Lao Journal of Economics and Business Management (LJEBM), Volume 1, Issue 1 (2024) 15-24
DOI: 10.5281/zenodo.11542611

Faculty of Economics and Business Management,
National University of Laos
Lao Journal of Economics and Business Management
ISSN: 2790-5705 Homepage: ljebm.org

The Spillovers from US Stock Market to ASEAN Markets Before and During COVID-19: Granger Causality in the Frequency Domain

Phongsili Soukchalern[a*], Phouphet Kyophilavong[b], Khaysy Srithilat[c], Kedtysack Xayxanadasy[d], Soukpaseuth Banchong[e]

[a b c] Faculty of Economics and Business Management, National University of Laos, Lao PDR
[d e] Faculty of Natural Science, National University of Laos, Lao PDR

Article History

Received: 12 May 2024
Received in revised: 05 June 2024
Accepted: 08 June 2024
Available online: 15 June 2024

Keywords:

Frequency Domain Granger causality test, US stock market spillover, ASEAN stock markets, COVID-19.

ABSTRACT

We investigate the spillovers from the US stock market to ASEAN stock markets before and during the COVID-19 pandemic. Our aim is to answer the question of whether any shock to the returns from the US stock market spills over to those from the ASEAN stock markets. We use daily data for the period from 4 January 2017 to 27 December 2021 for the Granger causality in the frequency domain. Our empirical results indicate that a shock to the returns the US stock market spills over to ASEAN stock markets both before and during COVID-19. This finding makes a potentially significant contribution to investors and regulators in the terms of risk management and hedging strategies.

Cite this article: *Soukchalern, P., Kyophilavong, P., SRITHILAT, . khaysy ; Xayxanadasy.K ; & Banchong.B. (2024). The Spillovers from US Stock Market to ASEAN Markets Before and During COVID-19: Granger Causality in the Frequency Domain. In Lao Journal of Economics and Business Management (Vol. 1, Number 1, pp. 15–24). Lao Journal of Economics and Business Management.* https://doi.org/10.5281/zenodo.11542611

1. Introduction

The financial markets have become increasingly integrated, and the global financial markets have become closely correlated and interdependent over time (Lim, 2009). The problems from these dynamic relationships have become significant issues in the advanced literature on financial markets (Majid et al., 2008). The degree of linkages or interconnectedness across stock markets has significant implications for the potential advantages of international risk diversification and a country's financial stability (Ibrahim, 2005). Due to this issue, the increased integration of a regional financial market like ASEAN can lead to contagion from it to other financial markets because of liberalized capital movements and financial reforms as well as advances in computer technology and information processing (Singh et al. 2010).

COVID-19 was declared a pandemic on 11 March 2020 by the World Health Organization (WHO). It had infected and killed a million people across the world at that point. Many countries tried to implement lockdowns, social distancing, travel restrictions, and other drastic measures to contain the pandemic that had unprecedented effects on the economic and financial landscapes of many countries. Global financial markets responded with enormous drops, volatility, and a deterioration in liquidity. Further, financial markets also experienced extraordinary movement, while risks grew significantly in reaction to the crisis (Kamaludin et al., 2021).

There are many studies related to the spillovers between the US and ASEAN stock markets before the COVID-19 pandemic that have gained the attention of researchers. For instance, Vo and Tran (2020); Mandigma (2014); Lee and Goh (2016); Majid et al. (2018); Lim (2009); Rijanto (2017); Tuan et al. (2013) investigated the global stock market and Asian stock markets, such as those in ASEAN countries (Li & Giles, 2015; Kim, 2003; Miyakoshi, 2003; Le & Kakinaka, 2010; Chevallier et al., 2018). Furthermore, researchers have paid attention to the spillovers between advanced and emerging stock markets across the region, including during the COVID-19 crisis (McIver & Kang, 2020; Singh et al., 2010; Xiao & Dhesi, 2010; Gamba-Santamaria et al., 2019; Li, 2021; Su, 2020;

[*] Corresponding author, E-mail: phong.soukchalern@gmail.com

Kim & Ryu, 2015; Zhang et al., 2021; Habiba et al., 2020; Gulzar et al., 2019; Belaid et al., 2021; Abounoori &Tour, 2019; Mohammadi & Tan, 2015; Lien et al., 2018; Song et al., 2022; Choi, 2022). But there are few studies on the spillovers from the US stock market to ASEAN markets during COVID-19 (Le & Tran, 2021; Kamaludin et al., 2021). Therefore, the objective of this study is to examine these spillovers by applying a nonlinear method: the Granger causality in the frequency domain. Furthermore, with this approach we can decompose the causality at various frequencies, as opposed to the traditional time-domain causality approach, which depends on a single statistical measure to describe the link between two series at all frequencies. As such, this method allows us to investigate causal relationships while separating between high, medium, and low frequencies (Breitung and Candelon, 2006).

This study has significant practical and policy implications. Analyzing volatility spillovers is critical for international investment and diversification. Furthermore, financial supervisory organizations must have a comprehensive awareness of foreign volatility spillovers in order to prevent excessive volatility in local equities markets (Vo& Tran, 2020).

The remainder of the paper is as follows: Section 2 is the literature review. Section 3 is the data and method-logy. Section 4 is the empirical results, and Section 5 is the conclusion.

