RESEARCH ARTICLE

Dynamic Connectedness in the ASEAN's Equity Markets during the COVID-19 Pandemic

Suthawan Prukumpai
Kasetsart University, Bangkok, Thailand

Lawrence B. Dacuycuy
De La Salle University, Manila, Philippines

Yuthana Sethapramote
National Institute of Development Administration, Bangkok, Thailand
yuthana.s@nida.ac.th

The COVID-19 pandemic unleashed shocks that triggered severe global economic contraction and spawned sizeable financial market fluctuations. This paper examines the dynamic connectedness between ASEAN stock markets and major global stock markets using the dynamic connectedness framework developed by Diebold and Yilmaz (2009, 2012). Empirical results reveal that ASEAN stock markets and other emerging markets have experienced higher spillovers from global equity markets during the pandemic than in normal times. In addition, the role of ASEAN region spillovers has increased significantly during the COVID-19 outbreak. This study contributes to the existing literature by investigating the extent of dynamic connectedness between ASEAN and global stock markets during the COVID-19 pandemic using an expanded period that includes vaccine development outcomes. Using linear panel data and time series models, results show that COVID-19-related variables such as mortality rates have increased spillovers. On the other hand, the number of vaccinated individuals has helped reduce spillovers. In addition to the CBOE Volatility Index (VIX), the infectious disease Equity Market Volatility tracker (EMV) provides a crucial proxy for the financial market's risk factors. These results provide insights into how ASEAN stock markets reacted during the pandemic, providing important lessons for investors and policymakers on how the pandemic's effect on stock market connectedness could be mitigated.

Keywords: COVID-19, Dynamic Connectedness, ASEAN, Equity markets

JEL Classification: C58, F37, G1, G15

Significant events, such as the Asian Financial Crisis, the Global Financial Crisis, the trade war, and the COVID–19 pandemic, have perturbed and reshaped the macroeconomic landscape and induced consequential policy and regulatory regime changes. Each major crisis has its precursors, conditioning environments, transmission mechanisms, durations, and aftermaths (see Gorton & Metrick, 2012; McKibbin & Fernando, 2021; Reinhart & Rogoff, 2009). What is evident is that markets react to crisis episodes, and connectedness becomes more apparent as shocks emerge and propagate throughout established or newly created channels. Moreover, spillovers and contagion are imminent by-products of crisis episodes, as shocks cannot be contained within the country where they first appeared.

Adverse shocks emanating from the novel viral outbreak known as COVID-19 have troubled the world for more than two years. Drastic measures to control the disease's spread, such as lockdowns, physical distancing, stay-at-home orders, and travel restrictions, have adversely affected the real economy and financial system. Most global equity markets have experienced significant downturns and fluctuations following the spread of the COVID-19 pandemic. Earnings growth has been dampened due to the unprecedented contraction of consumption and activities, causing stock market price movements. As cases continue to rise worldwide, COVID-19 still causes volatility in equity markets.

Like other developed markets, ASEAN equity markets also have been adversely affected by the outbreak of COVID-19. All these markets plunged from mid-February 2020 to late March 2020. The pandemic triggered the rushing out of foreign fund flows from the region, which then caused a plummet in the financial markets and a rapid currency depreciation. At a firm level, the COVID-19 pandemic had a negative impact on firms' financial performance, as reported by Panopio and Cudia (2021) and Ardiyono (2022). Later, the subsequent recovery in ASEAN equity markets was found to be weaker than that in the United States. Such recovery may be attributable to changes in risk appetite towards emerging markets or the adequacy of packages to support their economies. Therefore, this paper examines the risk and return characteristics in ASEAN equity markets during the COVID-19 pandemic.

Understanding the connectedness between equity markets remains essential for investors and policymakers. After all, it helps them make rational decisions about international portfolio diversification opportunities. Therefore, we investigate the dynamic spillovers and connectedness among the ASEAN equity markets. The Diebold and Yilmaz (2009, 2012) approach, based on generalized variance decompositions of a vector autoregressive (VAR) model, is applied to construct spillover or connectedness indices.

Focusing on ASEAN economies, we examine the underlying factors determining equity market connectedness before and during the pandemic. The spillover or connectedness indices are used to represent dynamic linkages. We also endeavor to explain spillovers by appealing to fundamental factors such as crude oil price changes and financial market risk factors, that is, the fear index (VIX), economic policy uncertainty index (EPU), and daily infectious disease equity market volatility tracker (EMV) are applied. As part of our modeling strategy, we also included the number of confirmed cases, deaths, and vaccine doses received as potential determinants.

This study contributes to the existing literature by investigating the extent of dynamic connectedness between ASEAN and global stock markets during the COVID-19 pandemic using an expanded period that includes key vaccine development episodes—events that proved important in determining the magnitude of spillovers. By constructing the connectedness indices, we can address how international equity markets' connectedness varies alongside the pandemic's severity. Additionally, we investigate the role of COVID-19 information and general financial market risk factors in driving the dynamic connectedness between ASEAN stock markets during the recent outbreak. Finally, as the COVID-19 pandemic is still ongoing, our study will stimulate further investigations on how ASEAN equity markets would respond to the progression of COVID-19 infection. Our results would provide insights into how ASEAN stock markets are connected, leading to significant implications regarding the pandemic's effect on equity markets' connectedness for investors and policymakers.

The remainder of the paper is structured as follows: Section 2 identifies relevant studies for characterizing the state of the literature on dynamic connectedness during the pandemic period. Section 3 details the methodologies used to generate spillover indices and empirically explore the linkages between dynamic connectedness and severity of the pandemic. Section 4 presents and discusses the results, and the last section concludes.

Literature Review

The current COVID-19 pandemic, which started as a health emergency in Wuhan, China, is not only an unprecedented human and health crisis but has been expected to become one of the costliest pandemics in recent history (Bahrini & Filfilan, 2020). Unlike previous pandemics (i.e., SARS and MERS), the COVID-19 outbreak led to an unprecedented slowdown in global economic activity, spawning contagion effects, propagating volatility spillovers, fanning policy uncertainty, and disrupting value chains and other linkages. The health shock has rapidly spread globally, resulting in widespread mobility restrictions, deep economic contractions, unprecedented loss of human lives, and reversal of structural transformation gains. To prevent economic meltdown and address lingering uncertainty, governments have embarked on massive spending programs to mitigate the pandemic's effects on the labor markets and business sectors. In addition, governments borrowed heavily to address the financial cost of the pandemic spread, facilitate the procurement of vaccines, and restore lost capacity.

To support the paper's empirical objectives, we focus on literature dealing with financial contagion, volatility and uncertainty spillovers, and the effects of health shocks.

Financial Contagion

Early in the pandemic, several studies focused on financial contagion effects by examining outcomes across stock markets. Using extremal dependence tests, Fu et al. (2021) determined that there is evidence of contagion in global equity markets, with North and Latin America predicted to be heavily affected by contagion effects. Studies that tracked the progression of financial contagion indicated a resemblance to how the pandemic has propagated. Akhtaruzzaman et al. (2021) studied contagion effects and traced them to firms listed across stock markets in China and G7 economies. They found that during the pandemic, financial contagion manifested itself through marked increases in the dynamic conditional correlations (DCCs). Not surprisingly, financial firms play a major role in the contagion transmission process relative to non–financial firms. Uddin et al. (2022) empirically confirmed that emerging economies manifested temporal dependence on global financial markets. In a related study, Nguyen et al. (2022) established the claim that contagion effects have emanated from the U.S., Japanese, and Chinese markets. Based on their findings, only 3 out of 10 Asian emerging markets have experienced contagion. Gunay and Can (2022) corroborated empirical facts that contagion emanated from the U.S. stock market but noted that the propagation of shocks has been more evident among developed than emerging economies.

An equally important and complementary topic focuses on the transmission of uncertainty. Uncertainty adds a layer of analytical complications, but it is considered essential, nonetheless. Using a time-varying framework, Antonakakis et al. (2018) investigated the issue of uncertainty spillovers involving developed economies such as the United States, the United Kingdom, Canada, Japan, and the European Union using a dataset of daily macroeconomic indices. Antonakakis et al. (2018) found significant uncertainty transmitted from the European Union to the United States. Instead of relying on the aggregate definition of economic policy uncertainty, Gabauer and Gupta (2018) investigated connectedness among the components of categorical uncertainty, which includes monetary, fiscal, trade, and currency market policies between Japan and the United States. They found that monetary policy uncertainty drives economic policy uncertainty, with the U.S. monetary policy uncertainties contributing significantly to Japan's. Using a more innovative approach, Li et al. (2021) investigated the relationship between policy uncertainty and financial risk contagion using complex network analysis. They found that geographic segmentation characterizes EPU and financial networks. Their study confirmed the centrality of China within the EPU network and identified China and the United States as the two biggest uncertainty transmitters in the network.

Volatility Spillovers

Different techniques have been developed to capture spillover or volatility transmissions across markets. Previous studies used correlation coefficients to describe interdependence among financial markets. Static and conditional (dynamic) correlation approaches were applied to examine spillover and contagion in financial markets – Billio and Caporin (2010), for instance.[2] Other major approaches used to examine connectedness include multivariate autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models (e.g., Abuzayed et al., 2021), and cointegration techniques (e.g., Longin & Solnik, 1995). But dimensionality issues may hound multivariate ARCH and GARCH models, as they may contain many parameters. This approach addresses the difficulties (or limitations) of multivariate GARCH in expanding the number of financial markets or countries to be analyzed simultaneously. Moreover, the cointegration technique may fail to show market connectedness evolution over time.

Diebold and Yilmaz (2009, 2012) developed the most prominent methodology for volatility spillover analysis based on generalized variance decompositions of a vector autoregressive (VAR) model. Due to its parsimonious approach, this methodology has attracted considerable attention in testing connectedness among the international financial markets (e.g., Manopimoke et al., 2018) and among several asset classes (e.g., Cronin, 2014).

The application of the Diebold-Yilmaz connectedness framework for examining the direction of volatility spillovers has been robust, especially during the pandemic period. The study by Corbet et al. (2021) is one of the papers that came out during the early days of the pandemic in China. The paper addresses the existence and formation issues associated with volatility spillovers. Using high-frequency data, Corbet et al. (2021) focused on the coronavirus index, influenza index, face mask index, CSI 300 index, gold futures price, oil futures price, soybean futures price, US Dollar/RMB spot exchange rate, and Bitcoin (BTC) price. What is most interesting about these new results is that there is a significant relationship between the outbreak of the COVID-19 pandemic and directional volatility spillovers into the Bitcoin market.

