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Dynamic correlation between Crude Oil Price and Exchange rate: The Case of ASEAN-5

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Abstract

This study examines the relationship between exchange rate and crude oil price of five Southeast Asia countries including Indonesia, Malaysia, Philippines, Thailand and Singapore from January 1979 to January 2022 using monthly data. Augmented Dickey-Fuller test is used to examine the stationarity of the data. DCC-GARCH model is used to investigate the correlation between oil price and exchange rate. The result shows that skewness, kurtosis, autocorrelation and ARCH effects were found in both oil price and exchange rate. Results suggested that both short run persistence (α) and long run persistence(β) are found to be highly significant for oil price and exchange rate of all countries except Indonesia. Furthermore, the correlation coefficients vary over times for all the countries studied. Negative relationship was found between oil price and exchange rate over most of the periods studied in all countries studied.

Keywords DCC GARCH, Exchange rate, Gold price

INTRODUCTION

Crude oil is one of the most essential commodities of the global economy. It is one of the most commonly traded commodities. Over the past five years, oil prices have been priced rather high at above $40 per barrel for most of the period except for March to June 2020 and August to October 2020. The decrease in oil prices in 2020 was mainly due to COVID-19 pandemic. People all around the world were under strict lockdown. The imposition of travel restrictions by numerous countries resulted in a rapid fall in demand for crude oil. Furthermore, the pricing war between Russia and Saudi Arabia, as well as an oversupply of crude oil also caused an unusual drop in oil prices. However, oil prices in 2022 have been erratic. Early March 2022, Libya, which owns the world's 9th largest known oil reserves, halted two of its oil fields [1]. The shutdown of oil fields which was caused by political crisis has resulted in the loss of 330,000 barrels of crude oil per day [2]. Furthermore, the United States has imposed sanctions on Russia's oil and gas as a result of the Russia-Ukraine war. Consequently, concerns about oil and gas supply disruptions arose since Russia is one of the largest oil producers of oil in the world, supplying 11% of global oil consumption in 2021. As a result of the sanctions and concerns about supply disruptions, Brent crude oil increased by more than $10 and WTI crude oil increased by over $9 in early March 2022. Oil prices are priced in US Dollars and most international crude oil transactions are conducted in US Dollars [3]. Thus, an increase in crude oil demand may cause the local currency to depreciate [3].

Commodity markets have exhibited significant price volatility. Commodities are more volatile than other assets such as equities, bonds, and currencies, especially during bull market periods [4,5]. Issues with liquidity, geopolitical risks, and potential exposure to natural disasters are some of the reasons commodities are relatively volatile [5]. The most commonly used model for modeling volatility is the generalized autoregressive conditional heteroskedasticity (GARCH) family model which was developed by [6] and extended by [7]. The GARCH models have been used to model time-varying volatility. The ability to effectively remove the excess kurtosis in return series is one of the reasons GARCH models are widely used [8] since having excess kurtosis market returns may display seriously skewed distributions.

According to [9], multivariate models generate more reliable models than separate univariate models. Multivariate GARCH was utilized by numerous studies [3, 10] to examine the correlation between time series data. Among the multivariate GARCH, dynamic conditional correlation GARCH (DCC-GARCH) model is largely used by empirical studies [3, 10, 11]. Compared to simple multivariate GARCH, DCC is more accurate. Besides that, DCC GARCH is relatively easier to compute in comparison to other complex multivariate GARCH. The purpose of this study is to investigate the correlation between oil price and exchange rate using DCC-GARCH.