2. Literature Review

The studies on the relationships between US and emerging stock markets across different regions (Table 1). For instance, McIver & Kang (2020) for BRICS countries; Singh et al. (2010) for Europe and Asia; Xiao & Dhesi (2010) for UK, French, and Germany; Gamba-Santamaria et al. (2019) for Australia, Canada, China, Germany, Japan, and UK. They used various econometric approach, including the Johansen and Juselius cointegration, Granger Causality test, BEKK-GARCH and DCC-GARCH approach Diebold and Yilmaz spillover approach (Table 1). In addition, there are many studies related to the spillovers between the US and ASEAN stock markets before the COVID-19 pandemic in Asia (Table 2). For instance, Vo & Tran (2020), Majid et al. (2008), Kamaludin et al. (2021), and Lim (2009) for ASEAN-5; Lee & Goh (2016) for Hong Kon and ASEAN-5; Li & Giles (2015) for Japan, China, India, Indonesia, Malaysia, Philippine, and Thailand; Miyakoshi (2003); Kim (2003) for Japan, Korea, Taiwan, Singapore, Thailand, Indonesia, Malaysia, and Hong Kong.

Moreover, many scholars have paid attention to the spillovers between advanced and emerging stock markets across the region during the COVID-19 crisis (McIver & Kang, 2020; Su, 2020; Zhang et al., 2021; Belaid et al., 2021; Abounoori &Tour, 2019; Lien et al., 2018; Song et al., 2022; Choi, 2022). However, there are few studies on the spillovers from the US stock market to ASEAN markets during COVID-19 (Le & Tran, 2021; Kamaludin et al., 2021). Le & Tran (2021) used the DCC – GARCH approach to studied the stock of US to stock of of Vietnam and Philippine during the 2019 to 2020 (during the COVID-19). They found that the stock of US had transmission to stock of Vietnam, but they did not find the spillover effects from the stock from US to the stock of Philippine. This study did not include other ASEAN member and did not consider the time frequency causality. Kamaludin et al. (2021) used the Wavelet analysis approach to investigate the spillovers of US' stock market to the stock of ASEAN-5. They divided the sample into two parts; February 15 to May 30, 2019 (pre-period) and February 15 to May 30, 2022 (during the pandemic period). The study found that all ASEAN-5 equity markets show strong coherence with the Dow Jones index during pandemic period. However, they found no coherency at the end of sample period. However, the short time period is limitation of this study.

3. Data and method

3.1. Data

For the examination, we applied the daily closing prices over the period from 4 January 2017 to 27 December 2021. The data were decomposed into two scenarios: the pre-COVID-19 period starting from 4 January 2017 to 29 November 2019 and the period during the COVID-19 pandemic starting from 3 December 2019 to 27 December 2021. We used the stock index to represent each country; for the US stock market, we used the S&P 500 and to represent ASEAN we used the stock markets in Indonesia, Malaysia, Philippine, Singapore, and Thailand as these countries have the most advanced financial markets. They were Jakarta Stock Exchange Composite Index (IDX), FTSE Bursa Malaysia KLCI (MYX), *Philippine Stock Exchange* Composite Index (PSE), FTSE Straits Times *Index (SGX)*, and *Stock Exchange* of *Thailand* (SET), respectively. The data were obtained from Investing (www.Investing.com) and trans-formed into return series as follows:

$$r_t = \ln \frac{P_t}{P_{t-1}}$$

where r_t is the return stock index at time t, ln is the natural logarithm, and P_t is the daily closing price of a stock index.

As we analyze the predictive power of returns, we applied the Brock et al. (1996) BDS test to capture the nonlinearity of the returns in residuals as a result of the financial series' high fluctuation or volatility over time. With the use of the test statistic, which has a standard normal limiting distribution, we tested the null hypothesis of stock returns.

Table 1. The studies on the relationships between US and emerging stock markets across different regions

No	Author	Country	Data	Method	Finding
1	McIver & Kang (2020)	US, BRICS	1998 to 2016	DECO-GJR-GARCH	US stock market is a net transmitter of return and volatility spillovers, with the Brazilian and Chinese markets also become net transmitters in the post-GFC period
2	Singh et al. (2010)	North America, Europe and Asia	2000 to 2008	VAR and AR with exogenous variables, two-step AR-GARCH	A greater regional influence among Asian and European stock markets
3	Xiao & Dhesi (2010)	US, Europe (UK, French, Germany)	2004 to 2009	BEKK-GARCH and DCC-GARCH	The UK stock market is the main volatility transmitter within the European stock market while the US stock market is the main exporter worldwide
4	Gamba-Santamaria et al. (2019)	US, Australia, Canada, China, Germany, Japan, and UK	2001 to 2016	DCC-GARCH	The US, the UK, Canada, and Germany are always net transmitters; while Canada, China, and Japan are net receivers.
5	Li (2021)	US, Japan, Germany, UK, France, Italy, Canada, China, India, and Brazil	2009 to 2020	Diebold-Yilmaz spillover index	Developed markets are the main risk transmitters, and emerging markets are the main risk receivers, including during the COVID-19 period
6	Su (2020)	G7, BRICS	1998 to 2017	quantile regression analysis	The US, Germany, France, and Canada are net transmitters; and the UK, Japan, Italy, and BRICS are net receivers of risk spillovers.
7	Kim & Ryu (2015)	US, Korea	2003 to 2012	BEKK-GRACH, CPR Jump Detection Model	US→Korea
8	Zhang et al. (2021)	G7, BRICS	2009 to 2020	DAG-SVAR mode	G7 is the source of risk spillover or exporter of risk in global financial markets, and BRIC is the receiver of risk
9	Habiba et al. (2020)	US, South Asia (India, Pakistan, Sri Lanka)	2000 to 2007	Johansen and Juselius cointegration test, Granger Causality test and bivaraite EGARCH model	Volatility spillover exist from US stock markets to all selected South Asian markets during and post-GFC period
10	Gulzar et al. (2019)	US, emerging Asian countries (Malaysia, Korea, Russia, India, China, Pakistan)	2005 to 2015	Johansen and Juselius cointegration test, VECM and BEKK-GARCH	US→All emerging Asian countries