Many studies measured volatility spillovers involving several economies or regional blocs. The most prominent strand deals with spillovers from developed economies directed toward financial markets in developing or emerging areas. Stock market volatility spillovers in G7 and BRIC were studied by Zhang et al. (2021), Mensi et al. (2016), and Malik et al. (2021). Krause and Tse (2013) focused on G7 countries, whereas Gamba-Santamaria et al. (2016) studied spillovers within Latin America. Hung (2019), Sadiq et al. (2021), Corbet et al. (2021), Engle et al. (2012), and Jebran et al. (2017) focused on Asia. Finally, Kim et al. (2015) and Bekiros (2014) studied spillovers involving the United States and emerging countries in Asia and the Middle East. Other notable studies that focused on pandemic-induced spillovers include Sharzad, Bouri, et al. (2021), Sharzad, Naeem, et al. (2021), and Youssef et al. (2021). ASEAN-centric studies that explored connectedness and COVID-19 uncertainty include Behera and Rath (2022).

How cryptocurrencies responded to the pandemic forms an integral part of burgeoning literature. Aside from Cobert et al. (2021), Polat and Gunay (2021) focused on several top cryptocurrencies using the frequency connectedness approach to measure the volatility impact before and during the pandemic. Finding evidence of connectedness, Polat and Gunay (2021) attributed this to herding behavior in the cryptocurrency market.

The pandemic has altered structural relationships over time or introduced new linkages. Notable studies that explored connections in the literature include Zhang et al. (2021), who analyzed the connectedness between energy and stock markets. Constructed spillover networks exhibited major differences before and during the pandemic. For instance, the energy sector was more independent before the pandemic. Le et al. (2021) asked whether the pandemic has changed fintech and other asset classes. Commodity and stock markets were the focus of Amar et al. (2021) found significant spillovers triggered by the pandemic.

Focusing on several ASEAN economies, Behera and Rath (2022) explored the relationship between interconnectedness and stock market returns during the COVID-19 pandemic. They found that stock market returns are interconnected—a robust result established by several studies conducted within and outside of ASEAN. Using an event study analysis of large and small firms operating within ASEAN, Ahmad et al. (2022) assessed the impact of COVID-19 on the economic integration of ASEAN countries. They noted that the impact of the pandemic could be explained using stringency, bilateral exports, and tourist arrivals.

Key studies have modified the Diebold and Yilmaz approach by using time-varying parameters and focusing on quantile distributions. In addition, network analyses were used to visualize pandemic-related shocks' depth, speed, and transmission to examine how market structural relationships have changed during the pandemic.

Bouri et al. (2021) documented stability among the connectedness of gold, crude oil, world equities, currencies, and bonds. TVP-VAR connectedness approach indicates that the bond index becomes the main transmitter of shocks during the crisis. Furthermore, it was found that the network of connectedness is not time-invariant. Like other studies, overall connectedness and cross-asset connectedness have increased, indicating instability in the network of the global financial system.

The pandemic also revealed evidence of asymmetry in the distribution of returns. Shahzad, Bouri, et al. (2021) analyzed the outbreak's impact on U.S. equity sectors, and they concluded that market network structure and spillovers are state-dependent. During normal times, clustering structures are evident. However, a dominant cluster within the network emerged with the onset of instability. Iqbal et al. (2022) investigated the pattern of volatility spillover and found that the U.S. equity market is the main transmitter of shock during the normal volatility state. However, the role of European and Chinese equity markets and crude oil prices have been increasing during high volatility states.

Emphasizing inter-sectoral volatility linkages in the Chinese market, Shahzad, Naeem, et al. (2021) extended the Diebold-Yilmaz framework using the quantile structure to examine extreme returns using high-frequency data during the period from January 2, 2019, to September 30, 2020. Their study decomposed realized volatility into good and bad components. Asymmetric volatility spillovers across sectors also indicate the nature of pandemic effects. Shahzad, Naeem, et al. (2021) established that bad volatilities dominate good volatilities during the pandemic.

Health Crisis Shocks and Stock Market Performance

Besides the financial crisis, several studies have investigated the impacts of health crises— the viral outbreaks such as the Spanish flu in 1918 and the SARS in 2003—on stock market performance. Nippani and Washer (2004) first compared the stock market performance before the onset of SARS and during the period when several nations were affected by SARS. They compared daily returns between pre-SARS and SARS-affected periods. They found that SARS significantly impacted China and Vietnam stock markets but not Canada, Hong Kong, the Philippines, and Singapore. Using the sample of airline firms across several countries, the results of Loh (2006) suggested that SARS imposed negative consequences on the risk profile of airline stocks by increasing volatility and systematic risk. Mishra et al. (2022) noted that death, vaccines, and stringency measures significantly affect the U.S. stock market.

Studies that examined the impact of COVID-19 health-related outcomes on stock market returns and volatility have emerged rapidly. For instance, Baker et al. (2020) reported that COVID-19 is far more powerful for the U.S. stock market than previous infectious diseases (e.g., Spanish flu) due to several factors, namely: the recent pandemic's severity, the more effective pandemic news transmission, and the tighter real economic and financial market interconnectedness between countries. A study by Yilmazkuday (2020) showed that an increase in the cumulative daily COVID-19 cases in the United States resulted in a negative daily return in the S&P 500 index. Likewise, Bahrini and Filfilan (2020), using the data from Gulf Cooperation Council (GCC) countries, found that stock market returns reacted negatively to the number of new cases and confirmed deaths. In addition, Zhang et al. (2020) examined the impact of COVID-19 on stock market volatility across 11 developed countries and China. They found that the volatility increased substantially during the first wave—February to March 2020. Finally, Bissoondoyal-Bheenick et al. (2021) characterized spillovers using a sample of G20 countries during the pandemic. One innovation in this study is the analytical benchmark provided by SARS03. It was shown that countries that experienced fatalities in 2003 exhibited less connectedness during the current pandemic.

Similarly, Albulescu (2021) reported a positive relationship between the mortality rate and the U.S. stock market volatility. Harjoto et al. (2021) demonstrated that global equity markets across 76 countries (53 emerging markets and 23 developed markets) reacted negatively to the COVID-19 spreads, measured by the percentage of daily new cases and the mortality rate. This anecdotal evidence suggests that COVID-19 affects the stock market performance according to the investors' pessimistic sentiment toward returns prospects and fear of uncertainties.

Data and Methodology

Data

This study investigates the impact of the COVID-19 pandemic on the connectedness between the ASEAN stock markets and critical global stock markets, totaling 19 markets, as presented in Table 1. Only six ASEAN members were selected in this study because their equity markets are more developed and liquid than the rest: Cambodia, Myanmar, Laos, and Brunei. In addition, those countries' real and financial markets are more separated from the others according to their national policy and political situation.

The data spans from January 2, 2018, to February 28, 2022. Although several studies have focused on the ASEAN, this study focuses on a period that includes key vaccine development and administration milestones.[3] From this sample, we created two subperiods: the pre-crisis period is January 2, 2018, to January 29, 2020, and the COVID-19 period is January 30, 2020, to February 28, 2022. This paper chooses January 30, 2020, as the starting date for the COVID-19 pandemic when the World Health Organization (WHO) first declared a Public Health Emergency of International Concern. The stock market data are sourced from the CEIC Global Database. Stock market returns are calculated from the log difference of the daily price indices.

Methodology

The Dynamic Connectedness (Spillover) Index

With financial markets becoming more tightly linked, modeling and quantifying spillovers between markets are essential tasks that have received considerable attention in the literature. To explore the time-varying connectedness between international stock markets during a specified period, including the COVID-19 pandemic, we followed the dynamic connectedness approach of Diebold and Yılmaz (2009, 2012), which can be summarized as follows.

Consider the simple case of the standard p-lag, N-variable stationary VAR model,

$$X_t = \Phi_1 X_{t-1} + \cdots + \Phi_p X_{t-p} + Bc + \varepsilon_t \quad (1)$$

where $X_t = \{X_{1,t}, X_{2,t}, \ldots, X_{N,t}\}$ is a matrix of endogenous variables, c is a matrix of a deterministic term (i.e., intercept term), and ε_t is a vector of disturbance terms where $\varepsilon_t \sim (0, \Sigma)$ Σ is a variance matrix for the error vector. Notably, Σ is assumed to have a contemporaneous correlation but is independently distributed over time.

Table 1. *List of International Stock Markets*

Stock Market	Abbreviation	Stock market index
ASEAN (6 markets)		
Indonesia	IDN	Jakarta Stock Exchange Composite Index (JCI)
Malaysia	MYS	FTSE Bursa Malaysia KLCI
The Philippines	PHL	Philippines Stock Exchange Index (PSEi)
Singapore	SGP	Straits Times Index
Thailand	THA	Bangkok SET index
Vietnam	VN	Ho Chi Minh Stock Exchange Vietnam Index
Other Asia (6 markets)		
South Korea	KOR	Korea Stock Exchange KOSPI Index (KOSPI)
China, PDR	CHI	Shanghai Stock Exchange: Index: Composite
Taiwan	TAI	Taiwan Stock Exchange Weighted Index (TWSE)
Hong Kong	HKG	Hong Kong Hang Seng Index (HIS)
Japan	JPN	Nikkei 225 Index (NKY)
India	IND	Bombay Stock Exchange: Index (SENSEX)
Other Pacific-rim (3 markets)		
Australia	AUS	Australian Stock Exchange All Ordinaries Index (AS30)
Brazil	BRA	Bovespa Index
Mexico	MEX	Mexican Stock Exchange Mexican Bolsa IPC Index (MEXBOL)
Developed countries (4 markets)		
The United States	US	S&P500
The United Kingdom	UK	FTSE 100 Index (UKX)
France	FRA	CAC 40 Index (CAC)
Germany	GER	Deutsche Boerse AG German Stock Index DAX (DAX)

When the variances in the VAR system are covariance stationary, the moving average representation of the VAR exists and is then given by

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (2)$$

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

The variance decompositions (VDs, $\theta_{i,j}(H)$) represent the contribution of X_j's one-standard-deviation shock to the H-step ahead forecast error variance X_i. Based on the generalized VAR framework, the H-step ahead forecast error variance decomposition is

$$\theta_{i,j}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_i)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (3)$$

where e_i is an Nx1 vector with one at i[th] element and σ_{jj} zeros elsewhere and is the standard deviation of the error term for the j[th] equation.

