicates that there is increase to nearly 2 percent and percentage for proportion of forecast error variance in stock market explained by innovation in WTI drop between 4-5 percent.

4.2 The Relationship between the Brent Crude Oil and FBMT 100

Table 4.5: Result of the Augmented Dickey-Fuller Unit Root Test for Brent Crude oil price

	FBMT 100		Oil price	
Brent	Level	First Difference	Level	First Difference
Pre-oil shocks				
Intercept	-1.2196 (1)	-13.8716*** (0)	5.2361 (1)	-9.7072*** (0)
Intercept and trend	-1.6561 (1)	-13.8931*** (0)	2.4976 (1)	-18.1697*** (0)
Post-oil shocks				
Intercept	-2.2519 (0)	-7.90424*** (0)	-1.9501 (0)	-7.8153*** (0)
Intercept and trend	-2.1289 (0)	-8.0335*** (0)	-2.0004 (0)	-7.8146*** (0)

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.

Table 4.5 shows that the null hypothesis of unit root test for level form of a series was not rejected at the significant level of 10 percent, 5 percent and 1 percent for the FBMT 100 and Brent crude oil price. After going through the first difference in the two series, the null hypothesis of non-stationary of stock and oil price is rejected by significant level at 10 percent, 5 percent and 1 percent. Therefore, we can conclude that FBMT 100 and Brent crude oil price follows the integrated at order one.

Table 4.6.: Result of the Johansen Co-integration Test for Brent and FBMT 100

	Test Statistic		Critical value (5%)	
	Trace	Max-Eigen	Trace	Max-Eigen
Pre-oil shocks				
r = 0	31.2322***	22.7880***	15.4947***	14.2646***
r = 1	8.4441***	8.4441***	3.8415***	3.8415***
Post-oil shocks				
r = 0	21.7860***	13.8616*	14.2646***	14.2646*
r = 1	7.9243***	7.9243***	3.8415***	3.8415***

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.

Table 4.6 show the results of Johansen Co-integration test based on Trace and Maximum Eigen value test statistic. Both of the tests provide consistent results for Brent's pre-oil shocks indicating that FBMT 100 and Brent crude oil price are not co-integrated because the null hypothesis of the co-integration vectors (r) equal to zero and one are rejected in Brent pre-oil shocks. Therefore, we can conclude that there are two co-integration vectors exist in the model, indicating that there is no long run relationship between FBMT 100 and Brent crude oil price during pre-oil shocks.

On the other hand, the results of FBMT 100 and Brent crude oil are consistent based on the Trace and Maximum Eigen value test statistic during post-oil shocks. Results in table 4.6 show that there is short run relationship between Brent crude oil price and FBMT 100 because the null hypothesis of the co-integration vectors (r) equal to zero and one was rejected. However, we can conclude that there is a short run relationship between the variables at the significant level of 10 percent, 5 percent and 1 percent

Vector Autoregressive (VAR) Model Analysis

Since the long run relationship between the FBMT 100 and Brent crude oil price has been rejected, the short-run dynamics effect that exists between the FBMT 100 and Brent crude oil return during pre and post-oil shocks has become a problem. In order to overcome the problem, VAR model is formed using the first difference of the FBMT 100 and Brent crude oil price, which are stock return and Brent crude oil return. Lag length one is the appropriate lag length selected based on Schwartz (SIC) and Akaike (AIC) information criteria. Afterwards, to conduct the VAR analysis, Granger Causality, impulse response functions and variance decomposition are employed to identify the causality linkage between the stock return and Brent crude oil return.