11	Belaid et al. (2021)	11 developed and 11 emerging countries	2019 to 2020	Diebold and Yilmaz spillover index and Toda–Yamamoto and Dolado and Lütkepohl causality approach	Emerging countries are affected by the financial markets of advanced economies during the COVID-19 crisis
12	Abounoori &Tour (2019)	US, Iran, Turkey, UAE	2008 to 2017	GARCH	US→Iran, US→Turkey, US→UAE
13	Mohammadi and Tan (2015)	US, Hong Kong, China	2001 to 2013	BEKK-GARCH and DCC-GARCH	US→Hong Kong, US→China
14	Lien et al. (2018)	US, Asia (Japan, Hong Kong, Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand)	AFC: 1997 to 1998, GFC: 2007 to 2009 Pre-AFC: 1995 to 1997, pre-GFC: 2005 to 2009	GARCH	Uni-directional volatility spillovers from the US market to other markets are observed during both crisis periods
15	Song et al. (2022)	US, China	2010 to 2021	Johansen and Juselius cointegration, Granger Causality test, EGARCH	US↔China
16	Choi (2022)	US, China, Japan, Korea	2000 to 2021	Diebold and Yilmaz's spillover index	The US has played a role as a net transmitter of volatility shocks during the entire period

Notes: The →, ↔, and ↛ indicate uni-, bi-, and no directional causality, respectively. ASEAN-5 denotes Indonesia, Malaysia, Philippines, Singapore, and Thailand. GFC refers to the global financial crisis.
Source: Author's summary

The BDS test was created to test the i.i.d assumption for raw series, but many studies have used it to assess the suitability of a model by applying it to the estimated residuals. Therefore, the test was performed using the residuals obtained by the VAR model. The rejection of the null hypothesis of an identically and independently distributed error term indicated the existence of a nonlinear relationship.The next step was to test the stationary of the series in which we used the nonlinear unit root tests of Bierens (1997a) and Breitung (2002) to robustly check the stationary of the series. The traditional unit root tests such as the ADF and PP tests might have led to a bias in the results due to the presence of nonlinearity in the data. The approaches by Bierens (1997a) and Breitung (2002) test for factors in the nonlinearity of the data, and it can be used to examine the null hypothesis of a unit root with a drift process against the alternative hypothesis of a nonlinear stationary process.

3.2. Nonparametric cointegration tests

Before conducting the Granger causality in the frequency domain, we used the nonparametric cointegration tests proposed by Bienrens (1997b) and Breitung (2001, 2002) if the variables are in the first order of integration, or I(1). The advantage of these tests is that they can counter the parametric method as the Johansen (1991) cointegration and the Engle and Granger (1987) cointegration may falsely reject the null hypothesis of no cointegration that might lead to bias in the results. With the Bierens (1997b) cointegration approach, the test statistic is λ_{min} and the null hypothesis is written as $r = 0$ against the alternative hypothesis of $r \geq 1$. A more improved Breitung (2002) approach is able to detect the cointegration of the variables in a structural break. Similarly, as with the Bierens (1997b) cointegration test, the null hypothesis of the Breitung (2002) cointegration test is $r = 0$ against the alternative hypothesis of $r = 1$, and if the test statistic rejects all hypotheses, then it indicates $r = 2$.

3.3. Granger causality in the frequency domain

Granger causality in the frequency domain was developed by Granger (1969), Geweke (1982), and Hosoya (1991). This approach uses simple empirical tests to assess the predictive power at some given frequencies. Geweke (1982) and Hosoya (1991) performed a causality measure at a particular frequency based on a decomposition of the spectral density. Yao and Hosoya (2000) developed a Wald-type test procedure for causality at some given frequency that was based on a complicated set of nonlinear restrictions on the autoregressive parameters.

To overcome this difficulty, we used the procedure proposed by Breitung and Candelon (2006) that is based on a set of linear hypotheses on the autoregressive parameters by using a vector autoregressive (VAR) model. This approach provides an interpretation of the Granger causality in the frequency domain as a decomposition of the total spectral interdependence, and Breitung and Candelon (2006) can be explained as follows:

Let $z_t = [x_t, y_t]'$ be a two-dimensional vector of time series observed at t = 1, …, T. It is assumed that z_t has a finite-order VAR representation of the form:

$$\Theta(L)z_t = \varepsilon \tag{1}$$

where $\Theta(L) = I - \Theta_1 L - \cdots - \Theta_p L^p$ is a 2 × 2 lag polynomial with $L^k z_t = z_{t-k}$. We assumed that the error vector εt was white noise with $E(\varepsilon_t) = 0$ and $E\left(\varepsilon_t \varepsilon_t^{'}\right) = \Sigma$, where Σ was positive definite. Any deterministic terms in (1) were neglected.

