"Examining contagion effects between global crude oil prices and the Southeast Asian stock markets during the COVID-19 pandemic"

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EXAMINING CONTAGION EFFECTS BETWEEN GLOBAL CRUDE OIL PRICES AND THE SOUTHEAST ASIAN STOCK MARKETS DURING THE COVID-19 PANDEMIC

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Abstract

Many previous studies identify the contagion effect among various types of assets, defined as the increase in correlation of these assets during a financial or economic crisis. During the COVID-19 outbreak, a historic fall in global fuel demand and oil prices has been witnessed. Because crude oil has a strategic position among the export products of the Southeast Asian economies, even a tiny global oil price change leads to a plunge in these stock markets. This study addresses the spillovers of the volatility between the West Texas Intermediate crude oil prices and stock indices across six ASEAN emerging economies. Besides, the study examines whether a contagion connecting the global energy prices and these stock markets exists during the coronavirus pandemic. The empirical results are acquired by applying the Bayesian test for equality of means on the dynamic conditional correlations computed from DCC-GARCH models. The findings present positive volatility transmission from crude oil prices toward these emerging equity markets. During the health crisis, co-movements intensify, indicating the occurrence of contagion effects. The empirical results provide valid implications for policymakers and international investors because a precise volatility forecast is vital for managing portfolio risk.

Keywords global crude oil prices, Southeast Asian stock markets, DCC-GARCH, volatility transmission, contagion effect, COVID-19

JEL Classification G01, G15, Q49

INTRODUCTION

The contagion analysis reveals that the correlation between two financial assets becomes significantly higher during a crisis or a pandemic (Forbes & Rigobon, 2002). Many attempts have been made in recent decades to highlight the fact that economic or financial crises cause volatility contagion between oil prices and equity markets. Wen et al. (2012) discovered that the US and Chinese markets were more dependent on WTI oil spot prices during the 2008 financial crisis. After the U.S. subprime crisis, the financial crisis, and the European debt crisis, Liu et al. (2022) demonstrated greater magnitudes of risk transmissions from global oil prices to the BRICS and G7 markets. Since 2020, the global healthcare systems and the economy have sustained severe damage because of COVID-19. The economic pain becomes exacerbated as governments attempt to restrain the spread of the coronavirus through shutdowns and travel bans. Because COVID-19 is considered a disastrous event, there are more and more studies about the contagion effects among various types of assets caused by this outbreak (Yousaf et al., 2020; Farid et al., 2021).

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Southeast Asian emerging markets are considered less liquid, less efficient, and more volatile than those in developed economies; hence, even small changes in the energy market can generate vulnerability to these markets. However, the spillovers of shock between global oil prices and Southeast Asian stock indices seem to be understudied in the existing literature. Besides, during the COVID-19 pandemic, a historic fall in fuel demand and oil prices has been witnessed. Because crude oil has a strategic position among the export products of ASEAN economies, ASEAN oil production and export levels have dropped as the oil price fell to its lowest point. For instance, Malaysia lost up to $68.8 million for a $1 increase in Brent crude oil, and the total loss due to collapsed sales in Thailand was predicted at $307.8 million (John, 2021). This phenomenon has sparked suspicion of volatility transmissions and contagious effects originating from global oil prices on Southeast Asian equity markets during the COVID-19 pandemic.

1. LITERATURE REVIEW

Various studies concentrate on the profound understanding of the connectedness between oil price variations and stock markets. Applying the vector autoregression model to a dataset from 1986 to 2005, Park and Ratti (2008) confirmed transmissions from oil volatility to stock return volatility in 13 European countries. The U.S. market had been hit by both types of oil price fluctuations, with the more significant impact inclining the demand-driven shocks, according to Kylian and Park (2009). Diaz et al. (2016) confirmed that the G7 stock prices reacted in the opposite direction to oil shocks, with a positive shock in spot oil prices causing a negative reaction in financial assets. Furthermore, the significant dependence of the volatility of airline stocks on oil price changes was elucidated by Yun and Yoon (2019) through a VAR-BEKK-GARCH model.

