Research article

Covid-19, Dow Jones and equity market movement in ASEAN-5 countries: evidence from wavelet analyses

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A B S T R A C T

This study gains insights into what drives the ASEAN-5 equity markets. Using several wavelet approaches, we examine the correlation between the ASEAN-5 equity markets with the daily new Covid-19 cases and the Dow Jones Industrial Average (DowJones), the lead-lag relationships and level of disorder (or randomness) between the ASEAN-5 domestic equity markets and DowJones between February 15 to May 30, 2019 (pre-period) and February 15 to May 30, 2020 (during the pandemic period) respectively. The pandemic period is further divided into three different phases; the beginning (February), mid (March and April), and end (May) of the period. This study finds that Malaysia, Indonesia, and Singapore equity markets react to Covid-19 cases at the beginning of the pandemic phase, whereas, Thailand and the Philippines showed coherency during the mid-period. As the pandemic progresses (mid-period), all ASEAN-5 equity markets exhibited strong coherence with the DowJones Index. However, at the end of the sample period, no coherency was observed among the ASEAN-5 equity markets, local Covid-19 cases, and DowJones index. This study has two main contributions to the literature: First, we provide insights on equity markets' reactions during an epidemic/pandemic crisis in the emerging markets, specifically, the ASEAN-5 countries, which is a less studied area. Second, examining the impact of the Covid-19 and DowJones Index on the ASEAN-5 equity markets using the wavelet method is a novel approach that captures both the time and frequency dimensions. The results of this study have a significant contribution to investors and regulators, particularly in navigating the new 'normal' and data-driven era.

1. Introduction

The Coronavirus outbreak, a twin crisis of human and financial health, has taken the world by storm. It was declared as Public Health Emergency of International Concern on January 20 and as a pandemic on March 11, 2020[1]. As of July 5, 2020, it has affected 216 countries, infected 11 125 245 of total cases, and 528 204 deaths globally[2]. The pandemic poses unprecedented health, economic, and financial stability challenges worldwide. According to the World Economic Outlook (WEO), 2020, global growth is now expected to decline by 3 percent in 2020, which is worse than during the global financial crisis.[3] Drastic measures taken to contain the disease, such as lockdowns, social distancing, travel bans, etc have caused an unparalleled impact on the economic and financial landscape of many economies. While the precise

global economic impacts due to the COVID crisis is still relatively indeterminate, the long-term consequences of this pandemic may arise from mass unemployment and business failures. Global financial markets have already responded with massive nose dives, volatility, and weakening of market liquidity. The financial markets have also seen dramatic movement on an unprecedented scale while risks have increased substantially in response to the pandemic. Investors are rushing into a financial asylum; looking for safe havens and liquidity for their funds, such as gold (Bredin et al., 2015) currencies (Ranaldo and Söderlind, 2010) and long-term treasury bonds (Flavin et al., 2014). Leveraged investors are also under pressure, thus closing out positions to meet margin calls and re-balancing their portfolios.

The equity market index is often referred to as the barometer of the economic and financial health of an economy. The global outlook of the

current equity market is very bearish as the market is looked upon as a risky platform during external shocks such as Covid-19. Together with the US crash and oil price fall, stock markets in Europe and Asia have also plunged. FTSE, the UK's main index, dropped more than 10% on 12 March 2020, on its worst day since 1987. The stock market in Japan plunged more than 20% from its highest position in December 2019. The emerging and frontier markets, including the ASEAN-5 economies, are not spared from this financial tsunami as a huge outflow of funds is sending these equity markets on a tailspin. Portfolio managers may have to cut losses and involuntarily sell assets into falling markets, potentially exacerbating price moves. Thus, the key question this research intends to address is: "***What moves the ASEAN-5 equity market: COVID-19 or leading equity indexes, specifically, Dow Jones?***"

Increasing number of studies are looking at the financial effects of the COVID-19 pandemic on the international financial markets and economies using multitude of econometrics analyses and methodologies (Ashraf, 2020; Ibrahim et al., 2020; Lahmiri and Bekiros, 2020a; Sharif et al., 2020; Zhang et al., 2020). From traditional time series econometrics to a more contemporary wavelet analyses and entropy, the COVID-19 pandemic had adversely affected many aspects of the financial, economic and social dimension in a very short span of time. At the point of writing, many countries are being hit by the second and third waves with different mutation of COVID-19 strains which make it impossible to produce the vaccines for every variant. Equity markets reacted rapidly at several junctures during the pandemic outbreaks (Akhtaruzzaman et al., 2020; Ali et al., 2020a; Ashraf, 2020; Lahmiri and Bekiros, 2020a; Mzoughi et al., 2020; Zhang et al., 2020).

