Empirical Analysis of Oil Price Volatility and Stock Returns in ASEAN-5 Countries Using DCC-GARCH

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ABSTRACT

This paper examines the dynamic correlation between oil volatility and five ASEAN stock markets using the DCC-GARCH approach. The oil volatility index (OVX or CBOE crude oil volatility index) was used and realised variance (RV) derived from WTI (West Texas Intermediate) crude oil prices. The aim was to examine optimal oil volatility measures between these proxies and to investigate the OVX index as a volatility measure for emerging countries. Findings show that both proxies had a negative correlation to these stock markets between 2007 and 2017, with the exception of the Philippines' stock market. Furthermore, results suggest RV is still a better measure compared with OVX for ASEAN-5 stock markets.

Keywords: ASEAN-5, DCC-GARCH, crude oil volatility index, oil volatility

INTRODUCTION

Oil is an essential commodity for an economy. For firms, future cash flows may depend on oil price as an input to the production process whereby higher oil prices will increase cost of production. For households, changes in the price of oil may

have an impact on oil-related spending. Higher oil prices will affect household expenditures on such needs. Many studies on oil volatility and stock markets mainly focus on developing countries. For example, Hamilton (2003) revealed that oil prices tended to remain stable until 1973 for the US economy. However, after 1973, oil price shocks had stronger impacts on the economy. Elder and Serletis (2010) showed that a structural break in the relationship between oil prices and macroeconomic variables in US happened in 1986 due to excessive supply of oil. Herrera, Lagalo and Wada (2011) reported that an increase

in oil prices will be more significant in affecting macroeconomic variables rather than decline in crude oil prices. Driesprong, Jacobsen and Maat (2008) claimed that oil price volatility has little impact on developed countries. However, similar studies, which focus on emerging countries, remain limited, particularly on a specific region. Narayan and Narayan (2010) showed that the Vietnam stock market has a positive correlation with oil prices. Wei and Guo (2017) reported an unstable relationship between oil price shocks and China's stock market.

This study examines the relationship between stock markets in five Southeast Asian countries (henceforth referred to as the ASEAN-5) and oil price volatility. Two indicators are used, namely oil volatility index (OVX) and realized variance (RV) derived from WTI (West Texas Intermediate) crude oil prices. The OVX index, published on May 10, 2007 by The Chicago Board Options Exchange (CBOE), is used as an oil price volatility proxy for emerging countries. . It is an option index of the United States Oil Fund (USO), which measures oil price volatility over 30 days. The USO is a collection of crude oil commodities comprising options for oil futures and forward contracts and traded on the New York Mercantile Exchange. This study employs the bivariate dynamic conditional correlation GARCH, proposed by Engle (2002), to examine the relationship between stock market prices and oil volatility. Realized variance (RV) estimates were used to compare against OVX estimates. From the theoretical perspective, this paper contributes to the modern portfolio theory such as Markowitz (1952, 1959) by examining the empirical aspects of oil as a hedging instrument, particularly in the context of investment in ASEAN-5 stock market.

The rest of this paper is organised as follows. Section 2 is a literature review of studies on oil volatility and emerging markets. Data and methodology are presented in Section 3 while Section 4 discusses the research findings and implications. Section 5 summarises and concludes the paper.

LITERATURE REVIEW

The relative importance of oil price to stock market has been widely studied. Arouri and Rault (2012) examined the long-run relationship between oil price volatility and stock markets in Gulf Cooperation Council (GCC) countries. They find that oil prices was a determinant and a predictor of stock returns for GCC countries that are major energy market players. Oil price increases have a positive relationship with stock markets, except Saudi Arabia. Other research focuses on the relationship between oil exporting and importing countries. Using BEKK GARCH models, Filis, Degiannakis and Floros (2011) reported no difference between oil-importing and oil-exporting countries regarding time-varying correlation. They also found that lagged oil prices have a positive relationship with those markets. However, during economic crises,

oil commodity does not serve as hedge instruments for stock investment.

