RESEARCH ARTICLE

The Effect of COVID-19 Pandemic on Volatility Transmission Between the U.S. and Emerging Asia Stock Markets: A Case Study of Tiger Cub Economies

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Abstract: The globalization in financial markets has highlighted the importance of a clear understanding of volatility transmission among equity markets in different countries. This paper looks into the effect of the COVID-19 pandemic on the volatility transmission between the U.S. stock market and five emerging equity markets called Tiger Cub economies in Southeast Asia. As the result of the dynamic conditional correlation GARCH (DCC-GARCH), the U.S. stock market's volatility links positively to these smaller economies' volatilities, and these linkages become stronger during the pandemic. We also find evidence of statistically significant co-volatility across five Tiger Cub markets. Due to the increase in financial globalization over the last few decades, the finding has relevant implications for policymakers, international investors, and portfolio managers.

Keywords: volatility transmission, DCC-GARCH, Tiger Cub economies, COVID-19, emerging market

The 2019 novel coronavirus disease outbreak (COVID-19) creates panic in both the goods and the global financial market. According to the World Bank (2020), the COVID-19 could cause a massive recession, which triggers a decrease by one-third of the GDP and about 70% of total employment in emerging and developing economies. Efforts in restraining the spread of the pandemic through economic shutdown have exacerbated the trend of slowing potential growth and productivity growth for a multi-decade period, especially in emerging and developing nations with limited low-income health care capacity. Since the beginning of 2020, the epidemic of COVID-19 has devastated many industries and services, for example, the air transportation industry, the oil and gas industry, and the bank industry. Many existent studies show that the aviation industry is facing a loss of billions of dollars in 2020. Rooley (2020) clarified that due to COVID-19, the passengers' demand was at the bottom in April 2020, a fall of 93% compared to April 2019. Revenues of the air transportation service could drop by $314 billion in 2020, a 55% drop compared to 2019.

Meanwhile, the pandemic also causes a historic decrease in fuel demand and the world shutdown of economic activities, leading to an extreme decline in travel, changes in consumer behavior, and a rise in unemployment. COVID-19 contributed to a decline of 18% in fuel prices in March 2020 (Schneider & Schwartz, 2020). The bank industry also suffered an adverse effect from the COVID-19 pandemic. Despite several solutions launched by the governments to support banking activities, the bank industry still suffers risks on their capital and liquidity position as the length and severity of the COVID-19 remain uncertain.

Most industries and services affected by COVID-19 experience a drop in stock prices. Many researchers have investigated how the coronavirus COVID-19 impacts the stock market and have measured the extent of damage caused by this pandemic. Ashraf (2020) used daily data from 64 countries, including COVID-19 cases and stock market returns over 86 days starting on January 22, 2020, and confirmed the stock market's negative response against the spread of confirmed cases. Maybe, the U.S. is one of the countries seriously affected by this pandemic. Yilmazkuday (2021) considered that the S&P 500 Index saw 0.01% and 0.03% declines after one day and after one month, respectively, for each percent increase in cumulative daily cases of COVID-19. Similarly, Sansa (2020) clarified that the COVID-19 pandemic related closely to the Chinese and the U.S. markets. Regarding volatility of the U.S. stock market, Albulescu (2020) showed evidence supporting that those daily official announcements of global and the U.S. new infection cases had amplified the S&P 500 volatility.

Being considered emerging and having significant growth in recent times, five Tiger Cub stock markets (Vietnam, Thailand, Malaysia, Philippines, and Indonesia) contribute to economic development in the Southeast Asia region. Specifically, these Tiger Cub countries' stock market capitalization percentage was in the top 20 with the world's highest value in 2019. These emerging markets' increased importance attracts more global investors' attention because of higher returns and diversified benefits. A large amount of literature found the potential connections between Tiger Cub stock markets and some developed equity markets (Chancharoenchai & Dibooglu, 2006; Mulyadi, 2009; Nartea et al., 2011). It is not an exaggeration to say that the U.S. equity market has sharply influenced these Tiger Cub markets due to its dominating role worldwide. Hence, the COVID-19 pandemic impacts these emerging markets through direct channels and volatility in the U.S. financial market. The study aims to answer whether the volatility transmission between the Tiger Cub and the U.S. stock markets experiences substantial change during the COVID-19 pandemic.

In this research, we apply the GARCH models for volatility transmission analysis, then link them to the volatility transmission analysis among the U.S. and the five Tiger Cub securities markets. A key goal in constructing multivariate GARCH models is ensuring them parsimoniously enough and still maintaining flexibility. There are several multivariate GARCH models. However, this study focuses on a specific multivariate GARCH model called dynamic conditional correlation GARCH (DCC-GARCH). The conditional correlation matrix in the DCC-GARCH model is allowed to vary over time. The DCC-GARCH model has advantages in computation that the number of parameters forecasted in the correlation process is independent of the number of series. Therefore, we can potentially estimate huge correlation matrices.