Let G be the lower triangular matrix of the Cholesky decomposition $G'G = \Sigma^{-1}$ such that $E(\eta_t \eta_t') = I$ and $\eta_t = G\varepsilon_t$. If the system is assumed to be stationary, the moving average representation of the system is:

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{2}$$

$$= \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \tag{3}$$

where $\Phi(L) = \Theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$. Using this representation, the spectral density of x_t can be expressed as follows:

$$f_x(\omega) = \frac{1}{2\pi}\{|\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2\} \tag{4}$$

The measure of causality suggested by Geweke (1982) is defined as:

$$M_{y\to x}(\omega) = log\left[\frac{2\pi f_x(\omega)}{|\Psi_{11}(e^{-i\omega})|^2}\right] \tag{5}$$

$$= \log\left[1 + \frac{|\Psi_{12}(e^{-i\omega})|}{|\Psi_{11}(e^{-i\omega})|}\right] \tag{6}$$

If $\left|\psi_{12}(e^{-i\omega})\right|^2 = 0$, then the Geweke's measure will be zero, and y will not Granger cause x at frequency ω.

If the elements of z_t are I(1) and co-integrated, then the measure of causality in the frequency domain can be defined by using the orthogonalized moving average representation:

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\Psi}(L)\eta_t, \tag{7}$$

Where $\tilde{\Psi}(L) = \tilde{\Phi}(L)G^{-1}, \eta_t = G\varepsilon_t$, and G remain as a lower triangular matrix such that $E(\eta_t \eta_t') = I$. A bivariate co-integrated system is formed as $\beta'\tilde{\Psi}(1) = 0$; β is a co-integration vector such that $\beta' z_t$ is stationary (Engle and Granger, 1987). As in the stationary case the resulting causality measure is:

$$M_{y\rightarrow x}(\omega) = log\left|1 + \frac{|\widetilde{\Psi}_{12}(e^{-i\omega})|}{|\widetilde{\Psi}_{11}(e^{-i\omega})|}\right|. \quad (8)$$

To test the hypothesis that y does not cause x at frequency ω, we consider the null hypothesis of:

$$M_{y\rightarrow x}(\omega) = 0 \quad (9)$$

Within a bivariate framework, Breitung and Candelon (2006) presented this test by reformulating the relationship between x and y in a VAR equation:

$$x_t = a_1 x_{t-1} + \ldots + a_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_{1t} \quad (10)$$

The null hypothesis tested by Geweke, $M_{y\rightarrow x}(\omega) = 0$, corresponds to the null hypothesis of:

$$H_0: R(\omega)\beta = 0 \quad (11)$$

where β is the vector of the coefficients of y and

$$R(\omega) = \begin{bmatrix} cos(\omega)\, cos(2\omega) \ldots\ldots cos(p\omega) \\ sin(\omega)\, sin(2\omega) \ldots\ldots\ldots sin(p\omega) \end{bmatrix} \quad (12)$$

The ordinary F statistic for (11) is approximately distributed as $F(2, T - 2p)$ for $\omega \in (0, \pi)$. Further, Breitung and Candelon (2006) suggest replacing x_t with Δx_t on the left-hand side of the equation (10), while leaving the other side unchanged.

4. Empirical results

The descriptive statistics of the return stock indices show a pattern. The results before and during the COVID-19 are presented in Tables 3 and 4, respectively. They show that the US stock market had the highest mean return in both scenarios, and the mean returns of the PSE and SGX were negative during the COVID-19 period. Yet the PSE showed the highest daily return volatility (0.0046 and 0.0085) followed by the S&P 500 (0.0038 and 0.0077) both before and during the pandemic. Furthermore, in both scenarios periods, all return series also showed negative skewness and positive excess kurtosis, indicating leptokurtic distribution. The Jarque-Bera test showed the strong rejection of the null hypothesis of normality at the 1% significance level that indicated the presence of a nonlinearity or non-normality distribution of the return series. Therefore, to provide more reliable results we used the BDS test proposed by Brock et al. (1987).

Table 3. Descriptive Statistics of Return Series Before COVID-19

Var	US	IDX	MYX	PSE	SGX	SET
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.021	0.011	0.010	0.017	0.011	0.012
Minimum	-0.018	-0.023	-0.019	-0.028	-0.016	-0.015
Std. Dev.	0.004	0.004	0.003	0.005	0.003	0.003
Skewness	-0.637	-0.649	-1.351	-0.369	-0.297	-0.364
Kurtosis	7.869	6.340	11.532	5.742	4.321	5.975
Jarque-Bera	645[a]	327[a]	2042	205[a]	53[a]	239[a]
Observations	612	612	612	612	612	612

Note: The [a] depicts significance at the 1% level.
Source: Authors' estimation.

Table 4. Descriptive Statistics of Return Series During COVID-19.

Var	US	IDX	MYX	PSE	SGX	SET
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.001	0.000	0.000	0.000	0.000	0.000
Maximum	0.057	0.020	0.029	0.053	0.032	0.033
Minimum	-0.055	-0.058	-0.02	-0.062	-0.033	-0.050
Std. Dev.	0.008	0.006	0.005	0.009	0.005	0.006
Skewness	-0.457	-2.219	-0.15	-0.550	-0.553	-1.538
Kurtosis	20.788	21.880	10.43	16.732	12.929	17.694
Jarque-Bera	5525[a]	6550[a]	964[a]	3305[a]	1738[a]	3925[a]
Observations	418	418	418	418	418	418

Note: The [a] depicts significance at the 1% level.
Source: Authors' estimation.

