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Covıd-19: Fınancıal Spıllover to Emergıng Asıa's Fınancıal Markets

Chandra Susilo[a]
Nur Dhani Hendranastiti[b*]

[a,b] Department of Management, Faculty of Economics and Business, Universitas Indonesia, Jakarta, Indonesia

Abstract
This paper aims to investigate the role of China compared to the US in transmitting spillover to ASEAN-5 countries (or vice versa) during COVID-19 recession. It uses the DECO GARCH model of Engle & Kelly (2012) to see the dynamic correlation between indexes and the spillover index by Diebold and Yilmaz (2012) to describe the direction of spillover between countries. This paper analyzes daily return data on stock market indexes of China, the United States, and ASEAN-5 for the period 2016 to 2022. The findings demonstrate an increase in positive spillover correlation during the COVID-19 crisis between China and ASEAN-5 as well as US and ASEAN-5 albeit with lower pre crisis correlation level than China. US acts as a net transmitter (spillover to ASEAN-5 is higher than in the opposite direction), while China is a net receiver. The findings are beneficial to provide insight into Emerging Asia market's connectedness, which in turn will be able to guide the hedging strategies and portfolio risk management of investment in the region.

Keywords
Financial contagion; DECO GARCH; ASEAN countries; COVID-19; connectedness; volatility spillover
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Introduction

Markowitz (1959) stated that uncertainty is a salient feature of security investment. Economic forces are not understood well enough for predictions to be beyond doubt or error. A second salient feature of security investment is the correlation among security returns. Like most economic quantities, the returns on securities tend to move up and down together. This correlation is not perfect: individual securities and entire industries have at times move against the general flow of prosperity. The fact that security returns are highly correlated, but not perfectly correlated, implies that diversification can reduce portfolio risk. To reduce risk, it is necessary to avoid a portfolio whose securities are highly and positively correlated with each other.

With the growing trend of financial globalization, investors can place their money in the financial markets of various countries or regions abroad.

*Corresponding author Email: nurdhani@ui.ac.id

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Due to the relatively low correlation of international securities, improved reward-to-risk performance can be achieved by holding an internationally diversified portfolio (Mo *et al.,* 2019). International investors face more complex variables and uncertainties that affect security returns in exchange for lower correlations. One thing to note is the global spillover phenomenon between markets and the financial crisis cycle. Empirical research shows that the financial crisis increases the correlation between markets and potentially reduces the benefits of diversification. Studying spillovers and correlations between markets is important to gain valuable insights into navigating the risky global investment market.

The COVID-19 recession crisis is a recent instance of a financial crisis on a global scale. The COVID-19 outbreak has triggered a global economic downturn. Epidemics with strict and voluntary restrictions on human interaction have resulted in massive economic downturns in developed countries and increased disruption in Emerging Markets and Developing Economies (EMDEs). Growth of global GDP (Gross Domestic Product) per capita contracted by -3.5% and is projected to remain around 2% below pre-pandemic in 2022. Per capita income losses incurred in 2019 will not be fully recovered in about two-thirds of EMDEs (World Bank, 2021).

Emerging markets are increasingly important as international investment destinations and there has been a large increase in the volume of investment in Asia, Eastern Europe, and Latin America from both investment funds and individuals (Marshall *et al.,* 2009). The Association of South-East Asian Nations (ASEAN) is one of the EMDEs, which was founded in 1967 by five founding members called ASEAN-5: Indonesia, Malaysia, Philippines, Singapore, and Thailand. Before the COVID-19 recession, the region experienced rapid growth and played a significant role in the world economy. In 2016, ASEAN was the 6th largest economy in the world and the 3rd largest in Asia with a combined GDP of US$2.55 trillion (Association of Southeast Asian Nations, 2017). At the same time, in a decade, 2006-2016, the market capitalization of the stock exchanges in ASEAN-5 countries also grew substantially: the Philippines (253%), Thailand (209%), Indonesia (207%), Singapore (67 %), and Malaysia (53%) (World Bank, 2022b). However, during the pandemic, the broader Asia Pacific market has been hit hard by COVID-19 uncertainty. Stock markets in Japan, the Philippines, Singapore, and Indonesia fell more than 20% from their highs, while Australian stock markets almost hit the same level and Hong Kong stocks fell less than 3% (Vishnoi & Mookerjee, 2020).

A strand of literature has examined the relationship between stock markets in the Asian region and other countries in the period before the COVID-19 recession with various methods and provides varying findings. Chien *et al.* (2015) used a cointegration test with a structural break and a recursive cointegration based on the VAR/VECM model to investigate the long-run and the time-varying relationship between the ASEAN and China stock market. Research by Lee & Jeong (2016) using the GARCH risk decomposition model to examine the stock markets of ASEAN, China, and the US reports that ASEAN is more influenced by regional events than global ones. Using data before the COVID-19 crisis, the DECO GARCH (Dynamic Equicorrelation – Generalized Autoregressive Conditional Heteroskedasticity) model developed by Engle & Kelly (2012) and the spillover index by Diebold & Yilmaz (2012) were used by Kang *et al.* (2019) to examine the directional spillover effect between ASEAN-5 and world stock markets from 2003 to 2019.

Diebold & Yilmaz (2012) introduced a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VARs). This method can be used to measure the spillovers in returns across individual assets, asset portfolios, and asset markets, both within and across countries, revealing spillover trends, cycles, and bursts. It was able to describe the directions of such spillover in which correlation models such as DECO or DCC were only able to measure its time-varying correlation intensity.

This paper aims to determine the role of China compared to the United States (US) in transmitting spillovers to ASEAN-5 countries (or vice versa) during the COVID-19 recession.

This paper analyzes daily returns on stock market indices of China, the United States, and ASEAN-5 for the period 2016 to 2022. We use the DECO GARCH model of Engle & Kelly (2012) to see the dynamic correlation between the index and the spillover index by Diebold & Yilmaz (2012) to describe the direction of spillover between countries.

This study offers three contributions to the literature on spillover and connectedness in Asian markets. First, this study extends the study of Kang *et al.* (2019) by investigating the role of China compared to the US in transmitting spillovers to ASEAN-5 countries. Although there is evidence against market linkages between developed and developing countries, most studies support information spillover from developed to developing countries (Song *et al.*, 2018). The 2007-2009 Global Financial Crisis (GFC) exemplifies a case where the world crisis started with a shock in the US, the world's largest economy. However, the role of China, which is also counted as an Emerging market, having the 2nd largest GDP per country is important to explore. In 2020, China's GDP reached US$14.72 trillion, just behind the US's US$20.95 trillion (World Bank, 2022a).

Previous empirical studies suggest that the GFC strengthens linkages among East Asian stock markets while the influence of the US market becomes weaker during the crisis (Wang, 2014). In contrast, Serkan Arslanal *et al.* (2016) highlights China's growing influence in Asian Financial markets. From a trade route point of view, investigating the spillover effects of China and the US from or to the ASEAN-5 countries is arguable because of their active trade connections with the region. In 2016, China was ASEAN's largest trading partner outside of intra-ASEAN trade with a total import of US$ 143 billion, while the US ranked 3rd with a total import of US$131 billion (ASEAN Statistics Division, 2022).

Second, the recent COVID-19 recession provides a rare opportunity to study this unique phenomenon. Unlike the previous crisis, the COVID-19 recession began as a health crisis that impacted the global economy. This was the first recession since 1870 to be triggered solely by a pandemic (World Bank, 2021). Empirical research shows that COVID-19 severely impacts the global economy with a total volatility spillover eight times greater than that of GFC (Gunay, 2021).

Third, this study uses the spillover index by Diebold & Yilmaz (2012), based on the generalized forecast error decomposition model of the VAR which can measure the direction of spillover and identify parties who act as net contributors or spillover transmitters to other countries. In addition, we also use the multivariate DECO-GARCH proposed by Engle & Kelly (2012) which corrects inconsistencies in the correlation matrix estimates of the more popular DCC model (Engle, 2002) as demonstrated by Aielli (2013).