Büyükşahin and Robe (2014) suggested that the subsequent analysis needed to deliberate about the dummy for the crisis period when explaining correlations between commodities and equity. The results of the contagion effects caused by crises are mixed. Choi et al. (2009) confirmed an increase in volatility spillovers from the New Zealand stock index to the exchange rate by considering the 1997 crash. Using the VECM and Granger causality tests, Boubaker et al. (2016) outlined that contagion effects caused by the subprime crisis occurred between the U.S. market and some chosen equity markets. Wang et al. (2019) confirmed the financial contagion among precious metal markets across different time horizons using a continuous wavelet transform. On the contrary, Białkowski and Serwa (2005) found no significant contagion running from the Japanese stock market to the Hong Kong stock markets, and vice versa, during the Asian crisis. Yiu et al. (2010) indicated that the contagion hypothesis between the U.S. and 11 Asian stock markets was rejected by employing the integration of VAR and DCC models.

Regarding studies exploring the contagion effects originating from crude oil volatility, Wen et al. (2012) used the time-varying copula technique to determine whether the spillovers in volatility from the WTI spot prices to the U.S. and Chinese markets were contagious around the financial crisis. Ghorbel and Boujelbene (2013) employed GARCH-class models to explore stronger transmissions of crude oil volatility to the Gulf Corporation Council (GCC), Brazilian, Russian, Indian, and Chinese markets through the financial crisis in 2008. Similarly, Guesmi and Fattoum (2014) applied a model called the asymmetric DCC-GARCH to demonstrate how global business cycle fluctuations altered the instability transmission between global oil and stock prices in five oil-importing countries and four oil-exporting countries. The findings reported a stronger correlation between oil and all equity markets in turmoil. In a study of the causes of financial contagion at various levels of time-varying correlations, Kocaarslan et al. (2019) used quantile regression analysis, and discovered that the global crisis of 2008 changed the dynamic conditional connectedness between equity markets and global macroeconomic indicators like financial stress, oil prices, and gold prices. Besides, Lin et al. (2019) employed the complete ensemble empirical mode decomposition with adaptive noise approach along with the Granger causality test to confirm unidirectional risk contagion from Brent oil to Chinese and European stock markets in irregular events.

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In the Asian context, Zhu et al. (2014) stated that the dependence of the Asia-Pacific securities markets on crude oil prices was positive but weak during the time prior to the financial crisis. Nonetheless, the strength of dependence significantly increases after the crisis. The empirical research of Sharma et al. (2018), using the VAR model with the one-standard-deviation impulse response function, reported that shocks from the global crude oil prices negatively affected India's stock market. The contagion effects between the global oil market and the Chinese market dramatically increased during a crisis, whereas they reduced significantly after that (Chen & Lv, 2015). As opposed to the above studies, Cong et al. (2008) found that almost all Chinese stock market indices were unaffected by changes in the price of Brent crude oil. The nonlinear cointegration between the Indian equity market and global energy prices was reported by Ghosh and Kanjilal (2016). The main finding revealed that fiscal deficit and inflation were indirect channels through which crude oil shocks were transferred to the Indian equity market. Similarly, a strong financial contagion between India's composite commodity futures and stock market could be found in the study of Roy and Roy (2017).

Until now, many studies have explored how COVID-19 affects the volatility of stock indices. The more severe the measures employed to curb the COVID-19 spread are, the more volatile the stock markets are (Zaremba et al., 2020). According to Ashraf (2020), stock returns showed an adverse reaction to the announcements of social isolation. Baek et al. (2020) found that the impact of bad COVID-19 news on the volatility of U.S. industrial stocks was worse than the good news. Applying the TGARCH model, Zhang et al. (2021) investigated how the COVID-19 outbreak impacted volatility spillovers between the Chinese and some of the most advantaged securities markets. The findings indicated that shocks in China's stock returns stimulated the volatility of Switzerland, Sweden, and U.K. financial assets during the pandemic. Conversely, no volatility emanating from these advantaged stock markets was transmitted toward the Chinese stock market. In addition, an empirical connection between stock market volatility and COVID-19 fear was discussed by Li et al. (2021). The study's findings reported that a 1% increase in coronavirus new cases resulted in a 0.8% decrease in market return, and that stock volatility in nations with more COVID-19 cases was lower.

