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IMPACT OF CRUDE OIL VOLATILITY ON STOCK RETURNS: EVIDENCE FROM SOUTHEAST ASIAN MARKETS

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ABSTRACT

The study investigates the connection between international oil indices and Southeast Asian stock markets. The outcomes of both employed models, namely EGARCH and GARCH-jump, confirm the significant oil-stock linkage in Southeast Asian region. While the oil price fluctuations have positive effect on stock returns, the impacts of the implied crude oil volatility index (OVX) are negative, implying that the increase in level of future oil prices uncertainty leads to downward movement on stock markets. This association is relatively stronger in crisis period and symmetric in most markets, except for Malaysia and Philippines. The research also finds a relatively weak volatility transmission from oil market to the stock returns after controlling for the impact of the implied volatility index (VIX). Additionally, the study further reports the existence of GARCH effects in Southeast Asian stock markets. Besides, the results from EGARCH models illustrate that the previously negative shocks seem to have greater effects on the current volatility of stock returns in analyzed countries than the positive shocks. Furthermore, the jump effects are found in most markets, as evidenced by the estimates for GARCH-jump models. Generally, the volatility driven by abnormal information positively affects the volatility of return while the jump behavior has negative impact on return in Southeast Asian markets. Providing greater understandings about new markets in Southeast Asian area, the research could be utilized in improving investment decisions and gaining the advantages of international portfolio diversification.

KEYWORDS: Southeast Asia, Oil market, OVX, GARCH-jump model.

1. INTRODUCTION

Crude oil has been considered as one of the most important input of economy. Therefore, the changes in price of crude oil have significant impact on economy in general and stock market particularly. There are numerous researches performed with the aim of finding the linkage between crude oil price and stock market return. The research of Jones & Kaul (1996) indicates that the fluctuation of oil price impacts cash flows and expected returns, affecting the stock markets. However, Kilian & Park (2009) argue the influences of oil price movements on stock returns are depended on the characteristic of the shocks. The changes in oil price initiated from demand or supply shocks would have different impacts on the stock markets. Furthermore, the instability of oil-stock relationship is found in the research of Lee & Chiou (2011) when the effects exist only during the period of high level of fluctuation in oil price, and the connection becomes insignificant in less fluctuation period. The time-varying characteristic of the association between oil price and stock return is also pointed in Ciner's (2013) research, arguing different oil price lags have dissimilar effects on the stock price.

Beside the relationship between the oil price and the market return, many researchers also found the transmission between oil price uncertainly and stock return volatility. The research of Malik & Ewing (2009) finds volatility transmission between oil market and five examined US sector indices. According to the research, the transmission is the evidence of spreading common information on the markets. Studying on G7 economies, Diaz, Molero, & Perez de Gracia (2016) also find the significant impacts of oil price volatility on stock returns. The oil price volatility has continuously attracted the attention with many recent contributions. The study of Dutta, Nikkinen, & Rothovius (2017) illustrates the significant effect of the implied crude oil volatility index (OVX) on Middle East and African stock markets; Luo & Qin (2017) with a research on Chinese stock indices also finds the correlation between OVX and stock market. The above findings show the importance of the crude oil price volatility which has notable impact on other financial indices and could be considered as an indicator for the risk on the stock markets.

While there has been an increasing amount of usage of renewable energy source, the crude oil still accounts for the most common energy source and the consumption has been rising for years. According to the International Energy Agency (IEA), the total oil demand is predicted to dramatically increase with high consumption from both developed countries and emerging markets (IEA, 2017). As a result, the crude oil price continuously has significant impacts on the global economy in general. In World Energy Outlook Special Report, the IEA established special document for the Southeast Asia area due to the large contribution of this region in future global energy demand. The report indicates the high growing oil demand in these economies due to the accelerated development in next decades. However, all Southeast Asian nations are net oil importers and might face the challenge of secure and sustainable energy when the energy sources of these countries are mainly depended on fossil fuel. Therefore, the fluctuations on international crude oil markets are predicted to have significant influences on the economies of the Southeast Asian region.

1.1. Purpose of the study

The aim of current study is to provide a further investigation on the effect of energy price volatility on the newly emerging and frontier stock markets. Basher & Sadorsky (2006) assert that the emerging economies tend to be more sensitive to oil price shocks and the fluctuations on oil market have much larger impact on the less developed countries generally. Therefore, it is necessary to analyze the influences of global oil markets on the returns of selected emerging and frontier markets. Besides, the findings on oil-stock linkages are not consent within the empirical results. For example, the oil price shocks are proved to have negative impact on US stock market (Sadorsky, 1999), but in the earlier study of Huang, Masulis, & Stoll (1996) there is no clear connection between oil futures price and US stock returns. Additionally, the sign of reactions to the fluctuations on oil markets are not similar among the countries examined, according to the research of Park & Ratti (2008) for US and 13 European nations. Moreover, most studies on market correlations mainly focus on advanced economies, some exceptions concentrating on developing markets in terms of oil-stock linkage are researches of Arouri, Lahiani, & Nguyen (2011), Fowowe (2013), Dutta et al. (2017), and Dutta, Noor, & Dutta (2017). Departing from most recent studies, this research explores the oil-stock relationship in the Southeast Asian region. The analyzed countries in the research, including Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam range from developed and emerging economies to frontier market. Consequently, the outcomes would provide the comparison between the response of different markets with unequally developing level in the same geographical area.

The oil-stock linkage in new markets could be the guideline for risk management activities when the Southeast Asian stock markets have gained much considerable attention from investors recently. Due to the openness of global trade, the international characteristic of portfolio diversification has been increasing to improve the performance of investments (Steinberg, 2018). The support for international diversification is also discussed by Elton, Gruber, Brown, & Goetzmann (2011), arguing that the investors could obtain the advantage of diversification even if the expected returns of foreign equities are lower than those of domestic stocks. However, the benefit of international diversification is questioned by the research of Hanna (1999) due to the greater integration of financial markets among developed countries examined. Bhargava, Konku, & Malhotra (2004), on the other hand, agree on the strength of diversification but this benefit is declining since the correlation between markets is increasing. Therefore, the new markets, especially emerging and frontier economies, have become the attractive investment opportunities for diversification. A recent study on 21 markets of Yarovaya, Brzeszczyński, & Lau (2016) demonstrates that the Asian markets generally could provide better possibilities for internationally diversifying the portfolio. Thus, it is vital to further explore the movements of Southeast Asian stock markets and their interactions to the volatility on other global indices.

1.2. Research hypothesis

The study formulates and tests the hypothesis concerning the dynamic link between global oil market and Southeast Asian stock returns. Besides using the traditional oil price index, the research utilizes the CBOE Crude Oil Volatility Index (OVX) in finding the impact of oil volatility on stock returns in selected markets. Furthermore, the volatility transmission from the oil market to the stock market is also examined in the study. With the main purpose to extend the understandings about the correlation between the global indices and the Southeast Asian stock markets, this document contributes to develop the literatures on new stock markets, especially emerging and frontier markets. The main hypotheses of this study are as follows:

H1: There is the significant relationship between oil price movement and stock return in Southeast Asian markets;

H2: The implied crude oil price volatility index (OVX) has negative impact on stock return in analyzed markets;

H3: The volatility on oil market is transmitted to the volatility of stock returns.

The exponential generalized autoregressive conditional heteroskedastic (EGARCH) model, proposed by Nelson (1991), is employed to capture the effects of international oil indices on stock markets investigated. Moreover, the study is advanced by applying the GARCH-jump model, proposed by Chan & Maheu (2002) to further explore the movements of Southeast Asian stock returns. In addition, the oil-stock relationship in separate time periods and the impacts of different types of oil price shocks are analyzed in current research.

1.3. Structure of the study

The research is divided into eight sections. The first section provides brief introduction about the study, the main purpose, and research hypotheses. Section 2 discusses the recent related literatures. Section 3 and 4 present an overview of the global crude oil and the Southeast Asian stock markets. The theories relating to the financial volatility estimation are addressed in section 5. Section 6 describes the data and methodology utilized in the research. Empirical results are reported in section 7. Finally, section 8 summarizes the findings and further ideas of study.

2. LITERATURE REVIEW

The oil price has been an interesting topic for researchers, investors, and authorities in the era of oil. There are many researches on the change of prices, returns, and volatilities conducted to test the association between oil price and financial markets. This section summarizes the most recent studies concentrating on the impact of oil price fluctuation and its uncertainty on stock markets, and the volatility spillover between these markets.

The impacts of oil price shocks on stock markets are investigated in the studies of Jones & Kaul (1996); Ciner (2001); Park & Ratti (2008); Driesprong, Jacobsen, & Maat (2008). Jones & Kaul (1996) indicate the adverse impact of oil price on stock return by applying the cash flow valuation model. For the period from 1947-1991, the US and Canada stocks significantly react to the oil price rising due to the change in real and expected cash flows, but the evidence is not strong for the UK and Japan markets. In line with the finding of Jones & Kaul (1996), Ciner (2001) also finds the linkage between oil futures price and S&P 500 index return. However, the research highlights non-linear causality and further discusses the feedback relation from stock price movements to oil market. In another literature of Driesprong et al. (2008), using simple linear model, the negative impacts of six global oil indices on stock returns of eighteen developed countries are illustrated for the period from 1973 to 2004. Besides, Park & Ratti (2008) analyze on the US and thirteen European countries for the period from 1986 to 2005, confirming the effect of world real oil price on all examined market stock returns. Additionally, there is no statistical difference among the impacts between positive and negative oil price shocks found in most European markets (Park & Ratti, 2008).

Joo & Park (2017) indicate the negative effect of oil price fluctuation on stock returns of the US, Japan, Korea, and Hong Kong markets but also find the time-varying characteristic by means of the VAR-DCC-BGARCH-in-Mean model. The magnitude and sign of effect are depended on the degree of correlation between oil price and stock return (Joo & Park, 2017). Similarly, the time-varying causality between WTI crude oil and S&P 500 is confirmed in work of Lu, Qiao, Wang, Lai, & Li (2017). Both negative and positive casual effect of WTI crude oil index return on the change of S&P 500 index are found in analyzed subsamples and vice versa (Lu et al., 2017). It means that not only the oil price impacts the stock return, but the stock markets also have some effects on the oil market, which is in line with the finding of Ciner (2001). Instead of analyzing oil price, Basher & Sadorsky (2006) use the oil risk factor to examine the impact of energy market on stock return for the emerging countries. By mean of multi-factor model, the oil risk factor is calculated and illustrated the high ability in pricing stock return of emerging markets with a positive and significant coefficient. Further explorations on other financial instruments relating crude oil and sectoral markets are also carried out to confirm the linkage. Chiang & Hughen (2017) reports the negative impact of oil futures prices on non-oil stock returns. Oil implied volatility shocks only have impact on industrial metal market, and no significant evidence is found for precious metal market (Dutta, 2017a).

It seems that the difference of oil shock type also affects the result when examining the relationship between oil and stock markets. Researching on the US market, Kilian & Park (2009) suggest that the reactions of stock returns to oil price fluctuation varies substantially, depending on the cause of the shock. They indicate the more important value of oil demand-side shock in explaining the change of stock price and the predicting ability of oil supply-side shock is weak and unclear. Using the structural VAR model, the paper of Wei & Guo (2017) explores the effects of different types of oil price shocks, namely oil supply shock, aggregate demand shock, and oil-specific demand shock in Chinese stock market. In the research, the correlation between oil and stock markets varies and is unstable across the sample. The oil demand-side shock has positive impact on Chinese stock market from 1996 to 2006 but the effect becomes negative for the period 2007-2015. Further examining the linkage between oil and stock market, Ciner (2013) uses the frequency domain regression methods to prove that different oil shocks have dissimilar effects on stock return. The study suggests that the oil price changes which are persistent less than 12 months or more than 36 months have negative impact while the continuous increase in oil price for the period from 12 to 36 months is statistically related to positive stock return.

Comparing the impact of oil price shocks on stock markets between oil-importing countries and oil-exporting countries, Wang, Wu, & Yang (2013) suggest that the effect of oil price shock on stock return is stronger in oil-exporting countries. The research also asserts the time-varying characteristic of oil-stock relationship and the dissimilar impacts of different types of oil price shock. However, the authors indicate that linear model is entirely suitable to explain the correlation between oil and stock market for the sample from 1999 to 2011. A recent work of Antonakakis, Chatziantoniou, & Filis (2017) also finds the significant impact of oil price shocks on the stock market returns and volatility in both major oil-importing and oil-exporting nations. Applying the extended structural vector autoregressive framework to distingue different types of oil shock, the research suggest that the oil demand shocks seem to have stronger effects on stock markets than the supply-side shocks. A positive oil demand shock is a sign of positive development of economy, leading to a higher market return and a low level of volatility period. However, the time-varying character of the impact is also discussed in the study. Generally, the oil demand-side shocks are important for all examined market returns during the crisis period (2007-2009) and geopolitical stage (2010-2011). In stable period, the oil demand shock and oil-specific demand shock of each nation have different impacts on separate stock market under investigation. The research indicates the dissimilarities in the effects are not only depended on the oil-importing or oil-exporting groups but also the characteristics of each nation, and time-variance.

Besides focusing on developed countries, many other emerging and developing markets have been addressed in the variety of studies. In the research of Driesprong et al. (2008), thirty emerging markets are examined to find the relationship between oil price and stock market. However, the reaction of stock returns in the investigated countries is not clear and significant to all six global oil indices for the period from 1988 to 2004. Dutta, Noor, & Dutta (2017) highlight the informative characteristic of the Crude Oil Volatility Index (OVX) in predicting emerging stock market returns which are highly sensitive to both negative and positive oil volatility shocks. Applying GARCH-jump model, the negative effects of OVX fluctuation on most Middle East and African stock market returns are indicated in the study of Dutta et al. (2017). The OVX also has negative effect on Chinese stock market index while the oil price change positively impacts on Chinese stock market and five sectoral indices examined (Luo & Qin, 2017). For the South Asian markets, using VAR(1)-GARCH(1,1) model, Noor & Dutta (2017) find the evidence, that is, the stock markets of India, Pakistan, and Sri Lanka receive the impacts from both global oil price and oil volatility.