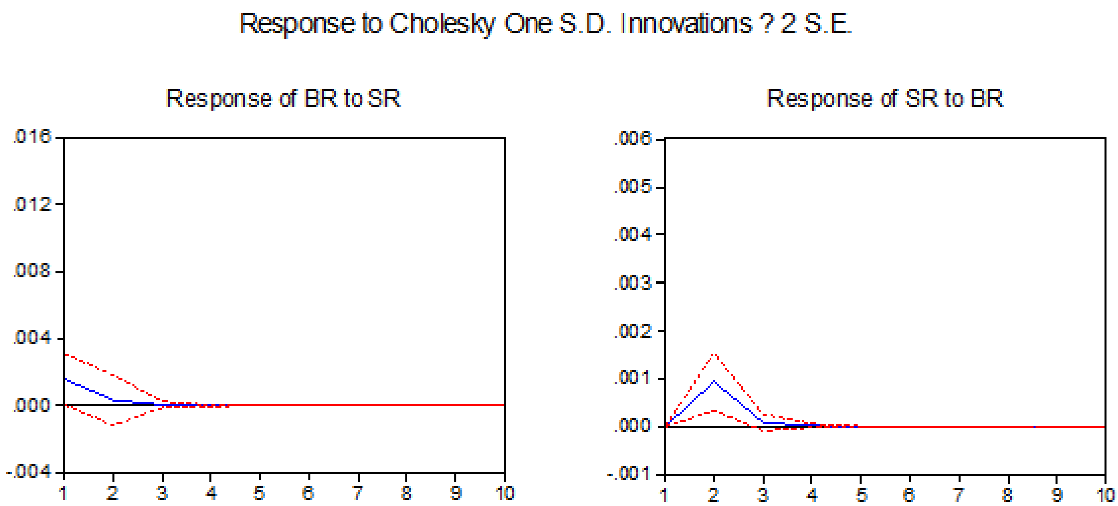
Table 4.7: Result of the Granger Causality Test for Brent and FBMT100

	Brent
	F-statistic
Pre-oil shocks	
O➔S	9.9490***
S➔O	0.3110
Post-oil shocks	
O➔S	2.5737
S➔O	0.0586

Notes: *, **, *** denote that reject the null hypothesis at the 10%, 5% and 1% significant level respectively.2) S represents FBMT 100 and O represents oil return.

According to table 4.7, results show that FBMT 100 have unidirectional causality relationship with the Brent pre-oil price shocks. In other words, Brent pre-oil price shocks does granger cause FBMT 100 at the significant level of 10 percent, 5 percent and 1 percent and WTI post-oil price shocks granger cause FBMT 100 at the significant level of 10 percent and 5 percent but no vice versa. Moreover, the results showed that FBMT 100 and Brent post-oil shocks do not granger cause each other.

Pre-oil price shock

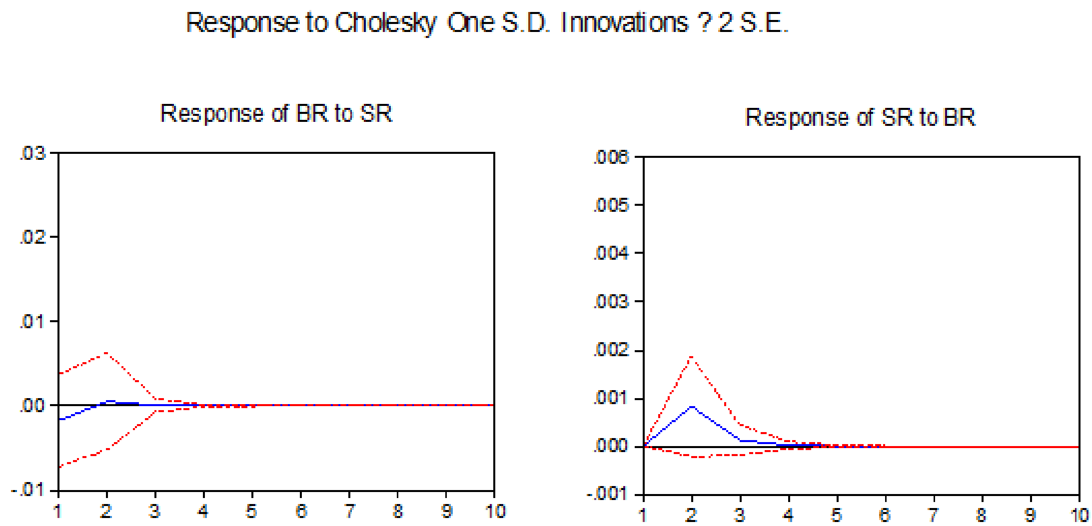


(a) The response of the Brent crude oil return due to shocks of FBMT 100 return.

(b) The response of the FBMT 100 return due to shocks of Brent crude oil return.