LITERATURE REVIEW

The relationship between oil prices and exchange rates has been examined by numerous empirical studies. However, the findings are inconsistent and remain inconclusive. For example, some studies have reported negative relationships between oil prices and exchange rates, implying that the rise of oil prices resulted in decrease in exchange rate. [12] investigated the relationship between dollar exchange rates, palm oil price, and crude oil price from 2007 to 2013 by employing GARCH (1,1) and C-vine copula models. A weak negative relationship was found between crude oil price and exchange rate. [13] used ARDL bound cointegration test to investigate the correlation between price of oil, price of gold, exchange rate, and stock market index in Mexico. The results show that as an oil-exporting country, the exchange rate of Mexico is negatively affected by oil price in long run [13]. Furthermore, [14] studied the relationship between the exchange rate of Fijian Dollar (FJD) against USD and oil price from 2000 to 2006 through GARCH and exponential GARCH (EGARCH) models. The result indicated that FJD/USD exchange rate decreased with the rise in oil price return [14]. Moreover, [3] investigated the relationship between gold prices, crude oil price, Indian Rupee (INR) against USD exchange rate, and Indian stock market using DCC-GARCH model. The result suggested that fall in both prices of gold and crude oil resulted in depreciation of INR and fall in stock index of India. In addition, [10] employed DCC-GARCH and CCC-GARCH to explore the dynamic relationship between Nigerian Naira against USD exchange rate and crude oil price using daily data. It was reported that higher oil price resulted in decreased of exchange rate and vice versa.

However, positive relationships between oil prices and exchange rates are also reported by literatures, implying that an increase in oil price resulted in increase of exchange rate. For example, [15] analyzed the effect of oil price shocks on Chinese stock market and exchange rate of US Dollar (USD) over Chinese Yuan Renminbi (RMB) through TVP-VAR model. The study reported that during periods of major political and economic events, the oil implied volatility index has positive impact on the changes of both USD/RMB and the stock implied volatility index of China [15]. However, significant positive effects were only observed in short term and faded with time. Additionally, [16] investigated the long-run relationship between oil prices and real exchange rates of G7 countries namely Canada, France, Germany, Italy, Japan, the UK, and the US. The study reported that high oil price increases real exchange rate in long run.

In contrast, some literature reported that the correlation between oil prices and exchange rates are statistically insignificant. For example, [17] discovered no significant relationship found between oil price and real effective exchange rate of Saudi Arabia and Norway. Additionally, [18] found no significant correlation between oil price and real effective exchange rate of Romania. Furthermore, [19] used vector autoregressive (VAR) model to analyze the correlation between crude oil price, Indonesian Rupiah (IDR) against Euro (EUR) exchange rate, and rice price. The study reported presence of short-term relationship between crude oil price, rice price, and IDR/EUR exchange rate but there were absence of long-term relationship between these variables.

Despite the fact that a number of researches have been conducted to investigate the relationship between the price of oil and exchange rate, the findings are inconsistent and remain inconclusive.

Furthermore, the literature in the case of ASEAN countries are rather limited. Hence, this study aims to examine the relationship between oil price and exchange rate of ASEAN countries including Singapore, Malaysia, Thailand, Indonesia, and Philippines to obtain a better understanding of the implications. Furthermore, multivariate GARCH is used in this study to estimate the time series data.

METHODOLOGY

Data and Variables

The correlations between oil price and exchange rate of ASEAN-5 are examined in this study. ASEAN-5 refers to the five original member of Association of Southeast Asian Nations, namely Malaysia, Philippines, Thailand, Singapore and Indonesia. These five countries are selected in this study due to the geographical location. Furthermore, these five countries are favorite destination for investors [20] due to the abundance of natural resources and human resources.

Oil price has been selected in this study since oil price shocks have different effect on economies for oil-exporting countries and oil-importing countries [21]. There are three primary benchmarks for crude oil namely Brent Crude, West Texas Intermediate (WTI) and Dubai crude oil [22]. Brent crude is the most extensively used benchmark, accounting for around two-thirds of the oil traded around the world [22]. It is also the international benchmark price used by the Organisation of Petroleum Exporting Countries (OPEC) [23]. Brent crude is extracted from different fields located in the North Sea. On the other hand, WTI is the main benchmark for United States. WTI is usually extracted from US oil fields in Texas, Louisiana, and North Dakota [23]. Brent has a Sulphur content of 0.37 percent while WTI has a Sulphur content of 0.24 percent, which is lower and considered sweeter. Furthermore, the American Petroleum Institute (API) gravity for WTI and Brent are 39.6° and 38° respectively, making WTI lighter comparatively. Both Brent crude and WTI are consider light and sweet and are useful for pricing sweet crude oil [23].