We consider this research to strengthen the understanding of the interrelations and volatility transmission among international stock markets. We find that the volatility transmission between the U.S. stock market and most Tiger Cub markets during the pandemic is stronger than in the previous period. However, the contagion effect in volatility between Vietnamese and the U.S. stock markets is likely to maintain steadily.

Literature Review

The international financial integration process brings benefits to countries in several ways. As Beck et al. (2013) argued, one of the significant advantages is having a greater supply of external financing available at a lower cost, allowing the import of knowledge and technology to boost national productivity. Financial globalization permits portfolio diversification, the ability of foreigners to participate in domestic banking systems, and the facilitation of credit assessment technology and risk management technology (Feldstein & Horioka, 1979). However, benefits come with risks. The specific risk is that when there are cohesive connections between countries in the financial system, adverse shocks in foreign markets can threaten domestic markets' stability (Beck et al., 2013). The co-movements of different financial markets arise from contagion between them.

In recent years, the linkages in returns and volatilities among the global stock index have been mentioned as one of the ways to measure contagion between financial markets. Increasing global financial integration has already engendered strong interest from researchers in investigating how the financial shock is transmitted across markets (Tokat, 2013). Jung and Maderitsch (2014) stated that volatility transmission had reflected the spillovers of uncertainty and valuation insecurity amidst market participants. Notably, the transmission has been essential because of its importance in pricing securities, trading, and hedging strategies within and across the markets (Karunanayake et al., 2010).

Some studies have concentrated on the volatility transmission between different stock markets. Because of the characteristics of financial data, linear models are inappropriate in analyzing stock market volatility. The GARCH family models proposed by Bollerslev (1986) are often used to capture this type of data. Moreover, multivariate versions of GARCH models have been developed to analyze the transmission volatility across markets. For instance, Natarajan et al. (2014) used the GARCH(1,1)-mean model to examine the degree of interdependence among some major stock markets, namely Australia, Germany, and the U.S. They found that cross volatility spillover existed in all three markets, and the U.S. was the most influential market. The past shocks in the U.S. market impacted current volatility in both Australia and German markets with different degrees of intensity. Similarly, Singh et al. (2010) assessed volatility spillovers across the U.S., European, and Asian stock markets, and they concluded a regional influence among these markets. Besides, the direction of the effect was from the U.S. to most other markets and from the emerging to some developed markets in the sample.

Regarding the context about how unexpected high severity events affect stock market integration, most studies about financial integration have looked at financial crises or political crises. Polasek and Ren (2001) presented supporting evidence of different volatility transmission patterns between the U.S., Germany, and Japan stock markets before and after the 1997–1998 Asian crisis. Karunanayake et al. (2010) focused on the Asian and 2008–2009 global financial crises for Australia, Singapore, the U.K., and the U.S., and they found that both crises increased the volatilities in stock returns and cross volatility spillovers across markets significantly. Notably, the cross-volatility spillover running from larger to smaller markets was generally more remarkable than their own volatility spillover. In a similar vein, Wang (2014) provided evidence of the global financial crisis's role in strengthening the interdependencies among six major stock exchanges in East Asia. Besides, the East Asiatic stock markets' volatilities were more heavily influenced by the South Korean and Japanese markets than the U.S. market. Moreover, political crises have diminished the level of integration in 19 emerging stock markets in three different continents of the world (Frijns et al., 2012).

The recent COVID-19 pandemic reminds us of the Severe Acute Respiratory Syndrome (SARS.) outbreak in 2002–2003, and many studies at that time explored the impact of SARS on stock returns. For instance, stock prices relating to the Taiwan Stock Exchange's tourism industry experienced a sharp decline during the SARS outbreak period (Chen et al., 2007). Nippani and Washer (2004) analyzed the influence of SARS on Canada and some Asia countries to conclude that only Chinese and Vietnamese stock markets were affected by SARS. Del and Paltrinieri (2017) pointed out that the Ebola epidemic disease critically altered the funds flows and returns of 78 mutual equity funds in the African region. Chen et al. (2018) investigated the SARS epidemic's impact on stock market integration in terms of stock returns between China and some infected countries, including Hong Kong, Taiwan, Singapore, and Japan. This study verified the time-varying co-integration in the stock price index between China and the other stock markets. Nevertheless, the SARS epidemic weakened the linkages in returns between these stocks. Unfortunately, little is known about the relationship between epidemic disease and volatility transmission.