The key difference between VDs computed from the generalized VAR method of KPPS and that of Cholesky factorization is that the sum of the contribution to the variance of the forecast error $(\sum_{j=1}^{N} \theta_{i,j}(H))$ in the former is not necessarily equal to one. Therefore, Diebold and Yilmaz (2012) normalized each of the VDs by the row sum as follows,

$$\tilde{\theta}_{i,j}(H) = \frac{\theta_{i,j}(H}{\sum_{j=1}^{N} \theta_{i,j}(H)}. \quad (4)$$

Therefore, by construction, $\sum_{j=1}^{N} \tilde{\theta}_{i,j}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{i,j}(H) = N$.

The total spillover index (TS) that measures the contribution of spillovers across N variables to total forecast error variances is then calculated as follows,

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{i,j}(H)}{N} \times 100. \quad (5)$$

Although the total spillover index is sufficient to understand how much shocks to the volatility spillover across markets (or asset classes), the generalized VAR framework enables us to learn more about the direction of volatility spillover across markets.

Specifically, the directional spillovers that gauge the direction spillovers GIVEN by market i to all other market j $(DS_{i\rightarrow \cdot}(H))$ and the amounts of spillovers RECEIVED by market i from all other markets j $(DS_{\cdot \rightarrow i}(H))$ are obtained as follows,

$$DS_{i\rightarrow \cdot}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{j,i}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{j,i}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{j,i}(H)}{N} \times 100, \quad (6)$$

$$DS_{\cdot \rightarrow i}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{i,j}(H)}{N} \times 100. \quad (7)$$

The directional spillover indices separate the total spillover into those coming from (or to) a particular source. This index captures the total information flow among all markets under examination and ranges between 0 and 100. A high spillover index refers to a robust exchange of spillover among markets under examination and vice versa.

Determinants of Spillovers for Overall International Equity Market

Although spillover indices remain informative, much can be empirically gained by developing a model that explains spillovers. Furthermore, health policies that reduce viral transmission rates through timely interventions can blunt the effects of spillovers. Such interventions may include a more proactive early warning system for disruptive illnesses with pandemic potential. Therefore, identification of the underlying determinants of international equity market connectedness is essential, not only for investors but also for policymakers. To explore the impact of the COVID-19 pandemic on dynamic connectedness, we posit that the connectedness indices, that is, total spillover indices at time t, can be explained by the following stochastic linear process:

$$TS_t = \mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\delta}\mathbf{Z} + \epsilon_t \quad (8)$$

where TS is the total spillover index calculated from Equation (5), **X** is a set of COVID-19-related variables, and is a list of the control variables. These explanatory variables are listed in Table 2.

Table 2. *List of Explanatory Variables*

Variables	Abbreviation	Definition	Source
COVID-19 related variables			
Case rate	Case_rate	The daily new confirmed cases divided by the cumulative cases	World Health Organization
Death rate	Death_rate	The daily new confirmed deaths divided by the cumulative cases	World Health Organization
Vaccination rate	Vacc_rate	The accumulative number of vaccinated (in number of doses) per 100,000 population	World Health Organization
Global risk factor variables			
VIX index	VIX	CBOE volatility index	Chicago Board of Exchange database
Economic policy uncertainty	EPU	The US Economic Policy Uncertainty Index (Baker et al., 2016)	www.policyuncertainty.com
Infectious disease risk	EMV	Daily Infectious Disease Equity Market Volatility Tracker	www.policyuncertainty.com
Crude oil price	OIL	WTI Oil Futures closing price	CEIC database

Following Harjoto et al. (2021), the daily number of newly confirmed cases and confirmed deaths from COVID-19 are scaled by cumulative confirmed cases and cumulative confirmed deaths, respectively.[4] The case rates and death rates are used to measure the stage of transmission of the COVID-19 outbreak, whereas the number of vaccinations allows us to track the vaccination coverage rate more intuitively.

Factors representing global risks are included as the control variables according to related literature, for example, the VIX index (VIX), the U.S. economic policy uncertainty (EPU) index, the infectious disease risk (EMV), and oil price (OIL). The VIX represents financial uncertainty (e.g., Antonakakis et al., 2014; Manopinoke et al., 2018), whereas the EPU measures economic policy uncertainty (e.g., Antonakakis et al., 2014; Manopinoke et al*.,* 2018; Youssef et al., 2021). Moreover, the financial risk related to the degree of an epidemic is controlled by the EMV (e.g., Bouri et al., 2020, 2021, Iqbal et al., 2022). Lastly, the oil price is included as an indicator of economic activity (e.g., Antonakakis et al., 2014, 2017).

Empirical Results

Patterns of Spillover in the International Equity Markets Before and After the COVID-19 Pandemic

This section estimates the return spillover indices to understand the dynamic pattern of connectedness among the international equity markets. As presented in Table 1, 19 equity markets are examined. In addition, data from January 2, 2018, to February 28, 2022, are used to measure the pandemic's influence on the degree of dynamic connectedness before and after the COVID-19 pandemic. Finally, to examine how equity market connectedness has evolved, the spillover index is also estimated using the 200-day rolling window and 10-day forecasting horizon[5], and the plot is presented in Figure 1.

As shown in Figure 1, the spillover index displays a time-varying pattern. It surged significantly at the beginning of 2020 when the COVID-19 outbreak started in Wuhan, China. The index jumped from 68.77% in early March to 86.95% on April 8, 2020. Since then, the value of the spillover index has varied within the range of 80% and 84% until 2020. The spillover index started exhibiting a downward trend after January 2021 because some brands of COVID-19 vaccines were found to have passed clinical trials satisfactorily, signaling better prospects for containing

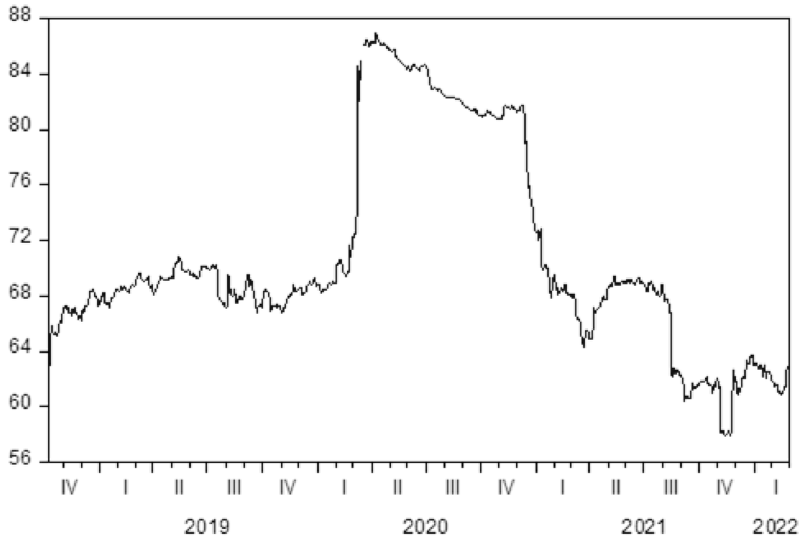

Figure 1. *Dynamic Connectedness (Spillover) Index in International Equity Markets*

Note: We used daily data from January 2, 2018, to February 28, 2022. Results are estimated from a 200-day rolling window generalized VAR of order 2 (AIC), and the predictive horizon for the underlying variance decomposition is 10 days.

spread and reducing infection rates. In February 2022, the spillover index fell, varying within the 60 to 62 percent range, close to its level during the pre-pandemic period.

To compare the degree of connectedness, the entire sample was divided into two sub-samples: the pre-COVID-19 outbreak (from January 2, 2018, to January 29, 2020) and during the COVID-19 outbreak (from January 30, 2020, to February 28, 2022). The spillover indices for whole and sub-samples are reported in Tables 3 to 5. Like the total spillover index presented in Figure 1, the overall spillover index for international equity markets in the whole sample is 70.9%, which displays strong linkages among equity markets across countries. Tables 4 and 5 show that the spillover index has increased from 63.0% to 74.5% since the COVID-19 outbreak.

Overall, results from the spillover index reveal that the COVID-19 outbreak has significantly impacted international equity market integration, intensifying the degree of market connectedness. The findings are consistent with the evidence from previous studies. For example, Youssef et al. (2021) and Shahzad, Naeem, et al. (2021) reported that the degrees of spillover in equity markets increase during the pandemic, whereas Bouri et al. (2021) found that the spillovers across the financial assets are more pronounced around the COVID-19 pandemic's period.

When considering the spillover indices of ASEAN-6 equity markets, it can be observed that Singapore receives the maximum spillover transmitted from other markets (79.1%), followed by Thailand (73.9%), Indonesia (68.3%), Malaysia (67.4%), and the Philippines (65.1%). On the other hand, Vietnam's equity market has experienced the lowest degree of connectedness to the international markets, as the spillover index is around 50.1%.

Among other equity markets in Asia, Korea (79.3%) and Hong Kong (76.5%) have the highest spillover received from the international market. Moreover, within the developed markets, France (79.4%), Germany (78.3%), and the United States (75.2%) have experienced the highest spillover received from others. Again, the spillover index has increased significantly in every country since the COVID-19 outbreak.

Comparing the degree of spillover in the different countries during the pandemic period (January 30, 2020, to February 28, 2022), we found that the degree of spillovers that the ASEAN received from the others are comparably lower than those of the European Union and the United States, except for Singapore. These results support the evidence from Fu et al. (2021), who found that Asian countries have stronger characteristics to resist financial contagion during the pandemic.