Brent crude oil price expressed in US dollar (USD) and exchange rates expressed in local currencies are used in this study. Exchange rate is stated in the amount of currencies needed for one unit of USD. The currencies used in this study are the Singapore Dollar (SGD), the Malaysian Ringgit (MYR), the Philippine Peso (PHP), the Indonesian Rupiah (IDR) and the Thai Baht (THB). Monthly sample data of Brent crude oil price and exchange rate of ASEAN-5 is obtained from Yahoo Finance, the period taken is from January 1979 to January 2022. The datasets for both price of Brent crude oil and exchange rate of all countries are transformed into natural logs.

Test of the stationarity of the data

Most of the parametric technique assumes that the data is normally distributed [24]. However, financial time series data posses nonlinear behaviour [25], thus Augmented Dickey-Fuller (ADF) test is used in this study to examine the stationarity of the data. ADF test is a unit root test for stationarity which is extended from Dickey Fuller test [26]. Both ADF test and Dickey Fuller test examine the stationarity of data by determining the presence of unit root in a time series [26]. The model can be written as:

$$\Delta Y_t = \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \delta_2 \Delta Y_{t-2} + \cdots + \delta_p \Delta Y_{t-p} + \varepsilon_t$$
$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_1 \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

GARCH Model

The GARCH model is extended by [7] from autoregressive conditional heteroskedasticity (ARCH) model by [6]. The linear GARCH (1,1) model is frequently employed in financial time series analysis. Due to its simple implementation, it is preferred by many economists over other stochastic models. The GARCH models are a combination of discrete-time stochastic difference equations and the likelihood functions in a model which is easier to compute [27]. A number of studies suggest that the GARCH model is useful to model volatility in the assets [28]. According to [29], GARCH model can deliver a very competitive forecasting performance, converge considerably quicker in maximum likelihood estimation and able to accommodate a significant number of additional parameters. GARCH model also allows for longer memory and a much more flexible lag structure. The GARCH(p, q) model is represented by:

$$\varepsilon_t|\psi_{t-1} \sim N(0, h_t)$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i} \tag{2}$$

where

$$p \geq 0, \;\; q > 0$$
$$\omega > 0, \;\; \alpha_i > 0, \;\; i = 1, \dots, q$$
$$\beta_i \geq 0, \;\; i = 1, \dots, p$$

h_t is the conditional variance, ε_{t-1}^2 is the past squared residual return, ω , α_i, β_j are constant parameters. ω , α_1 , β_1 are non-negative and $\alpha_1 + \beta_1 < 1$. GARCH (p, q) process allows for the entry of lagged conditional variances, which corresponds to an adaptive learning mechanism. The GARCH(p,q) regression model is obtained by allowing ε_t to be innovations in a linear regression,

$$\varepsilon_t = y_t - x'_t b \tag{3}$$

where y_t is the dependent variable, x_t is the vector of explanatory variables, and b is the vector of unknown parameters.

DCC-GARCH Model

The DCC-GARCH model is extended by [30] from constant conditional correlation GARCH (CCC-GARCH) model by [31]. In CCC-GARCH model, the conditional correlation matrix is constant over time, where $P_t = P$. However, the assumption that the conditional correlations are constant over time appears to be excessively restrictive. Assumptions of changes in correlation are often overlooked in empirical studies due to the difficulty of taking them into account.

Unlike CCC-GARCH model, DCC-GARCH allows conditional correlations to vary over time. DCC-GARCH model was proposed by [30] to capture the dynamic correlations of returns. Comparing to simple multivariate GARCH, DCC is more accurate. Besides that, DCC GARCH is relatively easier to compute in comparison to other complex multivariate GARCH. This is because the number of parameters estimated in the correlation process is independent of the number of series to be estimated, resulting in a significant computational advantage when estimating large covariance matrices [30].
Furthermore, [10] reported that DCC-GARCH model outperform CCC-GARCH model in determining the relationships between exchange rate and oil price in the context of Nigeria. Following [30],

$$H_t = D_t R_t D_t \tag{4}$$

where H_t is conditional variance matrix, D_t is the diagonal matrix with time varying standard deviation, $\sqrt{h_{it}}$ and R_t is the time-varying correlation matrix of the standardized disturbances ε_t. The diagonal matrix, D_t is written as:

$$D_t = \begin{bmatrix} \sqrt{h_{1,t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2,t}} & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{h_{3,t}} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \sqrt{h_{n,t}} \end{bmatrix} \tag{5}$$

where the conditional variance, h_{it} are estimated as:

$$h_{it} = \omega_i + \sum_{q=1}^{Q_i} \alpha_{iq} \varepsilon_{it-\mathrm{q}}^2 + \sum_{p=1}^{P_i} \beta_{ip}\, h_{it-p} \tag{6}$$