Literature Review

Portfolio theory explains that investments will be made to maximize return by having minimum risk or to have the lowest risk for the same level of return (Markowitz, 1959). In calculating the risk and return for the set of assets, it is important to understand the correlation among the assets. Portfolio diversification works when the assets have a low or even negative correlation, reducing the risk of the portfolio. High and positive correlated assets are avoided considering that when one asset goes down, the other assets also have a decreasing trend resulting in a decreasing performance for the portfolio (Fabozzi *et.al.,* 2002).

Empirical research shows that the financial crisis increases the correlation between markets and potentially reduces the benefits of diversification (Cho & Parhizgari, 2008; Kang *et al.,* 2019; McIver & Kang, 2020; Mo *et al.,* 2019; Rai & Garg, 2021). At the same time, the financial market's volatility generally increases sharply and spills across markets (Diebold & Yilmaz, 2012). In terms of contagion, it is said that it occurs when the volatility of asset prices spills over from the country having the crisis to other countries. On the other hand, to a particular extreme, contagion is not simply a high cross-market correlation after a shock; it is the significant increase in this correlation after the shock. It even strictly viewed some volatility spillover during crises such as the Asian crisis, the Mexican peso collapse, and the 1987 US market crash are interdependence and not contagion (Forbes & Rigobon, 1999).

Several studies consider the volatility spillover between countries or financial markets using variations of the AutoReg-ressive Conditional Heteroskedasticity (ARCH) multivariate model: DCC GARCH (Burdekin & Siklos, 2012; Cho & Parhizgari, 2008; Rai & Garg, 2021; Song *et al.,* 2018), DECO GARCH (Kang & Yoon, 2019; McIver & Kang, 2020), and BEKK GARCH (Azis *et al.,* 2013; Rai & Garg, 2021).

Another alternative method is to use the VAR model. Diebold & Yilmaz (2012) introduced a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VARs). This method can be used to measure the spillovers in returns across individual assets, asset portfolios, and asset markets, both within and across countries, revealing spillover trends, cycles, and bursts. It was used to study the asymmetric volatility spillover during COVID-19 in previous studies: among the corporate sector in the Chinese stock market (Shahzad *et al.,* 2021); global asset class (Bouri *et al.,* 2021); and regional financial markets (ben Amar *et al.,* 2020).

Methodology

Data dan stochastic analysis

The data for this study is taken from the Refinitiv Eikon database and consists of the closing prices of daily stock market indexes from China, the US, and ASEAN-5 markets, namely the Shanghai SE Composite (SH), S&P 500 (US), Jakarta Composite (ID), FTSE Bursa Malaysia KLCI (MY), Straits Times Index (SG), Philippine SE Composite (PH), and Thai SET Index (TH). The index from the Shanghai Stock Exchange was chosen to represent the Chinese stock market following previous research (Burdekin & Siklos, 2012; Fang *et al.,* 2021; Wang, 2014; Zhong & Liu, 2021). The daily return can then be calculated as the first differential of the log-transformed series. 31/12/2019 was when WHO first received information on coronavirus case in Wuhan, China (World Health Organization, 2021). The sample taken from 01/01/2016 to 30/12/2019 is classified as pre-crisis and 31/12/2019 to 31/12/2021 is included in the crisis period.

Econometric method

The study uses the DECO GARCH model of Engle & Kelly (2012) to see the dynamic correlation between indexes and the spillover index by Diebold & Yilmaz (2012) to describe the direction of spillover between countries.

DECO GARCH

$$r_t = \mu_t(\theta) + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (1)$$

$$\varepsilon_t = H_t^{1/2} u_t, \text{ where } u_t \sim N(0, I) \quad (2)$$

$$H_t = D_t R_t D_t \quad (3)$$

where:

$r_t = (r_{it}, \dots, r_{Nt})'$ is a N x 1 vector of variables (SH, US, ID, MY, SG, PH, TH, so N = 7)

$\mu_t(\theta) = (\mu_{it}, \dots, \mu_{Nt})'$ is the conditional N x 1 mean vector of r_t

H_t is the conditional covariance matrix

$D_t = diag\ (h_{iit}^{1/2}, \dots, h_{NNt}^{1/2})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH-type model.

To obtain the conditional variances, the study uses a univariate GARCH (1,1) process as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_1 \varepsilon^2_{t-1} + \dots + \alpha_p \varepsilon^2_{t-p} + \sum_{i=1}^{p} \beta_1 \sigma^2_{t-1} + \dots + \beta_q h^2_{t-q} \quad (4)$$

R_t is the $t\ x\ \left(\frac{N(N-1)}{2}\right)$ matrix containing the time-varying conditional correlations defined as:

$$R_t = diag\left(q_{ii,t}^{-\frac{1}{2}}, \dots, q_{NN,t}^{-\frac{1}{2}}\right) Q_t\ diag\left(q_{ii,t}^{-\frac{1}{2}}, \dots, q_{NN,t}^{-\frac{1}{2}}\right)$$

or

$$\rho_{ij,t} = \rho_{ji,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (5)$$

where $Q_t = (q_{ij,t})$ is a N × N symmetric positive definite matrix given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \quad (6)$$

$u_t = (u_{1t}, u_{2t}, \dots, u_{Nt})'$ is the N x 1 vector of standardized residuals,

$\bar{Q}$ is the N x N unconditional variance matrix of u_t, and

α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$

While the DCC model substantially simplifies multivariate requirements, the estimate gets progressively difficult as the size of the system expands. Estimation can fail for cross-sections of hundreds or thousands of stocks, which are prevalent in asset pricing applications.

Engle & Kelly (2012) then consider a system in which all pairs of returns have the same correlation on a given day, but this correlation varies over time. The model, called Dynamic Equicorrelation (DECO), eliminates the computational and presentational difficulties of high-dimension systems. Because equicorrelated matrices have simple analytic inverses and determinants, likelihood calculation is dramatically simplified, and optimization becomes feasible for vast numbers of assets.

Following Engle & Kelly (2012), it is defined as:

$$R_t^{DECO} = (1 - \rho_t) I_n + \rho_t J_n, \quad (7)$$

where:

R_t^{DECO} is an equicorrelation matrix of an N x 1 vector of variables (SH, US, ID, MY, SG, PH, TH, thus N = 7)

ρ_t is the equicorrelation

I_n denotes the n-dimensional identity matrix, and

J_n is the n x n matrix of ones

The basic ρ_t specification derives from the DCC model of Engle (2002) and its cDCC modification proposed by Aielli (2013).

$$Q_t = (1-\alpha-\beta)\bar{Q}^* + \alpha\left(Q_{t-1}^{*\frac{1}{2}} u_{t-1} u'_{t-1} Q_{t-1}^{*\frac{1}{2}}\right) + \beta Q_{t-1} \quad (8)$$

DECO sets ρ_t, equal to the average pairwise DCC correlation:

$$\rho_t^{DECO} = \frac{1}{n\,(n-1)}\left(\iota' R_t^{DCC}\iota - n\right) = \frac{2}{n\,(n-1)} \sum_{i>j} \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \quad (9)$$

where:
ι is a vector of ones
$\bar{Q}^*$ is the unconditional covariance matrix of $Q_t^{*\frac{1}{2}} u_t$
$q_{i,j,t}$ is the i, jth element of Q_t from the cDCC model.
α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$

The DECO model was estimated using a two-step procedure. In the first step, we specify residuals to be asymmetric GARCH (1,1) process with Student-t innovation (Engle & Kelly, 2012; Glosten *et al.*, 1993). GARCH regressions are estimated via maximum likelihood, and then volatility-standardized residuals are given as inputs to the second-stage DECO model. Here and throughout, second-stage models are estimated using correlation targeting for the intercept matrix $\bar{Q}^*$.