However, there is still dearth of studies on the integration between stock markets and oil price for emerging countries. Click and Plummer (2005) examined the relationship between ASEAN-5 stock market after the 1998 financial crisis. They found a cointegration between these markets using local currency and the US dollar in terms of daily and weekly data. Using Vietnam as a case study, Narayan and Narayan (2010) revealed a cointegration among stock prices, oil prices, and nominal exchange rates that is not consistent with theoretical models. They also found that internal factors such as local market participants play an important role in explaining this finding. Using G7 country data, Diaz, Molero and de Garcia (2017) showed that oil price volatility has a stronger relationship with stock markets as opposed to oil price volatility. Using Chinese stock market data from 1996 to 2015, Wei and Guo (2017) noted a significant impact of oil price shocks on the stock market. They also reported the shocks have stronger effects on stock return rather than on stock volatility.

There is no consensus on good volatility measures or indicators. Diaz et al. (2017) used different specifications of oil price volatility: nominal and real prices. Andersen, Bollerslev, Diebold and Ebens (2001), and Barndorff-Nielsen and Shephard (2002) argued that RV is a good measure of volatility modelling as it is an unbiased and highly efficient estimator of volatility of returns based on quadratic variation

theory. Degiannakis and Filis (2017) used RA to forecast oil prices using information channels from several assets such as exchange rates, stock markets, government bonds, and other commodity markets. Using different tests and specifications, they found that realised volatility estimators are robust. Luo and Qin (2017) showed that OVX is a more accurate measure of oil price volatility because it is forward-looking at the market's expectation against WTI price volatility.

Engle (2002) developed univariate GARCH models into multivariate GARCH models known as dynamic conditional correlation or DCC GARCH models. Laurent, Rombouts and Violante (2012) argued that the DCC GARCH is a cost-effective model because conditional volatility and multivariate model GARCH correlation analysis are limited to dimensional dimensions. Ferli and Husodo (2013) employed DCC GARCH to determine the correlation between oil price volatility and stock markets in 13 Asia Pacific countries and five Latin-America countries. They found substantial interdependence between several countries where the contagion effect emerges. Kuper (2007) argued the DCC model has an advantage because it assures a definite positive on the conditional correlation matrix for the time-dependent. Syllignakis and Kouretas (2011) showed that DCC GARCH models can obtain all possible pairwise correlation coefficients from the return index on the sample and at times of unusual events such as the financial crises.

METHODS

The paper aims to examine the dynamic correlation between oil price volatility with the index return of ASEAN-5 stock market comprising Indonesia (Jakarta Composite Index – JCI), Malaysia (FTSE Malaysia Composite Index – KLCI), Thailand (Bangkok Stock Exchange – SET), Philippine (Philippine Composite Index – PSE), Singapore (Singapore Stock Exchange – SGX). The OVX and RV, derived from the WTI oil price, were used. Data was collected on May 10, 2007, as the day of the launch of the OVX index. All data variables in this study are obtained from Bloomberg and are estimated using OxMetrics 7. The RV and the return, r_t, can be expressed as follows:

$$RV_t = r_t^2 \tag{1}$$

,

$$r_t = 100 \times (\log p_t - \log p_{t-1})$$

(1)... $\tag{}$

where p_t denotes the price at period t. Augmented Dickey Fuller tests were used to check stationarity condition for each variable. The DCC-GARCH model was used to examine the relationship between oil price volatility and stock market returns. Let H_t be the variance-covariance matrix as:

$$H_t = D_t R_t D_t \tag{2}$$

where D_t represents an $n \times n$ diagonal matrix of conditional standard deviation

in period t and R_t is the $n \times n$ matrix of conditional correlation in period t. Following Engle (2002), the coefficient correlation matrix of DCC-GARCH model can be expressed as:

$$R_t = diag\{Q_t^*\}^{-1} Q_t diag\{Q_t^*\}^{-1}$$

(3)

where Q_t denotes an $n \times n$ symmetric positive definite variance-covariance matrix, $diag(.)$ denotes a matrix that contains the main diagonal elements of $(.)$, and Q^* denotes a matrix that takes the square roots of each element in Q. The specification are estimated using maximum likehood methods. The coefficient correlation of DCC-GARCH model can be computed as follows:

$$\rho_{12t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1,t-1}\mu_{2,t-1} + \beta q_{12,t-1}}{\sqrt{\left((1-\alpha-\beta)\bar{q}_{11} + \alpha\mu_{1,t-1}^2 + \beta q_{11,t-1}\right)\left((1-\alpha-\beta)\bar{q}_{22} + \alpha\mu_{2,t-1}^2 + \beta q_{11,t-1}\right)}}$$