Regarding the volatility contagion between assets caused by the COVID-19 pandemic, Akhtaruzzaman et al. (2021) reported a remarkable growth in the transmissions of volatility between Chinese firms and G7 countries since the COVID-19 outbreak. The strong risk transmissions across commodities (oil, gold prices) and financial assets (stocks, bitcoin) are attributed to the health crisis (Adekoya & Oliyide, 2021). Ghorbel and Jeribi (2021) studied the volatility transmissions from the energy index to some financial assets through the multivariate Markov-switching GARCH models. The findings showed that the dependency of G7 stock indices on energy prices became stronger during the COVID-19 period. Similarly, the relationship between the main Chinese stock markets' volatility and Bitcoin witnessed a considerable alteration during the pandemic, according to Corbet et al. (2020). Furthermore, the volatility spillover between energy and stock markets during the coronavirus outbreak was observed to exceed the one during the financial crisis 2008 (Jebabli et al., 2022). Rehman et al. (2022) noted an apparent rise in cross-market spillover for the international forex markets during the outbreak.

Although studies related to the volatility transmission and contagion between crude oil and equity markets are numerous, this study relating to Southeast Asian economies seems to be ignored. Besides, research on the contagion during a disease pandemic is still restricted. Therefore, this study aims to clarify the difference in the volatility transmissions between WTI crude oil and the Southeast Asian stock markets before and during the healthy crisis caused by the coronavirus. This paper is considered to provide additional attestation to the contagion from WTI crude oil to financial assets. The results from the study will be informative for global investors and portfolio managers in their international diversification strategies, and helpful for policymakers in controlling volatility in domestic stock markets.

2. DATA AND METHODOLOGY

2.1. Data

The study employs the stock index of six ASEAN equity markets: JCI (Indonesia), FTSE KLCI (Malaysia), PSEi (The Philippines), STI (Singapore), SET (Thailand), and VNIndex (Vietnam). These stock indices and the oil price are downloaded from the website *finance.yahoo.com*. This study ignores the Cambodian, Laos, Myanmar, and Brunei stock markets due to the unavailability of data. As the world benchmark for oil prices, the WTI spot price is used. The daily time series from January 2017 to January 2021 is considered in this study. The returns of all series are yielded from the natural logarithm formula. The trend in stock and oil returns is presented in Figure 1.

The earliest COVID-19 case was reported in China on December 31, 2019. The data set in this study is split into two segments: pre-COVID (before December 31, 2019) and within-COVID (from December 31, 2019, and after) to test the change in volatility spillovers caused by COVID-19.

2.2. Methodology

2.2.1. The DCC-GARCH model

Let $Y_t = (Y_{1t}, Y_{2t}, ..., Y_{qt})$ be a random vector having q elements, each of length T ($t = 1, 2, \ldots, T$). The conditional mean equations with the information set I_{t-1} is given by

$$Y_t = m_t + \varepsilon_t, \qquad (1)$$
$$\varepsilon_t \mid I_{t-1} \sim N(0, \Sigma_t),$$

where $\mu_t = (\mu_{1t,} \mu_{2t, ...,} \mu_{qt})$ is the mean vector, $\varepsilon_t = (\varepsilon_{1t,} \varepsilon_{2t. ...,} \varepsilon_{qt})$ is the error vector at time t, the variance-covariance matrix $\Sigma = \text{var}(\varepsilon_t | I_{t-1})$ is a $(q \times q)$ symmetric square matrix.

The matrix Σ_t is decomposed as follows:

$$\Sigma_t = P_t Q_t P_t, \qquad (2)$$

in which, P_t is a (qxq) diagonal matrix with elements d_{it} being the standard deviations of the q^{th} variable at time t, denoted by σ_{kt} given by