Figure 3: Impulse response function for Brent and FBMT100 during pre (January 1, 2014 - January 12, 2015) and post-oil shocks (January 12, 2015 - April 30, 2015)

Post-oil price shock



(c) The response of the Brent crude oil return due to shocks of FBMT 100 return.

(d) The response of the FBMT 100 return due to shocks of Brent crude oil return.

Figure 3: continue.

Figure 3 shows the impulse response function of FBMT 100 to Brent crude oil during the pre and post-oil shocks. During pre-oil shocks, the response of the Brent crude oil return due to shocks of FBMT 100 return is positive impact compare to the other direction and during the post-oil shocks there is indicate that negative impact response of the Brent crude oil return due to shocks of FBMT 100 return. On the other hand, based on the results of (b) and (d), the response of the FBMT 100 return due to shocks of Brent crude oil return during the pre and post-oil shocks is consistent. There results have support the Granger causality test of Brent crude oil and FBMT 100 which indicates that there FBMT 100 does not granger cause Brent crude oil.

Table 4.8: Results of the Variance Decomposition of Stock Return and Brent during Pre and Post-oil price shocks

Market explained	Horizon (in day)	By innovations in	
		FBMT 100	Brent
Pre-oil shocks			
FBMT 100	2	96.4442	3.5558
	4	96.4182	3.5818
	6	96.4182	3.5818
	8	96.4182	3.5818
	10	96.4182	3.5818
Brent	2	1.6780	98.3220
	4	1.6796	98.3204
	6	1.6796	98.3204
	8	1.6796	98.3204
	10	1.6796	98.3204
Post-oil shocks			
FBMT 100	2	96.6410	3.3590
	4	96.5683	3.4317
	6	96.5682	3.4318
	8	96.5682	3.4318
	10	96.5682	3.4318
Brent	2	0.5791	99.4209
	4	0.5799	99.4200
	6	0.5799	99.4200
	8	0.5799	99.4200
	10	0.5799	99.4200

Results from table 4.8 shows that during pre-oil shocks, percentage for proportion of forecast error variance in Brent crude oil explained by innovations in stock market indicates that there is less than 2 percent. Yet, the percentage for proportion of forecast error variance in stock market explained by innovation in Brent indicates that there is around 4 percent.

On the other hand, during the post-oil shocks, percentage for proportion of forecast error variance in Brent crude oil explained by innovations in stock market indicates that there is increase to nearly 0 percent and percentage for proportion of forecast error variance in stock market explained by innovation in Brent is change slightly which around 4 percent. This finding is also consistent with the Granger

Causality test results as shown in table 4.7, which indicates that, there are no causality linkages between the FBMT100 and Brent crude oil during the post-oil shocks.

4.3 Comparisons of the Causal Direction between Crude Oil and Stock Market during Pre and Post-Oil Shocks.

This chapter analyzes the relationship between FBMT100 and WTI crude oil as well as FBMT 100 and Brent crude oil during pre and post-oil shocks. First of all, results from Augmented Dickey-Fuller Unit Root test concluded that FBMT100 and both crude oil prices follow the integrated at order one. Therefore, Johansen Co-integration test was conducted and results indicate a short-run relationship between FBMT100 and both crude oil prices during the pre and post-oil shocks.

Furthermore, table 4.9 shows the summary of Granger causality test, impulse response function and variance decomposition. Dynamic analysis is conducted using the VAR model formed by stock and oil returns. Granger causality test shows that FBMT 100 have unidirectional causality relationship with the WTI pre and post-oil shocks and Brent pre-oil price shocks. However, results show that FBMT 100 and Brent post-oil shocks do not granger cause each other. In addition, the results from impulse response function and variance decomposition are consistent with the Granger causality test.