Turning attention to the volatility of oil price, many other researches concentrate on the volatility transmission between oil and stock markets with the application of GARCH-family models in analyzing financial volatility. Malik & Ewing (2009) find the evidence of volatility spillover between oil price and five sectoral markets in the US for the sample from 1992 to 2008 by the mean of bivariate GARCH models. Employing VAR-GARCH approach, Arouri, Jouini, & Nguyen (2011) analyze the oil-stock volatility interaction in the US and Europe. According to the paper, the volatility transmission from oil price to stock markets is stronger than from stocks to oil for European markets. In the US, both directs of volatility transmission are clear and significant. Concentrating on oil-producing countries, the research of Arouri, Lahiani, & Nguyen (2011) confirms the volatility spillover between oil and stock markets in the Gulf Cooperation Council (GCC) countries, including Bahrain, Kuwait, Oman, Saudi Arabia, and the United Arab Emirates. The evidences of volatility transmission of the GCC nations are stronger for the crisis subsample from 2007 to 2010. Also researching on an oil-exporting economy, Lebanon, Bouri (2015), however, finds only weak evidences supporting for volatility transmission between oil and stock markets.

Among recent literatures, the VAR-GARCH model is widely used in analyzing the return and volatility linkages between oil and stock markets. Bouri (2015) finds positive effect of oil price change on Lebanese stock return from 1998 to 2014, the effect becomes stronger during crisis period, but there is no clear volatility transmission found. The effect of oil price volatility on stock market is also found for China over the period from 1997 to 2014 in the study of Caporale, Menla Ali, & Spagnolo (2014). The research distinguishes the oil price shocks into different demand and supply sides shocks following the studies of Kilian & Park (2009). Most of sectional stock returns positively response to the oil return volatility during the period of oil demand-side shock, but the returns are not significant related to the oil price change in the same period. A recent study on the US market (Alsalman, 2016), in contrast, finds no statistically significant relationship between oil price volatility and the US stock return for the sample data from 1973 to 2014. The explanation of author is that the companies widely apply hedging technique to reduce to risk from the change of oil price on the market.

The investigation on Chinese stock market of Bouri, Chen, Lien, & Lv (2017) continuously support for the association between international oil and stock markets. Focusing on causal relationship test, the study finds the impact of oil price volatility on most Chinese sectional stock price variances. The finding also confirms the time-varying characteristic of the relationship by employing a number of lag variables used in the test. Some sectional indices show the delayed response or no effect of the oil volatility, for example Health Care, Basic Materials, and Telecommunications. The research further investigates the reaction of causality to the change of oil pricing policy in China by dividing the sample into two subsamples before and after the reformation. Before 2013, Chinese government controlled the oil price centrally, leading a lower price comparing to the international one. With the reform in 2013, the oil price on Chinese market is closer to global market. Interestingly, the results of this study indicate that the volatility spillover from oil market to equity was reduced and disappeared after the policy change. According to the explanation of Bouri et al. (2017), the reform reduced the level of uncertainty in domestic oil price when the international oil price fluctuates, leading to the decrease in risk transmission between markets.

Dutta et al. (2017) modify GARCH (1,1) model by adding OVX variable in GARCH variance equation to examine the impact of oil implied volatility on the conditional volatility of Middle East and African stock markets. All twelve investigated markets excepted Qatar exhibit the sensitive reactions of stock volatility to the change of OVX. The finding supports for the volatility transmission between oil and stock markets and strengthens the importance of implied volatility indices in explaining the stock price fluctuations. By mean of VAR model, Maghyereh, Awartani, & Bouri (2016) find the oil-stock relationship through examining the connectedness of newly implied volatility indices. The volatility transmission is confirmed in their research, but the linkage is mostly established in the period from 2009 to 2012 and varies over the sample period. Analyzing three implied volatility indices, Dutta (2017) presents the association among OVX, VIX, and the US energy sector equity VIX (VXXLE), further confirming the connection between oil and stock markets. Not using OVX, Feng, Wang, & Yin (2017) apply oil volatility risk premium (VRP) which is defined as the difference between oil realized volatility and oil implied volatility as a predictor. The research finds strong forecasting ability of oil VRP in predicting stock price volatility in G7 countries. In the study, the long-time impact of oil VRP is relatively higher than short-time effect with the larger coefficient in ten-day-long oil VRP comparing to overnight volatility.

Fowowe (2013) uses GARCH-jump model developed by Chan & Maheu (2002) in examining the relationship between oil price and Nigerian Stock index. The research exploits the advantages of the GARCH-ARJI model in capturing the effect of extreme shocks in modelling the stock return movements. However, the result shows the insignificant impact of both Brent and WTI oil prices on Nigerian Stock Exchange. Integrating the exponential generalized autoregressive conditional heteroskedastic (EGARCH) with a time-varying conditional jump intensity, Zhang & Chen (2011) modify the model proposed by Chan & Maheu (2002) to explore the impact of international oil price on Chinese stock returns. By employing the jump component in the model, the researches could extensively investigate the fluctuations of stock markets and solidify the tests for oil-stock relationship. Another recent application of GARCH-jump model, the work of Dutta et al. (2017), finds the significant and negative impact of OVX on stock return in Nigeria as well as in most countries in Middle East and Africa for the period from 2007 to 2014. Researching on both OVX and WTI oil price, the study of Dutta et al. (2017) shows negative impact of OVX but positive influence of WTI oil index on global emerging stock market index return. The authors also highlight the greater magnitude of OVX impact comparing to the effect of WTI oil price change.

The ARCH and GARCH family models could be considered as the most common methods applied in analyzing the financial volatility. Some recent studies adopt advanced technique, namely wavelet methodology, in finding volatility transmission and in researching volatility generally. Basing on wavelet framework, the study of Boubaker & Raza (2017) illustrates unclear and undirect volatility spillover between markets while using GARCH model, the effect of oil volatility is ensured in the same data for BRICS stock markets. The result is in line with the findings of Khalfaoui, Boutahar, & Boubaker, (2015) about the indirectly volatility spillovers between oil and stock markets, as evidenced by the outcomes of Wavelet-based GARCH–BEKK model. Performing the analysis on the implied volatility indices by utilizing the wavelet methodology, Bašta & Molnár (2018) assert the high correlation between VIX and OVX and confirm the time-varying characteristic of the relationship. Another study for East Asian stock markets of Cai, Tian, Yuan, & Hamori (2017) employing the wavelet coherence analysis finds that the East Asian markets under investigation tend to be more sensitive to the oil price shocks comparing to China and Japan, and further illustrates the ability in risk reduction of oil-stock portfolios.

Based on the above findings, the oil price change and the volatility of global oil market could be a significant factor which causes the fluctuations in stock prices. However, the oil-stock linkage is not solid among all examinations. Furthermore, the relationship is time-varying and affected by other factors, for example economic policy uncertainties (Fang, Chen, Yu, & Xiong, 2017). Different markets have dissimilar reactions to the changes of oil price and its volatility. Therefore, it is necessary to examine the impact of international oil price indices and its uncertainty on new emerging and frontier markets in which the investors are mostly concentrating on finding new investment opportunities and benefits of international diversification.

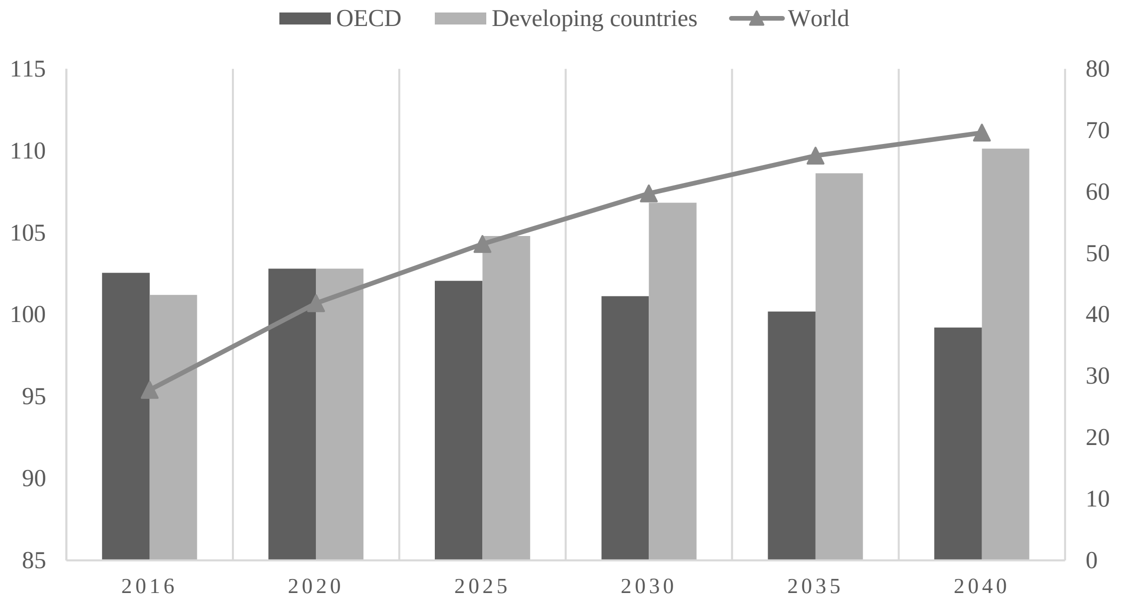
3. CRUDE OIL MARKET

For decades, crude oil has been a vital input of economy which significantly influences global development. Being an important energy source, the crude oil is also material for many types of product, particularly plastic. The importance of crude oil to society and economy makes the crude oil price become one of the most important global economic indicators of which all actors on the market have been keeping track strictly. There are several types of crude oil as well as different benchmark prices used for purchasing and researching activities. Two most used crude oil benchmarks are Brent and West Texas Intermediate (WTI), some other benchmarks are Dubai Crude and OPEC Reference Basket (ORB) which are named as the region where the oil is extracted. While the WTI oil is mainly consumed in the US, the Dubai crude oil is primarily exported to Asia.

The oil market would observe many pronounced change in the near future, but the era of oil will be continuing for next many years. A recent research of Gormus & Atinc (2016) continuously strengthens the knowledge about the relationship between crude oil on the economy by the evidence from the impact of oil price volatility on the US economy. In the history, the world saw several enormous oil price shocks which are called oil crisis resulting in huge effects on economic decision and activity. Individuals could have to pay higher for the cost of daily transportation, or a new gasoline-used car project needs to be re-analyzed due to the change in sale forecast initiated from the surge of oil production price (Baumeister & Kilian, 2016).

Crude oil demand is expected to increase for the period from 2017 to 2022 according to the reports of OPEC (2017) and International Energy Agency (2017). The demand growth is predicted to come from the development of transportation sector (OPEC, 2017). Furthermore, increase of demand is mostly driven by the consumption of the emerging markets, particularly the Asian developing countries. As can be seen from the figure 1, the oil demand is forecasted to increase to 111.1 mb/d in 2040, rising by 15.8 mb/d from 2016. However, while the demand growth is observed in developing countries for the period 2016-2040, the sharp decrease pattern is the prediction for the oil demand of OECB. The reduction in oil consumption in OECB market is caused by the implementation of tight energy policies, technological improvement, and renewable energy resource development (OPEC, 2017). China and India would become the largest oil consumers by 2030 and 2040 respectively. Other important demand centers, namely Indonesia, Malaysia, Thailand, and Singapore, are predicted to observe a sharp increase in oil consumption to 2021 with a high population growth (IEA, 2012).

Figure 1. Long-term oil demand (mb/d)



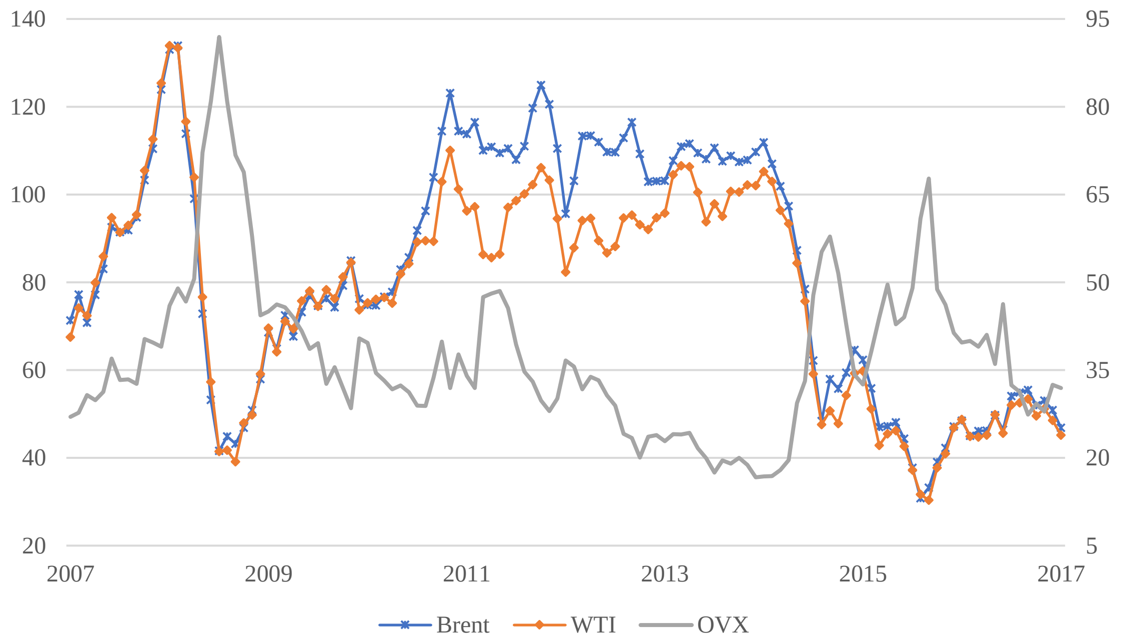
Source: World oil outlook 2040 (OPEC, 2017)

Regarding oil supply, OPEC[1] has been a main oil production suppliers for next several decades, accounting for 40% of total oil supply in the world according to projection until 2040 of OPEC (2017). The growth non-OPEC oil supply is mostly contributed by the increase of crude oil production quantity in the US, Brazil, and Canada while the China, Mexico, and some small contributors in Southeast Asia, namely Indonesia, Malaysia, Thailand, and Vietnam would see a profound decline in oil supply in medium-term (IEA, 2012). However, the oil supply of non-OPEC is expected to reach a peak in 2027, following by a slight decrease to 2040 (OPEC, 2017).