To answer our earlier question above, we examine the stock data of 5 ASEAN countries; Indonesia (Jakarta Stock Exchange Composite Index: JCI); Malaysia (Kuala Lumpur Stock Exchange Composite Index: KLCI); the Philippines (The Philippines Stock Exchange Index: PSEi); the Thailand (Stock Exchange of Thailand Index: SET); and Singapore (Straits Times Index: STI) before and during the Covid-19 period. Using several wavelet analyses, we examine the correlation between the ASEAN-5 equity markets with the daily new Covid-19 cases and the Dow Jones Industrial Average (DowJones), the lead-lag relationships and level of disorder (or randomness) between the ASEAN-5 domestic equity markets and DowJones between February 15 to May 30, 2019 (pre-period) and February 15 to May 30, 2020 (during the pandemic period) respectively.

We further divide our observation into three different periods; the beginning (*February*), mid (*March and April*), and end (*May*) of the sample period. This study finds that Malaysia, Indonesia, and Singapore's equity markets react to Covid-19 cases at the beginning of the study period, whereas, Thailand and the Philippines showed coherency during the mid-period. As the pandemic progresses (mid-period), all ASEAN-5 equity markets exhibited strong coherence with the DowJones Index. Interestingly, at the end of the sample period, no coherency was observed among the ASEAN-5 equity markets, local Covid-19 cases, and DowJones index.

This study makes two main contributions to the literature: First, we provide insights on equity markets' reactions during an epidemic/pandemic crisis in the emerging markets, specifically, the ASEAN-5 countries, which is a less studied area. Second, studying the impact of the Covid-19 and DowJones Index on the ASEAN-5 equity markets using the wavelet method is a novel approach that captures both the time and frequency dimensions. Several studies have been looking at the effects of the Covid-19 pandemic with the equity markets' performance by analyzing single-dimension time series using linear or nonlinear models (Al-Awadhi et al., 2020; Ali et al., 2020b; Zaremba et al., 2020). However, the interaction between the variables may behave differently within various time scales and this can only be captured through the wavelet analysis (Huang et al., 2018). The wavelet provides an in-depth analysis highlighting latent processes such as changing cycle patterns and trends, lead-lag interactions, and non-stationary movements in time-series analyses (Sharif et al., 2020). Additionally, wavelet methods are particularly useful when the interactive lead-lag relationship between the studied

time-series is non-linear (Struzik, 2001). We argued that both the equity markets and Covid-19 spread are non-linear. In the beginning, a lack of understanding about the potency of the virus and unsynchronised public health strategies in handling the outbreak contributed to the non-linearity of the Covid-19 spread (Sharif et al., 2020). Similarly, investors' sentiment and heterogeneous expectations may influence their short- and long-term investment horizons also engender a non-linear effect (Tung and He, 2015). The final reason that validates the use of wavelet for this study is the short time-frame of our investigation. Due to the recent occurrence of the pandemic (for many countries, the outbreak is entering its sixth month or less), the amount of data is very limited and using the traditional econometrics techniques will not provide high statistical inference to generate reliable conclusion from the tests (Sharif et al., 2020).

The rest of the paper is organized as follows: Section 2 provides a brief explanation of the ASEAN-5 equity markets movement since the pandemic outbreak. Section 3 outlines the empirical method employed for this study. Section 4 reports the results and empirical analyses. Section 5 and 6 present the discussion and conclusion of the study.

2. ASEAN-5 stock markets and Covid-19 pandemic

Figure 1 shows the movement of ASEAN-5 main equity market indexes compared to the DowJones between January 2 to May 31, 2020. We selected this period as it indicated the beginning of the coronavirus outbreak in these countries. As the figure indicates, there are several noticeable dips in the stock market indexes. The first one is the week surrounding January 31 which coincides with the early detection of Covid-19 patients in the ASEAN-5 countries (refer to Table 1 below) (except Indonesia). The second dip begins in the third week of February and continued to fall rapidly until the week ending March 23, 2020. The financial markets are increasingly concerned about the widespread of the coronavirus cases outside the epicenter, such as South Korea, Japan, and Italy[4]. In the week beginning March 9, 2020, major global stock indexes including the ASEAN market fell sharply at the start of trading following oil price disputes[5] alerting investors that it may be the beginning of the bear market[6]. The market decline has been compared to the 2008 Financial Crisis (Yarovaya et al., 2020). Subsequently, in the same week, WHO's declaration of the pandemic on March 12, 2020, and the imposing of US travel bans from the European countries had caused global stock indexes to plunge further to its lowest[7]. Table 1 details the spread of Covid-19 in these ASEAN-5 countries and the counter-measures undertaken by its respective government to contain the spread.