Spillover index

This study applies the spillover index Diebold & Yilmaz (2012) to examine the total spillover and net spillover between the ASEAN-5 market and China & the US. This index is based on forecast-error variance decomposition of the generalized VAR specification where they are invariant with respect to the order of variables. Following Diebold & Yilmaz (2012), the study assumed a stationary covariance of n-variable VAR (p), as follows:

$$x_t = \sum_{i=1}^{p} \Phi_i\, x_{t-1} + \varepsilon_t \quad (10)$$

where:
x_t = (N x 1) vector of endogenous variables
Φ_i = (N x N) autoregressive coefficient matrices, and
$\varepsilon_t \sim (0, \sum)$ = vector of errors that are assumed to be independently and identically distributed.
The VAR model contains seven variables (n = 7): the returns (volatility) of the ASEAN-5 and China, and US indices.

With the moving average representation:

$$x_t = \sum_{i=0}^{\infty} A_i\, \varepsilon_{t-1} \quad (11)$$

where the N x N coefficient matrix A_i obey a recursion of the form $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 being an N x N identity matrix and $A_i = 0$ for i < 0.

We rely on variance decompositions, which allow us to parse the forecast error variances of each variable into parts that are attributable to the various system shocks. The variance decompositions allow us to assess the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall j \neq i$, for each i.

<u>Variance shares</u>

Own variance shares are defined as the fractions of the H-step-ahead error variances in forecasting x_i that are due to shocks to x_i, for i=1, 2,..,N, and cross variance shares, or spillovers, as the fractions of the H-step-ahead error variances in forecasting x_i that are due to shocks to x_j, for i, j = 1, 2,.., N, such that i $\neq$ j. Denoting the KPPS H-step-ahead forecast error variance decompositions by θ_{ij}^{g}(H), for H = 1, 2, …, we have:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1}\left(\acute{e}_i A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(\acute{e}_i A_h \sum \acute{A}_h e_i\right)} \quad (12)$$

where $\sum$ is the variance matrix for the error vector ε, σ_{ii} is the standard deviation of the error term for the *j*th equation, and e_i is the selection vector, with one as the ith element and zeros otherwise. As was explained above, the sum of the elements in each row of the variance decomposition table is not equal to 1: $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

To use the information available in the variance decomposition matrix in the calculation of the spillover index, we normalize each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \qquad (13)$$

Note that, by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = \text{N}$.

Total spillovers

Using the volatility contributions from the KPPS variance decomposition, we can construct the total volatility spillover index:

$$S^{g}(H) = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \bullet 100 = \frac{\sum_{i,j=1\ i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \bullet 100 \qquad (14)$$

The total spillover index measures the contribution of spillovers of volatility shocks across seven markets to the total forecast error variance.

Directional spillovers

Although the total volatility spillover index is sufficient to understand how much shocks to the volatility spillover across markets, the generalized VAR approach enables us to learn about the direction of volatility spillovers across major asset classes. As the generalized impulse responses and variance decompositions are invariant to the ordering of variables, we calculate the directional spillovers using the normalized elements of the generalized variance decomposition matrix.

We measure the directional volatility spillovers received by market i from all other markets j as:

$$S_{i\bullet}^{g}(H) = \frac{\sum_{j=1\ j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \bullet 100 = \frac{\sum_{j=1\ j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \bullet 100 \qquad (15)$$

Similarly, we measure the directional volatility spillovers transmitted by market i to all other markets j as:

$$S_{\bullet i}^{g}(H) = \frac{\sum_{j=1\ j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \bullet 100 = \frac{\sum_{j=1\ j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \bullet 100 \qquad (16)$$

One can think of the set of directional spillovers as providing a decomposition of the total spillovers to those coming from (or to) a particular source.

Net spillovers

We obtain the net volatility spillover from market i to all other markets j as

$$S_{i}^{g}(H) = S_{\bullet i}^{g}(H) + S_{i\bullet}^{g}(H) \qquad (17)$$

The net volatility spillover is simply the difference between the gross volatility shocks transmitted to and those received from all other markets.

Net pairwise spillovers

The net volatility spillover in Eq. (17) provides summary information about how much each market contributes to the volatility in other markets, in net terms. It is also of interest to examine the net pairwise volatility spillovers, which Diebold & Yilmaz (2012) define as:

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)}\right) \bullet 100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N}\right) \bullet 100 \qquad (18)$$

The net pairwise volatility spillover between markets i and j is simply the difference between the gross volatility shocks transmitted from market *i* to market *j* and those transmitted from *j* to *i*.

Results and Discussions

Table 1 presents descriptive statistics of the daily returns of seven markets (calculated as the first difference of the log-transformed price index series). Based on the ADF test, all data series are stationary at the first difference or first-order integration level, I(1).

The largest daily returns in the pre-crisis period were in the US (0.04%), followed by ID (0.03%), SG, PH, and TH (0.01%). During the COVID-19 crisis, only US (0.07%) and SH (0.03%) made consistent daily positive returns. MY, SG, and PH even recorded negative returns, while other ASEAN-5 markets yielded returns that fell drastically from the pre-crisis period. Volatility, measured by the standard deviation, increases significantly across markets.

Positive excess kurtosis indicates that the data distribution is not normal and is leptokurtic (fat tail, higher peak). Excess kurtosis increases significantly during the crisis period. The Jarque-Bera statistic, at a significance level of 1% rejects the normal distribution hypothesis. At the 1% significance level, the ARCH – LM test (5) rejects the null hypothesis of no ARCH effect in all-time series data except SH in the crisis period.

Table 1. Descriptive Statistics

	SH	US	ID	MY	SG	PH	TH
ADF log level	-2,3024***	-0,4775***	-2,2258***	-2,0066***	-2,4958***	-2,3448***	-2,8359***
ADF (1st diff)	-42,2577	-12,0225	-37,8914	-40,0371	-15,1181	-41,0159	-14,8887
Pre-crisis (1 Jan 2016 s.d. 30 Des 2019) – 1042 obs.							
Mean	-0,0001	**0,0004**	**0,0003**	-0,0000	**0,0001**	**0,0001**	**0,0001**
Maximum	0,0544	0,0484	0,0281	0,0201	0,0265	0,0357	0,0448
Minimum	-0,0730	-0,0418	-0,0408	-0,0323	-0,0304	-0,0446	-0,0319
Std. Dev.	0,0111	0,0079	0,0077	0,0051	0,0072	0,0097	0,0066
Skewness	-1,1942	-0,6371	-0,3759	-0,5903	-0,1301	0,0197	-0,1526
Excess kurtosis	8,3855	4,8595	2,5002	3,2645	1,5066	0,9739	3,6967
Jarque-Bera	3297,5***	1094,7***	295,65***	522,73***	101,39***	41,215***	596,80***
ARCH (5)	20,572***	19,400***	7,1877***	18,352***	9,2215***	12,055***	18,166***
Crisis (31 Des 2019 s.d. 31 Des 2021) – 524 obs.							
Mean	**0,0003**	**0,0007**	**0,0000**	-0,0000	-0,0000	-0,0001	**0,0000**
Maximum	0,0555	0,0896	0,0970	0,0662	0,0589	0,0717	0,0765
Minimum	-0,0803	-0,1276	-0,0680	-0,0540	-0,0763	-0,1432	-0,1142
Std. Dev.	0,0107	0,0161	0,0129	0,0096	0,0115	0,0165	0,0139
Skewness	-0,8922	-1,0643	0,0666	-0,1306	-0,6432	-1,7906	-1,9692
Excess kurtosis	8,0011	15,417	9,4717	7,6627	9,3903	15,565	18,666
Jarque-Bera	1467,2***	5288,6***	1959,1***	1283,5***	1961,4***	5569,7***	7946,0***
ARCH (5)	0,7062	70,652***	24,906***	38,048***	65,221***	40,870***	14,038***