In more recent times, the new Southeast Asia Tiger Cub countries—Malaysia, Indonesia, Thailand, the Philippines, and Vietnam—have displayed outstanding performance in their rapid financial liberalization, stock market growth, and ongoing economic development. The Southeast Asia Tiger cub countries have become more critical to the region because of their rapid financial liberalization and growth in stock markets (Heng & Niblock, 2014). This has attracted researchers' attention to testing the transmission volatility within these countries and between them to developed markets. Vo and Ellis (2018) used the BEKK-GARCH model to indicate that the Vietnamese stock market depended on the leading world stock markets (the U.S., Hong Kong, and Japan) in terms of returns linkage and volatility transmission, and these linkages became stronger during and after the Global Financial Crisis. In et al. (2002) investigated whether linkages and interactions exist within the 11 Asian stock market indexes. This study reported a closer connection within Thailand, Indonesia, and the Philippines and between these three stock markets and Singapore, the U.S., Japan, and Australia during the financial crisis period. However, the external contribution to the Malaysian stock market tended to decrease during the crisis. On the contrary, Daly (2003) employed correlation and co-integration analysis to describe the interdependencies within the Southeast Asian stock markets, and revealed no significant difference in the integration between these equity markets before and after the Asian financial crisis.

Although the studies in the transmission of volatility between markets are copious, very little is in Southeast Asia economies context. Besides, the works on the relationship between pandemic disease and volatility transmission are still limited. This current study contributes to the literature on financial globalization by filling both two gaps.

Methodology and Data

Data

The empirical analysis has focused on a panel of countries, including the U.S. and five emerging Southeast Asia Tiger Cub countries. The used stock index for each market is detailed in Table 1. Data on each index is gathered from the website of each Stock Exchange. The returns of all series are obtained as the first difference in the stock index's natural logarithm. The final data set includes daily stock market returns for the period spanning from April 1, 2019, to April 8, 2020.

Table 1

List of Stock Index

Market	Stock market index
Indonesia	Jakarta Stock Price Index – JCI
Malaysia	The FTSE Bursa Malaysia KLCI Index – FTSE KLCI
Philippines	Philippine Stock Exchange Composite Index – PSEi
Thailand	Stock Exchange of Thailand – SET Index
Vietnam	Vietnam Ho Chi Minh Stock Index – VNI
The U.S.	The S&P500 Index

On December 31, 2019, China reported the Wuhan cluster of COVID-19 cases, and the World Health Organization had the first official report identifying coronavirus. Hence, we use December 31, 2019, as the starting point of the COVID-19 pandemic period. A dummy variable named COVID is generated, in which COVID = 1 from December 31, 2019, to then.

The summary key points of the return series are presented in Table 2. The means of return for Southeast Asia stock are not much different, and all are negative, opposite to the return of the S&P 500 Index. The U.S. can be considered the most volatile stock market because of the highest standard deviation, and the Philippines stock return is the most volatile series among Tiger Cub economies. The corresponding measure for Malaysia is 0.0097, which is the least value of the standard deviation. The strong rejections of the unit root tests by Dickey-Fuller (ADF) and Phillips – Perron (P.P.) method indicate that all series are stationary. Table 2 also presents the pair-wise Pearson correlation coefficients among six stock returns. There exists positive and high linear correction in stock returns among Southeast Asia stocks. Based on the correlation coefficient, we conclude that the U.S. stock return series is positively correlated with all other series, among them, the highest correlation between the Philippines and the U.S.