Since H_t is a quadratic form based on R_t it follows from basics in linear algebra that R_t has to be positive definite to ensure that H_t is positive definite. Furthermore, by the definition of the conditional correlation matrix all the elements have to equal or less than one. To guarantee that both these requirements are met R_t is decomposed into

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{7}$$

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{8}$$

The parameters a and b are scalars, and Q_t^* is the diagonal matrix with square root of diagonal element:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{q_{33t}} & & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \sqrt{q_{nnt}} \end{bmatrix} \tag{9}$$

To ensure that H_t is positive definite, Q_0 has to be positive definite, a and b are non-negative and $a + b < 1$.

RESULTS AND DISCUSSION

This section reports the results of the analysis. The stationarity of the variables including Brent crude oil price and exchange rate of ASEAN-5 are examined using Augmented Dickey-Fuller (ADF) unit root test. Brent crude oil price is labelled as BRENT and exchange rate of Indonesia, Malaysia, Philippines, Singapore and Thailand are labelled as IDR, MYR, PHP, SGD and THB respectively. Since ADF unit root test is very sensitive to lag length selection, VAR Lag Order Selection Criteria is performed to determine the optimal lag length of each variable. Schwarz Information Criterion (BIC) is used for the optimal lag lengths selection. Table 1 shows the results of ADF test.

Table 1 Augmented Dickey-Fuller test output

Variables	**Test Statistics**		**P-value**	**Order of Integration**
BRENT	Level	-1.706031	0.4276	I(1)
	First difference	-15.20958***	0.0000	
IDR	Level	-1.574443	0.4949	I(1)
	First difference	-5.909859***	0.0000	
MYR	Level	-1.434598	0.5660	I(1)
	First difference	-17.05827***	0.0000	
PHP	Level	-2.739287	0.0681	I(1)
	First difference	-5.751663***	0.0000	

SGD	Level	-1.313727	0.6246	I(1)
	First difference	-15.23470***	0.0000	
THB	Level	-2.041142	0.2692	I(1)
	First difference	-8.672712***	0.0000	

Note: *** indicates level of significance at 1%

The results of Table 1 show presence of unit root at level for all variables including Brent crude oil price, suggesting none of the variables are stationary at level. The series are tested again after first difference and results indicate absence of unit root in the first difference, *I* (1) with 1% significant level. Null hypothesis can be rejected by all the differenced series, indicating the absence of unit root and, thus, all variables are stationary after first difference.

The descriptive statistics for the differenced series are presented in Table 2. Differenced series are indicated prefixing the level variable name with "D".

Table 2 Descriptive statistics

	DBRENT	DSGD	DMYR	DIDR	DTHB	DPHP
Mean	0.0001268429	-0.000399469	0.0005384142	0.002636995	0.0004109125	0.001630916
Maximum	0.1878901	0.0255541	00.06809724	0.2941142	0.07486067	0.09532788
Minimum	-0.222112	-0.02320226	-0.06123982	-0.116758	-0.0667854	-0.03094799
Standard deviation	0.04026216	0.005553662	0.008035523	0.0226407	0.009289078	0.009621902
Skewness	-0.4935249	0.1019128	1.03887	5.334528	2.376164	4.294218
Kurtosis	7.157262	4.936909	24.1995	66.43646	31.30869	39.78385
Jaque-Bera	392.53 *** (0.0000)	81.553 *** (0.0000)	9755.3 *** (0.0000)	88967 *** (0.0000)	17715 *** (0.0000)	30676 *** (0.0000)
LB Q-Stat [12]	48.356 *** (0.0000)	47.188 *** (0.0000)	50.497 *** (0.0000)	73.695 *** (0.0000)	80.076 *** (0.0000)	91.216 *** (0.0000)
ARCH-LM [12]	92.22 *** (0.0000)	91.612 *** (0.0000)	255 *** (0.0000)	65.757 *** (0.0000)	196.6 *** (0.0000)	100.93 *** (0.0000)

Note: *** indicates level of significance at 1%. Lag length of Ljung-Box test (LB Q-Stat) and Lagrange Multiplier test (ARCH-LM) are given in brackets [ ].