Note: * indicates the rejection of the null hypothesis at the 10% level. ** indicates the rejection of the null hypothesis at the 5% level. ***indicates the rejection of the null hypothesis at the 1% level
Sources: Data Processed

Table 2. Estimation result of AR(2) DECO GARCH (1,1)

	SH	US	ID	MY	SG	PH	TH
Panel A: Univariate GARCH model estimation							
Const. μ	0,0001	0,0009	0,0004	-0,0000	0,0002	0,0002	0,0002
	(0,4430)	(0,0000)	(0,0219)	(0,6773)	(0,1526)	(0,3611)	(0,1945)
AR (1) ψ_1	-0,0158	-0,0828	-0,0115	0,0057	0,0107	-0,0341	0,0472
	(0,5921)	(0,0069)	(0,6797)	(0,8387)	(0,6982)	(0,2447)	(0,1110)
AR (2) ψ_2	0,0182	0,0278	-0,0694	0,0318	0,0195	-0,0603	0,0001
	(0,6587)	(0,3709)	(0,0115)	(0,2239)	(0,4685)	(0,0352)	(0,9970)
Const, ω	0,0126	0,0439	4,5429	0,2054	3,5717	0,0590	0,6186
	(0,0704)	(0,0001)	(0,1080)	(0,1283)	(0,0030)	(0,0791)	(0,1539)
ARCH α	0,0701***	0,2390***	0,1175***	0,0593***	0,1178***	0,1240***	0,0811***
	(0,0009)	(0,0000)	(0,0063)	(0,0002)	(0,0000)	(0,0078)	(0,0000)
GARCH β	0,9226***	0,7269***	0,8272***	0,9384***	0,8274***	0,8360***	0,9136***
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
$\alpha+\beta$	0,9927	0,9660	0,9447	0,9978	0,9453	0,9601	0,9947
Panel B: DECO China – ASEAN-5							
ρ	0,2516***						
	(0,0000)						
α	0,0214***						
	(0,0000)						
β	0,9603***						
	(0,0000)						
Q^2 (20)	14,9036		13,2237	29,6852	25,3440	15,6778	18,0334
	(0,7818)		(0,8675)	(0,0751)	(0,1885)	(0,7364)	(0,5852)
Hosking2 (20)	886,379						
	(0,0000)						
McLeod-Li2 (20)	885,122						
	(0,0000)						
Panel C: DECO US – ASEAN-5							
ρ		0,2428***					
		(0,0000)					
α		0,0162***					
		(0,0061)					
β		0,9610***					
		(0,0000)					
Q^2 (20)		11,3012	13,7307	34,4163	21,6948	15,6318	18,2466
		(0,9380)	(0,8438)	(0,0234)	(0,3572)	(0,7391)	(0,5711)
Hosking2 (20)		794,091					
		(0,0250)					
McLeod-Li2 (20)		794,417					
		(0,0246)					

Note: *P-values* are in parentheses. * indicates the rejection of the null hypothesis at the 10% level. ** indicates the rejection of the null hypothesis at the 5% level. *** indicates the rejection of the null hypothesis at the 1% level

DECO models

We selected the mean equation based on the information criteria (see Table 2) and found that the AR(2) process was the most suitable specification for the DECO-GARCH(1,1) model.

Panel A of Table 2 presents the estimates of AR(2) GARCH(1,1) univariate process for each index. Both ARCH and GARCH parameters are highly significant for all series with p values below the 1% level. The sum of ARCH and GARCH parameters ($\alpha+\beta$) is close to one, indicating that the shock to the conditional variance will be very persistent.

Panels B and C of Table 2 show the respective estimates of the China –

ASEAN-5 and US – ASEAN-5 DECOs. The positive correlation for China – ASEAN-5 (0.2516) and US – ASEAN-5 (0.2428) indicates the presence of co-movement between China and the US with ASEAN-5. The parameter for both DECO models is also significant at 1%. The parameter is significant with a below 1% value for both. The value of $\alpha+\beta$ is close to one in both cases indicating that the equicorrelation is nearly integrated. The diagnostic test Q2 (20) is a Q-statistic on standardized residual squares showing a *p-value* greater than 5%, thus rejecting serial correlation in each univariate time series. The results show that the model has been determined correctly. Diagnostic tests on multivariate estimates following Hosking (1980) and McLeod & Li (1983) accepted the null hypothesis of no serial correlation in the estimation of the conditional variance of the DECO model.

Figure 1 illustrates the dynamic equicorrelation of the two systems: i) China – ASEAN-5 and ii) US – ASEAN-5. The dotted line indicates the first time a COVID-19 case was identified (31 December 2019).

The degree of equicorrelation between the Chinese stock market and the ASEAN-5 increased significantly during the COVID-19 crisis. This correlation peaked throughout the period at 52% shortly after the crisis started and has returned to its pre-crisis average in 2022, suggesting a recovery in volatility. The correlation is time-varying and does not enter the negative territory in any case. DECO US – ASEAN-5 shows a similar pattern. The crisis also increased the equicorrelation between the US and ASEAN-5, although with a lower pre-crisis correlation level than China. The crisis triggered a significant increase in the correlation between China and the US with the ASEAN-5 market.