3. Methodology

3.1. Data and methodology

This paper analyses the relationship between the Covid-19 daily infections (number of new infected Covid-19 cases), DowJones, and equity market performance of five ASEAN countries; Indonesia, Malaysia, Philippines, Singapore, and Thailand. Data used in this study are sourced from the Worldometer website[8] for the Covid-19 daily cases and Bloomberg database. The information from Worldometer originates directly from the official websites of Ministries of Health or other government institutions and government authorities' social media accounts of the respective countries. Data span covers pre- and during the COVID-

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[4] https://www.washingtonpost.com/world/asia_pacific/coronavirus-china-live-updates/2020/02/25/f4045570-5758-11ea-9000-f3cffee23036_story.html.

[5] https://www.bbc.com/news/business-51796806.

[6] https://cnnphilippines.com/business/2020/3/12/Local-stocks-below-6000-coronavirus.html.

[7] https://www.bbc.com/news/51860099.

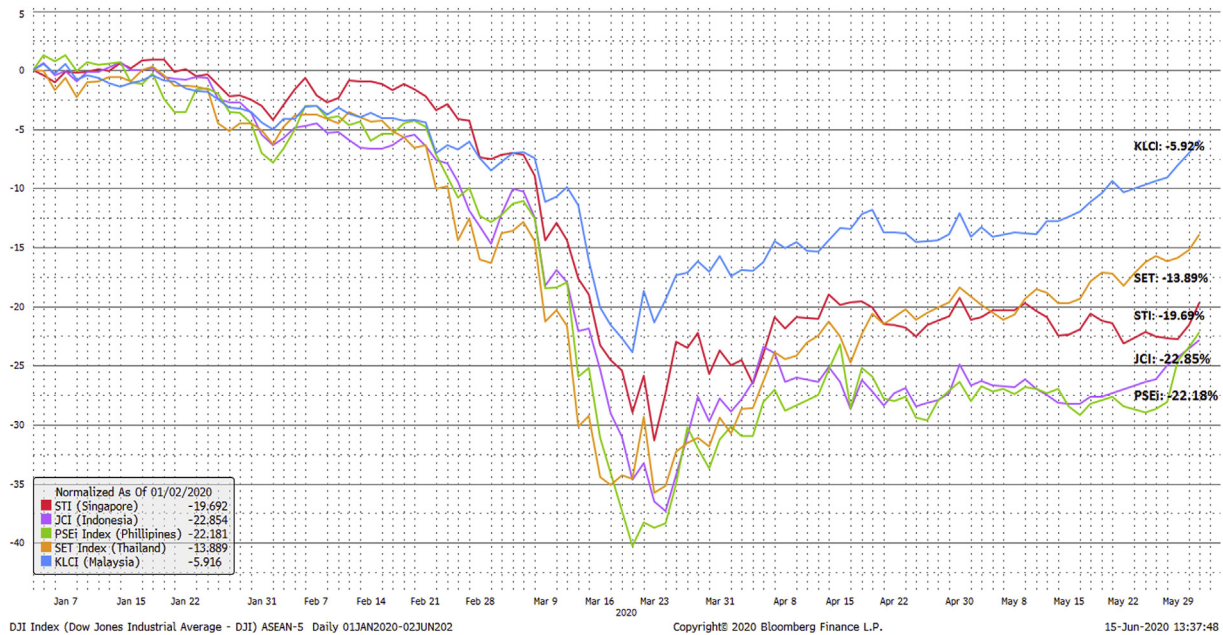[8] https://www.worldometers.info/coronavirus/about/#sources.

Figure 1. The impact of the coronavirus on the ASEAN-5 stock markets since the start of the outbreak (Jan 2nd to May 31st, 2020). Source: Bloomberg (June 15, 2020).

19 period. The pre-COVID-19 period is between February 15 to May 30, 2019, whereas the COVID-19 period is between February 15 to May 30, 2020. We used similar time period of different years to control for any seasonal variation in the data. We have omitted the non-trading days from the sample period.

The different structures at the different time scales of financial and economic time series resulting from the multiscale nature of the series (Khalfaoui and Boutahar, 2011). This multiscale nature can be captured in time and frequency domains. Most studies on these time-series data focused only on the time scale, thus leaving out information content of the frequency domain, resulting in less informed investment decisions. As such, adopting the continuous wavelet transformation (CWT) reduces the limitation from using the traditional time-series analysis methods.

3.2. The continuous wavelet transformation (CWT)

The CWT performs captures the time and frequency (or time signals) domains of the behavior of time-series data. This is undertaken by looking at the spectral characteristics of the signals in the time domain. Wavelet or "daughter wavelet" $\psi_{\tau,s}(t)$, provides the wavelet coefficients for the "mother wavelet" $\psi(t)$, and the normalized form is defined as,

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)s, \tag{1}$$

with, $\tau \in \Re$, a location parameter and $s \neq 0$, a scale smoothing parameter. Our analysis uses a scale of 2.