Table 4.9: Summary of Granger Causality Test, Impulse Response Function and Variance Decomposition

	WTI		Brent	
	Pre-oil shocks	Post-oil shocks	Pre-oil shocks	Post-oil shocks
Granger causality test	O➔S	O➔S	O➔S	O — S
Impulse Response Function	Positive (strong)	Negative (weak)	Positive (strong)	Negative (weak)
Variance Decomposition	-The proportion of variance in WTI crude oil explained by innovations in stock market indicates that there is nearly 0 percent. - The proportion of variance in stock market explained by innovation in WTI indicates 8 percent.	-The proportion of variance in WTI crude oil explained by innovations in stock market indicates that there is nearly 2 percent. -The proportion of variance in stock market explained by innovation in WTI indicates 4-5 percent.	-The proportion of variance in Brent crude oil explained by innovations in stock market indicates that there is less than 2 percent. - The proportion of variance in stock market explained by innovation in Brent indicates that there is around 4 percent.	- The proportion of forecast error variance in Brent crude oil explained by innovations in stock market indicates that there is increase to nearly 0 percent. -The proportion of variance in stock market explained by innovation in Brent is change slightly which around 4 percent.

Notes: (1) ➔ unidirectional causality, — does not Granger cause each other. (2) S represents FBMT 100 and O represents oil return.

Results from table 4.9 show that crude oil prices granger cause FBMT 100. This finding helps to achieve the first objective of the study which is to identify the causal direction between crude oil and Malaysian stock returns.

On the other hand, results from impulse response function show a positive response from both crude oil to FBMT 100 during pre-oil shocks. However, a negative response was identified during post-oil shocks. This helps to achieve the second objective which is to identify whether crude oil price that can be used as an inflation hedge for stock price fluctuation.

In addition, the results from variance decomposition show that impact of WTI and Brent crude oil on FBMT 100 becomes lesser and lesser from day 1 to day 5. However, the impact of WTI and Brent Crude oil on FBMT 100 is consistent from day 6 onwards. This helps to achieve the second objective of this study which is to identify whether crude oil price that can be used as an inflation hedge for stock price fluctuation.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.0 Overview

The objectives of this study are to analyze the causality direction between crude oil benchmark and Malaysia stock market as well as to identify whether if crude oil benchmark can be used as an inflation hedge during stock price fluctuations. This chapter consists of: summary of findings, implications of study and recommendation for future study.

5.1 Major Findings

First of all, results from Granger causality test demonstrates that FBMT 100 has unidirectional causality relationship with the WTI during pre and post-oil shocks and Brent during pre-oil price shocks due to most sectorial stock returns positively correlated to oil returns. However, there is a no causality relationship between Brent and FBMT100 during post-oil shocks due to significant fluctuations and unexpected asymmetric changes in the oil price. This is because asymmetric effect only takes place during high-fluctuation states, and it will happen in both stock market and oil price. Hence, we have achieved the first objective to identify the causal direction between crude oil benchmark and Malaysia stock market is achieved.

Furthermore, the results from impulse response function demonstrate that WTI and Brent crude oil return due to the shocks of FBMT100 is positive impact response during pre-oil shocks. However, it is negative impact response during post-oil shocks for both WTI and Brent crude oil return due to the shocks of FBMT100. Thus, crude oil benchmark can be used as inflation hedge during stock price fluctuation is achieved.

Moreover, the results from variance decomposition indicate that the response for both crude oil affect Malaysian stock market is getting lesser from day 1 to day 5. However, from day 6 onwards, the response becomes consistent. Therefore, we have achieved the second objective to identify the crude oil benchmark that can be used as an inflation hedge during stock price fluctuation.

5.2 Implications of Study

Findings from this study suggest investors in Malaysia to be more emphasize on crude oil price movements when hedging for risk in stock market during pre-oil shocks. This is due to Brent has a high causality effect towards Malaysian stock market during pre-oil shocks. This helps investors to react faster in stock market based on the sensitivity towards changes in crude oil price movements.

Moreover, findings of the causality effect between crude oil prices and FBMT 100 can help portfolio managers in Malaysia to develop appropriate hedging strategies for their investment portfolios. For example, portfolio managers should enter short position in crude oil future contracts during post-oil shocks period in order to offset the losses in stock market from falling oil price.

5.3 Recommendation of Future Study

Future researchers are recommended to conduct sectorial impact investigation to give a more detail analysis on the effect of crude oil shocks and also get more information on the oil shock impact to stock market. For example, sectorial analysis can be used to analyze the impact of oil price shocks on different industry sectors such as construction, consumer, technology, finance, property, and industrial.

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