(4)

To compare the estimated results, we use information criteria such as Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan–Quinn information criterion (HQ), and Shibata information criterion. These information criteria have advantages compared with the coefficient of determination method (R^2). Finally, we test whether extreme values may have an impact on DCC GARCH estimations for each specification. We use two distribution assumptions: Gauss distribution and Student's t-distribution.

RESULTS

Throughout the observation period, world oil markets have experienced dramatic price decreases between 2008 and 2010 due to several factors such as oil production, weather, and government policies. Another price shock came in 2014 as a result of growth in US production, high demand from China and Europe, and political disturbances in the Middle East. Due to these events, ASEAN-5 stock markets experienced a similar pattern during the same period, except in Singapore. Figure 1 provides data used this study and relate them to the stock markets in each ASEAN-5 country.

DCC – GARCH Estimation Results

Table 1 reports the results of DCC-GARCH estimations. All ASEAN-5 stock index returns have significant negative time-varying correlations with OVX and RV. These results are consistent with theoretical expectations. The plots for all DCC-GARCH estimations are provided in the next section.

Indonesia – Jakarta Composite Index (JCI)

Figure 2 (left panel) shows that JCI index returns have a negative correlation with the OVX return index. The time-varying correlation between the Indonesian stock market return and the OVX return is around
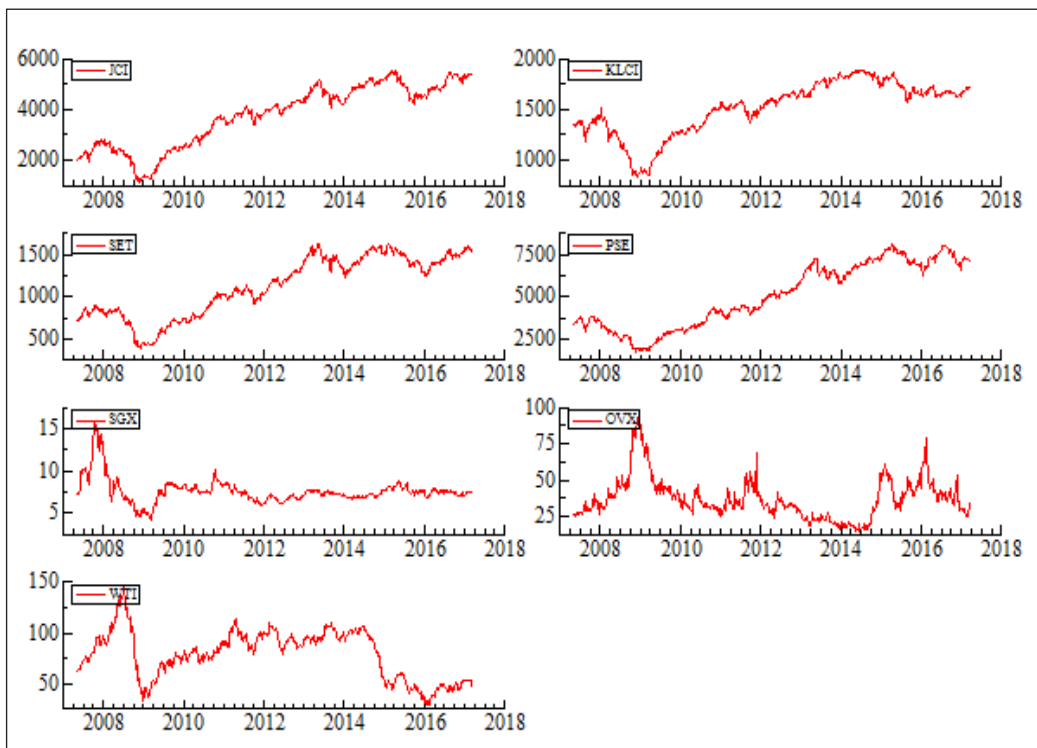