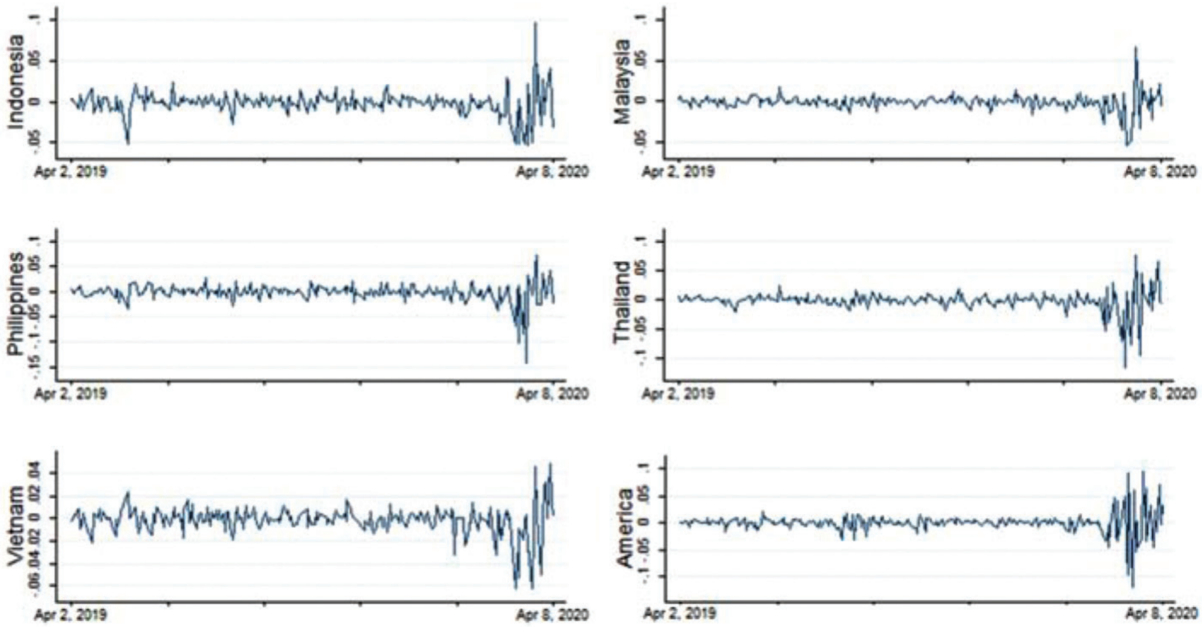

Figure 1. Time Series Plots of Stock Index Return

Table 2

Descriptive Statistics and Unit Root Rests for Stock Index Return

Key point	Returns of					
	Indonesia	Malaysia	Philippines	Thailand	Vietnam	The U.S.
Mean	-0.0014	-0.0007	-0.0014	-0.0013	-0.0011	0.0004
Median	0.0000	-0.0001	0.0000	-0.0002	0.0000	0.0009
Maximum	0.0970	0.0663	0.0717	0.0765	0.0486	0.0938
Minimum	-0.0534	-0.0540	-0.1432	-0.1143	-0.0627	-0.1198
Std. Dev.	0.0146	0.0097	0.0182	0.0164	0.0119	0.0194
Skewness	0.4039	-0.1444	-2.8255	-2.1576	-1.3544	-0.3593
ADF	-13.581***	-12.578***	-15.041***	-17.103***	-15.096***	-20.621***
PP	-13.498***	-12.607***	-15.276***	-16.995***	-14.980***	-19.659***
Correlation coefficient						
Indonesia	1					
Malaysia	0.543	1				
Philippines	0.562	0.474	1			
Thailand	0.626	0.633	0.532	1		
Vietnam	0.481	0.362	0.353	0.561	1	
US	0.140	0.043	0.378	0.336	0.2028	1

Note. *, **, *** indicate significance at the 10%, 5% and 1% levels of significance, respectively.

Methodology

Figure 1 shows that all series have heteroscedasticity characteristics; hence, we model the series as GARCH processes. In particular, the DCC-GARCH model proposed by Engle (2002) is applied in this study. DCC-GARCH has a significant advantage compared to other GARCH-family models because it assumes time-varying correlations.

Let $Y_t = \left(Y_{1t}, Y_{2t}, ..., Y_{kt}\right)$ be a ($k \times 1$) vector of multivariate data series. We present the mean equations as follows:

$$Y_t = \mu_t + \varepsilon_t \ ; \ \varepsilon_t \left| I_{t-} 1 - N\left(0, \Sigma_t\right) \right. \tag{1}$$

where $\mu_t = \left(\mu_{1t}, \mu_{2t}, ..., \mu_{kt}\right)$ is the conditional returns, $\varepsilon_t = \left(\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{kt}\right)$ is the vector of errors at time t.

Let D_t is a ($k \times k$) diagonal matrix with the time-varying standard deviations from univariate GARCH models, denoted by σ_{kt}. R_t is a conditional correlation matrix containing a conditional correlation coefficient $\rho_{ij} = cor\left(\varepsilon_{it}, \varepsilon_{jt} \left| I_{t-1} \right.\right)$. In particular, at time t, the forms of R_t and D_t are:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1k,t} \\ \rho_{21,t} & 1 & \rho_{23t} & \cdots & \rho_{2k,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \cdots & \rho_{3k,t} \\ \cdots & & & & \\ \rho_{k1,t} & \rho_{k2,t} & \rho_{k3,t} & \cdots & 1 \end{bmatrix} \qquad D_t = \begin{bmatrix} \sigma_{1t} & 0 & 0 & \ldots & 0 \\ 0 & \sigma_{2t} & 0 & \ldots & 0 \\ 0 & 0 & \sigma_{2t} & \ldots & 0 \\ \ldots & & & & \\ 0 & 0 & 0 & \ldots & \sigma_{kt} \end{bmatrix}$$