Table 3. *Spillover Table for International Equity Market Returns: Whole Period From January 2, 2018, to February 28, 2022*

To	From																			
	THA	PHL	IDN	MYS	SGP	VN	HK	CH	TAI	JPN	KOR	IND	AUS	BRA	MEX	GER	FRA	UK	US	Contribution from others
THA	26.1	3.5	3.1	4.3	6.0	1.2	4.2	1.8	2.5	1.4	3.5	7.0	3.7	5.4	3.1	6.9	7.6	4.0	4.8	73.9
PHL	4.1	34.9	6.4	4.7	4.2	1.5	2.7	0.8	3.0	1.8	4.2	3.4	4.3	5.2	3.1	4.5	4.9	2.8	3.4	65.1
IDN	4.0	6.3	31.7	3.7	5.2	1.3	3.3	1.5	4.0	1.4	4.7	4.7	3.8	5.1	3.5	4.2	4.5	2.6	4.4	68.3
MYS	5.9	4.4	3.6	32.6	5.9	0.8	4.6	1.5	4.5	2.2	4.5	3.8	2.0	4.3	2.4	5.1	5.1	2.6	4.0	67.4
SGP	5.5	2.4	3.4	4.0	20.9	1.0	6.8	2.5	4.6	3.4	6.6	4.6	4.0	3.9	3.1	7.0	7.5	4.0	4.8	79.1
VN	3.0	2.4	2.4	1.4	2.9	49.9	3.7	2.2	2.7	1.6	3.4	1.7	3.1	2.9	2.1	3.9	3.9	1.6	5.1	50.1
HK	4.3	1.8	2.6	3.7	8.1	1.7	24.7	7.9	7.1	4.5	8.6	3.7	2.7	1.9	2.2	4.6	4.8	1.8	3.3	75.3
CH	2.9	0.9	2.0	2.0	5.1	1.9	13.1	39.9	5.5	3.8	5.4	1.7	2.2	1.5	1.6	2.9	2.9	1.0	3.5	60.1
TAI	3.0	2.5	3.2	3.8	5.6	1.1	7.6	3.2	26.2	4.6	9.0	3.9	3.8	2.9	2.7	4.9	4.8	1.8	5.4	73.8
JPN	2.0	0.9	0.9	1.5	3.9	0.9	4.9	2.5	4.4	25.9	7.0	1.6	4.0	3.5	3.1	9.8	9.7	3.4	10.0	74.1
KOR	3.8	2.6	3.1	3.4	6.7	1.1	7.5	3.0	7.6	5.6	21.8	3.7	4.2	3.5	2.8	6.1	6.1	2.6	4.7	78.2
IND	7.5	3.0	4.0	3.5	5.4	0.8	3.8	1.2	3.8	1.9	4.4	25.9	4.2	4.3	3.4	6.9	7.2	4.2	4.7	74.1
AUS	4.1	3.7	3.6	2.0	4.5	1.4	3.0	1.7	4.1	3.9	4.5	4.2	27.4	4.3	3.5	6.5	6.5	3.9	7.1	72.6
BRA	5.7	3.5	3.0	1.9	3.2	0.9	1.5	0.8	1.2	1.3	2.0	4.5	4.7	29.0	6.3	7.7	8.5	4.3	10.0	71.0
MEX	2.7	1.5	2.7	1.4	2.4	0.8	1.8	0.9	1.9	2.2	3.1	3.0	2.6	8.0	35.1	8.0	8.7	4.5	8.5	64.9
GER	5.0	0.9	1.5	1.5	4.0	0.7	3.1	1.0	1.9	2.8	3.2	4.7	3.3	5.1	4.9	21.6	19.0	7.4	8.3	78.4
FRA	5.0	1.1	1.6	1.6	4.2	0.8	3.2	1.0	1.9	3.0	3.2	4.7	3.6	5.3	5.2	18.1	20.6	8.0	7.9	79.4
UK	4.1	0.9	1.7	1.0	3.5	0.7	1.7	0.6	1.3	2.0	2.0	4.6	3.6	4.5	4.4	11.3	12.8	33.6	5.8	66.4
US	4.8	1.9	2.4	1.0	2.7	1.0	1.8	1.0	1.7	2.7	2.0	4.5	5.3	8.7	6.0	11.0	10.9	4.8	25.8	74.2
Contribution to others	77.4	44.1	51.5	46.1	83.7	19.8	78.4	35.3	63.7	50.1	81.4	70.1	65.2	80.4	63.4	129.4	135.6	65.5	105.5	1346.6
Contribution including own	103.5	79.1	83.2	78.7	104.6	69.8	103.1	75.2	89.9	75.9	103.2	96.0	92.6	109.4	98.5	150.9	156.2	99.1	131.2	Spillover index 70.9%

Note: The underlying variance decomposition is based upon a daily generalized VAR of order 2 (AIC). The (i,j)-th value is the estimated contribution to the variance of the 10-day ahead stock return forecast error of country i coming from innovations to stock returns of country j. The abbreviations are defined in Table 1.

Table 4. *Spillover Table for International Equity Market Returns: Pre-COVID-19 From January 2, 2018, to January 29, 2020*

To	From																			
	THA	**PHL**	**IDN**	**MYS**	**SGP**	**VN**	**HK**	**CH**	**TAI**	**JPN**	**KOR**	**IND**	**AUS**	**BRA**	**MEX**	**GER**	**FRA**	**UK**	**US**	**Contribution from others**
THA	39.9	0.8	2.5	2.9	6.5	1.3	7.0	2.3	3.9	3.6	4.4	3.1	0.2	2.4	1.6	4.6	5.2	3.3	4.6	60.1
PHL	1.7	52.2	6.1	4.1	2.8	0.8	3.8	0.9	3.7	0.7	3.9	2.3	0.7	4.1	1.6	2.0	2.2	0.9	5.4	47.8
IDN	2.8	5.2	46.9	4.0	3.9	0.9	5.5	2.2	3.5	0.6	4.0	3.0	1.0	3.4	2.3	2.1	2.8	2.0	3.8	53.1
MYS	3.2	3.2	3.1	37.9	5.4	2.0	5.1	1.4	7.0	1.9	4.7	2.8	1.4	3.4	1.6	4.1	4.7	2.2	4.8	62.1
SGP	3.9	1.1	2.1	3.5	25.6	0.7	10.3	4.5	5.4	4.2	7.4	1.8	1.7	2.2	1.2	6.1	7.3	4.8	6.2	74.4
VN	1.9	1.0	0.9	2.2	1.6	55.6	3.1	3.1	3.7	2.8	3.3	1.5	1.6	1.3	1.3	4.3	4.2	1.3	5.4	44.4
HK	4.1	1.4	2.8	3.1	9.5	1.5	23.8	8.8	7.5	4.3	8.0	2.7	0.9	1.5	1.4	4.8	5.5	4.1	4.3	76.2
CH	2.5	0.5	1.6	1.2	6.7	2.3	13.3	35.2	6.0	4.2	5.2	1.2	1.0	1.1	1.1	4.8	5.0	3.6	3.4	64.8
TAI	2.6	1.9	2.1	4.8	5.5	1.9	8.4	4.4	26.3	4.9	7.2	2.8	1.8	3.1	2.0	4.5	4.9	2.8	8.0	73.7
JPN	2.1	0.9	0.5	1.5	4.0	1.2	4.3	3.3	4.3	22.8	6.7	1.7	2.1	3.0	2.3	8.7	9.6	6.1	15.1	77.2
KOR	3.0	2.1	2.1	3.0	7.7	1.6	8.4	4.3	7.0	6.7	25.8	2.7	1.5	1.7	2.0	5.1	5.8	3.9	5.4	74.2
IND	4.3	1.4	2.9	3.3	3.7	1.2	4.8	1.7	4.6	3.0	5.0	47.5	0.6	1.0	1.9	3.5	3.8	2.6	3.3	52.5
AUS	0.7	0.6	0.3	1.1	2.6	0.9	2.2	1.8	2.2	2.6	2.1	0.8	30.5	3.1	2.5	10.6	11.8	8.5	15.1	69.5
BRA	1.1	0.4	0.6	0.9	1.7	0.2	0.9	0.7	0.1	0.6	1.9	0.7	1.0	59.3	8.7	3.8	4.9	2.6	9.8	40.7
MEX	1.1	0.6	0.8	1.2	1.4	0.8	3.1	1.3	1.6	1.3	2.9	1.8	0.3	7.8	53.3	4.7	5.4	3.3	7.4	46.7
GER	3.3	0.1	0.5	0.9	3.3	0.6	3.7	2.5	1.6	3.2	3.2	1.5	0.9	1.6	2.2	26.0	21.5	15.0	8.3	74.0
FRA	3.0	0.2	0.5	1.1	3.7	0.8	3.7	2.2	1.7	3.1	3.4	1.5	0.9	1.9	2.5	20.5	24.8	15.3	9.1	75.2
UK	2.6	0.1	0.4	0.6	2.7	0.4	3.7	1.7	1.2	2.5	2.4	1.3	1.2	1.6	2.0	17.8	19.3	31.0	7.5	69.0
US	2.4	0.2	0.3	0.2	2.3	0.9	2.8	1.0	1.3	2.8	2.2	1.2	0.6	6.0	4.3	11.7	13.0	7.5	39.3	60.7
Contribution to others	46.4	22.0	30.2	39.5	75.0	20.2	93.9	47.9	66.0	53.0	78.1	34.5	19.5	50.3	42.5	123.6	136.8	89.8	127.0	1196.2
Contribution including own	86.3	74.2	77.1	77.3	100.6	75.9	117.8	83.1	92.3	75.8	103.9	82.0	50.0	109.6	95.9	149.6	161.7	120.8	166.2	Spillover index 63.0%

Note: The underlying variance decomposition is based upon a daily generalized VAR of order 2 (AIC). The (i,j)-th value is the estimated contribution to the variance of the 10-day ahead stock return forecast error of country i coming from innovations to stock returns of country j. The abbreviations are defined in Table 1.

Table 5 *Spillover Table for International Equity Market Returns: During COVID-19 From January 30, 2020, to February 28, 2022*