[1] OPEC stands for Organization of the Petroleum Exporting Countries which include 14 oil-exporting developing nations, namely Algeria, Angola, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates, and Venezuela. The mission of organization is "to coordinate and unify the petroleum policies of its Member Countries and ensure the stabilization of oil markets in order to secure an efficient, economic and regular supply of petroleum to consumers, a steady income to producers and a fair return on capital for those investing in the petroleum industry." http://www.opec.org/

The data of supply and demand gives a picture of oil expansion, leading the assumption of a clear pattern in oil price movement. However, many factors also affect the crude oil market in forming oil price due to its important characteristic in economy. Supply and demand, as the fundamental macroeconomic factors, play a vital key in forming the oil price, but geopolitical and economic events have been occurring daily would directly and indirectly contribute to the change of oil price. The figure 2 shows the fluctuation of the oil price indices and the CBOE Crude Oil Volatility Index from 2007 to 2017. Generally, there were many shocks on oil price markets and implied volatility index during this 10-year period. Nonetheless, most oil price and OVX peaks occurred during the time of crisis or geopolitical event.

Figure 2. Brent oil price, WTI oil price, and OVX



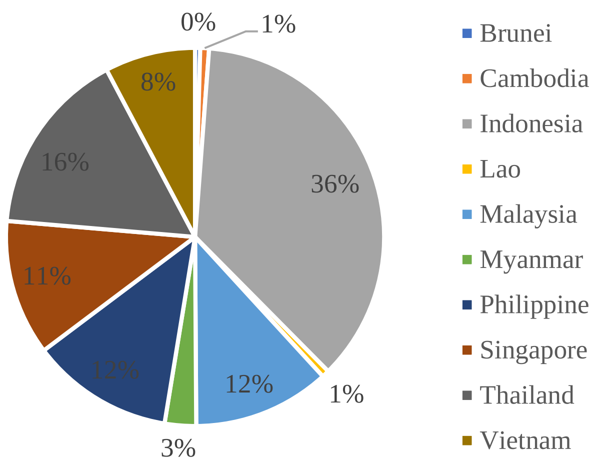
For the period from 2007 to 2017, some highs of oil price could be observed during the financial crisis 2008, the political turmoil, namely Arab Spring, in 2011, or the time geopolitical problem related to Iran in 2012. According to Baumeister & Kilian (2016), the hike of oil price in 2008 is contributed from the increase demand due to rapidly economic expansion in previous years. A decline following this peak is considered as a consequence of the demand reduction during crisis period. In contrast, the price fluctuation from between 2011 and 2014 is mainly driven by the public concerns about oil supply. Additionally, the oil price and the oil implied volatility OVX seem to fluctuate with adverse patterns. The OVX is relatively high during the period of low oil price and vice versa. Furthermore, gap between Brent oil and WTI oil benchmarks are clearly spot from 2011 to 2014, and the WTI oil price is lower than the price of Brent oil. The WTI oil is mostly consumed in the US market, the trade at discount price comparing to Brent's is caused by the growth of the US oil production in this period.

While there have been many researches in terms of oil price and its volatility to form a forecast about oil price in future, the oil price would still surprise economists, authorities, and all other market participants (Baumeister & Kilian, 2016). New socioeconomic determinants could cause oil price fluctuation through the change in demand and supply, oil price shock then would affect economy and stock market particularly.

4. SOUTHEAST ASIAN STOCK MARKETS

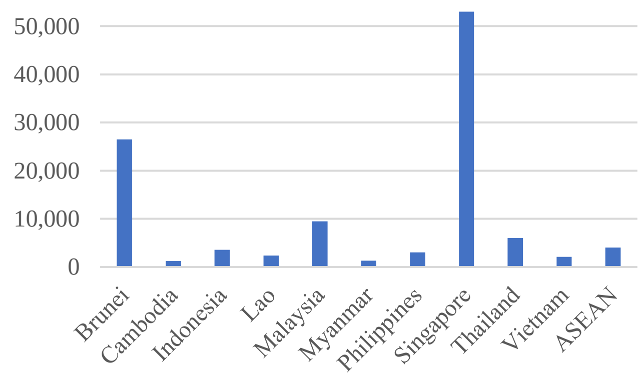
Southeast Asia is the region which includes eleven countries, namely Brunei Darussalam, Cambodia, East Timor, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Viet Nam. An association which accelerate the economic growth, social progress and cultural development in the region is called ASEAN[2]. The ASEAN stands for Association of Southeast Asian Nations (The ASEAN Secretariat, 2017b) was established on 8 August 1967. The members of ASEAN until 2017 are all Southeast Asia nations except East Timo. The group of ten-country has population of 637.5 million (2017) which accounts for 8.7% of total world population (The ASEAN Secretariat, 2017). Nominal GDP 2017 of ASEAN is 2.6 trillion US dollar (3.4% of world GDP) with GDP growth rate of approximately 5% annually (The ASEAN Secretariat, 2017a). However, the level of economic development is relatively varying across all Southeast Asia nations. Indonesia is the biggest economy in ASEAN, accounting for 36% of total GDP. Followings are Thailand (16%), Philippines (12%), Malaysia (12%), and Singapore (11%). Regarding GDP per capita, most Southeast Asian economies are considered as lower middle-income countries while Singapore and Brunei are both high income nations. The

Figure 3. Percentage share to ASEAN GDP, 2016



Source: ASEAN Economic Integration Brief 2017

Figure 4. ASEAN GDP per capita, 2016 (USD)



Source: ASEAN Statistical Yearbook 2016 / 2017

[2] http://asean.org/asean/about-asean/overview/

GDP per capita of Singapore (52,963 USD) is around twenty times higher than Philippines (3,017 USD), Lao PDR (2402 USD), and Vietnam (2,138 USD); or forty times higher than Cambodia (1,266 USD) and Myanmar (1,297 USD).

Table 1. Key information of six Southeast Asian stock exchanges at the end of 2016

MYX - Bursa Malaysia, IDX - Indonesia Stock Exchange, PSE - Philippine Stock Exchange, SGX - Singapore Exchange, SET - Stock Exchange of Thailand, HOSE - Ho Chi Minh Stock Exchange

Country	Year established	Number of listed firms		Domestic Market Capitalization (mil USD)	Market Capitalization to GDP ratio
		Domestic	Foreign		
Malaysia (MYX)	1964	893	10	359,788.3	119.31%
Indonesia (IDX)	1912	537	0	425,767.8	49.78%
Philippines (PSE)	1927	262	3	239,738.0	92.63%
Singapore (SGX)	1999	479	278	640,427.5	229.99%
Thailand (SET)	1975	656	0	432,956.2	112.13%
Vietnam (HOSE)	2000	320	0	66,395.7	42.24%

Source: World Federation of Exchanges Annual Statistics Guide 2016 and ASEAN Economic Integration Brief 2017

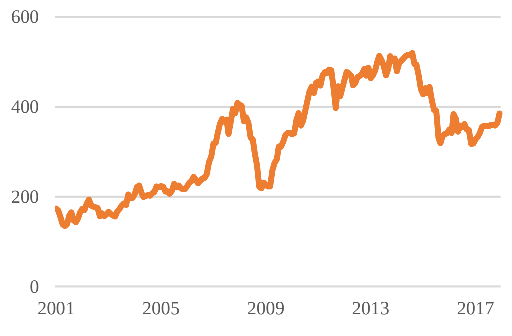
Along with development and globalization, the Southeast Asian nations have been more closely integrating into the international financial system. Most of Southeast Asian countries established their stock exchanges, and some markets are relatively newborn, for example the Yangon Stock Exchange (2015), Cambodia Securities Exchange (2011), and the Lao Securities Exchange (2011). These markets have been under the process of constructing governance regulation and market mechanism, with merely five firms listed on the exchange. Brunei and East Timor have not had stock market. Other more developed exchanges are showed in table 1. Singapore, Malaysia, and Thailand had the market capitalization to GDP ratio exceeding 100% at the end of 2016, stock market capitalization of Philippines was equal to more than 90% of GDP. As can be seen from table 1, there were total 3438 firms listed on six major stock exchanges in Southeast Asia at the end of 2016, accounting for 7.45% of all listed firm over the world[3]. Singapore exchange, by far, had much larger number of foreign listed firms than other Southeast Asian markets.

[3] The figure is calculated from the data in World Federation of Exchanges Annual Statistics Guide 2016. Total listed firms in the world at the end of 2016 is 46,170 firms.

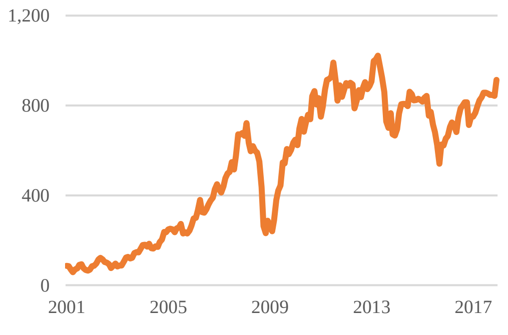
Table 1 also indicates market capitalization of six Southeast Asian stock exchanges as of December 2016. Together, total market capitalization of all 6 exchanges amounted to 2,165,073.5 million USD, accounting for 3.22% of the world's market capitalization[4]. The capitalization of Southeast Asian exchanges is quite small when comparing to other financial center, for example Hong Kong Exchanges and Clearing (4.75% of total world), Nasdaq (11.58% of total world), and NYSE Group (29.13% of total world). Nonetheless, the Southeast Asian region has been seen a rapid growth in market capitalization of most member's markets. From 2015 to 2016, the market capitalization increases 30.1% in HOSE, 18.1% in IDX, and 23.0% in SET (World Federation of Exchanges Annual Statistics Guide 2016).

Figure 5 illustrates the movements of six stock exchange indices in Southeast Asian markets from 2001 to 2017. The benchmarks used for Indonesia, Malaysia, Philippines, Singapore, and Thailand are MSCI indices, while VN index is used for Vietnam since MSCI Vietnam index was launched from December 2007. Generally, the period of sharp increase was observed in all countries between 2001 and 2007. All six indices then suddenly plunged to bottom from 2008 to 2009 as the effect of financial crisis 2008. However, the stock markets quickly recovered and increased during after-crisis period, except for Vietnam market whose index value was still much lower than level in pre-crisis period. The sign of increase is seen for VN index only from around 2016.

Figure 5. Stock market indices of Southeast Asian nations 2001-2017



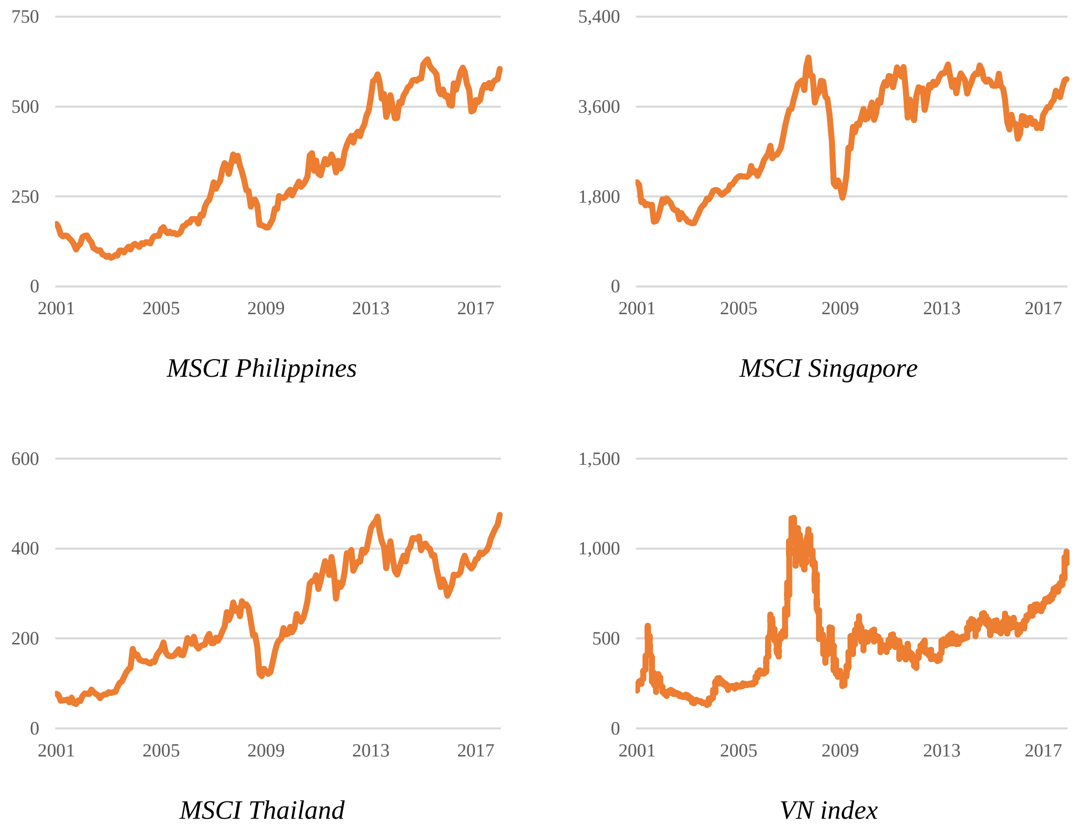
MSCI Malaysia



MSCI Indonesia

[4] The figure is calculated from the data in World Federation of Exchanges Annual Statistics Guide 2016. Total world's market capitalization at the end of 2016 is 67,203,252.6 million USD.