For the DCC-GARCH, the conditional variance-covariance matrix (Σ_t) can be expressed as:

$$var\left(\varepsilon_t \left| I_{t-1} \right.\right) = \sum_{k \times t} {}_t = D_t R_t D_t \tag{2}$$

The DCC-GARCH processes estimating conditional volatilities and correlation of the return comprises two steps. Firstly, estimating the univariate GARCH model for each return series to gain the conditional variance, which is given by the following expression:

$$\hat{\sigma}_{it}^2 = \omega_i + \sum_{p=1}^{p_i} \hat{\alpha}_i, p_i \hat{\varepsilon}_i,_{t-p} + \sum_{q=1}^{q_i} \hat{\beta}_{i,q_i} \hat{\sigma}_{i,t-q}^2 \tag{3}$$

For this study, we apply the GARCH(1,1) for each ε_i series. We use these above univariate variance estimates to form the standardized residuals:

$$\hat{z}_{it} = \frac{\hat{\varepsilon}_{it}}{\hat{\sigma}_{it}} \tag{4}$$

In the second step, we use the standardized residuals to model the pair-wise conditional covariance matrix R_t. The DCC(1,1) suggested by Engle (2002):

$$R_t = \left(diag\left(Q_t\right)\right)^{-1/2} Q_t \left(diag\left(Q_t\right)\right)^{-1/2} \tag{5}$$

where:

$$Q_t = \left(1-a-b\right)\bar{Q} + a\left(z_t z_t\right) + bQ_{t-1} \tag{6}$$

z_t is the $(k \times 1)$ vector of standardized errors, $\bar{Q}$ is the $(k \times k)$ unconditional variance matrix of z_t. The two parameters and must satisfy $a + b < 1$. Q_t refers to a symmetric positive definite matrix; $diag(Q_t)$ is the diagonal matrix containing the diagonal elements of Q_t. We focus on the estimates of the conditional correlation coefficient between two series i and j, ρ_{ij}:

$$\hat{\rho}_{ij} = \frac{\hat{q}_{ij}}{\sqrt{\hat{q}_{ii}\hat{q}_{jj}}} = \frac{\left(1-\hat{a}-\hat{b}\right)\bar{q}_{12} + \hat{a}\left(\hat{z}_{1t}\hat{z}_{2t}\right) + \hat{b}\hat{q}_{12,t-1}}{\sqrt{\left(1-\hat{a}-\hat{b}\right)+\hat{a}\left(\hat{z}_{1t}^2\right)+\hat{b}\hat{q}_{11,t-1}}\sqrt{\left(1-\hat{a}-\hat{b}\right)+\hat{a}\left(\hat{z}_{2t}^2\right)+\hat{b}\hat{q}_{22,t-1}}} \tag{7}$$

Finally, we need to test the consistency of volatility transmissions between two stock markets i and j in the pre-pandemic and during the pandemic. The null and alternative hypotheses are:

$$H_0 : \rho_{ij}^{pre-pandemic} = \rho_{ij}^{during-pandemic} \qquad H_1 : \rho_{ij}^{pre-pandemic} \neq \rho_{ij}^{during-pandemic}$$

To assess the statistical significance of the difference in conditional correlation for two periods, we use a t-test for the case the population variances of two sub-population are different and unknown:

$$t = \frac{\overline{\hat{\rho}_{ij}^{pre}} - \overline{\hat{\rho}_{ij}^{dur}}}{\sqrt{\frac{s_{pre}^2}{n_{pre}} + \frac{s_{dur}^2}{n_{dur}}}} \tag{8}$$

where $\overline{\hat{\rho}_{ij}^{pre}}$ and $\overline{\hat{\rho}_{ij}^{dur}}$ are the means of dynamic correlation coefficients between two stock markets i and j estimated by DCC-GARCH in the pre-pandemic and during the pandemic, n_{pre} and n_{dur} are the sub-sample size, s_{pre}^2 and s_{dur}^2 are the sample variances and calculated by $s_{pre}^2 = \frac{1}{n_{pre} -} \sum_{t=1}^{n_{pre}} \left(\hat{\rho}_{ijt}^{pre} - \overline{\hat{\rho}_{ij}^{pre}}\right)^2$ and $s_{dur}^2 = \frac{1}{n_{dur} -} \sum_{t=1}^{n_{dur}} \left(\hat{\rho}_{ijt}^{dur} - \overline{\hat{\rho}_{ij}^{dur}}\right)^2$.