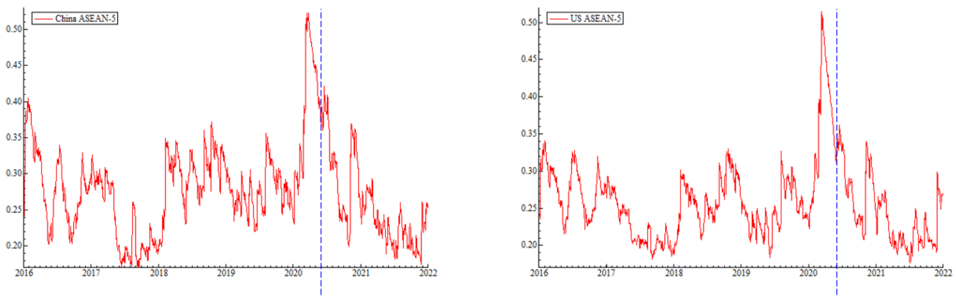

Figure 1. Dynamic Equicorrelation

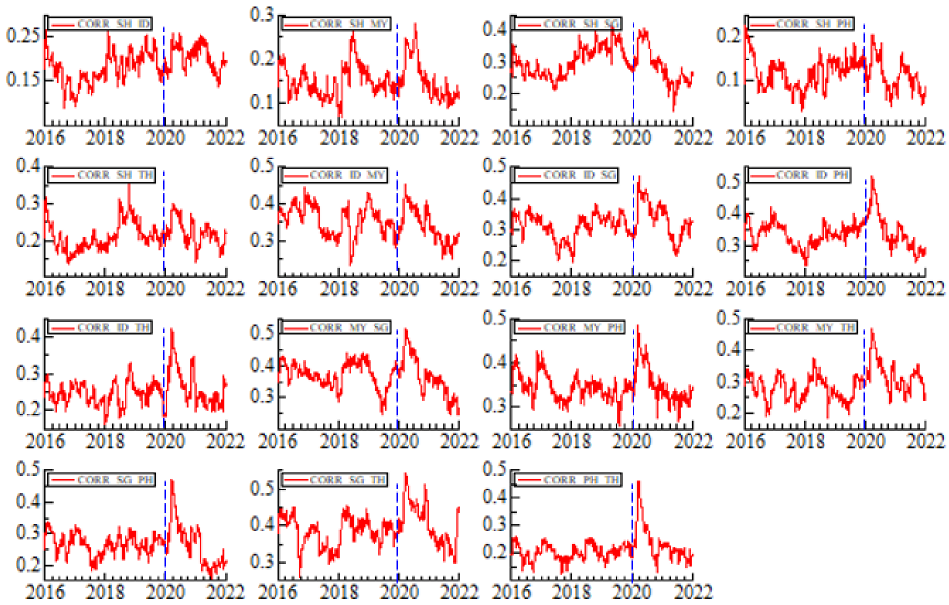

Figure 2. DCC between China and ASEAN-5

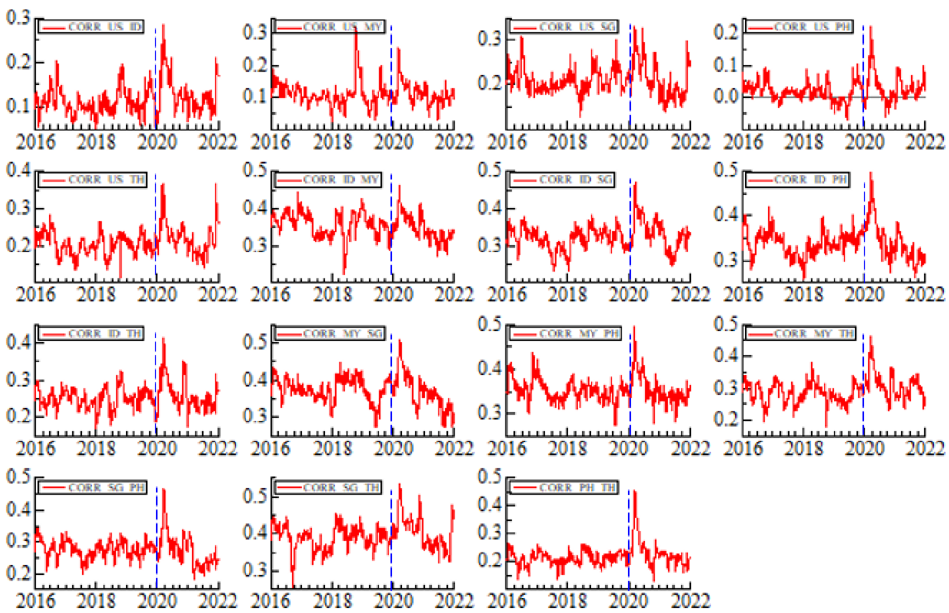

Figure 3. DCC between US and ASEAN-5

Robustness test

In addition, we developed a DCC model between the returns of ASEAN-5 countries and the US & China for robustness tests. In estimating DECO, the correlation between *i* and *j* depends on the history of all pairs. On the other hand, DCC information about the correlation of pairs *i*,*j* at time *t* depends on the history of *i* and *j* only (pairwise). Thus, if the DECO correlation between ASEAN-5 and China is a system-wide correlation graph, the DCC result will be a combination of each pair (pairwise) of correlations between two countries that may appear. Pairwise DCC between China and each ASEAN-5 country can be seen in Figure 2, while the US and ASEAN-5 are shown in Figure 3.

In general, the DCC results support the DECO estimation in Table 2. The correlation increased after the crisis period in early 2020 although at different levels for each country. For example, ID and SG have a higher correlation with China than other countries, indicating interdependence between markets even in the pre-crisis period. In addition, it can be seen that previously in 2018 there was a shock and a spike in the increase in correlation. This coincided with the Sino-US trade war in 2018. Like the DECO results, the US-ASEAN-5 pre-crisis correlation level was lower than China-ASEAN-5 indicating a closer relationship between China and ASEAN-5.

Volatility spillover index

The volatility spillover table (see Table 3) is the estimated contribution of TO (forecast variance) market *i* coming FROM (innovation to) market *j*. With a forecast horizon of 30 days ahead, all results are based on order 9 VAR and generalized variance decomposition. We selected the order of lag 9 based on the information criteria.

The total volatility spillover index is 35.47% which indicates that spillover accounts for 35.47% of the volatility forecast error variance in the seven markets. “FROM others” indicates the amount of volatility received by market *i* from market *j* and conversely “TO others” indicates volatility from market *i* to market *j*. Net spillover is the difference between FROM and TO.

Table 3. Spillover volatility from variable (j) to variable (i)

	SH	**US**	**ID**	**MY**	**SG**	**PH**	**TH**	**FROM others**
SH	**86,59**	2,89	0,64	1,90	3,76	1,55	2,67	13,41
US	1,19	**69,07**	4,09	2,22	3,33	2,58	17,51	30,93
ID	0,87	12,07	**59,67**	3,99	4,38	6,40	12,62	40,33
MY	1,52	11,96	3,08	**57,80**	7,72	5,61	12,30	42,20
SG	2,70	15,46	3,71	6,42	**52,76**	4,34	14,62	47,24
PH	1,26	9,20	5,26	5,41	6,72	**61,27**	10,87	38,73
TH	1,11	11,52	4,53	5,76	7,99	4,54	**64,56**	35,44
TOTAL	95,24	132,16	80,99	83,49	86,66	86,29	135,16	*Spillover index*: 35,47%*
TO lainnya	8,65	63,09	21,32	25,69	33,90	25,02	70,60	
Net (FROM – TO)	-4,76	32,16	-19,01	-16,51	-13,34	-13,71	35,16	

Note: * Spillover index: FROM others / TOTAL

SH receives directional spillover FROM other markets by 13.41% (the number of cells other than its own spillover at 86.59%). SH received the lowest directional spillover FROM others compared to the other six markets. The US was the second lowest to receive directional spillover from other countries at 30.93%.

In the system, TH and US send 70.60% and 63.09% TO other markets, respectively. The interesting point is that despite China's rapid economic development over the past few decades and fairly strong economic relations with ASEAN-5, the spillover of SH TO other markets is 8.65%, the smallest, indicating minimal influence from the Chinese stock market to the ASEAN-5 market. These results are consistent with the findings of Fang *et al.* (2021) who found that the financial spillover and spillback from the G7 countries were still higher than the spillover from China, indicating that the Chinese market is more influenced by other countries than vice versa.

The ASEAN-5 and China (SH) markets are net volatility receivers except for TH (35.16%). The study by Kang *et al.* (2019) regarding the directional spillover effect between the ASEAN-5 stock markets and the WORLD before the COVID-19 crisis also found that Thailand recorded the 3rd lowest net spillover effect from other markets.

Aside from that, the US is the net transmitter (32.16%), indicating that the US gives volatility to SH and ASEAN-5, compared to the other way around. This finding confirms the classical theory that directional spillover occurs from developed countries to developing countries. Lien *et al.* (2018) examined the volatility spillover between the US and eight East Asian stock markets between the 1997-1998 Asian financial crisis and the GFC suggests a certain hierarchy in which the direction of volatility spillover depends on a constant hierarchy rather than crisis-specific factors such as the geographic origin of the crisis, so that volatility spillovers tend to initiate from the US.

By identifying and separating net receivers and net transmitters, policymakers and financial regulators can develop an "early warning system", especially on the interdependence of ASEAN-5, China, and the US.

Rolling sample analysis

While the spillover table and index using Diebold & Yilmaz's (2012) method provide a useful summary of the "average" volatility spillover, it might miss important cyclical movements in the spillovers. To address this issue, volatility spillover is estimated using a 100-day rolling sample and a 30-day forecast horizon. It can assess the extent and nature of spillover variation over time in Figure 4.

If the total spillover based on the static index is 35.47%, it can be seen that the actual spillover is time-varying, from 54% to 86% (see Figure 4). The COVID-19 crisis increased the spillover significantly by up to 86%. Interestingly, the rolling window analysis clearly shows that there was a spike in volatility spillover equivalent to the COVID-19 crisis that occurred in 2018 during the Sino-US trade war which caused stock market instability. This result is in line with the results of the previous DECO and DCC analysis.