For time-series x(t), the convoluting the function $\psi_{\tau,s}(t)$ with the series produces the transformation,

$$W_x(\tau,s) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} x(t)\ \psi^*\left(\frac{t-\tau}{s}\right)dt \tag{2}$$

where * denotes the complex conjugate form. The mother wavelet $\psi(t)$ is used to generate other window functions at a location center ι. As the window shift through time, time information is obtained in the trans-

Table 1. Spread of Covid-19, government measure and stimulus for ASEAN-5 economies.

Country	Patient zero	Total number of infections	Total deaths	Government measures	Economic stimulus packages
Malaysia	25 January: Chinese travelers from Singapore	8,336	117 (1.40%)	18 March: Movement Control Order	S1: 27 Feb RM20b (US$4.68b) S2: 27 March RM 250b (US$58.5b) S3: 6 April RM 10b (US$2.34b) S3: 5 June RM 35b (US$8.19b)
Singapore	23 January: Chinese national from Wuhan	38,514	25 (0.06%)	3 April: Circuit breaker	S1: 18 Feb S$5.6b (US$4.01b) S2: 26 March S$48.4 b (US$34.68b) S3: 6 April S$5.1b (US$3.65b) S4: 26 May S$33b (US$23.65b)
Philippines	30 January: Chinese national from Wuhan	22992	1017 (4.66%)	9 March: Declaration of state of emergency 16 March: Enhanced Community Quarantine (ECQ)	S1: 22 March PHP200b (US$3.93b) S2: 4 June PHP1.3t (US$26b)
Thailand	13 January: Chinese national from Wuhan	3,121	58 (1.86%)	26 March: Bangkok on partial lockdown 3 April Curfew from 4 pm to 10 am	S1: 4 March US$3.2b S2: 24 March US$3.57b S3: 7 April US$58b
Indonesia	2 March: Locals who are infected from Japanese national	33,076	1,923 (5.8%)	4 April: Large-scale social restriction	S1: 25 Feb US$742.6m S2: 13 March US$8.1b S3: 18 March US$1.8b S4: 18 May US$1.68b S5: 3 June US$47.6b

Source: Government websites and Bloomberg. Information is correct as of 9th June 2020.

formed domain. The scale, s, controls the length of wavelet (referred to daughter wavelet), giving the frequency information from the time-series data by dilating ($|s| > 1$) and compressing ($|s| < 1$) the series.

Several wavelet functions have been suggested including, Coiflet, Symmlet, Haar, Debauchies, and Gabor wavelets. However, Morlet's wavelet is usually used for financial and economic data (Goupillaud et al., 1984). This is expressed as;

$$\psi_\eta(t) = \pi^{-\frac{1}{4}} \left(e^{i\eta t} - e^{-\frac{\eta^2}{2}} \right) e^{-\frac{t^2}{2}} \tag{3}$$

The function ensures the admissibility condition since it is negligible if $\eta \geq 5$. For $\eta \geq 5$, and since $e^{-\frac{\eta^2}{2}}$ is very small, we get Morlet's wavelet,

$$\psi_\eta(t) = \pi^{-\frac{1}{4}} (e^{i\eta t}) e^{-\frac{t^2}{2}} \tag{4}$$

For two time-series, using the wavelet transformation for each time-series will provide us the wavelet coherence transformation (cross-wavelet transformation), a measure of correlation, in a time-frequency domain. The cross-wavelet spectra will enable us to observe any change in the restrained variances, which identify specific "location" of significant variations in the co-movement of two time series in the time and frequency domain. This is similar and just an extension of two time-series that provide the correlation only in the time domain. Following Goupillaud et al. (1984), for two time-series x and y, the cross-wavelet transformation is given as;

$$W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s) \tag{5}$$

where $W_x(\tau, s)$ and $W_y^*(\tau, s)$ are defined in (2).

The absolute form of cross-wavelet transformation $|W_{xy}(\tau, s)|$ can be used to estimate cross-wavelet power. Webster (2000), expressed the squared wavelet coherence coefficient as;

$$R_t^2 \left(s \right) = \frac{\left| S \left(s^{-1} W_t^{xy}(s) \right) \right|^2}{S \left(s^{-1} |W_t^x(s)|^2 \right) S \left(s^{-1} |W_t^y(s)|^2 \right)} \tag{6}$$

The wavelet coherence coefficient behaves like a correlation coefficient of two time-series in the time-frequency domain, having values between 0 and 1.