At the level of significance α, if the absolute of calculated t-statistic is greater than the critical value $t_{a/2}^{df}$, we can reject the null hypothesis. is the degree of freedom and it can be attained from the following formula:

$$df = \frac{\left(\frac{s_{pre}^2}{n_{pre}} + \frac{s_{dur}^2}{n_{dur}}\right)}{\frac{1}{n_{pre}-1}\left(\frac{s_{pre}^2}{n_{pre}}\right)^2 + \frac{1}{n_{dur}-1}\left(\frac{s_{dur}^2}{n_{dur}}\right)^2} \tag{9}$$

(9)

Empirical Result

Table 3 reports the results for univariate GARCH(1,1) models in the first step. Several ARMA models are conducted to the mean equations to find the best-fitted model for each return series. Finally, conditional mean equations' form is ARMA(2,1) because it satisfies diagnostic tests such as stability conditions, serial correlation, and heteroscedasticity tests for all series.

For the mean equations, the absolute values of coefficients of AR(1), AR(2), and MA(1) are less than 1. Hence, the chosen ARMA models are stable. The return of each stock index depends on its 1-day lagged return. However, only the return of the Vietnamese stock market index is affected by its 2-day lagged return. The sum of coefficients relating to term ARCH(1) and term GARCH(1) in conditional variance equations is less than 1, so we conclude that the GARCH(1,1) model is stationary for all series. The own-volatility spillovers are significant for all six markets, which means that its first-lag volatility impacts each stock market's current volatility. Besides, any random change in the previous day in the stock return tends to enlarge the volatility because the terms' coefficients are all positive and statistically significant. However, the GARCH(1,1) plays an intermediary stage in estimating the DCC-GARCH model. Our interest in this study is the time-varying conditional covariance of each pair of stock markets; hence, we do not discuss more the results of the GARCH(1,1) model in this study. Panel C in Table 3 shows the diagnostic test for the GARCH(1,1). All volatility models successfully pass diagnostic tests, including the Ljung-Box for serial-correlation violation and the LM-ARCH test for heteroskedasticity violation, so the chosen GARCH(1,1) model is good enough to attain the standardized residuals for the next step.

Table 4 presents the mean of the time-varying conditional correlation coefficients from a multivariate DCC model in the pre-pandemic and pandemic periods. Based on the sign of the estimated mean correlation in all cases, innovations in the U.S. stock market influence the Southeast Asian "Tiger Cub" stock markets' volatility in the same direction. The values of t-statistic gained from the t-test for equality in means of two sub-population are all significant at level 1% for Indonesia, Malaysia, Philippines, and Thailand. However, we cannot reject the null hypothesis that the means of DCC correlation are the same in pre-pandemic and during pandemic periods for Vietnam. Volatility transmissions between the U.S. stock market and the other four Tiger Cub markets (excluding Vietnam) during the pandemic are stronger than the previous period. The contagion effect in volatility between Vietnamese and the U.S. stock markets is likely to vary steadily. The most substantial degree of cross-volatility is between Thailand and the U.S., followed by the pair-wise of Vietnam and the U.S. The U.S. stock market's volatility has the weakest impact on the Malaysia stock market's volatility in both pre-pandemic and during pandemic periods.

Within the Southeast Asian region countries, the result shows that there is evidence of positive volatility spillovers between any stock market index pair in both sub-sample, which means an increase in volatility of each market generates positive volatility spillovers to the others. Testing the equal in two sub-populations supports the evidence of a difference in transmission volatility between two countries in pre-pandemic and during the pandemic period, except for the contagion effect between Indonesia and the Philippines. Furthermore, the conditional correlations from the multivariate DCC-GARCH have increased during the pandemic period. The highest correlations have been observed between the Philippines and Indonesia's stock volatility in both sub-sample periods. Especially, Vietnam is the market with the weakest relationship with other markets in terms of volatility transmission.