Tables 5 and 6 show the results. They indicate the rejection of the null hypothesis of an independent and identically distribution that meant nonlinearity existed for all return series both before and during the COVID-19 pandemic.

Next, the nonparametric unit root proposed by Bienrens (1997a) and Breitung (2002) was applied to find the order of integration of the stock price series before and during the COVID-19 period. The findings (see Table 5) show that when the nonparametric of Bierens (1997a) and Breitung (2002) was applied to the data, it indicated the presence of nonstationary both before and during the pandemic; therefore, when the data were transformed into the first difference, the results rejected the null hypothesis of a unit root with a drift process. This rejection can be interpreted as our series being integrated at an order of one, or I(1)

Before we used the Granger causality in frequency domain from Breitung and Candelon (2006), we needed to test the cointegration of the variables. Because of the nonlinearity in the series, we used the nonlinear cointegration approaches proposed by Bierens (1997b), and Breitung (2002) to obtain reliable results. The results for before COVID-19 from Bierens (1997b) are in Table 8. They indicate the rejection of both null hypothesis of r=0 and r=0 as shown by the test statistic that is in-between the 5% critical value that means the cointegration vector is 2. To provide more robust results, we used an improved cointegration approach by Breitung (2002). The outcomes were similar to those from using the Bierens (1997b) approach; the acceptance of alternative hypothesis due to the 5% critical value was less than the t-statistic. Therefore, based on these findings, we could conclude that before the COVID-19 outbreak that the rank of cointegration was 2, Therefore, there was long-run cointegration between the stock returns of the US and ASEAN stock markets. When the COVID-19 period was considered, we found similar results as for the pre-COVID-19 period (see Table 8)

Table 5. BDS Statistics for Stock Return Series Before COVID-19

Length in S.D.	Embedding dimension (m)	US	IDX	MYX	PSE	SGX	SET
0.5	2	0.0128***	0.0074***	0.0101***	0.0028*	0.0036***	0.0017
0.5	3	0.0167***	0.0060***	0.0087***	0.0031***	0.0026***	0.0013
0.5	4	0.0139***	0.0036***	0.0052***	0.0019***	0.0014***	0.0012**
0.5	5	0.0089***	0.0020***	0.0028***	0.0013***	0.0006***	0.0008***
0.5	6	0.0050***	0.0011***	0.0014***	0.0008***	0.0002**	0.0005***

Notes: The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Results are based on the residuals obtained from the VAR model.
Source: Authors' estimation.

Table 6 BDS Statistics for Stock Return Series During COVID-19

Length in S.D.	Embedding dimension (m)	US	IDX	MYX	PSE	SGX	SET
0.5	2	0.0165***	0.0127***	0.0027	0.0102***	0.0191***	0.0089***
0.5	3	0.0198***	0.0110***	0.0025	0.0107***	0.0173***	0.0101***
0.5	4	0.0152***	0.0067***	0.0023***	0.0084***	0.0115***	0.0066***
0.5	5	0.0097***	0.0035***	0.0015***	0.0048***	0.0072***	0.0038***
0.5	6	0.0059***	0.0016***	0.0007***	0.0027***	0.0038***	0.0021***

Notes: The *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Results are based on the residuals obtained from the VAR model.
Source: Authors' estimation.

Table 7. Nonlinear Unit Root Test Results

Variable	Before COVID-19				During COVID-19			
	Bierens		Breitung		Bierens		Breitung	
	level	first dif.	level	first dif.	level	first dif.	level	first dif.
US	-22.5217	-494.4999***	0.0078	0.0001***	-19.3789	-228.8455**	0.0054	0.0001***
	(0.150)	(0.000)	(0.400)	(0.000)	(0.280)	(0.010)	(0.100)	(0.000)
IDX	-12.6766	-1413.1920***	0.0078	0.0001***	-9.1991	-204.8072***	0.0086	0.0003***
	(0.450)	(0.000)	(0.200)	(0.000)	(0.670)	(0.000)	(0.500)	(0.000)
MYX	-10.3621	-172.0810**	0.0162	0.0001***	-12.3305	-262.8996***	0.0061	0.0001***
	(0.570)	(0.040)	(1.000)	(0.000)	(0.490)	(0.000)	(0.200)	(0.000)
PSE	-12.8853	-802.6244***	0.0080	0.0001***	-12.6807	-323.8224***	0.0074	0.0001***
	(0.470)	(0.000)	(0.200)	(0.000)	(0.410)	(0.000)	(0.500)	(0.000)
SGX	-15.7808	-466.2090***	0.0112	0.0001***	-12.7857	-154.5194**	0.0131	0.0003***
	(0.290)	(0.000)	(0.600)	(0.000)	(0.440)	(0.010)	(0.600)	(0.000)
SET	-7.2582	-431.2632***	0.0142	0.0001***	-13.2069	-251.4618***	0.0094	0.0002***
	(0.790)	(0.000)	(0.700)	(0.000)	(0.370)	(0.000)	(0.200)	(0.000)

Notes: The p-values are in the parentheses. The null H_0: Series is non-stationary with a drift. The alternative H_A: Series is a nonlinear trend to the stationary process. The ** and *** denote rejection of H0 at the 5% and 1% significance levels, respectively. Bierens (1997a): Test statistic = $\hat{A}m$; the p-values were simulated for a relevant sample size using 100 replications. The optimal value of p is chosen by Akaike Information Criteria. Breitung (2002): the p-values were simulated using 10 replications

Source: Authors' estimation.