To	From																			
	THA	**PHL**	**IDN**	**MYS**	**SGP**	**VN**	**HK**	**CH**	**TAI**	**JPN**	**KOR**	**IND**	**AUS**	**BRA**	**MEX**	**GER**	**FRA**	**UK**	**US**	**Contribution from others**
THA	22.4	3.9	3.5	4.6	5.9	1.4	4.1	2.6	2.4	1.3	3.4	7.5	4.8	6.2	3.3	6.9	7.3	3.7	4.8	77.6
PHL	4.8	28.9	6.7	4.3	4.2	1.6	2.5	1.3	2.7	2.4	4.2	3.5	5.8	5.5	3.9	5.1	5.4	3.2	3.9	71.1
IDN	4.2	6.0	25.4	3.2	5.3	1.5	2.8	1.9	4.1	1.9	4.7	4.8	5.8	6.1	4.4	4.7	5.0	2.8	5.1	74.6
MYS	6.9	4.6	3.6	30.5	5.7	0.5	4.2	1.9	3.4	2.4	3.8	4.1	3.1	4.9	2.6	5.3	5.2	3.0	4.3	69.5
SGP	6.2	2.9	4.0	3.8	18.7	1.1	5.4	1.8	4.2	3.0	6.1	5.7	4.8	4.8	4.0	7.4	7.6	4.1	4.3	81.3
VN	3.3	2.9	3.1	1.1	3.1	45.2	3.5	2.6	2.1	1.5	3.4	2.0	4.8	3.6	3.0	3.9	3.9	2.2	4.9	54.8
HK	4.9	2.2	2.7	3.7	6.8	1.8	23.7	7.4	6.3	4.6	8.4	4.7	3.4	2.8	2.5	4.6	4.8	1.6	3.1	76.3
CH	4.3	2.0	2.8	2.3	3.9	1.7	11.6	36.2	5.0	3.2	5.2	2.9	3.2	3.1	2.0	2.5	2.7	1.5	3.7	63.8
TAI	3.3	2.7	3.9	3.2	5.2	0.6	6.5	3.0	24.5	4.3	9.6	4.7	5.0	3.6	3.2	5.1	4.9	1.8	5.0	75.5
JPN	2.4	1.1	1.5	1.3	3.5	1.0	5.1	2.3	4.2	24.9	6.7	2.0	4.8	4.2	3.8	10.0	9.7	3.1	8.3	75.1
KOR	4.2	2.7	3.8	3.1	6.2	0.9	7.2	3.0	8.3	5.2	20.0	4.2	4.9	4.4	3.1	6.1	5.8	2.4	4.4	80.0
IND	7.9	3.2	4.4	3.6	5.8	0.9	4.0	1.7	3.8	2.0	4.1	20.7	4.4	5.6	4.1	7.3	7.4	4.1	5.0	79.3
AUS	5.5	4.4	5.2	1.9	4.5	2.0	2.9	1.9	4.4	3.9	4.3	4.4	22.6	5.5	4.4	6.0	6.0	3.1	7.1	77.4
BRA	6.4	3.6	3.7	2.2	3.6	1.3	2.0	1.6	1.4	1.6	2.1	5.4	5.4	22.2	5.7	8.7	9.2	4.0	9.8	77.8
MEX	3.1	2.0	3.8	1.5	2.9	1.0	1.9	1.4	2.0	2.8	3.0	3.9	4.4	7.7	27.5	8.6	9.2	4.6	8.9	72.5
GER	5.1	1.1	2.0	1.6	4.5	0.9	3.2	0.9	2.1	3.0	2.9	5.6	4.1	6.4	5.9	19.2	17.4	6.0	8.2	80.8
FRA	5.2	1.3	2.1	1.6	4.5	0.9	3.3	1.1	1.9	3.3	2.9	5.5	4.4	6.5	6.1	16.8	18.7	6.6	7.4	81.3
UK	4.4	1.1	2.1	1.1	4.2	1.2	1.5	0.6	1.4	1.9	1.8	5.6	3.8	5.2	5.2	9.8	11.1	32.4	5.5	67.6
US	5.2	2.7	3.0	1.2	2.9	0.9	1.7	1.4	1.7	2.9	1.6	5.5	6.8	9.0	6.3	11.1	10.7	4.3	21.0	79.0
Contribution to others	87.5	50.4	61.7	45.4	82.8	21.3	73.3	38.5	61.6	51.5	78.3	82.0	83.6	94.9	73.5	130.0	133.2	62.2	103.8	1415.2
Contribution including own	109.8	79.3	87.1	75.9	101.4	66.5	97.0	74.7	86.0	76.4	98.3	102.7	106.2	117.1	101.0	149.2	151.9	94.6	124.7	Spillover index 74.5%

Note: The underlying variance decomposition is based upon a daily generalized VAR of order 2 (AIC). The (i,j)-th value is the estimated contribution to the variance of the 10-day ahead stock return forecast error of country i coming from innovations to stock returns of country j. The abbreviations are defined in Table 1.

Similar results are found in the spillover given or transmitted to other markets. Specifically, for countries within ASEAN-6, Singapore also presents the highest spillover to others (84.9%), followed by Thailand (76.7%). Among other Asia countries, Korea (82.5%) and Hong Kong (81.4%) contribute to others the most. Meanwhile, France (137.2%), Germany (130.4%), and the United States (106.8%) have the highest spillover transmitted to others.

Explaining Spillovers in International Equity Markets Using the Overall Spillover Index

This section uses time series data to examine the effects of the standard financial risk factors and COVID-19-related variables on the level of dynamic connectedness in international equity markets. Specifically, we estimate time series regression models using the overall dynamic spillover index as the dependent variable. Results are shown in Table 6.

We first examine models with only the standard financial risk factors. The results from Model 1 show that none of the financial risk factors, namely VIX, EPU, EMV, and crude oil price (OIL), have significant effects on the changes in spillover levels during January 2020 to February 2022. Hence, we include several COVID-19-related variables as identified in Section 3, namely the rate of new infections (CASE_RATE), the rate of the daily number of deaths (DEATH_RATE), and the number of new doses of vaccination (VACC_RATE) in Models 2 to 5. Based on the whole sample period, results from Model 2 reveal that only the volatility index (VIX) and the death rate can significantly explain the degree of spillover in international equity markets.

To search and establish robustness patterns, two sub-samples are examined. First, for the pre-vaccination period from January 30, 2020, to December 30, 2020 (Model 3), results still confirmed the significant impact of the death rate. Moreover, the EMV provides positive and significant effects on the spillover index, suggesting that the impact of COVID-19-related factors is the main variable influencing the transmission of risk in the international equity markets in 2020.

Next, we run regressions using the sub-sample range from January 2, 2021, to February 28, 2022, which falls within the vaccination period. The results from Model 4 show that none of the COVID-19-related variables (CASE_RATE, DEATH RATE, VACC_RATE, and EMV) are statistically significant. Only the percentage change in the oil price (OIL) negatively affected the degree of spillover. A possible explanation is that oil price is a proxy of economic activity. The spillover effects decreased after governments relaxed restrictions and stimulus economy with several fiscal and monetary measures in 2021, as presented in Figure 1.

However, the vaccination variable cannot significantly explain the degree of spillover directly in Model 4. Hence, Model 5 includes the squared vaccination rate to capture the nonlinear impact of vaccination. The estimated results show that spillovers decline at an increasing rate. Furthermore, the vaccination variable is negatively significant for the new vaccination level and positively significant in the squared number. These results imply that vaccination reduces the degree of spillover during the early phase of vaccination, and its effects weaken as vaccination increases. This result shows the importance of vaccination in reducing pandemic risk in the early stage (January 2020 to December 2020). Still, the importance of vaccination decreases and does not significantly affect the risk of the pandemic in the later phase (January 2021 to February 2022).

Overall, the results show that COVID-19-related factors have significantly influenced dynamic connectedness in international equity markets during the onset of the COVID-19 pandemic. The pandemic's severity indicator, that is, the new case rate, death rate, and vaccination rate, can explain the degree of financial market connectedness. However, the effects in the early and later phases are asymmetric.

Our results are consistent with other studies. For instance, Bissoondoyal-Bheenik et al. (2021) found that the number of confirmed global cases and deaths increased the degree of return and volatility connectedness in stock markets of developed markets (G20 countries) during the first half of 2020. In addition, Ashraf (2020) found that stock market movement reacts to the growing number of cases, not deaths. Harjoto et al. (2021) demonstrated that there is a time-varying effect of COVID-19 cases and mortality rates on the equity markets during the rising infection period (pre-April) and the stabilizing infection period (post-April). Moreover, pandemic-related financial risk factors such as crude oil prices and the EMV index could be used as indicators to monitor market connectedness. Bouri et al. (2021) found that EMV significantly and positively affects the degree of connectedness in the global asset class during 2020. The results provide an important note for policymakers and portfolio managers to consider the novel development in the risk indicators, which could be applied for implementing safeguard measures or portfolio rebalance during the turbulent market.

Explaining Spillovers in the International Equity Markets: Country-Level Spillover Indices

This section uses country-level data to explore the determinants of dynamic connectedness in equity markets. Based on data at the country level, we can characterize spillovers into two dimensions. The first dimension measures the degree of spillovers each country receives from the others. Diebold and Yilmaz (2012) defined this dimension of the index as "to receive" or "from" the others' indices. The second dimension quantifies the degree of spillovers each country contributed to fluctuations in the other markets. Again, this index is expressed as "to give" or "to" others.

First, we estimate the panel regressions using the spillover "received from" the others' indices as the explanatory variable. Then, we follow the results from the time-series overall spillover models. Hence, we estimate model 2 with the whole sample (January 30, 2020, to February 28, 2022), model 3 with the pre-vaccine period (January 30, 2020, to December 30, 2020), and models 4 and 5 with the post-vaccine period (January 2, 2021, to February 28, 2002). Model 4 investigates the linear impact of the vaccination progress, whereas model 5 assumes the nonlinearity in the effect of the vaccination progress to the degree of spillover using the quadratic form. The panel regression results are shown in Table 7.

Table 6. *Determinant Factors of Spillover: Time Series Regression for Overall Dynamic Spillover Index*

Period	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Overall 30/01/20 - 28/02/22	*Overall* 30/01/20 - 28/02/22	*Pre-vaccine* 30/01/20 - 30/12/20	*With vaccine* 04/01/21 - 28/02/22	*With vaccine* 04/01/21 - 28/02/22
Intercept	-0.0002 (0.0004)	-0.0005 (0.0005)	-0.0005 (0.0008)	0.0009 (0.0009)	0.0025 (0.0012)
Δ1n (VIX)	0.0072 (0.0044)	0.0073* (0.0044)	0.0083 (0.0070)	0.0018 (0.0054)	0.0014 (0.0054)
Δ1n (EPU)	-0.0002 (0.0009)	-0.0003 (0.0009)	-0.0008 (0.0018)	-0.0003 (0.0010)	-0.0002 (0.0010)
ΔEMV	3.56×10^{-5} (4.34×10^{-5})	3.58×10^{-5} (4.34×10^{-5})	0.0002** (6.37×10^{-5})	-5.64×10^{-5} (5.89×10^{-5})	-4.62×10^{-5} (5.88×10^{-5})
Oil	-7.20×10^{-6} (0.0007)	0.0002 (0.0007)	0.0003 (0.0007)	-0.0623*** (0.0223)	-0.0673*** (0.0223)
Δ1n ($Spillover_{t=3}$)	0.0970** (0.0432)	0.0885** (0.0430)	0.2462*** (0.0623)	-0.0637 (0.0581)	-0.0601 (0.0578)
Case rate		-0.0555 (0.0385)	-0.0568 (0.0430)	-0.0784 (0.1832)	-0.1463 (0.1854)
Death rate		0.0738** (0.0337)	0.0739** (0.0367)	-0.2354 (0.2490)	-0.2936 (0.2495)
Vacc_rate		8.74×10^{-15} (6.61×10^{-14})		1.35×10^{-14} (9.24×10^{-14})	-3.64×10^{-13}* (2.10×10^{-13})
Vacc_rate^2					1.54×10^{-23}** (7.70×10^{-24})
R-squared	0.0173	0.0380	0.1352	0.0553	0.0681
BG Test (p-value)	0.0019 (0.9991)	0.0540 (0.9734)	1.4279 (0.4897)	1.4280 (0.4897)	1.7683 (0.4131)

*Note: The first line reports the estimated coefficient, while the standard errors are reported in the parenthesis. The lagged dependent variable is included to control the autocorrelation in regression. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels.*