The wavelet transformation thus gives us the phase spectrum needed for computation wavelet coherence, which measures the correlation of two time series in the time-frequency domain.

$$RM^2(y, x_1, x_2) = \frac{R^2(y, x_1) + R^2(y, x_2) - 2[R(y, x_1).R(y, x_2).R(x_1, x_2)]}{1 - R^2(x_1, x_2)} \tag{7}$$

Similarly, the concept of correlation in coherence can be extended to partial correlation (Mihanović et al., 2009). The squared partial wavelet coherence of (y, x_1), after removing the effect of x_2, is given by,

$$RP^2(y, x_1 | x_2) = \frac{|R(y, x_1) - R(y, x_2).R(y, x_1)^*|^2}{[1 - R(y, x_2)]^2 [1 - R(x_2, x_1)]^2} \tag{8}$$

In this study, the time-frequency domain of the wavelet coherence and partial wavelet coherence is used to analyze the Partial Wavelet coherence of the country stock's index-Dow Jones index (Covid-19 cases) removing the effect of Covid-19 cases (DowJones Index).

3.3. The wavelet packet Shannon entropy

Shannon entropy provides a measurement of the randomness or disorder of data. Using wavelet packet transform domain to calculate the Shannon entropy, the original signal or information will not be lost. Lahmiri and Bekiros (2020a, 2020b) study the entropy of major world market and Bitcoins, Silver, WTI, Brent, Gold, Gas, S&P500 using Shannon and Renyi entropies. Lahmiri and Bekiros (2020a) cite the work of Shannon (1948) for Shannon entropy to analyse the measure of disorder (or order) of the wavelet packet transformation. This section heavily depends on Lahmiri and Bekiros (2020a)'s citing the work of Li and Zhou (2016). The wavelet transformation for Shannon entropy is recursively calculated as follows:

$$\begin{cases} d_{0,0}(t) = s(t) \\ d_{i,2i-1}(t) = \sqrt{2} \sum_k h(k) d_{i-1,j}(2t - k) \\ d_{i,2j}(t) = \sqrt{2} \sum_k g(k) d_{i-1,j}(2t - k) \end{cases} \tag{9}$$

where $h(k)$ is a high-pass filter, $g(k)$ is a low-pass filter, and $d_{i,j}$ are coefficients of the wavelet packet transform at the ith level for the jth node. The wavelet energy,

$$E_{i,j,k} = \|d_{i,j,k}\|^2 \tag{10}$$

can be used to measure the information of the kth coefficient.

The total energy is,

$$E_{i,j} = \sum_{k=1}^{N} E_{i,j,k} \tag{11}$$

where N denotes the number of coefficients in the node. The probability of the kth coefficients, where $\sum_k p_{i,j,k} = 1$, is given by;

$$p_{i,j,k} = \frac{E_{i,j,k}}{E_{i,j}} \tag{12}$$

Finally, the wavelet packet Shannon entropy (SE) is given by:

$$SE_{i,j} = - \sum_{k=1}^{N} p_{i,j,k} \times \log(p_{i,j,k}) \tag{13}$$

3.4. Granger causality

To complement our wavelet analysis, granger causality tests are done on the price and volume data. The Granger Causality is given by Granger (1969) in Eq. (14) below.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \dots + \alpha_n y_{t-n} + \beta_1 x_{t-1} + \dots + \beta_n x_{t-n} + \varepsilon_t$$
$$x_t = \alpha_0' + \alpha_1' y_{t-1} + \dots + \alpha_n' y_{t-n} + \beta_1' x_{t-1} + \dots + \beta_n' x_{t-n} + \mu_t \tag{14}$$

For the purpose of this study we run the Granger Causality equations for lag order of 1–6.

3.5. DCC Bi-GARCH (1,1)

For our final analysis, we run a Dynamic Conditional Correlation Bi-GARCH (DCC Bi-GARCH) (Engle, 2002) model to investigate the dynamic of the conditional correlation for the period of the study.

The development of the DCC Bi-GARCH can be traced from the general Bi-GARCH (1,1) model below:

The mean equations are given by:

$$y_{1,t} = \alpha_{1,0} + \alpha_{1,1} y_{1,t-1} + \alpha_{1,2} y_{2,t-1} + \varepsilon_{1,t}$$
$$y_{2,t} = \alpha_{2,0} + \alpha_{2,1} y_{1,t-1} + \alpha_{2,2} y_{2,t-1} + \varepsilon_{2,t} \tag{15}$$