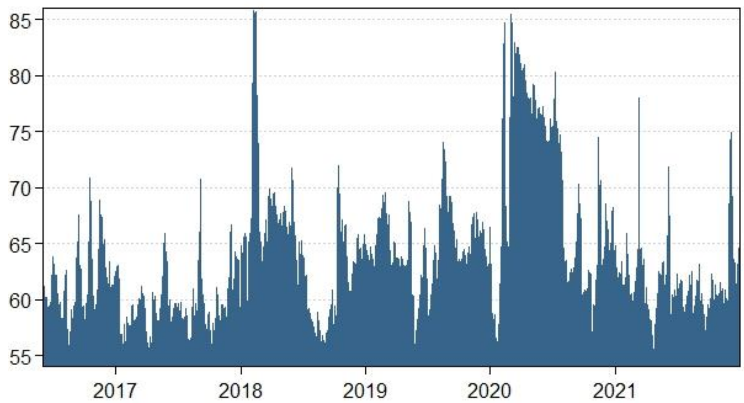

Figure 4. Rolling Window Total Volatility Spillover

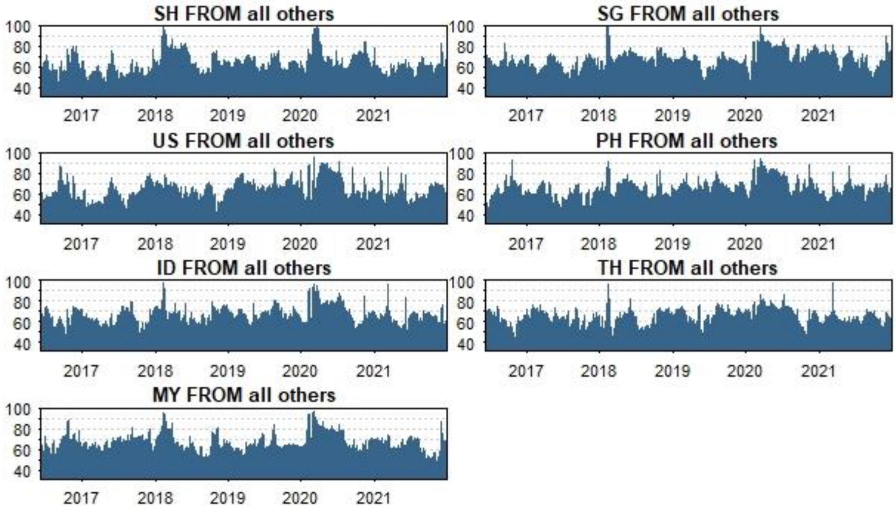

Figure 5. Directional Spillover Received By Every Market FROM Other

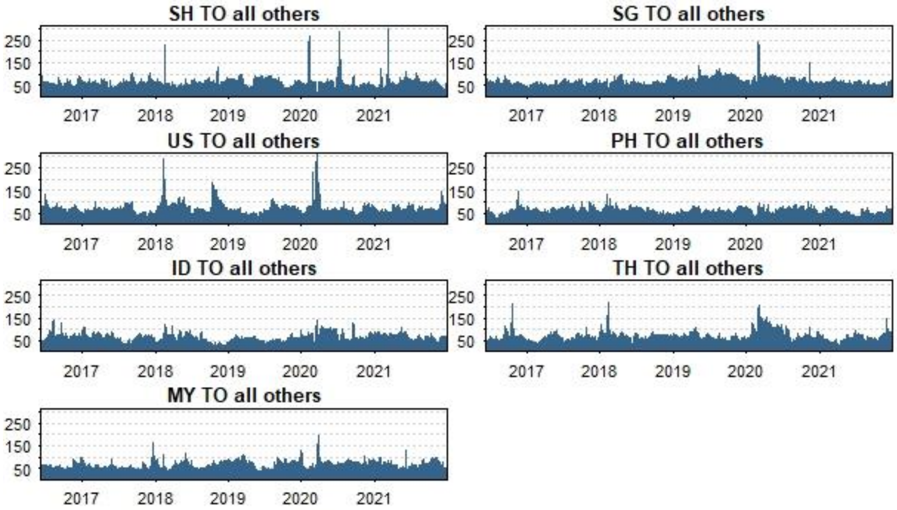

Figure 6. Directional Spillover from Each Other TO Market

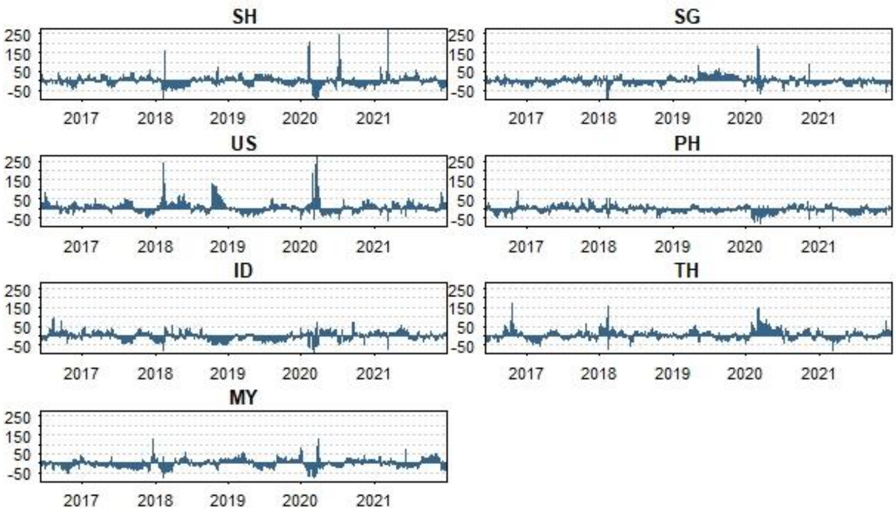

Figure 7. Net Directional Spillover for Each Market

Figure 5 shows a graph of the total spillover received by each country FROM other countries in the system, while Figure 6 illustrates the spillover from each country TO other countries. Figure 7 shows the net spillover for each country (difference between FROM and TO). It can be seen in Figure 7 how the US as a net transmitter has proven to send positive spillovers to other markets, at least three times, namely: during the China-US trade war (in early 2018 & late 2018) and the COVID-19 crisis (early 2020). China, despite being a net receiver in total, as shown in Table 3, has also been shown to send significant spillovers in 2018 and during the COVID-19 crisis. An interesting thing happened in TH, specifically during the COVID-19 crisis period, it has a net spillover although at levels below China and the US.

Net pairwise spillover

This study further analyzes the relationship between China and the US with ASEAN-5 by estimating the net pairwise spillover effect to determine which countries primarily transmit (receive) the volatility spillover effect on a net basis.

a. China

Specifically for China-US relations (see Figure 8), there have been at least three volatility spikes during the COVID-19 crisis: i) in early 2020, ii) in mid-2020, and iii) early 2021. In the first event, China sent a spike in volatility to the US market at the start of the crisis. This was short-lived followed by a deeper and more durable transmission from the US to China.

To provide a comparison, the rolling window total spillover in Figure 4 depicts the spike in volatility during the Sino-US trade war in 2018 that is comparable to the COVID-19 crisis. In both cases, as can be seen in China-US relations in Figure 8, the spillover has decreased to a negative number. It is also found that the negative spillover in 2018 lasted longer than the impact of the COVID-19 crisis.

Although in 2018 China also received negative spillovers from other ASEAN-5 countries, in general, these spillovers were at a lower level than during the COVID-19 crisis.