Figure 1. ASEAN-5 Stock Returns, OVX Prices, and WTI Prices.
Source: Bloomberg

Table 1
Results of DCC-GARCH estimations for ASEAN-5 countries

	JCI		KLCI		SET		PSE		SGX	
	OVX	RV	OVX	RV	OVX	RV	OVX	RV	OVX	RV
ρ_{21}	-2.668	-0.167	-0.247	-0.117	-2.668	-0.169	-0.275	-0.199	-2.66	-0.169
	(0.000)	(0.024)	(0.000)	(0.024)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)
α	0.019	0.006	0.01	0.006	0.019	0.099	0.043	0	0.189	0.208
	(0.394)	(0.878)	(0.478)	(0.613)	(0.000)	(0.077)	(0.295)	(0.911)	(0.000)	(0.008)
β	0.87	-0.818	0.975	0.898	0.975	0.898	0.74	0.817	0.008	0.102
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.043)	(0.978)	(0.398)

Note: t-probability Index in parentheses. JCI denotes Jakarta Composite Index, KLCI indicates Kuala Lumpur Stock Exchange Index, SET denotes Stock Exchange of Thailand Index, PSE denotes Philippine Stock Exchange Index, and SGX denotes Singapore Stock Exchange Index. *Source:* Authors' calculations
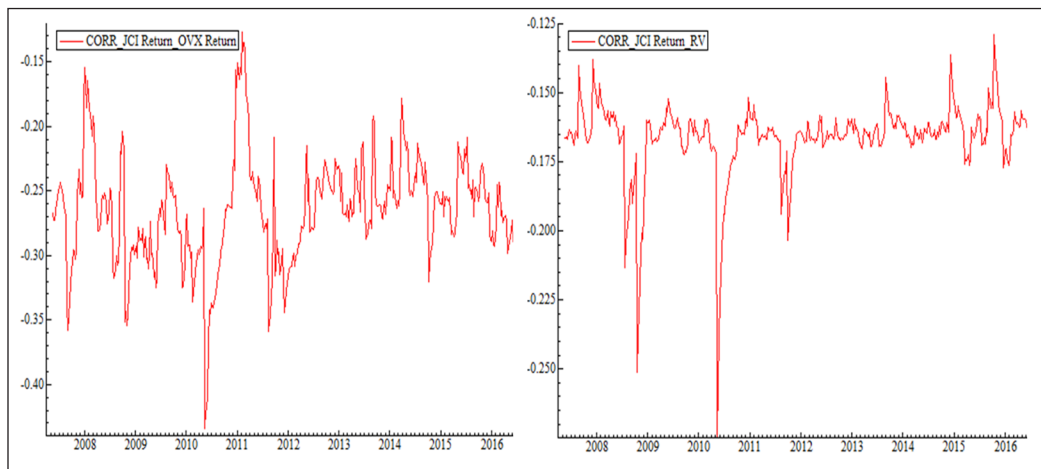

Figure 2. DCC GARCH results for JCI

the 0.25 level. During oil price shocks in 2008 and mid-2014, the former had the highest negative correlation, while in the latter period, the relationship was at an average level.

The correlation between the return of JCI and RV is also negative. However, during the 2008 financial crisis and the oil price shock in mid-2014, the correlation between JCI and RV is higher than between the JCI and OVX index. It can be concluded that the increase or decrease in JCI index returns is different from the OVX return index in the same week. The negative correlations show a distinct movement between JCI volatility with OVX and RV indices not occurring in the same week. The correlation between OVX and JCI volatility is more volatile than the correlation between RV and JCI volatility. This is possibly because OVX contains information across different markets.

Malaysia – Kuala Lumpur Composite Index (KLCI)

Figure 3 shows that the volatility in the KLCI index has a negative correlation to OVX and RV. The correlation between KLCI index volatility with OVX and RV is around -0.250 and -0.12 respectively. The different patterns of the Malaysian stock market index returns with OVX and RV show that the volatility between the two indices does not occur in the same week.