Before we used the Granger causality in frequency domain from Breitung and Candelon (2006), we needed to test the cointegration of the variables. Because of the nonlinearity in the series, we used the nonlinear cointegration approaches proposed by Bierens (1997b), and Breitung (2002) to obtain reliable results. The results for before COVID-19 from Bierens (1997b) are in Table 8. They indicate the rejection of both null hypothesis of r=0 and r=0 as shown by the test statistic that is in-between the 5% critical value that means the cointegration vector is 2. To provide more robust results, we used an improved cointegration approach by Breitung (2002). The outcomes were similar to those from using the Bierens (1997b) approach; the acceptance of alternative hypothesis due to the 5% critical value was less than the t-statistic. Therefore, based on these findings, we could conclude that before the COVID-19 outbreak that the rank of cointegration was 2, Therefore, there was long-run cointegration between the stock returns of the US and ASEAN stock markets. When the COVID-19 period was considered, we found similar results as for the pre-COVID-19 period (see Table 9)

Table 8. Bierens and Breitung cointegration tests before COVID-19

Nonparametric cointegration of Bierens (1997) - (Test Statistic)							
H0	H1	IDX	MYX	PSE	SGX	SET	5% Critical value
r=0	r=1	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	(0,0.017)
r=1	r=2	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	(0,0.054)
Nonparametric cointegration of Breitung (2002) - (Test Statistic)							
H0	H1	IDX	MYX	PSE	SGX	SET	5% Critical value
r=0	r=1	33088.57**	44407.63**	28552.03**	33304.72**	36172.30**	713.30
r=1	r=2	14638.27**	11412.13**	7887.58**	7733.41**	11159.65**	281.10

Notes: The r is the number of cointegrating vectors. The ** indicates the rejection of H0 at the 5% level of significance if test statistic < 5% critical value

Table 9. Bierens and Breitung cointegration test During COVID-19

Nonparametric cointegration of Bierens (1997) - (Test Statistic)							
H0	H1	IDX	MYX	PSE	SGX	SET	5% Critical value
r=0	r=1	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	(0,0.017)
r=1	r=2	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	(0,0.054)
Nonparametric cointegration of Breitung (2002) - (Test Statistic)							
H0	H1	IDX	MYX	PSE	SGX	SET	5% Critical value
r=0	r=1	45843.52**	57742.90**	44318.70**	31402.76**	47060.98**	713.30
r=1	r=2	3725.42**	6021.75**	6340.24**	3249.53**	4601.00**	281.10

Notes: The r is the number of cointegrating vectors. The ** indicates the rejection of H0 at the 5% level of significance if test statistic < 5% critical value

Next, we implemented the Granger causality in frequency domain proposed by Breitung and Candelon (2006). The null hypothesis is supported when X does not Granger cause Y at frequencies ω against the alternative hypothesis of X Granger causes Y at frequencies ω; the rejection of the null hypothesis means that there are returns spilling over from stock market X to Y at frequencies ω, and vice versa. Following Bekiros et al. (2017), we used 0.05, 1.5, and 2.5 to represent long, medium, and short frequencies, respectively. The results for before and during the COVID-19 period are reported in Table 10, in the case of the scenario before the COVID-19, the findings confirm a uni-directional spillover from the US stock market to each ASEAN stock markets at all frequencies (long, medium, and short-run). They indicate that there is a return spillover from the US stock market to ASEAN stock markets before the COVID-19 pandemic at three frequencies (long, medium, and short). These results are in line with other studies that have applied different methods to this analysis and found that the US stock market was the source of spillovers while ASEAN stock markets were receivers (Vo & Tran, 2020; Lee & Goh, 2016; Li & Giles, 2015; Kim, 2003; Abd et al., 2008; Miyakoshi, 2003; Lim, 2009; Rijanto 2017; Tuan et al., 2013; Le & Kakinaka, 2010; Le & Tran, 2021; Le & Tran, 2021)

Table 10. Tests for Granger causality in the frequency domain

Countries	Before COVID-19			During COVID-19		
	Long	medium	short	long	medium	short
	0.05	1.5	2.5	0.05	1.5	2.5
US→IDX	44.118***	44.118***	44.118***	29.784***	4.257	18.162***
IDX→US	0.426	0.426	0.426	1.548	0.312	6.674**
US→MYX	54.745***	54.745***	54.745***	24.913***	18.538***	24.577***
MYX→US	4.643	4.643	4.643	4.388	8.485**	5.409
US→PSE	56.543***	56.543***	56.543***	20.236***	12.391***	18.789***
PSE→US	0.595	0.595	0.595	2.697	5.240	1.067
US→SGX	92.450***	92.450***	92.450***	23.920***	4.923	9.517***
SGX→US	0.572	0.572	0.572	1.491	3.971	4.107
US→SET	29.489***	29.489***	29.489***	5.656	9.560***	0.999
SET→US	3.315	3.315	3.315	24.116***	12.917***	0.121

Note: The *** and ** indicate significance at the 1% and 5% levels, respectively.