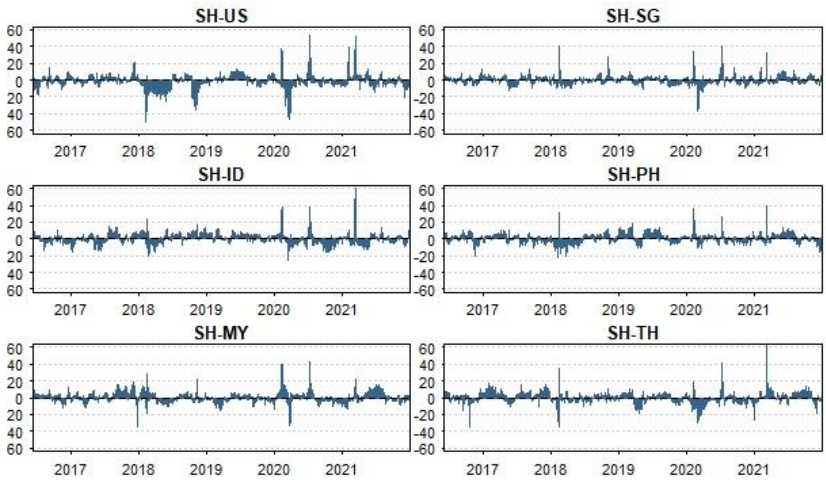

Figure 8. Net Directional Spillover from China to Other Countries

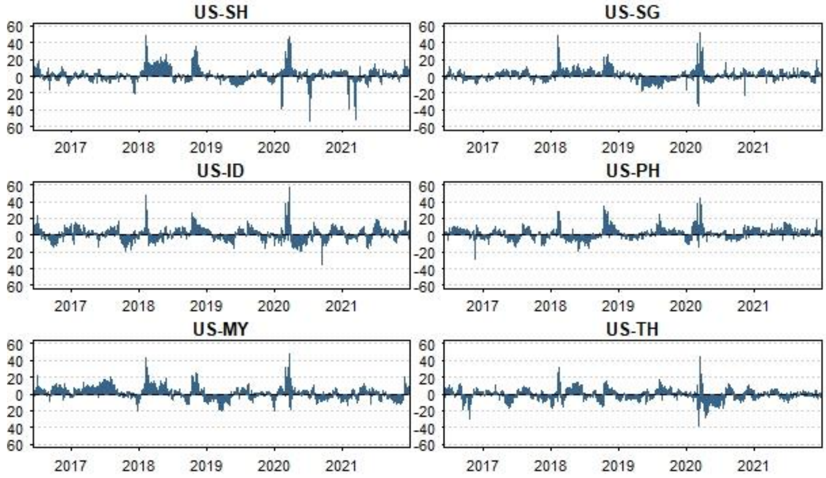

Figure 9. Net Directional Spillover from the US to Other Countries

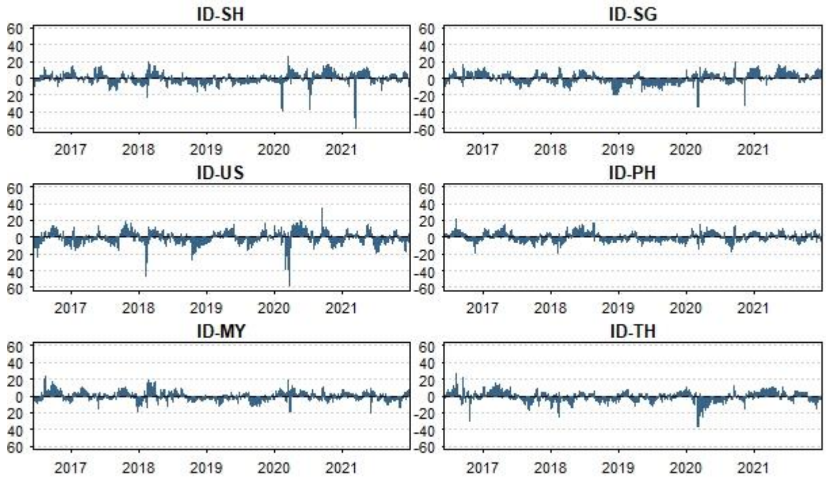

Figure 10. Net Directional Spillover from Indonesia to Other Countries

b. The United States

As shown in Figure 9, The US sent significant positive spillovers to all markets during COVID-19. It was also seen that the volatility transmission from the US was higher than the spillover rate from China to ASEAN-5. For example, the US transmits up to 60% of spillover to the SG, while China to the SG is only 40% during the COVID-19 crisis.

c. Indonesia

Although Indonesia has the largest GDP and stock market capitalization in the ASEAN-5 (World Bank, 2022a, 2022b), the Indonesian stock market has proven to be receiving more significant negative spillover from the US, China, Thailand, and Singapore (see Figure 10). China and the US are the two countries that provide significant spillover to the Indonesian stock market (60% negative spillover from both countries during 2020-2021).

d. Malaysia

As depicted by Figure 11, Malaysia also received significant negative spillovers from China, the US, Singapore, and Thailand. Malaysia and Indonesia send a positive spillover and receive a negative spillover towards each other at an equal rate.

e. Singapore

Figure 12 depicts the spillover relationship over time between Singapore and the rest of the system (China, the US, and ASEAN-5). Singapore plays a significant role in the ASEAN-5 regional stock market, as can be seen from the significant positive spillover from Singapore to other ASEAN-5 stock markets. But an interesting thing happened during the COVID-19 crisis in the SG – TH relationship. SG was recorded to have sent positive spillover to TH from mid-2019 but turned to receive negative spillover from TH since the COVID-19 crisis. Even so, it appears that this is only temporary and exclusive during the COVID-19 crisis because since mid-2020 Singapore has predominantly sent positive spillovers to TH although at a lower level than during the crisis.

f. Philippines

The Philippine stock market is a net receiver that receives more significant negative spillovers from the US, China, Singapore, and Thailand (see Figure 13). The highest negative spillover was received from the US at 43% during the COVID-19 crisis.

g. Thailand

Especially during the COVID-19 crisis, Thailand sent significant positive spillovers to all markets (see Figure 14). This positive spillover rate varies for each market but ranges between 30-40%. In general, the US sends spillovers to all markets. China provides spillover to Singapore and in turn, Singapore provides spillover to other ASEAN-5 markets such as Indonesia, Malaysia, and the Philippines. Thailand receives more spillovers from other markets, but in particular, the COVID-19 crisis has turned upside down all other markets.