Figure 5. Stock market indices of Southeast Asian nations 2001-2017



Comparing to developed economies, the stock returns in the emerging markets generally and the Asian nations in particular is relatively high but the greater level of risk is also involved in (Tran, 2017). For the Southeast Asian region, the study of Tran (2017) indicates the significant evidence of periodically collapsing stock price bubbles in Malaysia, Philippines, Singapore, and Thailand with the non-cointegration between price indices and expected returns in these markets. Despite having several weaknesses and displaying the signs of inefficient market, the Southeast stock markets have been improving the efficiency of investment and growing continuously and substantially (Niblock, Heng, & Sloan, 2014).

The fluctuation of six Southeast Asian stock indices illustrated in figure 5 could be considered as the evidence that the emerging and developing financial markets are significantly influenced by global factors. Balcilar, Cakan, & Gupta (2017) and Balcilar et al. (2017) indicate the shocks in developed economies, for example the US, the European Union, and Japan, have enormous impacts on stock return and volatility on the Asian emerging markets. Besides, the co-movement and interdependence among six Southeast Asian nations namely Indonesia, Malaysia, Philippine, Singapore, Thailand, and Vietnam are significantly strong for the period from 2009 to 2016, as evidenced by the literature of Jiang, Nie, & Monginsidi (2017). However, there is no statistically significant interlinkage of stock price fluctuations between China and three Southeast Asian neighbors (Thailand, Indonesia and Philippines) in the analysis of Jayasuriya (2011). Regarding oil-stock linkage, the research of Abdullah, Saiti, & Masih (2016) confirms the relationships between the international oil price and the Islamic stock indices of five examined countries (Indonesia, Malaysia, Philippine, Singapore, and Thailand), suggesting the opportunities to gain the benefits of portfolio diversification with different stock-holding periods.

5. VOLATILITY ESTIMATION

Volatility has been an important variable in a large variety of financial literatures, which drive many disciplines, namely derivatives pricing (options prices are strongly depended on the volatility of underlying assets), risk management (volatility forecasting plays a crucial role in determining the value-at-risk), and monetary policy making (financial volatility could be considered as a proxy for the vulnerability of economy) (Poon & Granger, 2002). Therefore, the understanding of volatility has become more essential in financial analysis. Poon & Granger (2002) indicated that the volatility is the proxy for the risk and a scale parameter which adjusts the fluctuation size of the variation following stochastic wiener process. In the research, Poon & Granger (2002) analyzed the volatility through the instantaneous returns generated by the continuous time martingale.

(1) $$d[\ln(p_t)] = \sigma_t dW_{p,t}$$

In the equation (1), p_t is the price and $dW_{p,t}$ denotes a standard wiener process. The volatility σ_t is unobservable but could be estimated by a sufficient large number of observations (returns) and an appropriate time interval. This term is called “realized volatility” which is the standard deviation of a set of previous return $\{r_i \mid t = 1, \dots, n\}$ whose mean is $\bar{r} = \frac{1}{n}\sum_{i=1}^{n} r_i$ (Taylor, 2005), the formula is as equation (2):

(2) $$\hat{\sigma} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2}$$

The estimate in equation (2) is also called historical volatility. However, the volatility is a stochastic variable (Hull, 2015) whose value changes day-by-day, for example the volatility tends to increase during the time of bad news and decrease in response to good news. Therefore, it is important to forecast the volatility that plays a vital key in risk management and derivatives, which mostly depend on the future uncertainty. Many researches have been taking an attempt in generalizing the pattern and projecting the volatility. Engle (1982) proposed the autoregressive conditional heteroscedastic (ARCH) process, which describes the distribution of return for period t which has constant mean μ but time-varying conditional variance σ_t^2. Assuming the returns are generated by the process:

(3) $$r_t = \mu + \varepsilon_t$$

(4) $$\varepsilon_t = \sigma_t z_t \qquad z_t \sim \text{i.i.d}\ (0,1)$$

(5) $$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2$$

where ω > 0, $\alpha_j \geq 0$, q is the number of autoregressive terms. The ARCH(q) model, as indicated above, formulates the conditional variance through an autoregressive model to capture the behavior of volatility by using the lagged variables. In the equation (5), the future volatility, also called conditional volatility, could be estimated from the past squared residual returns. Following the introduction of the Autoregressive Conditional Heteroskedastic process, a generalization of the ARCH model was proposed by Bollerslev (1986). This model is also created to simulate the conditional volatility by a historical set of return. However, the time-varying nature of conditional volatility is captured through not only the demeaned returns but also the previous lags of conditional variances. The GARCH(p,q) has similar asset return regression (3) (4), the volatility equation is defined as follows:

(6) $$\sigma_t^2 = \omega + \sum_{t=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{t=1}^{p} \beta_j \sigma_{t-j}^2$$

where ω > 0, $\alpha_j \geq 0$, $\beta_j \geq 0$, $\sum\alpha_j + \sum\beta_j < 1$; σ_t^2 is calculated from most recent q observations on residual return and p estimates of conditional variance. If p = 0, the GARCH(p,q) becomes the ARCH(q) model. The simplest and most popular GARCH process is GARCH(1,1) model (Hull, 2015), the conditional variance equation is:

(7) $$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

GARCH-family processes enjoy huge popularity among academics due to the ability in describing the stylized facts of financial volatility. The paper of Engle & Patton (2001) summarizes major stylized facts which should be capture by a good volatility model. These facts are volatility clustering, volatility persistence, mean-reversion, and asymmetric impact of innovations. The success of the GARCH models come from the ability of incorporating first three major stylized facts. However, the model cannot examine the asymmetric impact of positive and negative innovations because the conditional variance function of GARCH(p,q) only takes into account the magnitude of independent variables not their signs (Brooks, 2014). The GARCH-family process has been developing, many extensions was introduced to overcome this limitation, for example GJR-GARCH developed by Glosten, Jagannathan, & Runkle (1993), which adds the dummy variable I that takes value of one if $\varepsilon_{t-j} > 0$, and zero otherwise.

(8) $$\sigma_t^2 = \omega + \sum_{t=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{t=1}^{q} \gamma_j I_{(\varepsilon_{t-j}>0)} \varepsilon_{t-j}^2 + \sum_{t=1}^{p} \beta_j \sigma_{t-j}^2$$

Nelson (1991) proposes the exponential generalized autoregressive conditional heteroskedastic (EGARCH) model which shows the ability in capturing the asymmetric GARCH effect which occurs in financial time series. The variance equation of the EGARCH(1,1) model is as follows:

(9) $$\log(\sigma_t^2) = \omega_i + \frac{\alpha_i \left|\varepsilon_{i,t-1}\right| + \delta_i \varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta_i \log(\sigma_{t-1}^2)$$

The advantage of EGARCH model is the non-specification requirement for the sign of parameters in variance equation comparing to the strict conditions of GARCH model. Regarding the performance, the research of Hansen & Lunde (2005), however, finds no significant evidence, that is, the GARCH(1,1) is outperformed by other complex models in the same family.

Besides using the high-frequency data of return to estimate the volatility, implied volatility calculated from options price is also widely used by traders and researchers. In the financial derivatives pricing model, for example the Black-Scholes-Merton option pricing formulas, one parameter cannot be directly observed is the volatility of underlying asset (Hull, 2015), which is then implied from the option prices on the market. While the realized volatility is the backward looking on the historical volatility, the implied volatility is the thought of market about future volatility. Due to relying on the option valuation model, the implied volatility could be inaccurately measured, causing from the application of inappropriate model (Blair, Poon, & Taylor, 2001). The most popular implied volatility index, VIX published by CBOE, is a measure of implied volatility of 30-day-options on the S&P 500 index (Hull, 2015). It is notable that the approach of VIX has been based on S&P 500 index since 2003 rather than S&P 100 when it was introduced in 1993 (CBOE, 2015).

Many researches find the significant evidence that the implied volatility index is efficient and informative in forecasting the volatility of returns. Blair et al. (2001) compare the volatility forecasting ability of the VIX based on S&P 100 and the conditional volatility of ARCH models. The finding illustrates that the implied volatility is more informative and perform well in volatility forecasting. A more recent study of Han & Park (2013) further confirms the informative nature of the VIX based on S&P 500 in providing more accurate volatility prediction for the return of S&P 500 index on the out-of-sample forecasting test. Another index, Oil VIX[5], is also proved to have the more considerable power in projecting oil future price volatility comparing to realized volatility (Lv, 2018). Consequently, the OVX has been using as the proxy for oil price volatility in numerous research, for example Gokmenoglu & Fazlollahi (2015); Maghyereh, Awartani, & Bouri (2016); Luo & Qin (2017); Dutta, Noor, & Dutta (2017); Dutta, Nikkinen, & Rothovius (2017), Shahzad, Kayani, Raza, Shah, & Al-Yahyaee (2018).

[5] The Cboe Crude Oil ETF Volatility Index (OVX) measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX methodology to United States Oil Fund, LP (Ticker - USO) options. https://www.cboe.com/

6. DATA AND METHODOLODY

6.1. Methodology

The Exponential GARCH model, proposed by Nelson (1991), is employed in this research to investigate the impact of oil price and its volatility on Southeast Asian stock markets. The mean equation for each stock return series can be expressed as follows:

$$(10) \qquad R_{i,t} = \mu_i + \varphi_{1,i} R_{i,t-1} + \varphi_{2,i} RO_t + \varphi_{3,i} D_t RO_t + \varepsilon_{i,t}$$

where $R_{i,t}$ is the log return of stock market index i between time t and t -1, μ_i is a long-term drift coefficient, RO_t is the log return of oil price index between time t and t - 1, D is dummy variable (D = 1 if $RO_t > 0$, D = 0 otherwise), and $\varepsilon_{i,t}$ is error term for the return of series i at time t, which is assumed to be:

$$(11) \qquad \varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_{i,t} \qquad\qquad z_{i,t} \sim \text{i.i.d. } (0,1)$$

$$(12) \qquad \log(h_{i,t}) = \omega_i + \frac{\alpha_i \left|\varepsilon_{i,t-1}\right| + \delta_i \varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}} + \beta_i \log(h_{i,t-1}) + \gamma_i OVX_{t-1}$$

The equation (12) is a modified EGARCH(1,1) variance function, in which the OVX, as the proxy for oil volatility, is added into the model for investigating the impact of oil uncertainty on stock price return and volatility.

To control the influence of global volatility factors, the study further extends the EGARCH variance formula as in equation (13). Regarding the global factor, the study include directly into the equation the lagged value of VIX, which is also used in the variance equation in many analyses, for example Blair et al. (2001), Kambouroudis & McMillan (2016), and Dutta et al. (2017).

$$(13) \qquad \log(h_{i,t}) = \omega_i + \frac{\alpha_i \left|\varepsilon_{i,t-1}\right| + \delta_i \varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}} + \beta_i \log(h_{i,t-1}) + \gamma_i OVX_{t-1} + \varsigma_i VIX_{t-1}$$

The research is further consolidated by applying GARCH-jump model to analyze the relationship between oil and stock markets. While most GARCH-family models only take into account the effect of smooth changes in volatility, the mixed GARCH-jump model with autoregressive conditional jump intensity (ARJI) developed by Chan & Maheu (2002b) is proved to have considerable improvement in volatility forecast, especially during the extreme fluctuation period of stock return. The GARCH-jump model utilized in the research assumes the following form:

(14) $$R_{i,t} = \tau_i + \psi_{1,i} R_{i,t-1} + \psi_{2,i} RO_t + \psi_{3,i} \Delta OVX_t + \varepsilon_{i,t}$$

where $R_{i,\,t}$ is the log return of stock market index i between time t - 1 and t, RO_t is the log return of oil price index between time t and t - 1, $\Delta OVX_t = 100 \times [\log(OVX_t) - \log(OVX_{t-1})]$, the error term $\varepsilon_{i,t}$ at time t comprises two components $\varepsilon_{i,t} = \varepsilon_{1i,t} + \varepsilon_{2i,t}$.

The first component $\varepsilon_{1i,t}$ is the normal innovation which has mean of zero and follows normal stochastic process,

(15) $$\varepsilon_{1i,\,t} = \sigma_{i,t} z_{i,t} \qquad z_{i,t} \sim \text{i.i.d. } (0, 1)$$

(16) $$\sigma^2_{i,t} = \omega'_i + \alpha'_i \varepsilon^2_{1i,t-1} + \beta'_i \sigma^2_{i,t-1}$$

where $\omega' > 0$, $\alpha' \geq 0$, $\beta' \geq 0$ to guarantee the positivity of $\sigma^2_{i,t}$.

The second component $\varepsilon_{2i,t}$ is the jump innovation describing abnormal price movement with a mean of zero. The jump innovation is defined as the difference between the jump component and the expected total jump size between t - 1 and t:

(17) $$\varepsilon_{2i,t} = \sum_{k=1}^{n_t} Y_{it,k} - \theta\lambda_{i,t} \qquad Y_{it,k} \sim N(\theta, d^2)$$

where $Y_{it,k}$ denotes the jump size, $\sum_{k=1}^{n_t} Y_{it,k}$ refers the jump component, n_t is the number of jumps. The distribution of n_t is assumed to be Poisson with an autoregressive conditional jump intensity parameter λ_t given by:

(18) $\lambda_{i,t} = \lambda_{0i} + \rho_i\lambda_{i,t-1} + \nu_i\xi_{i,t-1}$

where λ_t is the time-varying expected number of jumps at time t on a given information set, $\lambda_{i,t} > 0$, $\lambda_{0i} > 0$, $\rho_i > 0$, $\nu_i > 0$.