When the period of the COVID-19 pandemic was considered, the results varied for different frequencies. As depicted in Table 10, in the case of IDX, the results showed that there was a return spillover from the US to IDX at long and medium frequencies, while the spillover was bi-directional at a short frequency. Similarly for the MYX, there was a uni-directional spillover from the US to MYX at the long and short frequencies but the medium frequencies showed a bi-directional causality. However, the PSE indicated only a uni-directional causality from the US stock market at all three frequencies (long, medium, and short). Furthermore, we also found return spillovers from the US stock market to the SGX at long and short frequencies, and no directional causality from SGX to the US stock market. Moreover, the dominant results occurred for the SET with bi-directional causality with the US stock market at a medium frequency, and uni-directional from SET to the US stock market at a long frequency. The overall results can be interpreted that the during the COVID-19 pandemic the US stock market still was a source of spillovers, while the ASEAN countries showed more predictive power of the rejection of the null hypothesis This rejection may mean that the ASEAN countries were more integrated into the global supply chain, especially SET, IDX, and MYX.

5. Conclusion

In this study, we investigated the returns spillovers from the US stock market to ASEAN stock markets before and during the COVID-19 pandemic. We used the daily data for the period from 4 January 2017 to 27 December 2021 and separated them into before and during the COVID-19 pandemic. To achieve our purpose, we applied the Granger causality in the frequency domain of Breitung and Candelon (2006).

In the order to achieve the aim of this study, we used the BDS test of the residuals before and during the COVID-19 to indicate the presence of nonlinearity in all series. Then, we identified the first order of integration in both periods through the nonparametric unit roots of Bierens (1997a) and Breitung (2002). They showed that there was long-run cointegration among the US and ASEAN stock markets both before and during Covid-19 from which we concluded that the cointegration vector was 2. When the Granger causality in frequency domain was implemented, the findings were in line with other studies and showed that before the COVID-19 period, the rejection of the null hypothesis existed for all three frequencies (long, medium, and short) that indicated the return spillovers from the US stock market to ASEAN stock markets but no directional causality from ASEAN to the US stock markets. Furthermore, during the COVID-19 the results varied for different frequencies that indicated the unidirectional causality from the US to ASEAN stock markets at all three frequencies, except IDX (long and short frequencies), SGX (long and short frequencies), and SET (medium frequency). Moreover, during the COVID-19, the return spillovers of some ASEAN stock markets to the US stock market were found for IDX (long frequency), MYX (medium frequency), and SET (long and medium frequencies) These findings indicate that the ASEAN stock markets were more integrated into the global stock market (US stock market) during the period of COVID-19 pandemic. This finding is critical to the hedging strategies of portfolio investors and risk managers. It is also important for policymakers to implement a system for monitoring and controlling volatility spillovers.

References

Abounoori, E., & Tour, M. (2019). Stock market interactions among Iran, USA, Turkey, and UAE. *Physica A: Statistical mechanics and its applications*, *524*, 297-305.

Bekiros, S., Boubaker, S., Nguyen, D. K., & Uddin, G. S. (2017). Black swan events and safe havens: The role of gold in globally integrated emerging markets. *Journal of International Money and Finance, 73,* 317-334.

Belaid, F., Ben Amar, A., Goutte, S., & Guesmi, K. (2021). Emerging and advanced economies markets behaviour during the COVID-19 crisis era. *International Journal of Finance & Economics*.

Bierens, H. J. (1997a). Testing the unit root with drift hypothesis against nonlinear trend stationarity, with an application to the US price level and interest rate. *Journal of Econometrics*, *81*(1), 29-64.

Bierens, H. J. (1997b). Nonparametric cointegration analysis. *Journal of Econometrics, 77*(2), 379-404.

Breitung, J. (2002). Nonparametric tests for unit roots and cointegration. *Journal of econometrics*, *108*(2), 343-363.

Breitung, J., & Candelon, B. (2006). Testing for short-and long-run causality: A frequency-domain approach. Journal of econometrics, 132(2), 363-378.

Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. (1996). A test for independence based on the correlation dimension. Econometric reviews, 15(3), 197-235.

Chevallier, J., Nguyen, D. K., Siverskog, J., & Uddin, G. S. (2018). Market integration and financial linkages among stock markets in Pacific Basin countries. *Journal of Empirical Finance*, *46*, 77-92.

Choi, S. Y. (2022). Volatility spillovers among Northeast Asia and the US: Evidence from the global financial crisis and the COVID-19 pandemic. *Economic Analysis and Policy*, *73*, 179-193.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.

Gamba-Santamaria, S., Gomez-Gonzalez, J. E., Hurtado-Guarin, J. L., & Melo-Velandia, L. F. (2019). Volatility spillovers among global stock markets: measuring total and directional effects. *Empirical Economics*, *56*(5), 1581-1599.

Geweke, J. (1982). Measurement of linear dependence and feedback between multiple time series. Journal of the American statistical association, 77(378), 304-313.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Gulzar, S., Mujtaba Kayani, G., Xiaofen, H., Ayub, U., & Rafique, A. (2019). Financial cointegration and spillover effect of global financial crisis: A study of emerging Asian financial markets. *Economic research-Ekonomska istraživanja*, *32*(1), 187-218.