Table 3

DCC-GARCH Models' Results

Coefficient	Indonesia	Malaysia	Philippines	Thailand	Vietnam	The U.S.
Panel A: Conditional Mean Equations (Robust standard errors in parenthesis)						
$\hat{\mu}$	-0.0034 (0.0565)	-0.0460 (0.0428)	-0.0201 (0.0230)	-0.0425 (0.0771)	-0.0561 (0.0595)	0.1380*** (0.0307)
$\hat{\gamma}_1$	-0.7024*** (0.1965)	0.7588** (0.3498)	0.8749*** (0.2528)	0.7483*** (0.1173)	-0.7884*** (0.0943)	0.9625*** (0.0732)
$\hat{\gamma}_2$	-0.0581 (0.0943)	-0.0343 (0.0750)	0.0434 (0.4024)	0.0771 (0.0883)	0.1709* (0.0908)	-0.0950 (0.0776)
$\hat{\theta}$	0.6990*** (0.1726)	-0.7018** (0.3277)	-0.9746*** (0.0867)	-0.7561*** (0.0794)	0.9491*** (0.0446)	-0.9412*** (0.0434)
Panel B: Conditional Variance Equations (Robust standard errors in parenthesis)						
Ω	0.1028** (0.0432)	0.0115 (0.0441)	0.2315** (0.0964)	0.0443 (0.0374)	0.0126 (0.0205)	0.0622*** (0.0208)
$\hat{\alpha}$	0.2956** (0.1239)	0.1109** (0.0463)	0.4528* (0.2616)	0.1682** (0.0684)	0.0781*** (0.0141)	0.4651*** (0.1194)
$\hat{\beta}$	0.6701*** (0.1145)	0.8881*** (0.1477)	0.5243*** (0.1518)	0.8255*** (0.0870)	0.9209*** (0.0318)	0.5339*** (0.0925)
Panel C: Diagnostic test for GARCH(1,1) (p-value in parenthesis)						
ARCH-LM(3)	0.2508 (0.6165)	0.9679 (0.3252)	0.1981 (0.6563)	1.0390 (0.3081)	1.4870 (0.2227)	1.604 (0.2053)
Q(1)	0.6789 (0.4100)	0.0069 (0.9339)	1.2890 (0.2562)	0.0352 (0.8513)	0.0015 (0.9695)	0.0013 (0.9715)
$Q^2(1)$	0.4317 (0.5112)	0.0016 (0.9686)	0.0188 (0.8908)	1.4590 (0.2271)	0.4598 (0.4977)	0.0187 (0.8882)
Panel D: Conditional Covariance Equations						
A	0.0503 (0.0670)	0.0000 (0.0000)	0.0010 (0.0183)	0.0000 (0.0000)	0.0000 (0.0000)	
B	0.5458* (0.3317)	0.9139*** (0.0836)	0.9425*** (0.1186)	0.9247*** (0.1443)	0.9107*** (0.0766)	

Note: This table shows the bivariate DCC-GARCH(1,1) model estimates for the return series of each Southeast Asian stock markets' index and the S&P 500. Panel A contains the results from the mean equations in the form of ARMA(2,1): $r_t = \hat{\mu} + \hat{\gamma}_1 r_{t-1} + \hat{\gamma}_2 r_{t-2} + \hat{\theta}\hat{\varepsilon}_{t-1} + \hat{\varepsilon}_t$, where r_t is the return of stock index at time t, $\hat{\varepsilon}_t$ is the estimates of error terms. Panel B contains the results from the variance equations in form: $\hat{\sigma}_t^2 = \hat{\alpha}\hat{\varepsilon}_{t-1}^2 + \hat{\beta}\hat{\sigma}_{t-1}^2$, where $\hat{\sigma}_t^2$ measures volatility of stock index at time t. Panel C contains the diagnostic tests for GARCH(1,1) models. ARCH-LM(3) indicates the test for the ARCH effect. Q(1) and $Q^2(1)$ are the Ljung-Box Q-statistics to test serial correlations in the residuals and squared residuals. Panel D contains the result of the condition covariance equation: $Q_t = (1-a-b)\bar{Q} + a\left(z_t z_t\right) + bQ_{t-1}$. *, **, *** stand for statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4

DCC Conditional Correlation and Transmission Volatilities Test Between Southeast Asian Stock Markets and the U.S. Stock Market

Correlation	Pre-COVID	During-COVID	Transmission test
Indonesia – US	0.0961063 (0.05628728)	0.1344270 (0.07946769)	3.6599***
Malaysia – US	0.09457616 (0.00000004)	0.09457617 (0.00000009)	4.0824***
Philippines – US	0.1312556 (0.00353930)	0.1346355 (0.00432529)	5.7735***
Thailand – US	0.2369198 (0.00000003)	0.2369199 (0.00000006)	7.8563***
Vietnam – US	0.2006976 (0.00000003)	0.2006976 (0.00000006)	-0.37302

Note: This table presents the equality hypothesis test results in conditional correlation for two periods between the U.S. and five Tiger Cub stock markets. Pre-COVID is from April 1, 2019, to December 30, 2019. During-COVID is from December 31, 2019, to April 08, 2020. *, **, *** stand for the significant difference at the 10%, 5%, and 1% levels, respectively.