Among the variables, the exchange rate of Singapore reports the lowest variability, followed by the exchange rate of Malaysia, Thailand, Philippines, and Indonesia, while Brent crude oil price reports the highest variability. Positive skewness is shown in the exchange rate of all countries while negative skewness is shown in Brent crude oil price. If skewness is negative, the market has a downside risk, or there is substantial probability of a big negative return. The kurtosis coefficient of all the time series data is greater than 3. This result indicates that the kurtosis coefficient is very high, confirming that all the time series data poses leptokurtic character, with tails fatter than normal distribution.

The result of Jaque-Bera test for all the variables are significant at 1% level, indicating that all the variables do not have a normal distribution. Furthermore, the result for Ljung-Box test is conducted. The result reported that the null hypothesis can be rejected at 1% significance level. This indicated that the variables are not independently distributed and exhibited a serial correlation, concluding that the time series contain an autocorrelation.

Lastly, ARCH-LM, which is the Lagrange Multiplier test for autoregressive conditional heteroskedasticity (ARCH) is done. Same lag number as Ljung-Box was chosen. The result was labelled as ARCH-LM[12] in Table 2. The null hypothesis can be rejected at 1% levels of significance. The presence of kurtosis, autocorrelation and ARCH effects in all the series confirms that GARCH-type models are suitable for the time series data.

The estimates of DCC-GARCH of oil price and exchange rate for Thailand, Malaysia, Indonesia, Philippines and Singapore are shown in Table 3 to Table 7 respectively. GARCH parameters shows the estimates of standard GARCH (1,1) model and the DCC parameters shows the estimates of DCC (1,1) which are the time-varying correlation. μ is the constant and ω is the variance intercept. α (ARCH term) indicates short run persistence that measure the effect of innovations on volatility while β (GARCH term) indicate the long run persistence which measure the level of volatility persistence. a and b of DCC parameters are scalars. The correlation process of DCC is driven by a and b. According to [30] and [32], the value of a + b must be less than 1.

Table 3 Results of DCC-GARCH of Thailand

GARCH parameters				
	DBRENT		**DTHB**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
μ	0.000178	0.001673	0.000034	0.000309
ω	0.000144 *	0.000085	0.000000	0.000271
α	0.459203 ***	0.146348	0.059135 ***	0.011491
β	0.539797 ***	0.090211	0.914145 ***	0.117189
DCC parameters				
	Estimate		**Std. Error**	
a	0.004946		0.018131	
b	0.995054 ***		0.024764	

Note: *,** and *** indicates 10%, 5% and 1% significant levels respectively

Table 3 shows that both the α and β of oil price and exchange rate of Thailand are statistically significant at 1% level. Lower value of α and higher value of β are shown in both Brent crude oil price and exchange rate of Thailand. Low value of α at 6% and high value of β at 91% are reported in exchange rate of Thailand. In comparison, the β of oil price are relatively low at 54% and the α are rather high at 46%. The value of α + β are less than 1 for both oil price and exchange rate of Thailand. For the DCC model, a is insignificant while b is significant at 1% level. The parameters a and b of DCC model are less than 1. Low values of a and high values of b are reported.

Table 4 Results of DCC-GARCH of Malaysia

GARCH parameters				
	DBRENT		**DMYR**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
μ	0.000178	0.001679	-0.000039	0.000120
ω	0.000144 *	0.000085	0.000000	0.000004
α	0.459203 ***	0.146297	0.266012 ***	0.036426
β	0.539797 ***	0.090164	0.725174 ***	0.045158

DCC parameters		
	Estimate	**Std. Error**
a	0.026683	0.037572
b	0.770344 ***	0.124729

Note: *,** and *** indicates 10%, 5% and 1% significant levels respectively

Table 4 shows that both the α and β of oil price and exchange rate of Malaysia are statistically significant at 1% level. α value for exchange rate of Malaysia is lower at 27% compare to β at 72%. Although α of oil price is also lower than β, comparatively, the β is relatively low at 54% and the α are rather high at 46%. The value of α + β are less than 1 for both oil price and exchange rate of Malaysia. For the DCC model, a is insignificant while b is significant at 1% level. The parameters a and b of DCC model are less than 1. Low values of a and high values of b are reported.