Habiba, U. E., Peilong, S., Zhang, W., & Hamid, K. (2020). International stock markets Integration and dynamics of volatility spillover between the USA and South Asian markets: evidence from Global financial crisis. *Journal of Asia Business Studies*, *14*(5), 779-794.

Hosoya, Y. (1991). The decomposition and measurement of the interdependency between second-order stationary processes. Probability theory and related fields, 88(4), 429-444.

Ibrahim, M. H. (2005). International linkage of stock prices: The case of Indonesia. *Management Research News*.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: journal of the Econometric Society*, 1551-1580.

Kamaludin, K., Sundarasen, S., & Ibrahim, I. (2021). Covid-19, Dow Jones and equity market movement in ASEAN-5 countries: evidence from wavelet analyses. *Heliyon*, *7*(1), e05851.

Kim, J. S., & Ryu, D. (2015). Return and volatility spillovers and cojump behavior between the US and Korean stock markets. *Emerging Markets Finance and Trade*, *51*(sup1), S3-S17.

Kim, S. J. (2003). The spillover effects of US and Japanese public information news in advanced Asia-Pacific stock markets. *Pacific-Basin Finance Journal*, *11*(5), 611-630.

Le, T. N., & Kakinaka, M. (2010). International transmission of stock returns: mean and volatility spillover effects in Indonesia and Malaysia. *Global Journal of Business Research*, *4*(1), 115-131.

Le, T. P. T. D., & Tran, H. L. M. (2021). The contagion effect from US stock market to the Vietnamese and the Philippine stock markets: The evidence of DCC-GARCH model. *The Journal of Asian Finance, Economics and Business*, *8*(2), 759-770.

Lee, S. S. P., & Goh, K. L. (2016). REGIONAL AND INTERNATIONAL LINKAGES OF THE ASEAN-5 STOCK MARKETS: A MULTIVARIATE GARCH APPROACH. *Asian Academy of Management Journal of Accounting & Finance*, *12*(1).

Li, W. (2021). COVID-19 and asymmetric volatility spillovers across global stock markets. *The North American Journal of Economics and Finance*, *58*, 101474.

Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. *International Journal of Finance & Economics*, *20*(2), 155-177.

Lien, D., Lee, G., Yang, L., & Zhang, Y. (2018). Volatility spillovers among the US and Asian stock markets: A comparison between the periods of Asian currency crisis and subprime credit crisis. *The North American Journal of Economics and Finance*, *46*, 187-201.

Lim, L. K. (2009). Convergence and interdependence between ASEAN-5 stock markets. *Mathematics and Computers in Simulation*, *79*(9), 2957-2966.

Mandigma, M. (2014). Stock market linkages among the ASEAN 5+ 3 countries and US: further evidence. *Management and Administrative Sciences Review*, *3*(1), 53-68.

McIver, R. P., & Kang, S. H. (2020). Financial crises and the dynamics of the spillovers between the US and BRICS stock markets. *Research in International Business and Finance*, *54*, 101276.

Miyakoshi, T. (2003). Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions and Money*, *13*(4), 383-399.

Mohammadi, H., & Tan, Y. (2015). Return and volatility spillovers across equity markets in mainland China, Hong Kong and the United States. *Econometrics*, *3*(2), 215-232.

Rijanto, A. (2017). Lead-lag relationship: Did the financial crisis affect the interdependence of ASEAN-5 and the Global Stock Market?. *Int Journal of Economics and Management*, *11*(2), *393-409*.

Shabri Abd. Majid, M., Kameel Mydin Meera, A., & Azmi Omar, M. (2008). Interdependence of ASEAN-5 stock markets from the US and Japan. *Global Economic Review*, *37*(2), 201-225.

Singh, P., Kumar, B., & Pandey, A. (2010). Price and volatility spillovers across North American, European and Asian stock markets. *International Review of Financial Analysis*, *19*(1), 55-64.

Song, G., Xia, Z., Basheer, M. F., & Shah, S. M. A. (2022). Co-movement dynamics of US and Chinese stock market: Evidence from COVID-19 crisis. *Economic Research-Ekonomska Istraživanja*, *35*(1), 2460-2476.

Su, X. (2020). Measuring extreme risk spillovers across international stock markets: A quantile variance decomposition analysis. *The North American Journal of Economics and Finance*, *51*, 101098.

Tuan, T. K., Hwa, Y. S., & Yean, C. S. (2013). Synchronisation of Stock Market Cycles: The Importance of Emerging and Developed Markets to ASEAN-5. *Prague Economic Papers*, *22*(4), 435-458.

Vo, X. V., & Tran, T. T. A. (2020). Modelling volatility spillovers from the US equity market to ASEAN stock markets. *Pacific-Basin Finance Journal*, *59*, 101246.

Xiao, L., & Dhesi, G. (2010). Volatility spillover and time-varying conditional correlation between the European and US stock markets. *Global Economy and Finance Journal*, *3*(2), 148-164.

Yao, F., & Hosoya, Y. (2000). Inference on one-way effect and evidence in Japanese macroeconomic data. Journal of Econometrics, 98(2), 225-255.

Zhang, P., Sha, Y., & Xu, Y. (2021). Stock market volatility spillovers in G7 and BRIC. *Emerging Markets Finance and Trade*, *57*(7), 2107-2119..