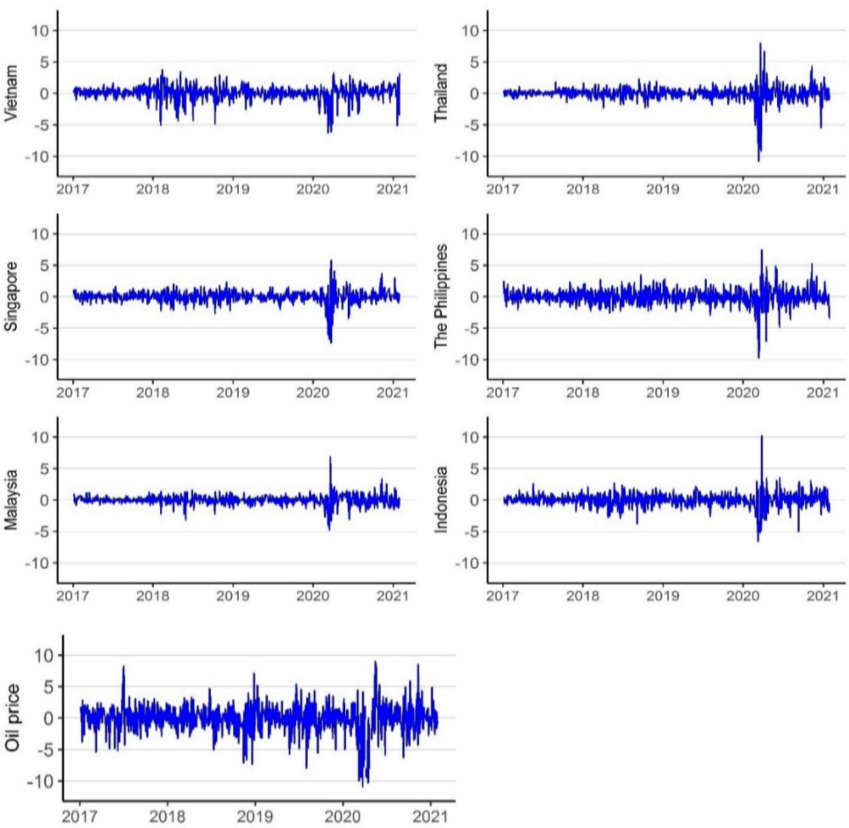

Figure 1. Plots of returns of ASEAN stock indices and oil prices

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$$P_t = \begin{bmatrix} \sigma_{1t} & 0 & 0 & \dots & 0 \\ 0 & \sigma_{2t} & 0 & \dots & 0 \\ 0 & 0 & \sigma_{2t} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & \sigma_{qt} \end{bmatrix}, \quad (3)$$

and Q_t is a conditional correlation matrix that has terms at row i and column j being ρ_{it} = cor(ε_{it}, $\varepsilon_{jt}|I_{t-1}$). At time t, Q_t has the form

$$Qt = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \dots & \rho_{1q,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \dots & \rho_{2q,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \dots & \rho_{3q,t} \\ \dots & \dots & \dots & \dots & \dots \\ \rho_{q1,t} & \rho_{q2,t} & \rho_{q3,t} & \dots & 1 \end{bmatrix}. \quad (4)$$

A two-step process is used to fit the DCC-GARCH model. To begin with, the conditional standard deviation matrix P_t is obtained by fitting the univariate GARCH model for each series. Different types of GARCH models for different series are applied based on the goodness of fit.

Denote $\hat{z}_t = (\hat{z}_{1t}, \hat{z}_{2t}, ..., \hat{z}_{qt})^T$ to be the vector of standardized residuals at time t. $\hat{z}_t$ is derived by

$$\hat{z}_t = \left(P_t^{-1}\varepsilon_t\right), \quad (5)$$

and the unconditional correlation matrix $\bar{R}$ is computed as

$$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} \hat{z}_t \hat{z}_t^T. \quad (6)$$

Engle (2002) proposes that the matrix Q_t can be decomposed as

$$Q_t = diag(R_t)^{-1} R_t diag(R_t)^{-1}, \quad (7)$$

where R_t is a positive semidefinite matrix and is generated from the recursive process

$$Rt = (1-a-b)\bar{R} + a(\hat{z}_{t-1}\hat{z}_{t-1}^T) + bR_{t-1}, \quad (8)$$

with a and b must be in the interval [0,1], and the sum $a + b$ is less than 1.

The log-likelihood function of the observation ε_t,

$$\ell_t = -\frac{1}{2}\ln|Q_t| - \frac{1}{2}\sum_{j=1}^{q}\sigma_{jt}^2 - \frac{1}{2}\varepsilon_t^T P_t^{-1} Q_t^{-1} P_t^{-1}\varepsilon_t, \quad (9)$$

is conditional on the initial fixed matrix R_0. Often, R_0 is chosen as the identity matrix.

Let $\theta = (\beta, a, b)$ be the vector of all model parameters, where β is the vector of parameters of the GARCH-class models. The estimator θ^* of θ is obtained by maximizing the log-likelihood function (9).