A sharp decline of the Malaysian stock market between 2008 and 2009 which resulted in a negative correlation between KLCI and OVX, can be offset by investing in the stock market. During this period,

KLCI may provide a better investment opportunity compared with the Singapore market, according to the correlation between OVX and KLCI. The correlation between KLCI with OVX and RV in 2008 is -0.225 and -0.10 respectively. Therefore, it can be stated that the volatility of KLCI has more correlation with RV, although negatively correlated. The same can be found during the oil price shock in mid-2014, where the correlation between KLCI with OVX and RV is -0.225 and -0.12respectively. Despite the negative correlation, volatility in the KLCI index seems to better correlate with RV than OVX, either overall or in the event of oil price shocks.
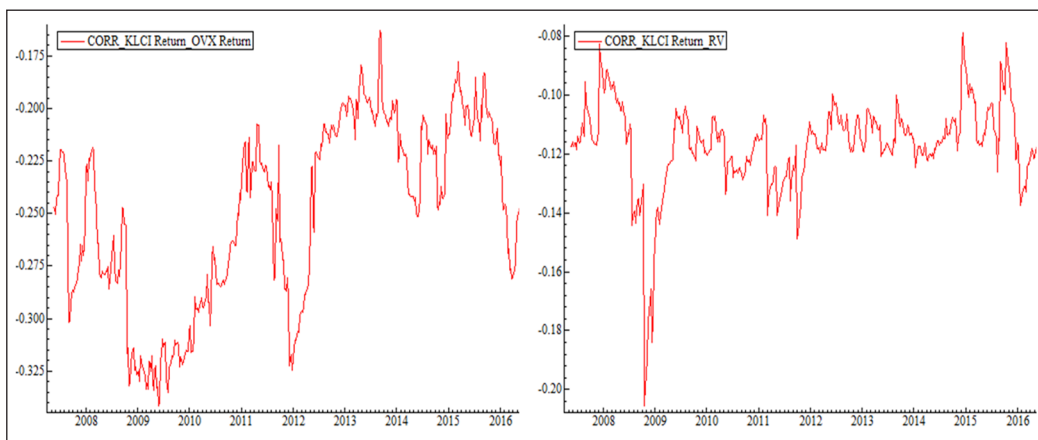

Figure 3. DCC GARCH results for KLCI

Thailand – Stock Exchange of Thailand (SET)

Figure 4 shows a negative correlation between SET with OVX (left panel) and RV (right panel). The correlation between SET returns and OVX is about -0.3, while the correlation between SET and RV is about -0.2. Compared with the results of

other markets such as Indonesia, Malaysia, and the Philippines, the Thai stock market seems be more stable. Although there are positive correlations between volatility in the SET index with OVX and RV for several periods, overall it has a negative correlation. Looking at two oil price shock events that occurred in 2008 and 2014, the SET index

shows a different correlation to both events. In 2008, oil shocks that coincided with the financial crisis, both the OVX and RV, show a positive correlation, despite its small value of 0.1. In contrast with the oil price shocks of 2014, SET index returns have a negative correlation value concerning OVX and RV. However, during the period of oil price shocks, there is a time where a positive correlation exists between the SET index and the OVX and RV indices in 2008 but negatively correlated with the oil price shocks of 2014.
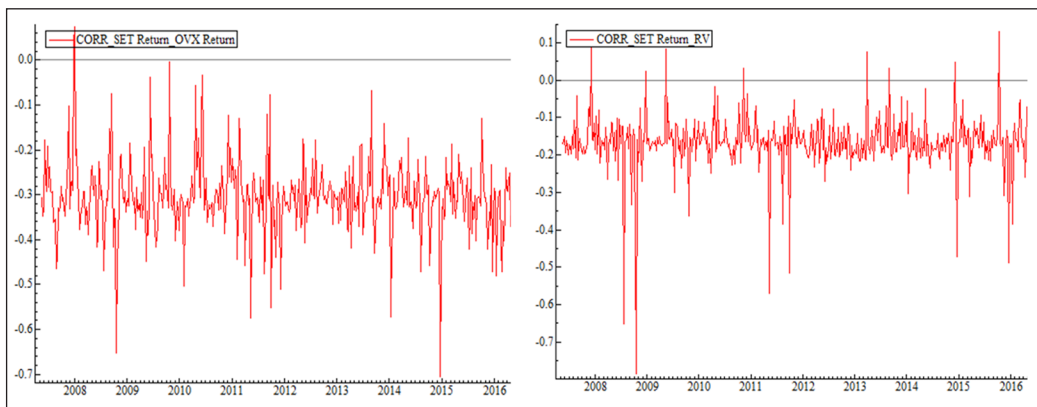