Table 7. *Determinant Factors of Spillover: Panel Regression (Spillover "Receive From" the Others' Indices) in the International Equity Markets*

	Model 2	**Model 3**	**Model 4**	**Model 5**
Period	*Overall* *30/01/20 - 28/02/22*	*Pre-vaccine* *30/01/20 - 30/12/20*	*With vaccine* *04/01/21 - 28/02/22*	*With vaccine^2* *04/01/21 - 28/02/22*
Intercept	-0.0008 (0.0001)	-0.0007*** (0.0002)	-0.0005** (0.0002)	-0.0005** (0.0002)
Δ1n (VIX)	0.0056*** (0.0012)	0.0073*** (0.0016)	0.0015 (0.0016)	0.0015 (0.0016)
Δ1n (EPU)	-0.0003 (0.0002)	-0.0004 (0.0004)	-0.0003 (0.0003)	-0.0003 (0.0003)
ΔEMV	2.23 x 10-5* (1.18 x 10-5)	8.95×10^{-5}*** (1.48×10^{-5})	-5.72×10^{-5}*** (1.68×10^{-5})	-5.84×10^{-5}*** (1.69×10^{-5})
R_Oil	0.0002 (0.0002)	0.0003* (0.0002)	-0.0606*** (0.0065)	-0.0605*** (0.0065)
Δ1n (Spill from $_{t=2}$)	-0.0275*** (0.0102)	-0.0819*** (0.0159)	0.0195 (0.0132)	0.0203 (0.0132)
Case rate	0.0041** (0.0020)	0.0061*** (0.0018)	-0.0123 (0.0092)	-0.0125 (0.0093)
Death rate	0.0200*** (0.0021)	0.0208*** (0.0020)	0.0130* (0.0078)	0.0133* (0.0078)
Vaccinated	3.42×10^{-9} (3.05×10^{-9})		2.23×10^{-9} (2.27×10^{-9})	2.26×10^{-9} (3.82×10^{-9})
Vaccinated^2	-6.25×10^{-16} (1.10×10^{-14})			1.52×10^{-16} (1.12×10^{-14})
R-squared	0.0191	0.0705	0.0203	0.0204

*Note: The first line reports the estimated coefficient, while the standard errors are reported in the parenthesis. The lagged dependent variable is included to control the autocorrelation in regression, while the fixed effects are included to control the country-specific effect. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively*

Based on estimates reported in Table 7, Model 2 reveals that the VIX, EMV, case rates, and death rates have positively impacted spillovers "received from" the other markets. Similar results are obtained in Model 3 when the pre-vaccine period is examined from January 30, 2020, to December 30, 2020. The results confirm the roles of the VIX and EMV index as the main risk factors that increase the spillover each country received from the others. Moreover, the case and death rates are the main factors that global equity investors could pay attention to during the early stage of the pandemic in 2020.

From January 4, 2021, to February 28, 2022, Models 4 and 5 show that only the death rate matters, whereas the case and vaccination rates are insignificant. Interestingly, the coefficient on VIX is no longer significant during the vaccination period. Moreover, EMV and oil return relate negatively to the spillover received from other markets during the vaccination period, which is contradictory to those found in the whole sample period and pre-vaccine period. In sum, irrespective of the period examined (i.e., with or without vaccines), the death rate is the most significant factor in determining the spillovers received from other markets. Higher death rates cause a higher degree of spillover from other markets. Despite the vaccination rate not being significant, the death rate's effect on the spillover declines by about one-half during the vaccination period. Our results also extend recent literature (e.g., Ashraf, 2020; Harjoto et al., 2021) by demonstrating a time-varying effect of COVID-19-related variables on the equity markets in terms of market connectedness.

Table 8. *Determinant Factors of Spillover: Panel Regression (Spillover "Give to" the Others' Indices) in the International Equity Markets*

	Model 2	Model 3	Model 4	Model 5
Period	*Overall* *30/01/20 - 28/02/22*	*Pre-vaccine* *30/01/20 - 30/12/20*	*With vaccine* *04/01/21 - 28/02/22*	*With vaccine^2* *04/01/21 - 28/02/22*
Intercept	-0.0010** (0.0004)	-0.0012* (0.0006)	-0.0009 (0.0006)	-0.0008 (0.0007)
Δ1n (VIX)	0.0060* (0.0036)	0.0190*** (0.0065)	0.0025 (0.0048)	0.0026 (0.0049)
Δ1n (EPU)	8.19×10^{-5} (0.0007)	-0.0008 (0.0017)	-0.0007 (0.0009)	-0.0007 (0.0009)
ΔEMV	1.30×10^{-5} (3.57×10^{-5})	0.0002*** (6.08×10^{-5})	-9.44×10^{-5}* (5.15×10^{-5})	-9.42×10^{-5}* (5.18×10^{-5})
R_Oil	0.0002 (0.0005)	0.0007 (0.0007)	-0.0620*** (0.0200)	-0.0628*** (0.0198)
Δ1n (Spill to $_{t=2}$)	-0.0629*** (0.0099)	-0.0850*** (0.0144)	-0.0251* (0.0133)	0.0112 (0.0132)
Case rate	-0.0092 (0.0060)	-0.0101 (0.0074)	0.0480* (0.0251)	0.0479* (0.0251)
Death rate	0.0406*** (0.0061)	0.0477*** (0.0077)	-0.0251 (0.0251)	-0.0260 (0.0252)
Vaccinated	1.18×10^{-9} (9.36×10^{-9})		5.57×10^{-9} (6.94×10^{-9})	5.74×10^{-9} (1.22×10^{-8})
Vaccinated^2	1.42×10^{-14} (3.25×10^{-14})			-1.87×10^{-15} (3.60×10^{-14})
R-squared	0.0094	0.0240	0.0049	0.0044

*Note: The first line reports the estimated coefficient, while the standard errors are reported in the parenthesis. The lagged dependent variable is included to control the autocorrelation in regression, while the fixed effects are included to control the country-specific effect. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively*

Subsequently, we consider the regressions of the spillover "given" to the other markets, and the results are presented in Table 8. Using the whole sample period, Model 2 reveals that only VIX and death rate positively impact the spillover given to other markets. During the pre-vaccination period, Model 3 reports similar results to Model 2, except the EMV relates positively with the spillover given to other markets. Remarkably, the results associated with Models 4 and 5 contradict the evidence generated by Models 2 and 3. Specifically, case rate positively relates to the spillover given to other markets, whereas death and vaccination rates do not matter. The results from models 4 and 5 were similar to those of the previous cases where the spillover "received from" the other markets is used as the dependent variable. EMV and oil return negatively affect the spillover given to other markets, whereas VIX is no longer a significant factor.

These controversial results could be explained as follows. During the pre-vaccination period, in which information about COVID-19 containment was sparse and uncertainty was more pronounced, markets tended to overreact to the rising cases and especially deaths of COVID-19. However, during the vaccination period, the satisfactory performance of some vaccines and other forms of treatment may have soothed market anxiety, with some governments openly advocating for dismantling some pandemic protocols to stimulate demand.

Explaining Spillovers in the ASEAN-6 Equity Markets

In this section, we focus on the ASEAN-6 equity markets. For this purpose, we use the spillover indices computed from the previous sections. In addition, we employ only the spillover indices of the ASEAN-6

Table 9. *Panel Regressions (Spillover "from" Indices) in the ASEAN-6 Equity Markets*

	Model 2	Model 3	Model 4	Model 5
Period	*Overall* *30/01/20 - 28/02/22*	*Pre-vaccine* *30/01/20 - 30/12/20*	*With vaccine* *04/01/21 - 28/02/22*	*With vaccine^2* *04/01/21 - 28/02/22*
Intercept	-0.0014*** (0.0003)	-0.0012*** (0.0003)	-0.0008 (0.0007)	-0.0014** (0.0003)
Δ1n (VIX)	0.0079*** (0.0003)	0.0158*** (0.0040)	-0.0027 (0.0049)	0.0079*** (0.0003)
Δ1n (EPU)	-0.0006 (0.0006)	-0.0002* (0.0001)	-7.49×10^{-5} (0.0009)	-0.0006 (0.0006)
ΔEMV	2.29 x 10-5 (3.03 x 10-5)	0.0001*** (3.78×10^{-5})	-9.17×10^{-5}* (5.18×10^{-5})	2.29×10^{-5} (3.03×10^{-5})
R_Oil	0.0003 (0.0005)	0.0005 (0.0004)	-0.0606*** (0.0065)	0.0003 (0.0005)
Δ1n (Spill from$_{t=2}$)	-0.0698*** (0.0180)	-0.1191*** (0.0278)	-0.0669*** (0.0198)	-0.0698*** (0.0179)
Case rate	-0.0132** (0.0052)	-0.0067 (0.0047)	-0.0334 (0.0205)	-0.0132** (0.0052)
Death rate	0.0554*** (0.0054)	0.0561*** (0.0051)	0.0188 (0.0296)	0.0553*** (0.0054)
Vaccination rate	1.55×10^{-9} (9.60×10^{-9})		3.48×10^{-9} (6.70×10^{-9})	1.55×10^{-9} (9.60×10^{-9})
Vaccination rate^2	1.20×10^{-14} (3.71×10^{-14})			1.20×10^{-14} (3.71×10^{-14})
R-squared	0.0435	0.1339	0.0157	0.0399

*Note: The first line reports the estimated coefficient, while the standard errors are reported in the parenthesis. The lagged dependent variable is included to control the autocorrelation in regression, while the fixed effects are included to control the country-specific effect. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels.*

countries (Indonesia, Malaysia, Singapore, the Philippines, Thailand, and Vietnam) in estimating the panel regression. The results are shown in Table 9 (Table 10) for the panel regressions with the spillover indices "received from" ("given to") the other countries as the dependent variables.

From Table 9, the VIX index is still the key risk factor explaining the degree of spillover in the case of ASEAN-6's equity markets. Moreover, the EMV indices also positively explain the degree of spillover. However, the respective impacts during pre-vaccine and vaccine periods move in opposite directions. During the pre-vaccine period, the high degree of anticipation of positive outcomes along the vaccine development front has interacted with bad news highlighting the seemingly unstoppable nature of COVID-19. Thus, spillovers increased due to the uncertainty that effective vaccines will be developed rapidly.[6] However, information about vaccine effectiveness and treatment regimens has reduced spillovers during the post-vaccine period. The positive news is valued in financial markets, and expectations were formed on the assumption that effective vaccines can render feasible policies that relax mobility restrictions, leading to a partial reopening of the economy. Therefore, an increase in the EMV index is associated with a reduction in spillovers. For COVID-19-related variables, the death rate significantly affects the spillover in the ASEAN-6's equity markets. The progress of vaccination in the ASEAN-6 countries is insignificant. These results align with the international equity markets reported in the previous section. However, the role of the vaccination progress in the ASEAN-6 countries is insignificant, which is different from the case of the international markets.