2.2.2. *The Bayesian t-test*

The null and alternative hypotheses supporting the stability of volatility transmission between series i and j in the pre-COVID and within-COVID is given by

$$H_0: \ \rho_{ij}^{pre-COVID} = \rho_{ij}^{within-COVID}, \qquad H_1: \ \rho_{ij}^{pre-COVID} < \rho_{ij}^{within-COVID}. \quad (10)$$

As mentioned above, the correlation in volatility between stock and oil is more likely to be unstable over time. This study applies the Bayesian statistic for comparing two population means instead of the classical t-test because this method considers the concerned parameter as a random variable. Kruschke (2013) assumed that each subgroup followed the Student distribution with three parameters: mean (μ), standard deviation (σ), and degree of freedom (ν). The prior distribution on the mean is Gaussian, while the prior on the standard deviation is expressed as a uniform distribution. Finally, the degree freedom parameter has an exponentially distributed prior and the same for two groups. Denoting D as the observed dataset, the posterior probability of the interested parameters is derived from the Bayesian analysis

$$P(\mu,\sigma,\nu|D) = \frac{P(\mu,\sigma,\nu)P(D|\mu,\sigma,\nu)}{P(D)}. \quad (11)$$

The credible value of each parameter is ascertained from the Markov chain Monte Carlo algorithm and calculated posterior distribution. The effect size is derived by the following formula:

$$z = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}, \quad (12)$$

where μ_1 and μ_2 are the means of conditional correlation coefficients between two interested series in the pre-pandemic and during the pandemic, respectively. σ_1^2 and σ_2^2 are the correspondent population variances. Clearly, the effect size is typically the standardized difference of conditional correlations between two phases. Thus, it can be considered as the degree of contagion effect of each stock market.

This method also yields the 95% highest density interval (HDI) of z, indicating that 95% of the distribution is inside the HDI. Every value within the HDI has a probability density exceeding the probability of one outside the HDI. If zero falls within the 95% HDI, hypothesis H_0 is more likely to be chosen. This study uses the programming language R, with the *rmgarch* package (Ghalanos, 2019) to fit of the DCC-GARCH models, and *BEST* package (Kruschke, 2012) to conduct the Bayesian test for equality in mean.

3. RESULTS AND DISCUSSION

Table 1 presents the summary statistics of all return series. The average return for each Southeast Asian stock is relatively small, but the standard errors are notably high. Oil price gets a negative return in mean and too high standard deviation because of the outlier on the date April 21, 2020, when the oil prices went to negative for the first time in history and decreased by over 300 percent. The unit root tests, including augmented Dickey-Fuller and Phillip Perron, indicate the stationarity of all return series. Table 1 also reports the unconditional Pearson correlation coefficients for each pair of variables in the dataset. The positive correlation coefficients state that the oil returns and all ASEAN stock index returns shift in the same direction. Among them, the highest correlations are related to Malaysia and Vietnam.

Figure 2 presents the rolling estimator of the correlation between each stock return and oil price return with an estimation window of 30 days. These plots prove the highly time-vary characteristics of the correlation, so it is more suitable when assuming that these correlations are random variables, not a constant in population. Besides, the mean of correlations during the COVID-19 period for all series seems greater than during the pre-outbreak period. Thus, the hypothesis that spillover effects between global oil and ASEAN stock markets enhance during the COVID period is proposed.

In the first step, univariate GARCH models must be carried out to attain the standardized residual for the stock index returns. The DCC-GARCH model is run for each pair of variables $\left(r_{jt}, r_{oil,t}\right)$, where r_{jt} denotes the return of stock j, and $r_{oil,t}$ is the return of crude oil at time t. The GARCH model used in step 1 must be suitable for both the stock return and the oil series. The chosen model has to satisfy the diagnostic tests, including stability conditions, heteroskedasticity, and serial correlation tests. Initially, the model with conditional mean equation ARMA(0,0) and condition-

Table 1. Descriptive statistics summary, unit root tests, and correlation coefficients