Figure 4. DCC GARCH results for SET

The Philippines – Philippine Stock Exchange (PSE)

Figure 5 shows that the relationship between the return of the PSE volatility and OVX index has a negative correlation with an average value of -0.30 throughout the observation period. However, the correlation between PSE and RV has a positive value in the same period. The correlation between RV and the PSE volatility was positive during the entire study period. It indicates that the increase or decrease in return of the PSE index has the same upward trend or decline in that week. The positive correlation between PSE volatility and RV is possibly due to the Philippines being a net importer.

This study look specifically at two events that occurred during oil price shocks. The correlation between the PSE volatility and OVX is above the average negative correlation and is close to zero during the 2008 financial crisis. However, in regard to the 2014 oil price shocks, the correlation value is average. The correlation between PSE volatility and RV tends to be the same, around 1.998, at the time the two events take place. The correlation between OVX and PSE volatility is still similar to that of other countries. Thus, if we use RV as our volatility measure, it may not be a good idea to invest in the Philippines stock market, especially during an economic turmoil.
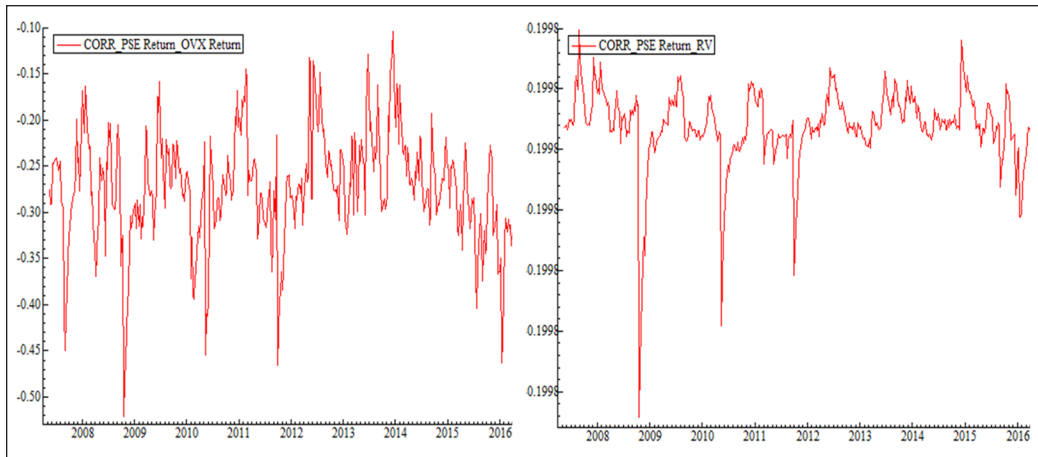
Figure 5. DCC GARCH results for PSE

Singapore – Singapore Stock Exchange (SGX)

Similar to the results for the Thailand stock market, the Singapore stock market seems to have more stable effects with oil price volatility. In Figure 6, the SGX index returns have a negative correlation with OVX and RV during the observation period. For oil price volatility, the average correlation between SGX return and both volatility measures is -0.2.