Table 5

DCC Conditional Correlation and Transmission Volatilities Test Within Southeast Asian Stock Markets

Correlation	Pre-COVID	During COVD	Transmission test
Indonesia – Malaysia	0.4411628 (0.00000003)	0.441629 (0.00000003)	8.1965***
Indonesia – Philippines	0.5738691 (0.04010288)	0.58375177 (0.04300807)	1.6472
Indonesia – Thailand	0.4666573 (0.09562025)	0.5157617 (0.08548027)	3.9048***
Indonesia – Vietnam	0.0939340 (0.1456393)	0.3057406 (0.01692547)	9.1454***
Malaysia – Philippines	0.4639610 (0.00000000)	0.4639611 (0.000000001)	2.3322**
Malaysia – Thailand	0.5337467 (0.00000000)	0.5337468 (0.00000000)	3.2429***
Malaysia – Vietnam	0.3481823 (0.01527743)	0.3607140 (0.03548581)	2.8318***
Philippines – Thailand	0.4458955 (0.000000006)	0.4458956 (0.00000002)	2.905***
Philippines – Vietnam	0.2515489 (0.02133254)	0.28079722 (0.05524527)	4.2739***
Thailand – Vietnam	0.2517079 (0.05391181)	0.3850196 (0.11792851)	9.0257***

Note: This table presents the equality hypothesis test results in conditional correlation for two periods between each pair of countries of five Tiger Cub stock markets. Pre-COVID is from April 1, 2019 to December 30, 2019. During-COVID is from December 31, 2019, to April 08, 2020. *, **, *** stand for significant difference at the 10%, 5%, and 1% levels, respectively.

Conclusion

In the trend of financial market globalization, volatility transmission among international stock markets has attracted enormous attention in the last decades. This paper contributes to the current understanding of how volatility transmissions between the U.S. stock market and the five Tiger Cub stock markets in the Southeast Asia region change before and during the COVID-19 pandemic period. We use the DCC-GARCH model applying for daily time series data to analyze volatility linkage.

Our results imply that the increase in the volatility of the U.S. equity markets will impulse instability in these emerging markets over time. This result is consistent with Beirne et al. (2013), who concluded that volatility transmission from mature markets to the emerging stock markets was significant. As a result of the analysis, we also find a significant cross-market correlation on five emerging Tiger Cub markets. This tallies with Yarovaya et al. (2016) that volatility spillover effects exist within the Asian stock markets. In addition to this study, Singh et al. (2010) discovered the price and volatility spillover and found the regional effects across Asia stock markets.

Hwang (2014) confirmed the stronger linkages between the U.S. and Latin American stock volatility during the global financial crisis. Along the same line, Li and Giles (2015) revealed that volatility spillovers from the U.S. and Asian emerging markets are closely associated with the Asian currency crisis. These are evidence of changes in the volatility transmission during the turbulent period. Our paper contributes to this topic by analyzing the change in volatility spillover among different stock markets during the disease pandemic. The COVID-19 pandemic hit the volatility transmission from the U.S. to the Tiger Cub markets and across these emerging markets.

The findings of this study are important for policymakers in the context of emerging markets. The more vital interdependence between the Tiger Cub markets and the U.S. market in terms of volatility transmission indicates that the U.S. equity market's shock can lead to an intense instability in these emerging markets, affecting their developments. Besides, the co-movement in volatilities of these emerging markets reveals evidence that the Tiger Cubs stock markets are driven more by the U.S. market than country-specific and region-specific factors. Hence, policymakers have to recognize the need for vigilance of the lousy situation relating to the U.S. stock market and find ways to decrease these markets' instability at the lowest level during the COVID-19 pandemic period.

From the international investors' and portfolio managers' views, the study's findings may be of interest to them. Firstly, the high correlation in volatility across Southeast Asia stock markets implies that the investors could not take advantage of long-run diversification benefits concerning minimizing risks of loss by holding a portfolio including stocks from these emerging countries. The stronger conditional correlation indicates that diversification benefits attained during the pandemic periods will reduce. Secondly, these markets' co-movement shows that information from one stock market can be applied to predict the other markets' fluctuation. In summary, the investors who care about diversifying their portfolios should be more cautious at this time.

Despite investigating stock markets within Asia, we ignore the spatial dependence of these markets, which is proved to exist between neighboring countries (Ades & Chua, 1997; Murdoch & Sandler, 2002). Our estimates are therefore subject to the problem of omitted-variable bias. For future research, the more complex approach, DCC-GARCH copula, can be conducted to account for the spatial effects. Besides, to test the equality in conditional correlation for two periods, we apply the t-test (as well as the p-value) in frequentist methods, in which parameters are unknown but fixed. Cumming (2014) judged that the non-significant p-values did not quantify evidence supporting the null hypothesis. Hence, the Bayesian t-test can be applied to deal with this problem.

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Declaration of ownership

This report is our original work.

Conflict of interest

None.

Ethical clearance

This study was approved by our institution.

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