Key point	Returns of						
	JCI	**KLCI**	**PSEi**	**STI**	**SET**	**VNIndex**	**WTI**
Mean	0.017	0.007	–0.013	0.003	–0.005	0.048	–0.450
Maximum	10.191	6.851	7.435	5.756	7.954	3.770	37.662
Minimum	–6.579	–4.868	–13.344	–7.353	–10.799	–6.276	–306.00
Std. Dev.	1.095	0.744	1.343	0.952	1.089	1.108	11.709
ADF	–9.788***	–8.293***	–7.984***	–7.539***	–8.017***	–8.793***	–8.957***
PP	–28.082***	–31.058***	–30.794***	–32.124***	–29.930***	–27.702***	–20.824***
Unconditional correlation coefficients							
JCI	1						
KLCI	0.434	1					
PSEi	0.504	0.472	1				
STI	0.459	0.570	0.451	1			
SET	0.415	0.529	0.439	0.629	1		
VNIndex	0.285	0.251	0.261	0.333	0.311	1	
WTI	0.074	0.137	0.099	0.101	0.067	0.136	1

Notes: *, **, and *** indicate that the null hypothesis of non-stationarity is rejected at the 10%, 5%, and 1% levels, respectively.

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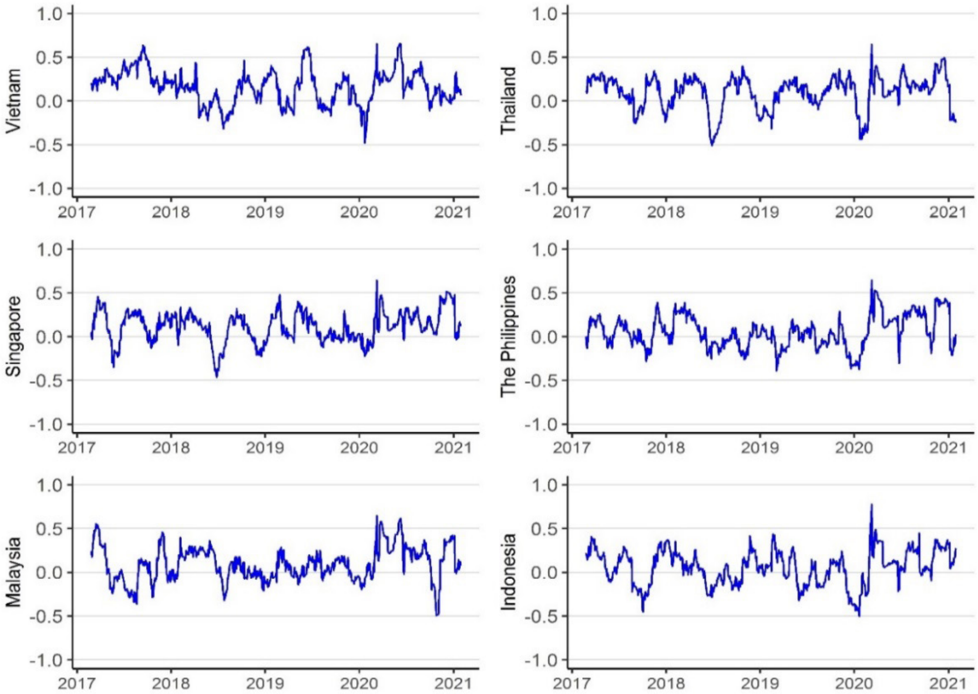

Figure 2. Rolling correlation (30 days)

al variance equation GARCH(1,1) is applied. If it is good, the second step is carried out. If not, another model in the GARCH family is applied until the good one is found. Based on AIC, the best error distribution for all considered series is Student distribution. The appropriate model for each case is presented in the row entitled "Model" of Table 2.

In the mean equations, the estimated coefficients of the terms AR(1), AR(3), and MA(1) are all less than one, confirming that the selected models are causal and invertible. The positive and statistically significant coefficient of ARCH(1) illustrates that any shock in the one day prior in stock returns would surge volatility. Furthermore, the significant GARCH elements in the variance process-