Table 5 Results of DCC-GARCH of Indonesia

GARCH parameters				
	DBRENT		**DIDR**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
μ	0.000178	0.001671	0.001255 ***	0.000416
ω	0.000144 *	0.000085	0.000001	0.000984
α	0.459203 ***	0.146809	0.051463 ***	0.016893
β	0.539797 ***	0.090415	0.911003	0.592202
DCC parameters				
	Estimate		**Std. Error**	
a	0.022210		0.068416	
b	0.769503		0.631979	

Note: *,** and *** indicates 10%, 5% and 1% significant levels respectively

Table 5 shows that the α and β of oil price are statistically significant at 1% level. On the other hand, only the α value is significant at 1% level while β is insignificant for exchange rate of Indonesia. For the DCC model, both the parameters a and b of DCC model are insignificant.

Table 6 Results of DCC-GARCH of Philippines

GARCH parameters				
	DBRENT		**DPHP**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
μ	0.000178	0.001667	0.000733	0.000606
ω	0.000144 *	0.000085	0.000002 ***	0.000000
α	0.459203 ***	0.146065	0.236502 ***	0.056954
β	0.539797 ***	0.090529	0.762498 ***	0.006602
DCC parameters				
	Estimate		**Std. Error**	

a	0.019486	0.018983
b	0.945176 ***	0.034922

Note: *,** and *** indicates 10%, 5% and 1% significant levels respectively

Table 6 shows that both the α and β of oil price and exchange rate of Philippines are statistically significant at 1% level. α value for exchange rate of Philippines is lower at 23% while β is higher at 76%. Comparatively, the β of Brent crude oil price is relatively low at 54% and the α are rather high at 46%. The value of α + β are less than 1 for both oil price and exchange rate of Philippines. The value of α + β for Philippines' exchange rate is very close to 1, indicating high persistence of shocks. For the DCC model, a is insignificant while b is significant at 1% level. The parameters a and b of DCC model are less than 1. Low values of a and high values of b are reported.