6.2. Data

The data consists of daily continuously compounded index returns, computed as difference in the logarithms of daily value of oil index and stock market indices for six Southeast Asian nations, namely Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam. Daily data on stock market is collected from Morgan Stanley Capital International (MSCI) indices including MSCI Indonesia, MSCI Malaysia, MSCI Philippines, MSCI Singapore, MSCI Thailand, and MSCI Vietnam. The study utilizes Dubai crude oil index to calculate oil returns. Additional, the crude oil volatility index (OVX), published by Chicago Board of Options Exchange (CBOE), is used in the research to measure the oil market volatility. Furthermore, the CBOE Volatility Index (VIX) is obtained to indicated global market risk. The sample data covers a period of 10 years from May 2007 to December 2017. This sample period is to satisfy the availability of all indices. Returns of stock and oil markets are calculated as follows:

(19) $$R_{i,t} = 100 \times [\log(P_{i,t}) - \log(P_{i,t-1})]$$

where $R_{i,t}$ is the log return of market index i between time t - 1 and t, $P_{i,t}$ is the index price of market i at time t.

Figure 6. Dynamics of selected index returns from 2007 to 2017

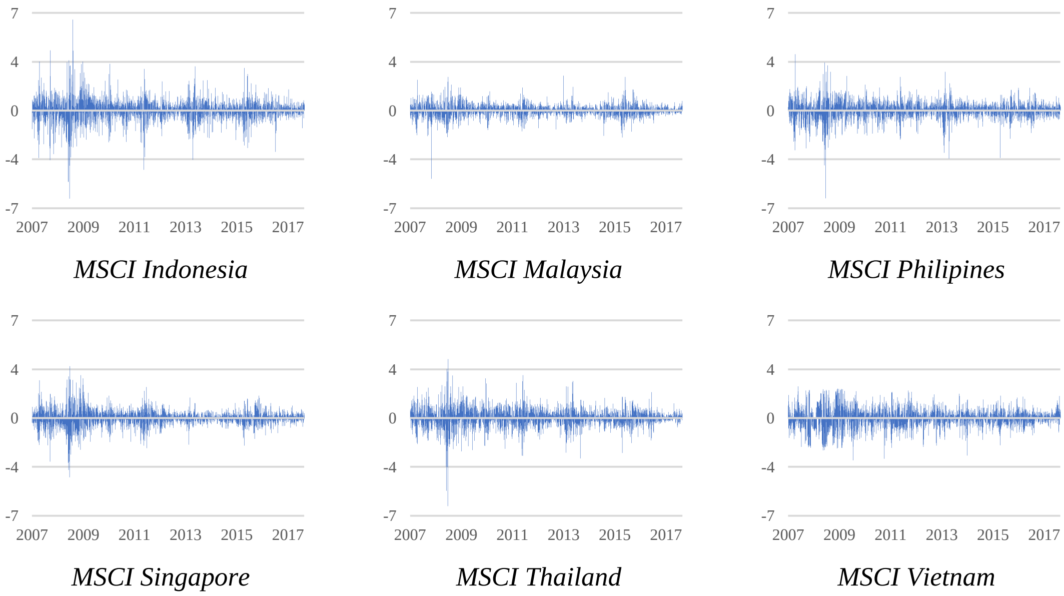


Figure 6. Dynamics of selected index returns from 2007 to 2017

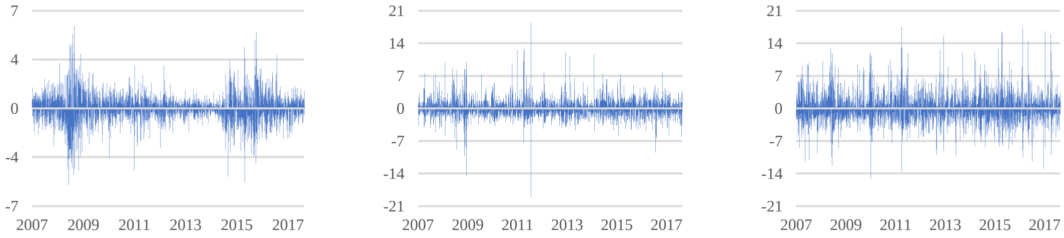


Figure 6 shows the movements of stock market return series for six Southeast Asian nations from 2007 to 2017. As can be seen from the charts, the stock returns are highly volatile in the period of global financial crisis around 2008. This fluctuated pattern is observed obviously for the returns on the Indonesia, Philippines, Singapore, and Thailand markets, while there is no large movement in MSCI Vietnam index return in the analyzed period. The Dubai crude oil return also displays an extreme volatility during crisis and in the period from 2014 to 2015 when the oil price decreased due to the excess supply on the market. In terms of OVX and VIX, the returns show no particular pattern.

Table 2. Descriptive statistics

	Mean	Max.	Min.	Std. error	Skewness	Kurtosis	Jarque-Bera
Panel A: Index returns							
MSCI Indonesia	0.009455	6.533	-6.330	0.791172	-0.241701	7.714645	6911.016049
MSCI Malaysia	0.000339	2.512	-4.898	0.440375	-0.383373	8.429915	8287.674767
MSCI Philippines	0.010785	4.051	-6.295	0.636541	-0.608473	7.327920	6382.414082
MSCI Singapore	0.000494	3.719	-4.260	0.579901	-0.173159	6.289586	4589.517824
MSCI Thailand	0.013139	4.227	-6.330	0.668183	-0.414979	7.482530	6555.650455
MSCI Vietnam	-0.009487	2.265	-3.036	0.674576	-0.159209	1.507027	274.421574
Dubai Crude Oil	0.000002	0.059	-0.055	0.010124	-0.030461	4.094093	1939.187781
Panel B: Volatility indices							
OVX	36.825839	100.42	14.50	13.873574	1.399837	2.813010	1821.889423
VIX	20.069532	80.86	9.14	9.701939	2.297684	7.065198	8216.315160

The descriptive statistics for the variables employed the research are shown in table 3. Panel A indicates the information for the index returns which have positive means except the return of MSCI Vietnam. MSCI Thailand and MSCI Philippines exhibit the better performance among six markets during the investigated period with the higher mean of daily returns. Generally, the stock index returns present greater volatility than the crude oil return series which has smaller value in standard error. Negative skewness in all return series illustrates that negative return accounts for the large proportion among whole sample. Most of the index returns show positive excess kurtosis, implying that the distribution of these series are leptokurtic while MSCI Vietnam return has platykurtic distribution with kurtosis lower than 3. Panel B indicates the descriptive statistics of OVX and VIX. The OVX seems to exhibit higher fluctuation than VIX index, indicated by the difference in standard error.

7. EMPIRICAL ANALYSIS

7.1. Unit root test

Empirical analysis models employed in the research are based on stationary process. Therefore, it is crucial to know whether the return series investigated are integrated of order zero. Before finding the relationship between oil and stock markets, unit root tests are used to test the hypothesis of presentation of unit root in time series. In this research, the Augmented Dicke-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are all utilized for checking the sample. While the null hypothesis of ADF and PP tests are to reject the covariance stationary characteristic of time series, the KPSS method tests the null hypothesis of stationary.

Table 3. ADF, PP, and KPSS unit root tests

*The table presents the values of test statistic for ADF, PP, and KPSS tests. The null hypothesis of ADF and PP tests is that the data is unit root process, and null hypothesis for the KPSS test is that the time series is stationary. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Variables	ADF	PP	KPSS
MSCI Indonesia	-47.2575**	-47.2491**	0.060771
MSCI Malaysia	-47.8484**	-47.8748**	0.127625
MSCI Philippines	-47.4126**	-47.3201**	0.082786
MSCI Singapore	-51.6816**	-51.7150**	0.086579
MSCI Thailand	-51.3368**	-51.3971**	0.069967
MSCI Vietnam	-42.6015**	-42.6525**	0.333579
Dubai Crude Oil	-58.7213**	-58.5775**	0.121747
OVX	-58.2659**	-58.4820**	0.049689

The results of unit root tests are shown in table 4. The null hypotheses of unit root in the ADF and PP tests are both rejected at significant level of 5%. Finding of KPSS test suggests that the unit root in alternative hypothesis is also rejected, accepting the hypothesis of stationary. However, it is notable that the KPSS test concentrates on testing trend stationary, then the series might be non-stationary even the null hypothesis is accepted. In overall, we could conclude that all return series in the research are significantly stationary and proceed with the time series model analysis.

7.2. Estimation results of modified EGARCH(1,1) model

This section presents the empirical outcomes of the research from the estimation of the exponential generalized autoregressive conditional heteroscedastic (EGARCH) model. By adding the OVX variable into the volatility equation as indicated in previous section, the analysis examines not only the relationship between oil and stock returns, but also the volatility transmission between international oil price and stock market returns.

Table 4. Effects of crude oil return, OVX, and VIX on Southeast Asian stock markets

*The table presents the estimates for Indonesia, Malaysia, and Philippines markets according the model defined by equations (10) to (13). The sample period is from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia			Malaysia			Philippines		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
μ	-0.0009 (0.93)	0.0167 (0.19)	0.0153 (0.28)	0.0006 (0.93)	0.0179** (0.03)	0.0164** (0.01)	0.0110 (0.25)	0.0300** (0.02)	0.0232* (0.08)
φ_1	0.0684*** (0.00)	0.0662*** (0.00)	0.0717*** (0.00)	0.1015*** (0.00)	0.0990*** (0.00)	0.1006*** (0.00)	0.0642*** (0.00)	0.0659*** (0.00)	0.0687*** (0.00)
φ_2	0.0694*** (0.00)	0.0988*** (0.00)	0.1020*** (0.00)	0.0678*** (0.00)	0.1010*** (0.00)	0.0991*** (0.00)	0.0529*** (0.00)	0.0847*** (0.00)	0.0810*** (0.00)
φ_3		-0.0558*** (0.00)	-0.0459 (0.15)		-0.0598*** (0.00)	-0.0560** (0.01)		-0.0628** (0.01)	-0.0489*** (0.00)
ω	-0.1149*** (0.00)	-0.1179*** (0.00)	-0.2867*** (0.00)	-0.1916*** (0.00)	-0.2011*** (0.00)	-0.2244*** (0.00)	-0.1423*** (0.00)	-0.1457*** (0.00)	-0.1883*** (0.00)
α	0.1336*** (0.00)	0.1342*** (0.00)	0.1857*** (0.00)	0.1660*** (0.00)	0.1698*** (0.00)	0.1657*** (0.00)	0.1468*** (0.00)	0.1464*** (0.00)	0.1434*** (0.00)
β	0.9863*** (0.00)	0.9863*** (0.00)	0.9225*** (0.00)	0.9744*** (0.00)	0.9736*** (0.00)	0.9659*** (0.00)	0.9776*** (0.00)	0.9790*** (0.00)	0.9563*** (0.00)
δ	-0.0721*** (0.00)	-0.0726*** (0.00)	-0.0999*** (0.00)	-0.0675*** (0.00)	-0.0668*** (0.00)	-0.0715*** (0.00)	-0.0822*** (0.00)	-0.0831*** (0.00)	-0.0945*** (0.00)
γ	0.0002 (032)	0.0002 (0.21)	-0.0013** (0.02)	0.0005 (0.10)	0.0006* (0.06)	0.0000 (0.95)	0.0001 (0.47)	0.0002 (0.15)	-0.0008** (0.02)
ξ			0.0066*** (0.00)			0.0017*** (0.00)			0.0028*** (0.00)
Log Likelihood	-2763.55	-2762.24	-2739.19	-1230.34	-1226.64	-1220.51	-2269.20	-2266.73	-2254.45

Table 5 and table 6 illustrates the findings for six Southeast Asian markets. As can be seen from the tables, the oil index return significantly and positively impacts the stock returns in all six nations considered from 2007 to 2017. The estimated coefficient φ_2, which indicates the effect of Dubai crude oil price movement on stock return, seems to be higher for Singapore and Thailand, and lower for Vietnam. In model (2) and (3) in table 5 and table 6, dummy variable is added to investigate the asymmetric impact of oil return on stock markets. Across six countries, the estimates for parameter φ_3 are all negative, implying that the negative shocks on oil market has more considerable impact on stock returns in Southeast Asia. However, the significant evidences are found only in Malaysia, Philippines, and Vietnam. In terms of Indonesia and Singapore, the asymmetric effects are only statistically significant in the model (2) and rejected in the model (3). For Thailand market, there is no significant difference between the impact of positive and negative oil price shocks to stock return.