Furthermore, when observing two oil price shocks in 2008 and 2014, the SGX index has a different response. In 2008, the SGX returns tended to have negative correlations with OVX, but it had a positive correlation at the beginning of 2008. This positive correlation is stronger for the relationship between SGX return and RX. In 2014, the SGX return had a negative correlation with a value equal of -0.2 for the two oil price indices. In summary, the
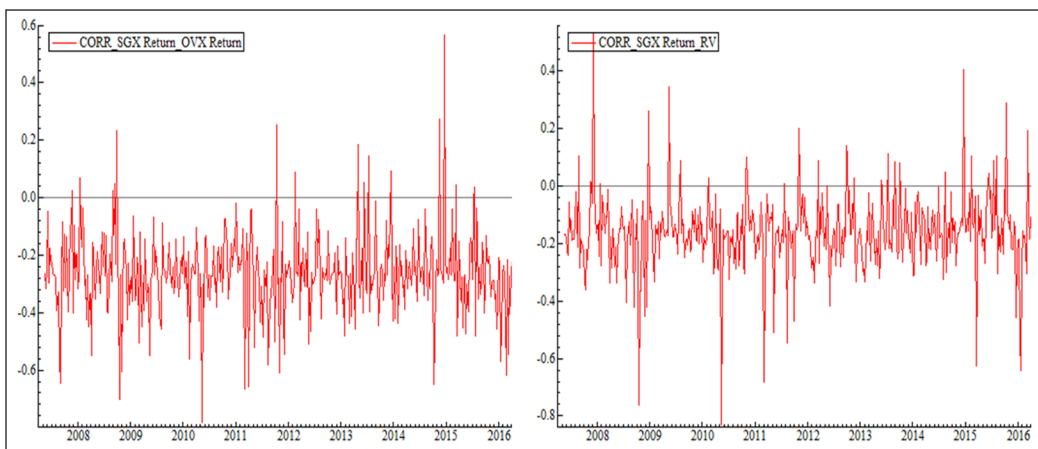

Figure 6. DCC GARCH results for SGX

dynamic correlation between volatility in the SGX index and OVX exhibit a similar pattern to the correlation between SGX volatility and RV.

Information Criterion Analysis

In comparing which oil price volatility measures has better precision with regards to the stock market, we use information criterion for determining the validity of each volatility measure. Table 2 provides the results of information criterion for each specification: JCI, KLCI, SET, PSE, and SGX to OVX and RV index.

Overall, the information criteria (AIC, BIC, HQ, and Shibata) for each specification that uses RV as a volatility measure has a lower value than the results with OVX index

on any index in the ASEAN-5 stock market. It shows that RV can serve as a better volatility measure compared with OVX. That is, in volatility measured by the RV approach, it has a cost of information that is more affordable than OVX. Our results are different compared with those of Luo and Qin (2017) who argue that the OVX index is a better in measuring oil price volatility. The difference is due to the stock markets in ASEAN-5 countries. Although the average value difference between OVX and RV is only 0.50, the RV approach retains a low score on each of the ASEAN-5 stock market indexes. Therefore, it can be concluded that in measuring oil price volatility on the market return in the ASEAN-5 countries, the RV approach is a better.

Table 2
Information criterion

	JCI		KLCI		SET		PSE		SGX	
	OVX	RV	OVX	RV	OVX	RV	OVX	RV	OVX	RV
AIC	-6.21	-6.75	-7.3	-7.83	-6.36	-6.89	-6.27	-6.82	-5.94	-6.46
BIC	-6.12	-6.65	-7.2	-7.74	-6.27	-6.8	-6.18	-6.73	-5.85	-6.37
HQ	-6.17	-6.71	-7.26	-7.79	-6.33	-6.85	-6.24	-6.78	-5.9	-6.43
Shibata	-6.21	-6.75	-7.3	-7.83	-6.36	-6.89	-6.28	-6.82	-5.94	-6.46

Note: JCI denotes Jakarta Composite Index, KLCI indicates Kuala Lumpur Stock Exchange Index, SET indicates Stock Exchange of Thailand Index, PSE denotes Philippine Stock Exchange Index, and SGX denotes Singapore Stock Exchange Index. AIC indicates Akaike's Information Criterion, BIC denotes Bayesian's Information Criterion, HC denotes Hannan-Quinn Information Criterion, and Shibata denotes Shibata Information Criterion. *Source*: Authors' calculations

DCC GARCH with Gauss and Student's t-Distribution

In this section, distribution assumption is examined to see if it influences the results due to the presence of fat tails in each specification. Table 3 reports the results

of the distribution of Gauss and Student's *t*-distribution for the returns for each ASEAN-5 stock market index with the OVX index. The coefficients of α and β from each specification of the ASEAN-5 stock market index to the OVX index is shown in Table 4.