Table 2. DCC-GARCH models

Index	JCI	KLCI	PSEi	STI	SET	VNIndex
Model	ARMA(1,1) GARCH(1,1)	ARMA(3,0) GARCH(1,2)	ARMA(1,0) NGARCH(1,1)	ARMA(3,1) GARCH(1,1)	ARMA(3,0) TGARCH(1,1)	ARMA(1,1) GARCH(1,1)
Panel A: Conditional mean equations						
Constant	0.063*** (0.024)	−0.004 (0.017)	0.015 (0.025)	0.033 (0.024)	0.021 (0.014)	0.151*** (0.040)
AR(1)	−0.755*** (0.172)		−0.109*** (0.036)	0.532*** (0.166)		0.965*** (0.037)
AR(3)		0.059* (0.034)		0.071** (0.030)	0.064** (0.028)	
MA(1)	0.777*** (0.164)			−0.556** (0.165)		−0.945*** (0.047)
Panel B: Conditional variance equations						
Constant	0.044** (0.020)	0.005 (0.003)	0.056 (0.054)	0.053* (0.030)	0.010** (0.006)	0.036** (0.015)
ARCH(1)	0.186*** (0.046)	0.129*** (0.038)	0.092** (0.039)	0.161*** (0.061)	0.091*** (0.027)	0.146*** (0.037)
GARCH(1)	0.788*** (0.053)	0.344** (0.135)	0.856*** (0.098)	0.764*** (0.093)	0.922*** (0.022)	0.845*** (0.033)
GARCH(2)		0.526*** (0.131)				
$\hat{\theta}$			2.387*** (0.757)		0.406*** (0.141)	

Table 2 (cont.). DCC-GARCH models

Index	JCI	KLCI	PSEi	STI	SET	VNIndex
Panel C: Diagnostic test						
ARCH(5)	1.294	2.877	2.571	1.686	0.794	1.108
Q(5)	2.456	2.945	5.991	2.969	3.350	1.235
Q2(5)	1.507	4.109	5.736	2.131	3.321	0.736
Panel D: Conditional covariance equations						
a	0.016	0.002	0.004	0.002	0.006	0.004
	(0.015)	(0.021)	(0.009)	(0.016)	(0.015)	(0.007)
b	0.941***	0.858***	0.820***	0.894***	0.810***	0.986***
	(0.068)	(0.293)	(0.047)	(0.135)	(0.071)	(0.012)

Notes: *, **, and *** stand for statistical significance at the 10%, 5% and 1% levels, respectively. Standard deviations are in parentheses. NGARCH is the abbreviation of the nonlinear GARCH model, TGARCH is the abbreviation of the threshold GARCH model. In panel B, θ is either the power of the term GARCH in NGARCH or the coefficient of indicator for negative in TGARCH. Diagnostic tests are shown in panel C. Panel D contains the result of the condition covariance equation Q_t.

es for all six markets indicate that own volatility spillovers exist for all stocks and oil returns, with the Thai stock market exhibiting the highest own volatility dependency. Results indicate high persistence in GARCH models because the sum of two parameters in each conditional covariance equation, a and b, is close to one. Besides, the sum of coefficients in the conditional variance equations is not greater than one, so the chosen GARCH model is stationary. The small observed Ljung-Box statistics mean that the null hypothesis of no serial correlation cannot be rejected. The LM-ARCH test results show that the homoskedasticity assumption does not violate, so the model for each series is good enough. The GARCH models for oil returns are not presented because there is no fixed model for the oil price. After all, it depends on the model chosen for the stock return series. However, it is ensured that the used models for the oil price returns all match the model assumptions.

Table 3 presents credible values of the average conditional correlation coefficients derived from the Bayesian method in the pre-COVID and within-COVID periods. The DCC correlations are positive for all markets in both phases. The results imply that oil and stock market volatility show a highly and persistently positive correlation before and during the pandemic. These findings are consistent with previous studies about the spillover effects from the oil market to emerging stock markets. For instance, Uwubanmwen and Omorokunwa (2015) showed that oil volatility created and stimulated Nigerian stock volatility. Arouri et al. (2011) also confirmed transmissions in return and volatility from oil prices to equities in a study of the Gulf Cooperation Council stock markets.