Table 5. Effects of crude oil return, OVX, and VIX on Southeast Asian stock markets

*The table presents the estimates for Singapore, Thailand, and Vietnam markets according the model defined by equations (10) to (13). The sample period is from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Singapore			Thailand			Vietnam		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
μ	-0.0007 (0.92)	0.0102 (0.19)	0.0070 (0.41)	0.0249*** (0.00)	0.0394*** (0.00)	0.0344*** (0.00)	-0.0076 (0.21)	0.0414*** (0.00)	0.0421*** (0.00)
φ_1	0.0360* (0.08)	0.0335*** (0.00)	0.0333* (0.06)	0.0462** (0.01)	0.0478** (0.01)	0.0524*** (0.00)	0.1546*** (0.00)	0.1512*** (0.00)	0.1538*** (0.00)
φ_2	0.0927*** (0.00)	0.1118*** (0.00)	0.1094*** (0.00)	0.0885*** (0.00)	0.1132*** (0.00)	0.1095*** (0.00)	0.0179* (0.09)	0.0641*** (0.00)	0.0651*** (0.00)
φ_3		-0.0399** (0.01)	-0.0319 (0.14)		-0.0483 (0.50)	-0.0426 (0.11)		-0.0995*** (0.00)	-0.1004*** (0.00)
ω	-0.1354*** (0.00)	-0.1375*** (0.00)	-0.1661*** (0.00)	-0.1468*** (0.00)	-0.1500*** (0.00)	-0.1771*** (0.00)	-0.2510*** (0.00)	-0.2662*** (0.00)	-0.3586*** (0.00)
α	0.1253*** (0.00)	0.1253*** (0.00)	0.1249*** (0.00)	0.1676*** (0.00)	0.1673*** (0.00)	0.1646*** (0.00)	0.2340*** (0.00)	0.2425*** (0.00)	0.2658*** (0.00)
β	0.9854*** (0.00)	0.9855*** (0.00)	0.9773*** (0.00)	0.9859*** (0.00)	0.9856*** (0.00)	0.9733*** (0.00)	0.9528*** (0.00)	0.9495*** (0.00)	0.9137*** (0.00)
δ	-0.0780*** (0.00)	-0.0780*** (0.00)	-0.0814*** (0.00)	-0.0630*** (0.00)	-0.0639*** (0.00)	-0.0770*** (0.00)	-0.0265** (0.01)	-0.0232* (0.06)	-0.0254* (0.05)

Countries	Singapore			Thailand			Vietnam		
γ	0.0004* (0.06)	0.0005** (0.04)	0.0003 (0.15)	0.0001 (0.80)	0.0001 (0.50)	-0.0007* (0.08)	0.0006* (0.09)	0.0007* (0.08)	-0.0009 (0.13)
ξ			0.0011** (0.02)			0.0022*** (0.00)			0.0046*** (0.00)
Log Likelihood	-1649.64	-1648.26	-1645.38	-2265.85	-2264.25	-2255.23	-2433.83	-2429.84	-2419.02

Regarding oil volatility, the results reveal that the influence of OVX on stock return volatility is relatively small. In the model (1) and model (2), the estimated coefficient γ is only significant at the level of 10% for almost half of all markets investigated. After controlling the effect of VIX, the estimates for parameter of OVX are still significant at the level of 10% in most of markets. However, while there is no significant estimate of parameter γ found for Indonesia and Philippines in model (1) and model (2), the coefficient of OVX becomes statistically significant in model (3) for both countries after adding VIX into the model. In contrast, Malaysia, Singapore, and Vietnam exhibit an opposite pattern with significant estimated coefficients in model (1) and model (2), and insignificant estimates in model (3). The outcomes also illustrate the important role of VIX in analyzing the volatility of stock market returns with considerable and significant magnitude of the parameter estimates, implying a strong influence of the US stock market volatility on the variance of stock return in Southeast Asia.

Additionally, the estimation results indicate the considerable dependence of current equity return on lagged value, as evidenced by the significant estimates of coefficient $R_{i,t-1}$ in all six markets. Moreover, the negative values of coefficient δ imply that the previously negative shocks seem to have greater impact on volatility than the positive one. The positive and significant values of estimation for coefficient $|\varepsilon_{i,t-1}|$ and $\log(h_{i,t-1})$ generally suggest that the volatility on Southeast Asian markets is affected by its own shock and volatility.

The study further examines the impact of oil price uncertainty on stock markets in two subsamples. The first subsample represents the crisis period 2007-2009, and the second subsample spans from 2010 to 2017, which is post-crisis period. The results are reported in table 6 and table 7. Generally, the changes in oil price have positive influences on stock market returns for both crisis and post-crisis periods. Most estimates for coefficient φ_2 are significant at the level of 1%, except for Philippines and Vietnam in crisis period only at the 10% and 5% level respectively.

Table 6. Effects of crude oil return, OVX, and VIX on Southeast Asian stock markets, crisis period

*The table presents the estimates for Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam markets according the model defined by mean equations (10) and variance equation (13). The subsample spans from 2007 to 2009. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.0155 (0.71)	0.0229 (0.15)	-0.0091 (0.81)	0.0073 (0.84)	0.0701** (0.04)	0.0134 (0.75)
φ_1	0.0880** (0.01)	0.1297*** (0.00)	0.1136*** (0.00)	0.0137 (0.72)	0.0701** (0.04)	0.3357*** (0.00)
φ_2	0.1635*** (0.00)	0.1298*** (0.00)	0.0765** (0.07)	0.2345** (0.00)	0.2551*** (0.00)	0.0933** (0.04)
φ_3	-0.0021 (0.98)	-0.0766*** (0.00)	0.0019 (0.98)	-0.0838 (0.21)	-0.1542*** (0.00)	-0.1576*** (0.00)
ω	-0.5019*** (0.00)	-0.3841*** (0.00)	-0.3111*** (0.00)	-0.4170*** (0.00)	-0.5031*** (0.00)	-0.3447*** (0.00)
α	0.0433 (0.45)	0.2578*** (0.00)	0.1552*** (0.00)	0.2024*** (0.00)	0.2540*** (0.00)	0.2999*** (0.00)
β	0.6367*** (0.00)	0.8995*** (0.00)	0.8088*** (0.00)	0.8646*** (0.00)	0.7885*** (0.00)	0.9015*** (0.00)
δ	-0.2658*** (0.00)	-0.1353*** (0.00)	-0.1156*** (0.00)	-0.1324*** (0.00)	-0.1409*** (0.00)	-0.0675** (0.03)
γ	-0.0067** (0.03)	-0.0010 (0.46)	-0.0037 (0.12)	-0.0040** (0.04)	-0.0014 (0.49)	-0.0006 (0.69)
ξ	0.0256*** (0.00)	0.0038* (0.09)	0.0096* (0.05)	0.0122** (0.01)	0.0093** (0.02)	0.0033 (0.19)

Table 7. Effects of crude oil return, OVX, and VIX on Southeast Asian stock markets, post-crisis period

*The table presents the estimates for Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam markets according the model defined by mean equations (10) and variance equation (13). The subsample spans from 2010 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.0192	0.0159*	0.0288**	0.0086	0.0297***	0.0452***
	(0.21)	(0.07)	(0.03)	(0.37)	(0.00)	(0.00)
φ_1	0.0548**	0.1002***	0.0440**	0.0388*	0.0479**	0.0888***
	(0.01)	(0.00)	(0.04)	(0.06)	(0.03)	(0.00)
φ_2	0.0857***	0.0913***	0.0806***	0.0966***	0.0846***	0.0583***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
φ_3	-0.0549	-0.0568***	-0.0574**	-0.0341	-0.0256**	-0.0838***
	(0.10)	(0.00)	(0.05)	(0.20)	(0.02)	(0.00)
ω	-0.2039***	-0.2849***	-0.1873***	-0.1818***	-0.1568***	-0.4161***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α	0.1597***	0.1344***	0.1219***	0.0821***	0.1416***	0.2658***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9543***	0.9514***	0.9499***	0.9695***	0.9768***	0.8880***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
δ	-0.0817***	-0.0717***	-0.1126***	-0.0743***	-0.0806***	-0.0131
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.45)
γ	-0.0007*	0.0008	-0.0008**	0.0007**	-0.0007**	-0.0009
	(0.06)	(0.10)	(0.03)	(0.02)	(0.02)	(0.20)
ξ	0.0035**	0.0029***	0.0028***	0.0019**	0.0022***	0.0055**
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)

The increase in oil price could be considered as the growth in total demand of global economy, leading to the positive movement on the stock market. However, the magnitude of impact seems to be higher during crisis period comparing to post-crisis period. The estimated values of coefficient RO, Dubai crude oil index return, for crisis period double the estimates for post-crisis period in Indonesia, Singapore, Thailand, and Vietnam markets. For Malaysia and Philippines, the differences of oil price impact between crisis and post-crisis are also notable.

Regarding the asymmetric impact of oil price index, the negative shocks in oil price has greater effect on six markets investigated, as evidenced by the negative estimates of coefficient for dummy variable $D_t \times RO_t$ in all nations. Indonesia and Philippines stock markets are sensitive to both negative and positive oil price change during crisis period. Nonetheless, the impacts of oil shock are not symmetric in these two nations for post-crisis period, with the significance level of 10%. Similar to the result for whole sample, there is no significant evidence of asymmetric in Singapore market. The reason might be that Singapore is a developed market and one of the global financial centers, which seems to be sensitive to all types of shock on global markets.

The estimated results from variance equation shown in table 6 and table 7 reveal the influences of OVX and VIX on several Southeast Asian stock markets in crisis and post-crisis period. Only two out of six nations exhibit significant estimates for coefficient OVX in the period of global financial crisis. For post-crisis period, after controlling VIX variable, the estimated values become statistically significant for four analyzed markets with the significance level of 10%. However, the magnitude of the OVX effect on the volatility of stock return is relatively small when comparing to the impact of VIX. As reported in table 7, the stock return volatilities in all countries positively react to the fluctuation of VIX at the significance level of 1%. Although the magnitude of VIX's effect is still high during crisis period, the estimates of coefficient become insignificant in half markets investigated in this subsample. This could be the evidence that Southeast Asian markets behave more independently from the US stock market during the crisis which was initiated from this nation.

7.3. Estimation results of GARCH-Jump model

In this section, the study analyzes the impact of both oil price change and the movement of OVX on Southeast Asian stock returns by using GARCH-jump models. The conditional jump models are proved to attain ability in capturing the effect of abnormal information on market through the researches of Fowowe (2013), Dutta et al. (2017), and Dutta (2018). In this research, both GARCH-jump model with constant jump intensity and time-varying jump intensity are employed to exploring the movement of stock markets. The estimations for the GARCH-jump models are indicated in table 8 and table 9. In general, most parameters in variance equation are significant, suggesting the existence of GARCH effect and jump in stock returns of Southeast Asian markets.

In line with the findings in previous section, the oil price movement positively affects stock market returns in Southeast Asian region. The estimates of oil return coefficient are significant at the 1% level in all models and for most markets analyzed, except for Vietnam. An increase in oil price might lead to push up economic cost but this is also a sign of the growth in total demand, resulting the positive fluctuation on stock markets. In contrast, the effect of OVX on stock return is negative, as evidenced by the significant and negative estimated coefficient for Indonesia, Malaysia, Philippines, Singapore, and Thailand. This results are similar to the study on 23 emerging markets of Dutta et al., (2017) which also finds negative impact of OVX on stock returns. Possible explanations could be that the higher oil price volatility implies the increase of uncertainty and risk level in economic activities, leading to the change of expected returns on stock markets. For Vietnam, after controlling OVX return, the movements of Dubai crude oil price have no significant impact on stock market. The estimated coefficients RO in GARCH-jump models for Vietnam are only significant at the 10% level. Among six countries investigated, the stock market of Vietnam is smallest in terms of capitalization and is the most recently established. Therefore, Vietnamese stock market seems to be less integrated into global financial system and less sensitive to global shocks. As a developed financial market, Singapore, by contrast, exhibits more sensitive to fluctuation of oil price index, with the highest magnitude of estimated value for coefficient ψ_2.

Table 8. Impact of crude oil index and OVX fluctuations on stock returns in Indonesia, Malaysia, and Philippines

*The table reports estimation results of three GARCH-family models, namely GARCH(1,1), GARCH-constant jump intensity, and ARJI-GARCH. All models are defined by mean equation (14). The variance model for GARCH(1,1) is given as equation (16) and for GARCH-conditional jump models are defined as equations (15) to (18). The sample period is from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia			Malaysia			Philippines		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
μ	0.01742 (0.12)	0.0359*** (0.00)	0.0329*** (0.00)	0.0103 (0.10)	0.0105* (0.08)	0.0123** (0.04)	0.0262*** (0.00)	0.0378*** (0.00)	0.0388*** (0.00)
ψ_1	0.0648*** (0.00)	0.0390** (0.04)	0.0415** (0.03)	0.1071*** (0.00)	0.0967*** (0.00)	0.0976*** (0.00)	0.0720*** (0.00)	0.0779*** (0.00)	0.0647*** (0.00)
ψ_2	0.0611*** (0.00)	0.0520*** (0.00)	0.0481*** (0.00)	0.0569*** (0.00)	0.0529*** (0.00)	0.0546*** (0.00)	0.0469*** (0.00)	0.0380*** (0.00)	0.0393*** (0.00)
ψ_3	-0.0238*** (0.00)	-0.0208*** (0.00)	-0.0195*** (0.00)	-0.0135*** (0.00)	-0.0103*** (0.00)	-0.0092*** (0.00)	-0.0145*** (0.00)	-0.0127*** (0.00)	-0.0107** (0.03)
ω'	0.0060*** (0.00)	0.0042** (0.01)	0.0004* (0.05)	0.0022*** (0.00)	0.0009** (0.03)	0.0003** (0.01)	0.0069*** (0.00)	0.0054*** (0.00)	0.0037*** (0.00)
α'	0.08112*** (0.00)	0.0800*** (0.00)	0.0034*** (0.00)	0.0932*** (0.00)	0.0585*** (0.00)	0.0082*** (0.00)	0.0913*** (0.00)	0.0901*** (0.00)	0.0338*** (0.00)
β'	0.9107*** (0.00)	0.8747*** (0.00)	0.9901*** (0.00)	0.9000*** (0.00)	0.9238*** (0.00)	0.9828*** (0.00)	0.8926*** (0.00)	0.8749*** (0.00)	0.9366*** (0.00)
θ		-0.1941** (0.02)	-0.1008*** (0.00)		-0.1129 (0.29)	-0.0550* (0.07)		-0.3687* (0.05)	-0.2509** (0.01)
d^2		0.9872*** (0.00)	0.9678*** (0.00)		0.7556*** (0.00)	0.5676*** (0.00)		0.8178*** (0.00)	0.8228*** (0.00)
λ_0		0.1482*** (0.00)	0.0184*** (0.00)		0.0514* (0.08)	0.0139*** (0.00)		0.0724 (0.15)	0.0135** (0.02)
ρ			0.9443*** (0.00)			0.9389*** (0.00)			0.9132*** (0.00)
ν			0.5114*** (0.00)			0.5364*** (0.00)			0.5352*** (0.00)
Log Likelihood	-2776.12	-2682.80	-2651.29	-1245.78	-1156.29	-1128.60	-2287.88	-2223.22	-2205.91