It suggests that the coefficients estimated by DCC for all indexes of the ASEAN-5 stock market against the OVX index are less than 1. This shows that α and β have positive scalar parameters. The values may vary for each specification.

The results in Table 4 show that the Student's t-distribution has a more substantial log-likelihood value compared with the Gauss distribution on the five ASEAN stock market indices. The value of larger log-likelihood is an indication that Student's t-distribution is distribution because it can capture the fat tails of an empirical distribution. It can be concluded that extreme events during the observation period have impacts on each market in ASEAN-5 countries with respect to oil price volatility.

Table 3
DCC-GARCH-OVX with Gauss and Student's t-distribution: The correlation coefficients

	Gauss (ρ_{21})			Student's t (ρ_{21})		
	Coefficient	Std. error	Log-likelihood	Coefficient	Std. error	Log-likelihood
JCI - OVX	-0.267	0.049	1603.07	-0.219	0.048	1657.49
KLCI - OVX	-0.247	0.063	1882.36	-0.225	0.052	1915.07
SET - OVX	-0.307	0.047	1642.84	-0.28	0.049	1689.84
PSE - OVX	-0.275	0.049	1620.35	-0.252	0.049	1653.64
SGX - OVX	-0.266	0.057	1534.13	-0.268	0.048	1559.18

Source: Authors'calculations

Table 4
DCC-GARCH – OVX with Gauss and Student's t-Distribution: α and β

	Gauss		Student's t	
	Coefficient	Std. error	Coefficient	Std. error
DCC - JCI (α)	0.02	0.023	0.091	0.049
DCC - JCI (β)	0.87	0.149	0.291	0.132
DCC - KLCI (α)	0.01	0.014	0.011	0.021
DCC - KLCI (β)	0.974	0.041	0.947	0.095
DCC -SET (α)	0.091	0.065	0.093	0.053
DCC -SET (β)	0.208	0.763	0.217	0.316
DCC -PSE (α)	0.043	0.041	0.086	0.055
DCC -PSE (β)	0.741	0.328	0.513	0.365
DCC -SGX (α)	0.19	0.053	0.169	0.058
DCC -SGX (β)	0.008	0.268	0.021	0.241

Source: Authors'calculations

CONCLUSIONS

Using DCC-GARCH methods, the results for each stock market in ASEAN-5 countries are mixed due to different characteristics in each market. The JCI index return has a negative correlation with the OVX and RV for all observation periods. The results for KLCI are similar to the JCI index return and have a negative dynamic correlation to the OVX index and RV throughout the study period. For Thailand, the return of the SET index has a negative dynamic correlation to the OVX index and RV. However, we also find a positive correlation dynamic between the Thai stock market and oil price volatility in 2008. For the Philippines, the volatility in PSE index has a negative correlation to the OVX index but has a positive relationship to RV over the observation period. The SGX index return has a negative correlation to the OVX and RV, but some periods have a positive correlation. Only Singapore has a similar pattern of dynamic correlation between stock market volatility and OVX and RV.

This study finds a negative correlation between the stock market returns of ASEAN-5 countries and oil price volatility, with an exception for the Philippines' stock market estimates with RV as a volatility measure. During an economic turmoil, Malaysia's stock market may provide a better investment opportunity in a portfolio, which comprises oil commodity and equity investments. Findings also show that the RV is a better measure than the OVX index to estimate the relationship between stock market returns for each ASEAN-5 country and oil price volatility. The relationship between oil price volatility and stock market returns is also characterised by extreme events during the observation period. Findings also point to the importance of volatility in commodity and stock markets for asset pricing, investment portfolio, and risk management.

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