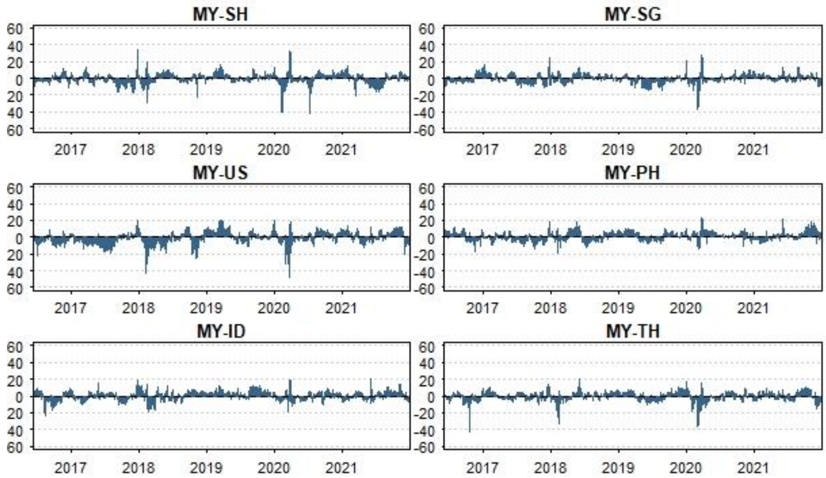

Figure 11. Net Directional Spillover from Malaysia to Other Countries

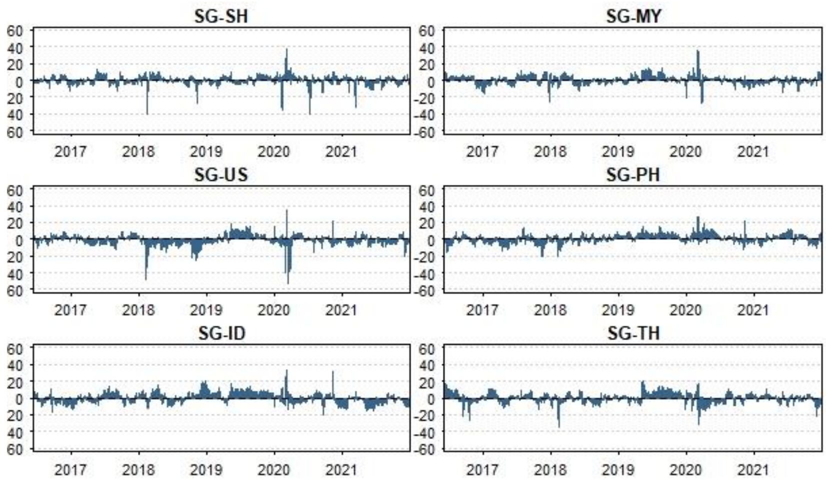

Figure 12. Net Directional Spillover from Singapore to Other Countries

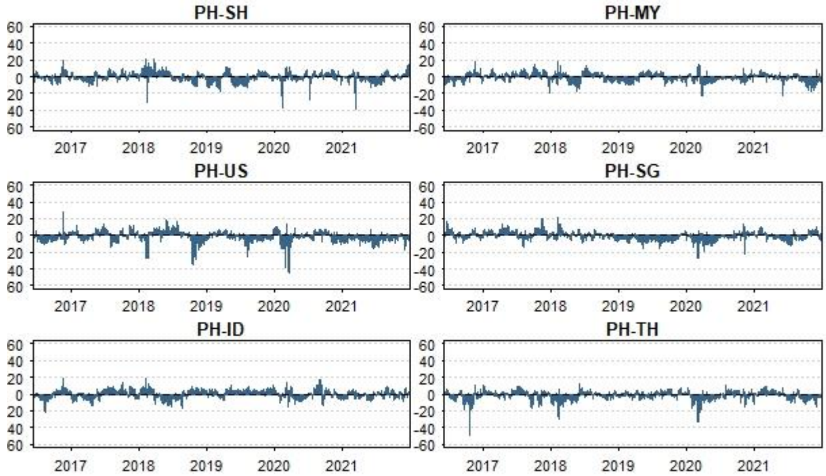

Figure 13. Net Directional Spillover from The Philippines to Other Countries

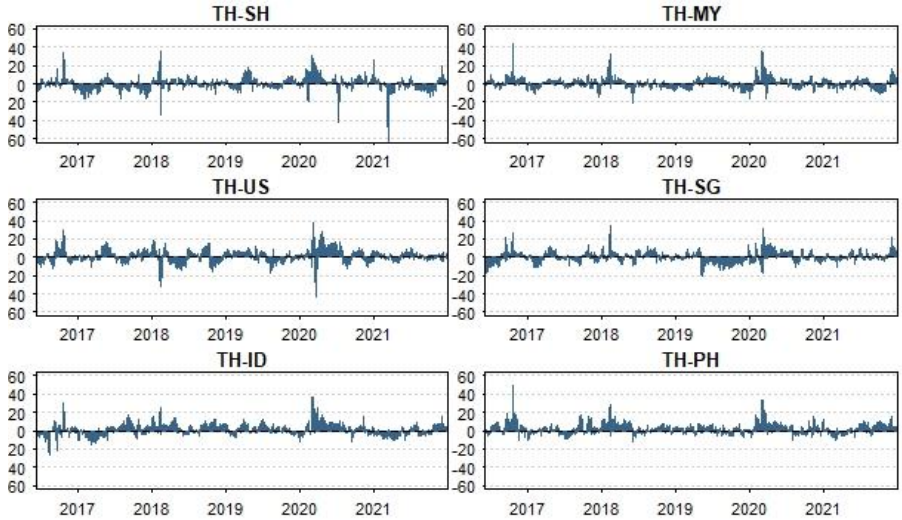

Figure 14. Net Directional Spillover from Thailand to Other Countries

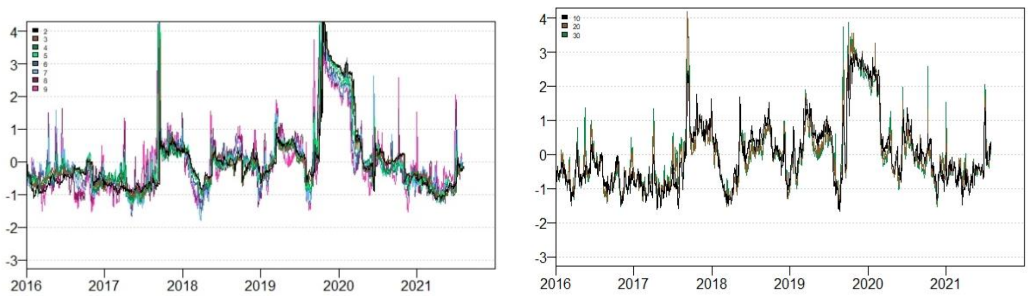

Figure 15. Index Sensitivity to VAR Lag Structure (Orders 2 to 9) and Sensitivity to Forecast Horizon (10 to 30 Days)

Robustness test

Following previous studies (e.g., Akhtaruzzaman *et al.,* 2021; Diebold & Yilmaz, 2012; Kang *et al.,* 2019), for robustness, we examined the sensitivity of the results to the choice of order VAR orders of 2 to 9 and forecast horizons of 10 to 30 days. The test results show a robust VAR-based spillover index estimation where the total spillover results are not sensitive to the choice of VAR sequence or the choice of forecast horizon (see Figure 15).

Conclusion

This study uses the DECO GARCH model from Engle & Kelly (2012) to see the dynamic correlation between the index and the spillover index by Diebold & Yilmaz (2012) to describe the direction of spillover between countries. This model was chosen because it corrects inconsistencies found in the estimation of the more popular DCC model.

This dynamic equicorrelation (DECO) estimate shows an increase in positive spillover correlations during the COVID-19 crisis for China and ASEAN-5 as well as the US and ASEAN-5. The pre-crisis correlation in the US-ASEAN-5 is lower than that of China-ASEAN-5. The robustness test using the dynamic conditional correlation (DCC) model from the same time series supports DECO estimation in this study.

The spillover index shows that despite the rapid development of China's economy over the past few decades and fairly strong economic relations with the ASEAN-5, the Chinese stock market has minimal influence on the ASEAN-5 market, indicated by the small percentage of spillover to the ASEAN-5 stock market. The ASEAN-5 and China (SH) markets are net volatility receivers except for TH. The US acts as a net transmitter (spillover to ASEAN-5 is higher than vice versa) while China acts as a net receiver.

China sent a spike in volatility to US markets at the start of the crisis that lasted only a moment followed by a deeper and more durable transmission from the US toward China. Thus, while the upward trend of the spike in volatility was first introduced by China, the crisis that hit the US left a more lasting and severe transmission of volatility to the ASEAN-5 market. Especially for the US and China relations, the spike in volatility during the Sino-US trade war in 2018 was comparable to COVID-19 although with a different pattern. The impact of the 2018 trade war left China experiencing deeper and longer volatility as compared to the US during the COVID-19 crisis.

The findings of this study are useful for providing insight into the connectedness of the Emerging Asia market. To reduce the spillover risk from stock market interdependence, regulators should pay attention to the dynamic connectedness of volatility shocks in the market. Policymakers in Indonesia, for example, who receive spillovers from China, the US, and Singapore, must be vigilant and prepare response policies if at any time these three countries have the potential to experience shocks.

Portfolio managers or investors can also develop hedging strategies that diversify their international stocks from contagion risks, particularly from other countries to Emerging Asia. Investors can diversify their portfolio with stocks with a low spillover index.

Notes on Contributors

Chandra Susilo is a student at the Magister Management Program, Faculty of Economics and Business, Universitas Indonesia. His research interest includes financial assets and corporate finance.

Nur Dhani Hendranastiti is a lecturer at the Magister Management Program, Faculty of Economics and Business, Universitas Indonesia. Her research interest includes finance, Islamic finance, and sustainability.

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