Table 7 Results of DCC-GARCH of Singapore

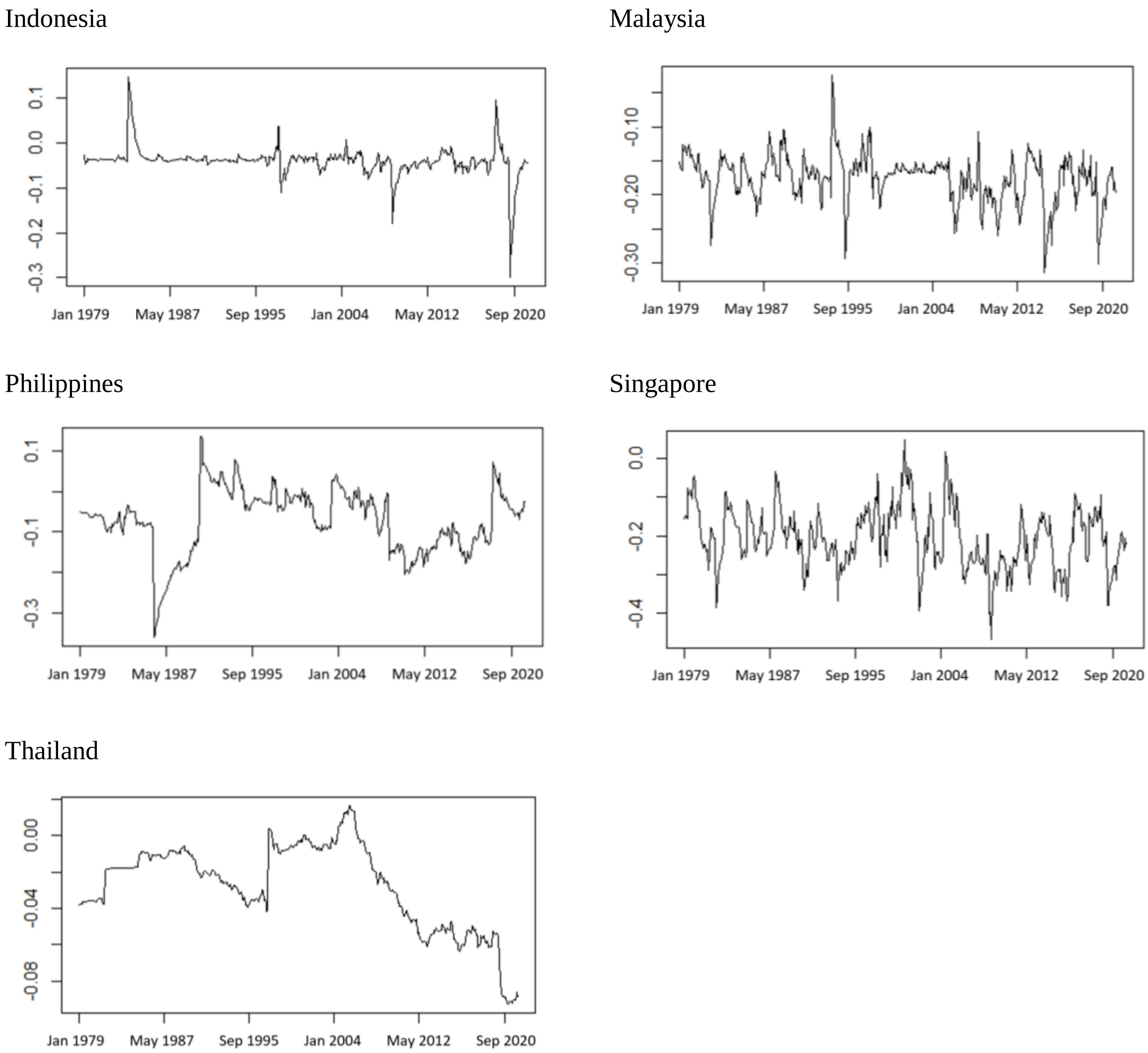
GARCH parameters				
	DBRENT		**DSGD**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
μ	0.000178	0.001669	-0.000664 **	0.000303
ω	0.000144 *	0.000085	0.000005 ***	0.000000
α	0.459203 ***	0.148453	0.143473 ***	0.018754
β	0.539797 ***	0.090979	0.677290 ***	0.036375
DCC parameters				
	Estimate		**Std. Error**	
a	0.042956		0.026601	
b	0.821661 ***		0.099579	

Note: *,** and *** indicates 10%, 5% and 1% significant levels respectively

Table 7 shows that both the α and β of oil price and exchange rate of Singapore are statistically significant at 1% level. Lower value of α and higher value of β are shown in both Brent crude oil price and exchange rate of Singapore. Lower value of α at 14% and higher value of β at 68% are reported in exchange rate of Singapore. In comparison, the β of Brent crude oil price are relatively low at 54% and the α are rather high at 46%. The value of α + β are less than 1 for both oil price and exchange rate of Singapore. α + β of Singapore's exchange rate is comparatively lower among ASEAN-5, indicate lower persistence of shocks. For the DCC model, a is insignificant while b is significant at 1% level. The parameters a and b of DCC model are less than 1. Low values of a and high values of b are reported.

The results show that both the α and β are statistically significant at 1% level for both oil price and exchange rate for all countries studied except Indonesia where the β is not significant. The highly significant α and β indicates that the model is good fit for both Singapore, Thailand, Malaysia and Philippines. Lower value of α and higher value of β are reported in exchange rate of all countries. Among all the countries, Thailand reported the highest β of 91%. High value of β indicate high level of volatility persistence. This suggested that that volatility of return in future is affected by current and past volatility. In comparison, the β of oil price are relatively low at 54% and the α are rather high at 46%., indicating that oil price is more sensitive to new information. The value of α + β are less than 1 for all oil price and exchange rate of all countries. Exchange rate of Singapore reported the lowest value of α + β while exchange rate of Philippines reported the value of α + β closest to 1. This indicate that the correlation process is resistant to shocks for all countries and Singapore reverts to the mean quicker compare to the other ASEAN-5 countries. For the DCC model, the parameters a and b of DCC model are less than 1, which indicates that the conditional correlations in the models are not constant over time. The low values of a and high values of b indicate that the correlation process is resistant to shocks and reverts to the mean quickly.