The variance and covariance equations are given by:

$$h_{1,t} = \beta_{1,0} + \beta_{1,1} \varepsilon_{1,t-1}^2 + \beta_{1,2} h_{1,t-1}$$
$$h_{2,t} = \beta_{2,0} + \beta_{2,1} \varepsilon_{2,t-1}^2 + \beta_{2,2} h_{2,t-1}$$
$$cov_t(h_1, h_2) = \gamma_0 + \gamma_1 (\varepsilon_{1,t-1} \cdot \varepsilon_{2,t-1}) + \gamma_2 cov_{t-1}(h_1, h_2)$$
$$\nu_{i,t} = \varepsilon_{i,t}^2 - h_{i,t} \tag{16}$$

In general, we can represent the MGARCH model as;

$$\mathbf{y_t} = \mathbf{Cx_t} + \boldsymbol{\varepsilon_t}$$
$$\boldsymbol{\varepsilon_t} = \mathbf{H_t^{1/2}}\boldsymbol{\nu_t} \tag{17}$$

where

$\mathbf{y_t}$ is an mx1 vector of dependent variables;

C is an m x k matrix of parameters;

$\mathbf{x_t}$ is a k x 1 vector of independent variables, which may contain lags of $\mathbf{y_t}$;

$\mathbf{H_t^{1/2}}$ is the Cholesky factor of the time-varying conditional covariance matrix $\mathbf{H_t}$; and

$\boldsymbol{\nu_t}$ is an m x 1 vector of zero-mean, unit-variance, and independent and identical distributed innovations.

$\mathbf{H_t}$ is a matrix generalization of the univariate GARCH model, and for GARCH(1,1), where,

$$\text{vech}(\mathbf{H_t}) = \mathbf{s} + \mathbf{A}\text{vech}\left(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}\right) + \mathbf{B}\text{vech}(\mathbf{H_{t-1}}) \tag{18}$$

where vech() stacks unique non-elements in a symmetric matrix into vector, **s** is a vector parameters, and **A** and **B** are conformable matrices of parameters.

For conditional correlation MGARCH, H_t is decomposed into a matrix of conditional correlations R_t and a diagonal matrix of conditional variances D_t:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{19}$$

Thus, $h_{ij,t} = \rho_{ij,t}\sigma_{i,t}\sigma_{j,t}$

Finally, the dynamic conditional correlation (DCC) allows the conditional correlations R_t to follow a GARCH (1,1)-like process.

4. Results and analysis

4.1. Descriptive statistics

Table 2 below provides the descriptive statistics for DowJones, oil prices and ASEAN five equity market indexes during the pre- and COVID-19 period. The pre- and COVID-19 period spans between February 15 to May 30 2019, and 2020 respectively. We used similar time period to

control for any seasonal variation which may be affecting market index movement. The descriptive statistics below are presented for both equity markets' volume and price indexes. Both measurements are used in our wavelet analyses respectively (see Table 2 (Panel A and B)).

The following section analyses the relationships between the Covid-19 daily infections (number of new infected Covid-19 cases), Dow-Jones, and equity market performance of five ASEAN countries; Indonesia, Malaysia, Philippines, Singapore, and Thailand using three different wavelet methods. The first method utilises the partial wavelet coherence analysis as presented in Figure 2 below. In order to gain a complete understanding about the effect of the pandemic on the equity markets, we adopted the wavelet coherence analysis as presented in Figure 3. Our analyses examine the equity market performance before (pre) and during the COVID-19 pandemic period. Our final wavelet analysis uses the wavelet packet Shannon entropy (WSPE) to measure the randomness of the equity market movements. This provides insights into the stability of the equity markets measured using both the market index prices and volumes traded.

Our final part of this section reports on the robustness of this study. We adopted the Granger causality between the ASEAN-5 equity markets and DowJones and finally we also used the DCC Bi-Garch to investigate the dynamic conditional correlation of the variables.

For both Figures 2 and 3 (a and b), the level of coherency is given by the color bar next to the wavelet plots. The blue-colored area indicates insignificant coherence, while the red-colored island indicates strong significant coherence and dependence between the variables under investigation. The x-axis is the sample period in this study. For Figure 3b, the sample period of the pre-pandemic is given by the same time-period during the pandemic but in the previous year.

The y-axis indicates the frequency bands which may be short, medium, and long-term periods relative to the pandemic outbreak. This study defines the period as following: short-term period is within 0–4 days frequency bands, medium-term is 5-8-days frequency bands, the medium-to-long term is 9–15-days frequency bands and long-term is 16-days onwards. Additionally, For Figure 3, the black arrows represent the phase difference among the two-time series. If the arrows turned to the right (left) indicate that the two-time series are in phase (anti-phase), to the right and down (up), the first variable is leading (lagging), and to the

Table 2. Descriptive statistics of pre-and during the COVID-19 period using the market index volume and price.