Table 10. *Panel Regression (Spillover "to" Indices) in the ASEAN-6 Equity Markets*

	Model 2	**Model 3**	**Model 4**	**Model 5**
Period	*Overall* *30/01/20 - 28/02/22*	*Pre-vaccine* *30/01/20 - 30/12/20*	*With vaccine* *04/01/21 - 28/02/22*	*With vaccine* *04/01/21 - 28/02/22*
Intercept	-0.0019**	-0.0016	-0.0016	-0.0021
	(0.0009)	(0.0012)	(0.0014)	(0.0016)
Δ1n (VIX)	0.0250***	0.0357***	0.0103	0.0104
	(0.0076)	(0.0115)	(0.0101)	(0.0101)
Δ1n (EPU)	-0.0024	-0.0054*	-0.0016	-0.0016
	(0.0016)	(0.0030)	(0.0018)	(0.0018)
ΔEMV	0.0001	0.0004***	-0.0002*	-0.0002*
	(7.58 x 10^{-5})	(0.0001)	(00001)	(00001)
R_Oil	0.0008	0.0011	-0.0360	-0.0366
	(0.0011)	(0.0012)	(0.0411)	(0.0411)
Δ1n (Spill $to_{t=2}$)	0.0256	0.0435	0.0557	0.0557
	(0.0403)	(0.0714)	(0.0490)	(0.0490)
Case rate	-0.0135	-0.0202	0.0744*	0.0729*
	(0.0126)	(0.0135)	(0.0424)	(0.0425)
Death rate	0.0490***	0.0478***	-0.0224	-0.0189
	(0.0133)	(0.0142)	(0.0614)	(0.0617)
Vaccinated	1.95 x 10^{-8}		3.21 x 10^{-9}	1.85 x 10^{-8}
	(2.35 x 10^{-8})		(1.39 x 10^{-8})	(2.97 x 10^{-8})
Vaccinated^2	-6.50 x 10^{-14}			-5.81 x 10^{-14}
	(8.98 x 10^{-14})			(9.97 x 10^{-14})
R-squared	0.0101	0.0319	0.0072	0.0074

*Note: The first line reports the estimated coefficient, while the standard errors are reported in the parenthesis. The lagged dependent variable is included to control the autocorrelation in regression, while the fixed effects are included to control the country-specific effect. ***, **, and * indicate that the null hypothesis is rejected at the 1%, 5%, and 10% significance levels, respectively*

Considering the case of the spillover "given to" the other countries, results from Table 10 show that the EMV index and the case rates are the two crucial factors affecting the degree of spillover given to the others. The VIX and death rates are significant only during the pre-vaccine period. During the post-vaccine period, the case rate significantly affects spillover given to other countries. In addition, the increased number of new cases provides indicators for spillover to those of the other equity markets after 2021. Overall, the R-squared in Table 10 is higher than in Table 9. Hence, the financial risk factors and the pandemic's related variables could explain the spillover each country received from the others better than the spillover each country gave to the others.

Conclusion

The COVID-19 pandemic has caused a severe global economic contraction and has propagated negative shocks across financial markets. This paper examines the dynamic connectedness between ASEAN stock markets and major global stock markets using the dynamic connectedness indices proposed by Diebold and Yilmaz (2009, 2012). In addition, this study contributes to the existing literature by investigating the extent of dynamic connectedness between ASEAN and global stock markets during the COVID-19 pandemic using an expanded period of vaccine development outcomes.

Empirical results reveal that equity markets have become more closely connected during the COVID-19 pandemic. In addition, the role of ASEAN markets in global connectedness increased significantly during the pandemic. Spillovers transmitted within the ASEAN region have also increased significantly during the COVID-19 outbreak. After the spillover effects had been estimated and characterized, we focused on the linkage between the degree of connectedness and the severity of the pandemic using regression analysis.

Empirical results indicate that the fear index (VIX) and the EMV can explain the level of dynamic connectedness during 2020. Moreover, regression results also show that the death rate has increased the degree of spillover, whereas the vaccination rate has helped lower the degree of spillovers across equity markets. Finally, the effect of vaccine progression follows a nonlinear pattern in which the effect is high initially and then eventually declines.

Key implications from our study are as follows. First, the pattern of connectedness in global equity markets is time-varying, and the role of emerging markets, for example, ASEAN countries, increase during the pandemic period. Therefore, investors and policymakers should be more concerned about the spillovers in emerging markets during the crisis. Second, the death rate should be a key variable to monitor and measure the pandemic's impacts on the financial markets. Third, the progress in vaccine development is also crucial, especially in the early stage, and then significantly diminished later. Lastly, the VIX should not solely be the global risk factors indicator. Using existing indicators such as the EPU and the EMV, and the development of other indices, such as the trade policy uncertainty, geo-political risk, and global risk aversion index, provide ways to improve spillovers monitored in international financial markets. Hence, policymakers could apply these indicators to monitor the markets and prove the timing response with effective safeguard measures to protect financial markets from contagion during a future crisis. Finally, an important policy realization highlights the indispensable role of health warning systems, public investments in medical infrastructures, and human resource development for medical personnel. Moreover, portfolio managers could use these factors as leading indicators to quickly rebalance their portfolios and protect their investments.

This study is not without limitations, however. First, this study mainly focused on equity markets. Future research could explore the spillover effect across different asset classes, such as gold, bond, commodity, and cryptocurrency. Second, this study used a relatively short event period. As a result, we could only gain information on the immediate and short-term effects of the pandemic. Therefore, future researchers may investigate the spillovers over a longer period, especially during the COVID-19 recovery period. In addition, the recent development in the time-varying parameter vector autoregression (TVP-VAR) model suggested by Antonakakis et al. (2020) provides an alternative estimation method to compute variance decomposition for the dynamic connectedness index. Such methodology requires no arbitrary set of the rolling window size and no observation loss. However, this method requires a long span of data, which could be explored in future research. Third, future extensions should consider complex network analysis to deepen the understanding of financial and policy uncertainty networks within the ASEAN, given that there are political sources of volatility. Fifth, now that many economies are transitioning toward the post–pandemic era, future extensions should also consider the transmission of fiscal and monetary policy uncertainty. Finally, it is important to evaluate how international policies can be counteracted properly should they adversely affect domestic outcomes. Finally, the continued development in the leading indicators can be applied as the factors affecting spillover in the financial market, for example, the global risk aversion (GRA) index (Bekaert et al. 2021), Twitter economic uncertainty (TEU) index (Baker et al., 2021). All in all, this would provide clearer insights for investors to develop better international portfolio diversification benefits.

Funding: This research was funded by the faculty of business administration at Kasetsart University, Thailand.

Acknowledgments: The authors thank all anonymous referees and editors for their valuable suggestions.

Notes

[1] Contagion and spillovers are two concepts that are used interchangeably. But what distinguishes contagion from the latter is that it is associated with a crisis. Spillovers may be present even during normal times and become more intense during periods of crises.

[2] However, strong linkages between markets do not necessarily imply financial contagion. Therefore,

correlations should be applied in studying the determinants of market interdependence, not spillovers (see Corsetti et al., 2005, for detailed discussion).

[3] For instance, Aziz et al. (2022) used daily data from May 10, 2005, to February 24, 2021 to examine return and volatilities of ASEAN+3 stock markets. Ahmad et al. (2022) focused on the period May 2, 2019, to October 31, 2020.

[4] Scaling is done to properly represent the speed of COVID-19 infection and the mortality rate.

[5] The forecast horizon is 10-day as suggested in Diebold and Yilmaz (2012) where spillover index is not sensitive to the choice of order of the VAR or the choice of the forecast horizon. For robustness check, the spillover indices are estimated based on 150- and 250-day rolling window; similar patterns are found in which indices rise significantly in March 2020 and then gradually revert to the previous level at the end of 2021. Robustness results are available upon request.

[6] Abnormal returns in some stock markets have been documented following announcements on key vaccine development milestones, such as the 9 November 2020 announcement made by Pfizer and BioNTech. For details, please go to How has the news of a vaccine affected world stock markets? - Economics Observatory

Reference

Abuzayed, B., Bouri, E., Al-Fayoumi, N., & Jalkh, N. (2021). Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. *Economic Analysis and Policy, 71*, 180–197. https://doi.org/10.1016/j.eap.2021.04.010

Ahmad, W., Chalal, R., & Rais, S. (2022). Understanding the impact of the coronavirus outbreak on the economic integration of ASEAN countries. *Asia and the Global Economy, 2*(2), Article No. 100040. https://doi.org/10.1016/j.aglobe.2022.100040

Akhtaruzzaman, Md., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. *Finance Research Letters, 38*, Article No. 101604. https://doi.org/10.1016/j.frl.2020.101604

Albulescu, C. (2021). COVID-19 and the United States financial markets' volatility. *Financial Research Letters, 38*, Article No. 101699. https://doi.org/10.1016/j.frl.2020.101699

Amar, A. B., Belaid, F., Youssef, A. B., Chiao, B., & Guesmi, K. (2021). The unprecedented reaction of equity and commodity markets to COVID-19. *Finance Research Letters, 38*, Article No. 101853. https://doi.org/10.1016/j.frl.2020.101853.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics, 44*, 433–447. https://doi.org/10.1016/j.eneco.2014.05.007

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2017). Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest. *International Review of Financial Analysis, 50*, 1–26. https://doi.org/10.1016/j.irfa.2017.01.004

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management, 13*(4), Article No. 84. https://doi.org/10.3390/jrfm13040084

Antonakakis, N., Gabauer, D., Gupta, R., & Plakandaras, V. (2018). Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters, 166*, 63–75. https://doi.org/10.1016/j.econlet.2018.02.011

Ardiyono, S. K. (2022). COVID-19 pandemic, firms' responses, and unemployment in the ASEAN-5. *Economic Analysis and Policy, 76*, 337–372. https://doi.org/10.1016/j.eap.2022.08.021

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance, 54*, Article No. 101249. https://doi.org/10.1016/j.ribaf.2020.101249

Aziz, M., Ahmad, N., Zichu, J., & Nor, S. (2022). The impact of COVID-19 on the connectedness of stock index in ASEAN+3 economies. *Mathematics, 10*(9), Article No. 1417. https://doi.org/10.3390/math10091417