Table 3. Bayesian t-test results for the equality of DCC conditional correlation in the period prior to and within the coronavirus outbreak

Markets	Pre-COVID	Within-COVID	Effect size *z*
JCI	0.0597	0.0796	0.7999
	(0.0160)	(0.0313)	(0.6069; 0.9923)
KLCI	0.0855	0.0864	0.4267
	(0.0011)	(0.0024)	(0.2189; 0.6335)
PSEi	0.0608	0.0617	0.3601
	(0.0019)	(0.0030)	(0.1572; 0.5614)
STI	0.0943	0.0948	0.3465
	(0.0010)	(0.0017)	(0.1391; 0.5558)
SET	0.0662	0.0659	–0.0610
	(0.0028)	(0.0063)	(–0.2704; 0.1484)
VNIndex	0.1289	0.1443	0.9622
	(0.0113)	(0.0197)	(0.7716; 1.1469)

Notes: The entire period is from January 4, 2017, to January 29, 2021, in which pre-COVID is from the starting day to December 30, 2019, and within-COVID is from December 31, 2019, to the last day of the sample. In pre-COVID and within-COVID columns, the credible values of mean and standard deviation derived from the Bayesian method are reported. The final column illustrates the effect size with the correspondent 95% HDI.

Moreover, the effect size coefficients are positive for five markets, including Indonesia, Malaysia, Singapore, the Philippines, and Vietnam. Besides, the value zero is not contained in the 95% HDI. Also, the conditional correlations between the oil volatility during the COVID-19 pandemic are higher than in the period before the COVID-19 outbreak. The volatility transmissions from global oil to these markets is more critical due to the infectious disease outbreak, confirming the contagious effect from global oil price variations in most Southeast Asian stock markets. The exception is Thailand, with an insignificant decrease in the magnitude of transmission during COVID-19. These results align with recent studies that the

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COVID-19 pandemic exaggerates integration and risk contagions among international financial markets (Davidovic, 2021; Guo et al., 2021). Uddin et al. (2022) confirmed that COVID-19 was a new source of risk contagion between the developing equity markets and the global financial market index.

The oil price volatility substantially impacts the Vietnamese and Indonesian stock markets volatility. The mean conditional dependency of Vietnamese and Indonesian stock indices on oil returns increase from 0.1289 and 0.0597 before the health crisis to 0.1443 and 0.0796 during the outbreak, respectively. Also, the Vietnamese economy experiences the highest degree of contagion with an effect size of 0.9622, followed by Indonesia with 0.799. This result is apparent because Vietnam and Indonesia are the two youngest stock markets with the lowest market capitalization. Thus, they are the most sensitive and vulnerable due to external shocks. Holding Vietnamese equities implies the lowest diversification benefits because of their highest risk transmission in both pre-COVID and within-COVID periods.

Thailand even witnesses a decrease in the magnitude of transmission. Nevertheless, the finding does not offer statistical evidence of a difference in volatility transmission from oil prices before and during COVID-19. The null hypothesis cannot be rejected for the case of Thailand, which exhibits no evidence of contagion effects in volatility from oil prices to the Thai market. The model fitting the SET index in Table 2 shows that the parameter relating to the GARCH term is 0.92, which is too high. These results indicate that the Thai stock volatility could be explained mainly by its past volatility rather than global oil price volatility.

CONCLUSION

The paper elucidates whether the coronavirus disease outbreak significantly spread the spillovers from the WTI oil volatility to the Southeast Asian equity markets. The DCC-GARCH models and the Bayesian t-test are implemented to detect contagion effects. The study shows that during the COVID-19 crisis, the link between global crude oil and most Southeast Asian stock markets (except the Thai market) becomes more robust.

This study provides some suggestions for risk management for international investors and portfolio managers. Firstly, the positive and high correlations in volatility between global oil prices and Southeast Asian stock markets indicate that investors could not attain diversification benefits by holding a portfolio of stocks from these emerging markets and crude oil. Secondly, paying attention to the stronger conditional correlation helps investors comprehend the investment risk during the pandemic. The contagion indicates that the benefits of international portfolio diversification decrease, and crude oil is no longer the right choice for portfolios in turmoil. The findings are also relevant for policymakers attempting to control the excessive volatility in developing stock markets. The co-movement shows that information about oil price fluctuations can help forecast these emerging markets' movements. Hence, timely detection of the lousy situation of the global crude oil market can help policymakers minimize the undesirable volatility transmission effect and diminish the instability of the financialization process at the lowest level.

AUTHOR CONTRIBUTIONS

Conceptualization: Mien Thi Ngoc Nguyen.
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Supervision: Mien Thi Ngoc Nguyen.

Validation: Mien Thi Ngoc Nguyen.
Visualization: Mien Thi Ngoc Nguyen.
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