Panel A: Market index volume

| Statistics	COVID-19 period							Pre-COVID-19						
	DJI	JCI	KLCI	OIL	PSEi	SET	STI	DJI	JCI	KLCI	OIL	PSE	SET	STI
Mean	0.048	0.058	0.102	-0.002	0.081	0.039	0.096	0.045	-0.002	0.094	0.001	0.188	0.012	0.072
Median	0.006	0.043	-0.022	-0.011	0.022	0.014	0.028	-0.007	-0.017	0.061	0.001	-0.017	-0.016	0.041
Maximum	1.257	1.388	2.144	0.219	2.058	0.976	2.663	2.175	0.674	3.538	0.036	5.175	0.754	3.137
Std. Dev	0.286	0.291	0.468	0.082	0.415	0.257	0.477	0.390	0.165	0.587	0.015	0.890	0.219	0.503
Skewness	1.540	1.340	1.881	-0.351	1.889	1.328	2.859	2.357	0.877	3.254	-0.256	3.431	0.875	3.273
Kurtosis	6.701	8.663	7.596	5.132	9.097	5.898	14.528	14.676	6.046	18.984	3.344	18.114	4.104	20.908
Jarque-Bera	69.55	111.21	102.90	15.74	145.78	45.72	489.88	462.42	35.53	868.69	1.13	769.19	11.96	1060.37
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.569	0.000	0.003	0.000
Observations	72	68	70	75	68	71	71	70	69	70	71	67	67	70
Panel B: Market index price														
Mean	-0.001	-0.003	-0.001	-0.002	-0.003	-0.001	-0.003	0.001	0.000	0.000	0.001	0.000	-0.001	0.000
Median	-0.001	-0.002	0.001	-0.011	0.002	0.004	-0.002	0.001	0.001	0.000	0.001	-0.001	-0.001	0.000
Maximum	0.114	0.102	0.069	0.219	0.074	0.080	0.061	0.014	0.020	0.014	0.036	0.021	0.019	0.010
Std. Dev	0.039	0.026	0.017	0.082	0.033	0.030	0.023	0.006	0.007	0.005	0.015	0.009	0.006	0.005
Skewness	-0.123	0.594	-0.007	-0.351	-1.284	-1.048	-0.106	-0.561	0.270	-0.360	-0.256	0.193	0.132	-0.250
Kurtosis	4.781	5.705	6.644	5.132	6.752	6.434	4.631	4.168	3.073	4.861	3.344	3.353	3.856	2.573
Jarque-Bera	9.69	24.72	38.73	15.74	58.57	47.88	8.01	7.65	0.85	11.62	1.13	0.76	2.24	1.54
Probability	0.008	0.000	0.000	0.000	0.000	0.000	0.018	0.022	0.653	0.003	0.569	0.682	0.326	0.463
Observations	72	68	70	75	68	71	71	70	69	70	71	67	67	70
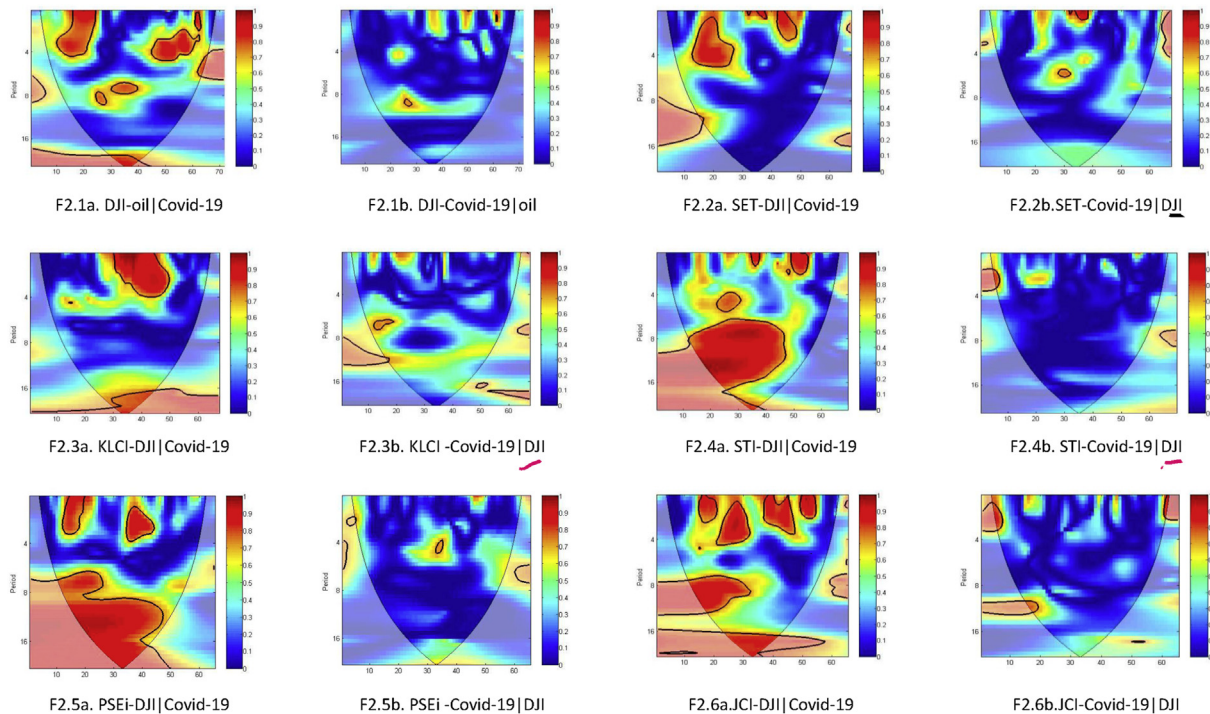
Figure 2. Partial Wavelet Coherence Plots of ASEAN-5 equity market, Covid-19 cases, and DowJones index.