Bahrini, R., & Filfilan, A. (2020). Impact of the novel coronavirus on stock market returns: Evidence from GCC countries. *Quantitative Finance and Economics, 4*(4), 640–652. https://doi.org/10.3934/QFE.2020029

Baker, S., Bloom, N., & Davis, S. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Baker, S., Bloom, N., Davis, S., & Terry, S. J. (2020). *COVID-induced economic uncertainty* (NBER Working Paper No. 26983). https://doi.org/10.3386/w26983

Baker, S., Bloom, N., Davis, S., & Renault, T. (2021). *Twitter-derived measures of economic uncertainty* (National Science Foundation). http://policyuncertainty.com/media/Twitter_Uncertainty_5_13_2021.pdf

Behera, C., & Rath, B. N. (2022). The interconnectedness between COVID-19 uncertainty and market returns in selected ASEAN countries. *Emerging Markets Finance and Trade*. https://doi.org/10.1080/1540496X.2022.2096434

Bekaert, G., Engstrom, E. C., & Xu, N. R. (2021). The time variation in risk appetite and uncertainty. *Management Science, 68*(6), 3975–4004. https://doi.org/10.1287/mnsc.2021.4068

Bekiros, S. (2014). Contagion, decoupling, and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis, 33*, 58–69. https://doi.org/10.1016/j.irfa.2013.07.007

Billio, M., & Caporin, M. (2010). Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. *Computational Statistics and Data Analysis, 54*(11), 2443–2458. https://doi.org/10.1016/j.csda.2009.03.018

Bissoondoyal-Bheenick, E., Do, H., Hu, X., & Zhong, A. (2021). Learning from SARS: Return and volatility connectedness in COVID-19. *Finance Research Letters, 41*, Article No. 101796. https://doi.org/10.1016/j.frl.2020.101796

Bouri, E., Demirer, R., Gupta, R., & Pierdzioch, C. (2020). Infectious diseases, market uncertainty and oil market volatility. *Energies, 13*(16), Article No. 4090. https://doi.org/10.3390/en13164090

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis, 73*. https://doi.org/10.1016/j.irfa.2020.101646

Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'Some contagion, some interdependence': More pitfalls in test of financial contagion. *Journal of International Money and Finance, 24*(8), 1177-1199. https://doi.org/10.1016/j.jimonfin.2005.08.012

Corbet, S., Hou, Y., Hu, Y., Oxley, L., & Xu, D. (2021). Pandemic related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics and Finance, 71*, 55–81. https://doi.org/10.1016/j.iref.2020.06.022

Cronin, D. (2014). The interaction between money and asset markets: A spillover index approach. *Journal of Macroeconomics, 39*, 185–202. https://doi.org/10.1016/j.jmacro.2013.09.006

Diebold, F., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal, 119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*, 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Engle, R., Gallo, G., & Velucchi, M. (2012). Volatility spillovers in East Asian financial markets: A MEM-based approach. *The Review of Economics and Statistics, 94*(1), 222–233. https://www.jstor.org/stable/41349171

Fu, S., Liu, C., & Wei, X. (2021). Contagion in global stock markets during the COVID-19 crisis. *Global Challenges, 5*(10), Article No. 2000130. https://doi.org/10.1002/gch2.202000130

Gabauer, D., & Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters, 171*, 63–71. https://doi.org/10.1016/j.econlet.2018.07.007

Gamba-Santamaria, S., Gomez-Gonzalez, Hurtado-Guarin, J., & Melo-Velandia, L. (2017). Stock Market Volatility Spillovers: Evidence for Latin America. *Finance Research Letters, 20*, 207-216. https://doi.org/10.1016/j.frl.2016.10.001

Gorton, G., & Metrick, A. (2012). Getting up to speed on the financial crisis: A one-weekend-reader's guide. *Journal of Economic Literature, 50*(1), 128–150. https://doi.org/10.1257/jel.50.1.128

Gunay, S., & Can, G. (2022). The source of financial contagion and spillovers: An evaluation of the COVID-19 pandemic and the global financial crisis. *PLOS ONE, 17*(1), Article No. e0261835. https://doi.org/10.1371/journal.pone.0261835

Harjoto, M., Rossi, F., Lee, R., & Sergi, B. (2021). How do equity markets react to COVID-19? Evidence from emerging and developed countries. *Journal of Economics and Business, 115*, Article No. 105966. https://doi.org/10.1016/j.jeconbus.2020.105966

Hung, N. T. (2019). Return and volatility spillover across equity markets between China and Southeast Asian countries. *Journal of Economics, Finance and Administrative Science, 24*(47), 66–80.

Iqbal, N., Bouri, E., Liu, G., & Kumar, A. (2022). Volatility spillovers during normal and high volatility states and their driving factors: A cross-country and cross-asset analysis. *International Journal of Finance and Economics, 73*. 1–21. https://doi.org/10.1002/ijfe.2717

Jebran, K., Chen, S., Ullah, I., & Mirza, S. (2017). Does volatility spillover among stock markets varies from normal to turbulent periods? Evidence from emerging markets of Asia. *Journal of Finance and Data Science, 3*(1), 20–30. https://doi.org/10.1016/j.jfds.2017.06.001

Kim, B., Kim, H., & Lee, B. (2015). Spillover effects of the US financial crisis on financial markets in emerging Asian Countries. *International Review of Economics and Finance, 39*, 192–210. https://doi.org/10.1016/j.iref.2015.04.005

Krause, T., & Tse, Y. (2013). Volatility and return spillovers in Canadian and U.S. industry ETFs. *International Review of Economics and Finance, 25*, 244–259. https://doi.org/10.1016/j.iref.2012.07.009

Le, L.-T. N., Yarovaya, L., & Nasir, M. A. (2021). Did COVID-19 change spillover patterns between Fintech and other asset classes? *Research in International Business and Finance, 58*, Article No. 101441. https://doi.org/10.1016/j.ribaf.2021.101441

Li, Y., Luo, J., & Jiang, Y. (2021). Policy uncertainty spillovers and financial risk contagion in the Asia-Pacific network. *Pacific Basin Finance Journal, 67*, Article No. 101554. https://doi.org/10.1016/j.pacfin.2021.101554

Loh, E. (2006). The impact of SARS on the performance and risk profile of airline stocks. *International Journal of Transport Economics, 33*(3), 401–422. https://www.jstor.org/stable/42747811

Longin, F., & Solnik, B. (1995). Is the correlation in international equity returns constant: 1960-1990? *Journal of International Money and Finance, 14*(1), 3–26. https://doi.org/10.1016/0261-5606(94)00001-H

Malik, K., Sharma, S., & Kaur, M. (2021). Measuring contagion during COVID-19 through volatility spillovers of BRIC countries using diagonal BEKK approach. *Journal of Economic Studies, 49*(2), 227–242.

Manopimoke, P., Prukumpai, S., & Sethapramote, Y. (2018). Dynamic connectedness in emerging Asian equity markets. In B. William & S. Sergi (Eds.), *Banking and finance issues in emerging markets* (pp. 51–84). Emerald Publishing Limited. https://doi.org/10.1108/S1571-038620180000025004

McKibbin, W., & Fernando, R. (2021). The global macroeconomic impacts of COVID-19: Seven scenarios. *Asian Economic Papers, 20*(2), 1–30. https://doi.org/10.1162/asep_a_00796

Mensi, W., Hammoudeh, S., Nguyen, D., & Kang, S. (2016). Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics and Finance, 42,* 257–276. https://doi.org/10.1016/j.iref.2015.11.005

Mishra, R., Sharma, R., Karedla, Y., & Patel, N. (2022). Impact of COVID-19 cases, deaths, stringency and vaccinations on the US stock market. *Vision*. https://doi.org/10.1177/09722629221074901

Nguyen, T.N., Phan, T.K.H., & Nguyen, T.L. (2022). Financial contagion during global financial crisis and COVID-19 pandemic: The evidence from DCC-GARCH model. *Cogent Economics and Finance, 10*(1), Article No. 2051824. https://doi.org/10.1080/23322039.2022.2051824

Nippani, S., & Washer, K. (2004). SARS: a non-event for affected countries' stock markets? *Applied Financial Economics, 14*(15), 1105–1110. https://doi.org/10.1080/0960310042000310579

Panopio, E. L., & Cudia, C. P. (2022). Impact of COVID-19 on the 2020 financial results of selected Philippine publicly-listed companies. *DLSU Business & Economic Review, 32*(1), 92–102.

Polat, O., & Gunay, E. (2021). Cryptocurrency connectedness nexus the COVID-19 pandemic: Evidence from time-frequency domains. *Studies in Economics and Finance, 38*(5), 946–963.

Reinhart, C., & Rogoff, K. (2009). The aftermath of financial crisis. *American Economic Review, 99*(2), 466–472. https://www.jstor.org/stable/25592442

Sadiq, M., Hsu, C., Zhang, Y., & Chien, F. (2021). COVID-19 fear and volatility index movements: Empirical insights from ASEAN stock markets. *Environmental Science and Pollution Research, 28*, 67167–67184. https://doi.org/10.1007/s11356-021-15064-1

Shahzad, S., Bouri, E., Kristoufek, L., & Saeed, T. (2021). Impact of the COVID-19 outbreak on the US equity sectors: Evidence from quantile return spillovers. *Financial Innovation, 7,* Article No. 14. https://doi.org/10.1186/s40854-021-00228-2

Shahzad, S. J. H., Naeem, M. A., Peng, Z., & Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis, 75*, Article No. 101754. https://doi.org/10.1016/j.irfa.2021.101754

Uddin, G., Yahya, M., Goswami, G, Lucey, B., & Ahmed, A. (2022) Stock market contagion during the COVID-19 pandemic in emerging economies. *International Review of Economics and Finance, 79*, 302–309. https://doi.org/10.1016/j.iref.2022.02.028

Yilmazkuday, H. (2020). COVID-19 effects on the S&P 500 index. *Applied Economics Letters, 30*(1), 7–13. https://doi.org/10.1080/13504851.2021.1971607

Youssef, M., Mokni, K., & Ajmi, A. (2021). Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: Does economic policy uncertainty matter? *Financial Innovation, 7,* Article No. 13. https://doi.org/10.1186/s40854-021-00227-3

Zhang, D., Hu, M., & Ji, M. (2020). Financial markets under the global pandemic of COVID-19. *Financial Research Letters, 36*, Article No. 101528. https://doi.org/10.1016/j.frl.2020.101528

Zhang, P., Sha, Y., & Xu, Y. (2021). Stock market volatility spillovers in G7 and BRIC. *Emerging Markets Finance and Trade, 57*(7), 2107–2119. https://doi.org/10.1080/1540496X.2021.1908256