Table 9. Impact of oil price index and OVX fluctuations on stock returns in Singapore, Thailand, and Vietnam

*The table reports estimation results of three GARCH-family models, namely GARCH(1,1), GARCH-constant jump intensity, and ARJI-GARCH. All models are defined by mean equation (14). The variance model for GARCH(1,1) is given as equation (16) and for GARCH-conditional jump models are defined as equations (15) to (18). The sample period is from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Singapore			Thailand			Vietnam		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
μ	0.0103 (0.15)	0.0314*** (0.00)	0.0320*** (0.00)	0.0338*** (0.00)	0.0371*** (0.00)	0.0355*** (0.00)	0.0003 (0.94)	0.0241** (0.02)	0.0277** (0.01)
ψ_1	0.0279 (0.15)	0.0246 (0.19)	0.0217 (0.27)	0.0436** (0.04)	0.0387** (0.04)	0.0144 (0.40)	0.1562*** (0.00)	0.1397*** (0.00)	0.1323*** (0.00)
ψ_2	0.0792*** (0.00)	0.0755*** (0.00)	0.0752*** (0.00)	0.0707*** (0.00)	0.0609*** (0.00)	0.0498*** (0.00)	0.0119 (0.31)	0.0179* (0.08)	0.0190* (0.07)
ψ_3	-0.0202*** (0.00)	-0.0197*** (0.00)	-0.0194*** (0.00)	-0.0210*** (0.00)	-0.0173*** (0.00)	-0.0200*** (0.00)	-0.0017 (0.75)	-0.0022 (0.64)	-0.0013 (0.78)
ω'	0.0017*** (0.00)	-0.0006 (0.17)	-0.0006 (0.14)	0.0015** (0.03)	0.0007 (0.19)	0.0005** (0.03)	0.0122*** (0.00)	0.0030 (0.10)	0.0028** (0.04)
α'	0.0756*** (0.00)	0.0741*** (0.00)	0.0720*** (0.00)	0.0860*** (0.00)	0.0769*** (0.00)	0.0156** (0.01)	0.1334*** (0.00)	0.1444*** (0.00)	0.1098*** (0.00)
β'	0.9186*** (0.00)	0.9141*** (0.00)	0.9164*** (0.00)	0.9153*** (0.00)	0.9066*** (0.00)	0.9674*** (0.00)	0.8387*** (0.00)	0.8160*** (0.00)	0.8484*** (0.00)
θ		-0.0978** (0.02)	-0.1001** (0.01)		-0.1363* (0.05)	-0.0439** (0.01)		-0.1140** (0.02)	-0.1115** (0.01)
d^2		0.3393*** (0.00)	0.3382*** (0.00)		0.6921*** (0.00)	0.5208*** (0.00)		0.5236*** (0.00)	0.4950*** (0.00)
λ_0		0.2997** (0.02)	0.3690* (0.07)		0.1298*** (0.00)	0.0280*** (0.00)		0.2522** (0.01)	0.1295** (0.03)
ρ			-0.2126 (0.65)			0.9591*** (0.00)			0.6369*** (0.00)
ν			0.2222 (0.22)			0.6335*** (0.00)			0.6865** (0.04)
Log Likelihood	-1665.79	-1626.37	-1625.51	-2276.31	-2230.89	-2225.80	-2419.11	-2368.73	-2365.91

As shown in the table 8 and table 9, the GARCH parameters are all significant at the 1% level and satisfied with the requirement of non-negativity. The results confirm the GARCH effect in all Southeast Asian stock market returns with high degree of persistence in conditional volatility. Additionally, the impact of previous return on current movement is found in five out of six markets analyzed, as evidenced by the significant estimated coefficient for $R_{i,t-1}$. In terms of jump parameters, the existence of jumps is found in most markets and the jump is time-varying. The mean parameter θ of jump is significant at the 5% level for Indonesia, Philippines, Singapore, Thailand, and Vietnam; at the 10% level for Malaysia. The variance parameter d^2 of jump is all significant at the 1% level. It is observed that coefficient of jump variance is positive in all markets, implying that volatility driven by abnormal information has a positive impact on the volatility of stock returns (Fowowe, 2013). Furthermore, the jump intensity parameters (λ_0, ρ, ν) are significant in most of investigated markets at the 1% level, suggesting that the jumps exist in Southeast Asian market returns with the time-varying characteristic. For Singapore, the parameter λ_0 is only significant at the level of 10% while parameters ρ and ν are insignificant. This result indicates the jump does exist in Singapore market but is not time-varying, leading a conclusion that Singapore stock market seems to be more stable comparing to others in the research. Moreover, the high and positive estimates of ρ and ν show that the most recent intensity ($\lambda_{i,t-1}$) and intensity residual ($\xi_{i,t-1}$) strongly influence the current jump intensity ($\lambda_{i,t}$), which has a high degree of persistence (Dutta et al., 2017).

In this section, the research also split the sample into two subsamples, namely crisis period (2007-2009) and post-crisis period (2010-2017) to analyze the impact of oil indices' fluctuation on stock market returns and the existence of jump in stock return after controlling the crisis effect. In this sub-period analysis, the study only employs the ARJI-GARCH model which is proved being appropriate to describe the jump behavior of Southeast Asian markets with the highest Log Likelihood ratio among three estimated models discussed previously. The test results for crisis period showed in table 10 and for post-crisis period in table 11. In both periods, the impacts of crude oil index movement on stock returns are positive and significant in all examined Southeast Asian market. The magnitude of the impact is higher during the time of crisis, with greater estimated coefficient comparing to the estimates for post-crisis period.

Table 10. Impact of oil price and OVX fluctuations on Southeast Asian stock returns, crisis period

*The table reports estimation results of ARJI-GARCH model defined as equations (14) to (18). The subsample spans from 2007 to 2009. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.0647*	0.0151	0.0518	0.1655***	0.2829***	-0.0361***
	(0.08)	(0.40)	(0.13)	(0.00)	(0.00)	(0.00)
ψ_1	0.0721*	0.1272*	0.0909**	0.0078	0.0384	0.2901***
	(0.07)	(0.07)	(0.02)	(0.44)	(0.34)	(0.00)
ψ_2	0.1197***	0.0689**	0.0497**	0.2117***	0.1670***	0.0290***
	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)
ψ_3	-0.0395**	-0.0132	-0.0259*	-0.0281**	-0.0203	-0.0109***
	(0.01)	(0.25)	(0.08)	(0.02)	(0.15)	(0.00)
ω'	0.2161*	0.0167***	0.0005	-0.0124***	0.0210*	-0.0095***
	(0.06)	(0.00)	(0.79)	(0.00)	(0.07)	(0.00)
α'	0.0610*	0.1647***	0.0047	0.1387***	0.1117***	0.1955***
	(0.07)	(0.00)	(0.41)	(0.00)	(0.00)	(0.00)
β'	0.5091**	0.7898***	0.9614***	0.9062***	0.8456***	0.7618***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
θ	-0.1766	-0.6363***	0.5741***	-0.0357***	-0.0433	-0.0388***
	(0.19)	(0.00)	(0.00)	(0.00)	(0.75)	(0.00)
d^2	1.4789***	-1.1930	-0.0373	0.0841***	-0.0061	-0.3512***
	(0.00)	(0.29)	(0.16)	(0.00)	(0.97)	(0.00)
λ_0	0.0095	0.0013***	0.1020*	0.1388***	0.1495	0.2397***
	(0.17)	(0.00)	(0.05)	(0.00)	(0.69)	(0.00)
ρ	0.9645***	0.2045*	0.9423***	0.9763***	0.9779***	0.8408***
	(0.00)	(0.60)	(0.00)	(0.00)	(0.00)	(0.00)
ν	0.2851*	-0.0016	0.5112***	0.5578***	0.4077	0.3720*
	(0.06)	(0.99)	(0.00)	(0.00)	(0.63)	(0.07)
Log Likelihood	-953.62	-538.28	-811.72	-751.74	-819.90	-515.38

Table 11. Impact of oil price and OVX fluctuations on Southeast Asian stock returns, post-crisis period

*The table reports estimation results of ARJI-GARCH model defined as equations (14) to (18). The subsample spans from 2010 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.0282**	0.0114*	0.0392***	0.0186**	0.0317***	0.0282***
	(0.01)	(0.08)	(0.00)	(0.02)	(0.00)	(0.00)
ψ_1	0.0268	0.0938***	0.0522**	0.0303	0.0329	0.0629***
	(0.24)	(0.00)	(0.03)	(0.17)	(0.14)	(0.00)
ψ_2	0.0322***	0.0456***	0.0370***	0.0546***	0.0362***	0.0256**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
ψ_3	-0.0196***	-0.0093***	-0.0079	-0.0211***	-0.0193***	0.0004
	(0.00)	(0.00)	(0.13)	(0.00)	(0.00)	(0.93)
ω'	0.0010**	0.0002*	0.0075***	0.0009**	0.0004**	0.0005
	(0.03)	(0.07)	(0.00)	(0.03)	(0.04)	(0.14)
α'	0.0045**	0.0094***	0.0531***	0.0169**	0.0140*	0.0072**
	(0.01)	(0.00)	(0.00)	(0.01)	(0.05)	(0.02)
β'	0.9823***	0.9800***	0.8917***	0.9613***	0.9675***	0.9761***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
θ	-0.0685*	-0.0467	-0.3181**	-0.0569	-0.0343**	-0.0274*
	(0.07)	(0.15)	(0.02)	(0.16)	(0.01)	(0.07)
d^2	0.7766***	0.4867***	0.7695***	0.4453***	0.4668***	0.4382***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
λ_0	0.0280***	0.0141**	0.0103*	0.0119**	0.0235***	0.1358***
	(0.00)	(0.03)	(0.07)	(0.02)	(0.00)	(0.00)
ρ	0.9216***	0.9377***	0.8901***	0.9642***	0.9635***	0.8489***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ν	0.4943***	0.4659***	0.3591***	0.3771***	0.4674***	1.1428***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Likelihood	-1679.35	-588.64	-1380.28	-846.47	-1385.90	-1472.79

Regarding the effect of OVX, only three out of six countries analyzed show the significant evidence of the connection between OVX return and stock price fluctuation during crisis from 2007 to 2009. Differing from the result for whole sample, the estimated value for parameter ψ_3 for Vietnam in crisis subsample is statistically significant at the 1% level, implying the link between OVX and Vietnam stock market becomes more obvious during this period. Generally, the influence of OVX on stock returns is found in most Southeast Asian markets in both crisis and post-crisis periods. Stock prices negatively response to the changes of OVX and the connection is stronger during crisis, as evidenced by greater magnitude of estimated coefficients. This result is different from the findings of Dutta et al. (2017), which indicates that the effect of oil price volatility on stock market returns tends to be weak during the global financial crisis period.

As can be seen from table 10 and table 11, the mean parameters of jump seem to be more significant in crisis period comparing to the post-crisis period. However, time-varying characteristic of jumps are found to more likely exist during post-crisis period. Contrast to the result for whole sample, the estimates of jump intensity parameters (λ_0, ρ, ν) for Singapore are all significant in subsample analysis, suggesting that the jumps in return are time-varying in both crisis and post-crisis period. Additionally, the findings in subsample analysis are consistent with the result of whole sample estimation in suggesting that jump behavior driven by abnormal information has a negative impact on stock returns, as evidenced by negative coefficients of the jump mean.

7.4. Testing the asymmetric effect of OVX on Southeast Asian stock returns

The stock market returns in Southeast Asia are significantly influenced by the volatility of crude oil prices, as the findings in previous part of current research. In this section, the study explores the asymmetric impact of OVX on stock returns. The research of Dutta et al. (2017) indicate that the effects of OVX return on 23 emerging stock markets are symmetric. However, the asymmetric evidences are found in the study on EUA markets of Dutta (2018), suggesting that the increase and decrease of OVX do not have similar impact on stock markets.