Figure 1 Time varying correlations of oil price and exchange rate



The dynamic correlation coefficients of oil price and exchange rate for all country are shown in Figure 1. The correlation coefficients are not constant. And vary over times for all the countries studied. Over the majority of the time periods analyzed, the estimations for all countries showed a negative relationship between oil price and exchange rate, indicating that increase in oil price resulted in decreased in exchange rate. Among the countries, only Malaysia reported no positive correlation between MYR/USD exchange rate and oil price. Negative correlation between oil price and Malaysia's exchange rate was found over the whole period studied. For the other 4 countries including Thailand, Singapore, Indonesia and Philippines, Singapore reported the least amount of positive correlation with only 3 months, following by Indonesia, Thailand and Philippines with positive correlation between oil price and exchange rate of 18 months, 31 months and 81 months respectively. Positive correlation was recorded on April and May 2000 for Singapore, Philippines and Indonesia. Furthermore, all countries except Malaysia reported positive correlation on April 2004. The correlation of oil price and exchange rate for Singapore and Thailand remained negative to date since 2004 and 2006 respectively. On the other hand, Indonesia and Philippines reported negative correlation since 2004 and 2005 respectively until October 2018 to 2019 where correlation appeared to be positive for both countries.

CONCLUSION

This study examines the relationship between oil price and the exchange rate of Malaysia, Philippines, Indonesia, Thailand, and Singapore from January 1979 to January 2022 using DCC-GARCH model. Presence of skewness, kurtosis, autocorrelation, and ARCH effects were found in both oil price and exchange rate. Both short-run persistence (α) and long-run persistence (β) are found to be highly significant for oil price and exchange rate of all countries except Indonesia. This suggested that the volatility for both oil price and exchange rate react to new information and is affected by current and past volatility. α of oil price is rather high compared to exchange rates, suggesting that oil price react more to new information while exchange rates are more affected by current and past volatility. Furthermore, negative relationship was found between oil price and exchange rate over most of the periods studied in all countries studied, indicating that increase in oil price resulted in decrease of exchange rate. These findings are consistent with the study of [33]. [33] reported significant negative relationship between real oil price and real exchange rate in the case of ASEAN-5. This indicated that all the countries benefited from the rise of oil prices.

Even though ASEAN-5 is oil-importing countries, at the same time, all the selected countries are exporters of crude petroleum. According to the Observatory of Economic Complexity [34], Malaysia exported 5.188 billion USD in crude petroleum in 2020, which is the highest among the ASEAN-5. In the same year, Indonesia, Thailand, Singapore, and Philippines exported 1.44 billion USD, 395 million USD, 333 million USD, and 192 million USD in crude petroleum respectively. Although Singapore exported fewer amounts of crude petroleum compared to other ASEAN-5, it exported the highest amount of refined petroleum among ASEAN-5 at 27 billion USD in 2020. The oil revenue has contributed to ASEAN-5, hence rise in oil price resulted in decrease of exchange rate of ASEAN-5. This explains the reason Malaysia reported no positive correlation between exchange rate and oil price and Philippines reported the most amount of positive correlation between exchange rate and oil price among ASEAN-5.

There are some suggestions in this study that future studies can address. One of the suggestions is that other than standard GARCH (1,1), other GARCH-type model such as GJR-GARCH, TGARCH, or EGARCH can be used to estimate the time series data. This is because previous study reported that asymmetric effect was observed in oil price and exchange rate [35]. GJR-GARCH and TGARCH specifications introduce asymmetries in the variance and standard deviation equations respectively [36]. Modeling oil price and exchange rate with models which are designed to capture asymmetric effect might produce more accurate results. Comparison between the models can also be done between the models to find the best fit model. Besides that, daily data may be used in future studies instead of monthly data for a better understanding of the relationship between oil prices and exchange rate.

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