Table 12. Test for asymmetric impact of OVX

*The table presents the estimates of the model defined by equations (20) to (22). The subsample spans from 2007 to 2017. The last row indicates the test statistics for Wald test with the null hypothesis H_0: $\phi_2 = \phi_3$. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	-0.0041 (0.78)	0.0171* (0.05)	0.0332** (0.01)	0.0017 (0.85)	0.0362*** (0.00)	0.0128 (0.30)
ϕ_1	0.0698*** (0.00)	0.0892*** (0.00)	0.0622*** (0.00)	0.0362* (0.07)	0.0448** (0.02)	0.1567*** (0.00)
ϕ_2	-0.0235*** (0.00)	-0.0300*** (0.00)	-0.0333*** (0.00)	-0.0299*** (0.00)	-0.0428*** (0.00)	-0.0114 (0.11)
ϕ_3	-0.0301*** (0.00)	-0.0095 (0.12)	0.0020 (0.83)	-0.0291*** (0.00)	-0.0221** (0.01)	0.0088 (0.36)
ω	-0.1050*** (0.00)	-0.1220*** (0.00)	-0.1257*** (0.00)	-0.1004*** (0.00)	-0.1376*** (0.00)	-0.2167*** (0.00)
α	0.1323*** (0.00)	0.1322*** (0.00)	0.1385*** (0.00)	0.1133*** (0.00)	0.1613*** (0.00)	0.2257*** (0.00)
δ	-0.0670*** (0.00)	-0.0492*** (0.00)	-0.0778*** (0.00)	-0.0690*** (0.00)	-0.0572*** (0.00)	-0.0260*** (0.00)
β	0.9892*** (0.00)	0.9878*** (0.00)	0.9815*** (0.00)	0.9918*** (0.00)	0.9870*** (0.00)	0.9597*** (0.00)
Chi-Sq. Statistic	0.2161 (0.64)	4.8626** (0.03)	6.9990*** (0.00)	0.0087 (0.92)	2.4644 (0.12)	2.1129 (0.14)

The model for testing the asymmetric impact of the implied crude oil volatility index shocks on the Southeast Asian stock markets is as follows:

(20) $$R_{i,t} = \mu_i + \phi_{1,i} R_{i,t-1} + \phi_{2,i} \Delta OVX_t^+ + \phi_{3,i} \Delta OVX_t^- + \varepsilon_{i,t}$$

where $R_{i,t}$ is the log return of stock market index i between time t and t -1, μ_i is a long-term drift coefficient, $\Delta OVX_t^+ = \max(\Delta OVX_t, 0)$ and $\Delta OVX_t^- = \min(\Delta OVX_t, 0)$ with $\Delta OVX_t = 100 \times [\log(OVX_t) - \log(OVX_{t-1})]$, and $\varepsilon_{i,t}$ is error term for the return on series i at time t, which is assumed to be:

(21) $$\varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_{i,t} \qquad z_{i,t} \sim \text{i.i.d. } (0, 1)$$

(22) $$\log(h_{i,t}) = \omega_i + \frac{\alpha_i \left|\varepsilon_{i,t-1}\right| + \delta_i \varepsilon_{t-1}}{\sqrt{h_{i,t-1}}} + \beta_i \log(h_{i,t-1})$$

In order to examine whether the impacts of positive and negative oil volatility shocks are asymmetric, the null hypothesis of the test is: H_0: $\phi_2 = \phi_3$.

Table 12 illustrates the results for testing the asymmetry of OVX effect on Southeast Asian markets. Four out of six nations exhibit the symmetry while the test for Malaysia and Philippines show the asymmetric impacts of positive and negative shocks on the OVX. In Malaysia, the difference of effects is significant at the 5% level and in Philippines the null hypothesis of symmetry is rejected at the 1% level. There is no significant evidence of the asymmetric impact found in Indonesia, Singapore, Thailand, and Vietnam. Generally, the OVX shocks have negative influences on the stock returns in Southeast Asian markets, but an increase in the OVX seems to have higher magnitude than a negative movement.

7.5. Robustness test

To strengthen the exploration for the connection between international oil market and stock returns in Southeast Asian area, the research conducts the tests by using weekly data. Some researchers (Hedi Arouri & Khuong Nguyen, 2010; Lin, Wesseh, & Appiah, 2014) suggest the ability of weekly observations in countering potential biases that may occur from using daily data. In the test, West Texas Intermediate (WTI) price index replace the Dubai crude oil price. The ARJI-GARCH models are used to analyze the impact of oil price and oil volatility indices in stock returns separately. The results using WTI price are shown in table 13, and the estimates using OVX are presented in table 14.

As illustrated in table 13, the estimated coefficients for return of WTI index confirm the positive impact of international oil price on the Southeast Asian stock markets. The outcomes of models using OVX in table 14 also report the adverse effect of oil price volatility on six markets investigated. Therefore, the findings hold for both oil price and oil volatility index, suggesting the linkage between international crude oil and Southeast Asian stock markets. Moreover, the GARCH effect are significant and satisfied the requirement of positivity, except for Singapore in the test using WTI index and for Philippines in the test employing OVX. However, the estimated coefficients for these case is statistically in significant.

The evidences of jump effects on Southeast Asian stock returns are also found in the tests using weekly data, and the jump intensity is time-varying most markets examined. Additionally, the test results illustrate the negative impacts of jump behavior on stock returns and the positive influences of volatility driven by abnormal information on the volatility of returns in Southeast Asian markets.

In overall, the findings are consistent with those reported in previous sections, suggesting the significant impacts of the international crude oil price and the implied oil volatility index on the Southeast Asian stock returns.

Table 13. Impact of WTI index on stock returns using weekly observations

The table reports estimation results of ARJI-GARCH model defined as follows:

$$R_{i,t} = \tau_i + \psi_{1,i} R_{i,t-1} + \psi_{2,i} RWTI_t + \varepsilon_{i,t} \qquad \varepsilon_{i,t} = \varepsilon_{1i,t} + \varepsilon_{2i,t}$$

$$\varepsilon_{1i,t} = \sigma_{i,t} z_{i,t} \qquad z_{i,t} \sim i.i.d.\ (0,1) \qquad \sigma^2_{i,t} = \omega'_i + \alpha'_i \varepsilon^2_{1i,t-1} + \beta'_i \sigma^2_{i,t-1}$$

$$\varepsilon_{2i,t} = \sum_{k=1}^{n_t} Y_{it,k} - \theta\lambda_t \qquad Y_{it,k} \sim N(\theta, d^2) \qquad \lambda_{i,t} = \lambda_{i0} + \rho_i \lambda_{i,t-1} + \nu_i \xi_{i,t-1}$$

*where $R_{i,t}$ is the log return of stock market index i between time t - 1 and t, $RWTI_t = 100 \times [\log(WTI_t) - \log(WTI_{t-1})]$ with $WTI_{i,t}$ is the WTI index value at time t. The weekly data used for estimation spans from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.2457***	0.1218***	0.3624***	0.2487***	0.2547***	0.0759
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)
ψ_1	-0.1638***	-0.2220***	-0.1413***	-0.0921*	-0.1551***	0.0463
	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.26)
ψ_2	0.0581**	0.2141***	0.1281***	0.1624***	0.1612***	0.1455***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ω'	0.0061	0.0341***	0.0115	-0.0025	0.0071	0.0151
	(0.45)	(0.00)	(0.38)	(0.47)	(0.40)	(0.22)
α'	0.0510**	0.1502***	0.0999**	0.0723***	0.0803***	0.0689**
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.04)
β'	0.9112***	0.8683***	0.8405***	0.8929***	0.8834***	0.8728***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
θ	-1.5881**	-2.2922***	-1.2145***	-0.9305***	-1.5140***	-0.1893
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.47)
d^2	1.7179***	2.8006***	-0.0000	-0.0000	0.0000	1.9853***
	(0.00)	(0.00)	(0.99)	(0.99)	(0.99)	(0.00)
λ_0	0.0303	0.1145***	0.1346**	0.1421**	0.0504	0.1029
	(0.15)	(0.00)	(0.03)	(0.02)	(0.27)	(0.13)
ρ	0.7731***	-0.3341***	0.4676*	0.5289***	0.6631**	0.6111**
	(0.00)	(0.00)	(0.05)	(0.00)	(0.02)	(0.02)
ν	0.2573	-0.0875**	0.3126**	0.3833**	0.2933	0.3806
	(0.12)	(0.04)	(0.04)	(0.02)	(0.12)	(0.22)
Log Likelihood	-886.65	-507.30	-821.15	-707.73	-845.50	-977.46

Table 14. Impact of OVX on stock returns using weekly observations

The table reports estimation results of ARJI-GARCH model defined as follows:

$$R_{i,t} = \tau_i + \psi_{1,i} R_{i,t-1} + \psi_{2,i} \Delta OVX_t + \varepsilon_{i,t} \qquad \varepsilon_{i,t} = \varepsilon_{1i,t} + \varepsilon_{2i,t}$$

$$\varepsilon_{1i,t} = \sigma_{i,t} z_{i,t} \qquad z_{i,t} \sim i.i.d.\ (0,1) \qquad \sigma^2_{i,t} = \omega'_i + \alpha'_i \varepsilon^2_{1i,t-1} + \beta'_i \sigma^2_{i,t-1}$$

$$\varepsilon_{2i,t} = \sum_{k=1}^{n_t} Y_{it,k} - \theta\lambda_t \qquad Y_{it,k} \sim N(\theta, d^2) \qquad \lambda_{i,t} = \lambda_{i0} + \rho_i \lambda_{i,t-1} + \nu_i \xi_{i,t-1}$$

*where $R_{i,t}$ is the log return of stock market index i between time t - 1 and t, $\Delta OVX_t = 100 \times [\log(OVX_t) - \log(OVX_{t-1})]$. The weekly data used for estimation spans from 2007 to 2017. Values in the parentheses indicate the p-value. ***, **, and * indicate the significant level of 1%, 5%, and 10% respectively.*

Countries	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
μ	0.2302***	0.0582***	0.3086***	0.0886*	0.1983***	0.0607
	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.22)
ψ_1	-0.1538***	-0.0316	-0.1080**	-0.0244	-0.1016**	0.0549
	(0.00)	(0.45)	(0.02)	(0.63)	(0.03)	(0.21)
ψ_2	-0.0323***	-0.0234***	-0.0495***	-0.0507***	-0.0435***	-0.0273**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
ω'	0.0078	0.0001	-0.0057	0.0136*	-0.0029	0.0156
	(0.41)	(0.95)	(0.21)	(0.06)	(0.48)	(0.17)
α'	0.0599*	0.1146***	0.0857**	0.0796***	0.0745***	0.0560*
	(0.05)	(0.00)	(0.04)	(0.00)	(0.00)	(0.06)
β'	0.8997***	0.8365***	0.8511***	0.8841***	0.8975***	0.8930***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
θ	-1.6149**	-0.2573**	-0.2223*	-1.0011**	-0.5606**	-0.1035
	(0.04)	(0.04)	(0.06)	(0.01)	(0.04)	(0.67)
d^2	1.7331***	0.6952***	0.6756***	0.7109*	-0.8838***	1.9656***
	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)
λ_0	0.0254	0.2031	0.5941**	0.0378	0.0422	0.0955
	(0.17)	(0.30)	(0.04)	(0.31)	(0.30)	(0.15)
ρ	0.7977***	0.1415	0.4777**	0.6818***	0.8815***	0.6708**
	(0.00)	(0.85)	(0.02)	(0.00)	(0.00)	(0.01)
ν	0.2501	-0.1689	1.1303*	0.7802*	0.3416	0.5324
	(0.14)	(0.34)	(0.06)	(0.09)	(0.31)	(0.15)
Log Likelihood	-884.32	-514.08	-822.15	-720.45	-851.91	-987.26

8. CONCLUSION

The main purpose of the research is to explore the connection between international oil indices and Southeast Asian stock markets. In the study, besides using EGARCH model, the GARCH-jump models are employed to capture the movement of stock returns. The findings confirm the significant impacts of oil price fluctuations on stock markets, especially for six markets investigated. In five emerging and frontier markets, namely Indonesia, Malaysia, Philippines, Thailand, and Vietnam, the magnitude of the impact of oil price return on stock markets is as high as in the developed market in the region, Singapore. Additionally, the oil price shocks have positive effects on stock returns for all analyzed Southeast Asian markets in both crisis and post-crisis period. However, the impact seems to be higher during global financial crisis period, and most examined stock markets exhibit stronger response to the negative shocks on the oil price index than the positive movements. This result, therefore, strengthen the understandings on oil-stock relationship which is examined in many existing literatures for various markets (Zhang & Chen, 2011; Cunado & Perez de Gracia, 2014; Raza, Jawad Hussain Shahzad, Tiwari, & Shahbaz, 2016; Noor & Dutta 2017).

Similar to the study of Dutta et al. (2017), the outcomes indicate the significant relationships between the implied crude oil volatility index (OVX) and stock markets in Southeast Asian region. While the changes of oil price have positive effect on stock returns, the impacts of OVX are negative, implying that the increase in level of uncertainty future oil prices leads to negative fluctuation on stock markets. This association is relatively stronger in crisis period and symmetric in most markets, except for Malaysia and Philippines. The research also analyzes whether the volatility is transmitted from oil market to stock markets, but the evidences found is relatively weak after controlling for the impact of implied volatility index (VIX).

The study further reports the existence of GARCH effects in Southeast Asian stock markets, suggesting the current conditional volatility of return is affected by the previous shock and its past volatility. Besides, the results from EGARCH models illustrate that the previously negative shocks seem to have greater effects on the current volatility of stock returns in Southeast Asian countries than the positive one. Furthermore, the jump effects are found in most markets, as evidenced by the estimates for GARCH-jump models. Generally, the volatility driven by abnormal information positively affects the volatility of returns while the jump behavior has negative impact on returns in the Southeast Asian markets.

In overall, the outcomes of research suggest the significant interaction between the Southeast Asian stock markets and the global oil indices. Besides confirming the oil-stock markets relationship, the study indicated the negative influences of oil volatility shocks on stock market returns in Southeast Asian countries. The results of empirical analysis could be utilized in improving the prediction of stock price movements, forming a proper investment decision. Furthermore, the stock return volatility investigations in this study also support developing a diversified portfolio and enhancing risk management activities when the linkages between some new markets in Southeast Asian region and the global markets are deeply comprehended. The exploration on asymmetric effect of oil index and the dissimilarity of the oil-stock relationship through different time periods could be considered as a vital information for building appropriate strategies and policies in each type of global shocks. Additionally, the jump effect in stock returns could be considered in forecasting stock price movement, and the existence of time-varying characteristic of jumps could illustrate possible crash in the stock markets (Noor & Dutta, 2017).

Although the study has a number of implications, it also has a limitation. The future research could further examine the return of each sector in Southeast Asian markets and considers the individual characteristic of stock indices. Besides, the gap between domestic and global oil price should be considered since the domestic economy is directly affected by the national energy prices rather than international oil index. Moreover, due to the different culture, the business cycles in these Asian countries might be dissimilar with the other economies. Consequently, some other specific component could be added to the model to improve the explanation of stock price movements in Southeast Asia markets.

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