left and up (down), the first variable is leading (lagging). When the arrows point downwards, the first variable is leading by 90°, and when the arrows point upwards, the second variable is leading by 90°. When the two series are in phase, it indicates that they move in the same direction, and anti-phase means that they move in the opposite direction. Arrows pointing to the right-down or left-up indicate that the first variable is leading, while arrows pointing to the right-up or left-down show that the second variable is leading.

4.2. Coherence between DowJones and oil price

The first graph (F2.1a) in Figure 2 examines the relationship between the DowJones index and the oil price effects, removing the effect of the daily number of Covid-19 cases in the US. The second graph (F2.1b) in Figure 2 examines the relationship between the DowJones index and the daily number of Covid-19 cases in the US, removing the effects of the oil prices.

Notably, F2.1a indicates the wavelet coherence between the US stock market and oil prices that reveals several islands of red-color throughout the sample period, which indicates strong dependency mostly over the short-term period of 0-4-days. Strong coherence is also observed between days 24–40 *(Mar 20 to Apr 14)* over a medium-term frequency band of 6-9-days. Between days 30–40 *(Mar 30 to Apr 14)*, evidence of high coherence over long-term periods of greater than 16-days. At the end of the sample period, days 62 *(May 14)* onwards, the results reveal strong dependency over medium-term of 4–6 days. The wavelet coherence plot appears consistent with Sharif et al. (2020) in which the authors found strong dependency between the US stock market and oil prices throughout their sample period between Jan 21 to Mar 30. As the US stock markets and the oil prices indicate strong coherency with each other, this study will use the DowJones index as a resonance for both the effects of the US economy and oil prices in the analysis. We also study the dependency of the US stock markets with COVID-19 daily infections in the US. The wavelet plots do not show many dependencies throughout

the sample period except for between days 25–28 *(Mar 23 to 26),* which reveal strong dependency over the medium-term of 8–10-days.

4.3. Coherence analysis between ASEAN-5 stock market indexes with DowJones

The wavelet coherence (WC) plots of F2.2a – F2.6a in Figure 2 above show the coherence between each ASEAN-5 stock market indexes with the DowJones index. The WC plots of F2.2b – F2.6b in Figure 2 show the coherence between each ASEAN-5 stock market indexes with the respective countries' daily number of Covid-19 cases. The visual inspection of all figures in the b-series (F2.1b-F2.6b) reveals a pronounced blue-colored island in each of the wavelet coherence plots, with some exceptions. By contrast, the a-series (F2.1a-F2.6a) plots showed more distinct red-colored islands in each WC plot. As such, our hypothesis suggests that the dependency of the ASEAN-5 equity market's performance with the severity of the Covid-19 infection is relatively limited to certain phases or periods only. This will be discussed in detail in the following section based on county-specific wavelet plots. Nevertheless, strong coherence is observed in all ASEAN-5 financial markets with the DowJones index which may indicate the prevalence of strong dependency with the US economy and the global oil price effects (Aloui and Hamida, 2019).

4.4. Coherence analysis between DowJones and country-specific equity indexes

In F2.2a, we observed several islands of very high coherence between Thailand's stock market with the US market between days 12–28, 32 to 40, and 42 to 48 over high-frequency bands of 1-5-days, 0-3-days, and 0-1-days, respectively. The most notable is between days 12–28 *(Mar 4 to 26)* indicating a significantly high dependence in every 1 – 5-days frequency bands for more than two weeks of the sample period. The WC plot of Figure 2.3a shows a very strong coherence between Malaysia's stock
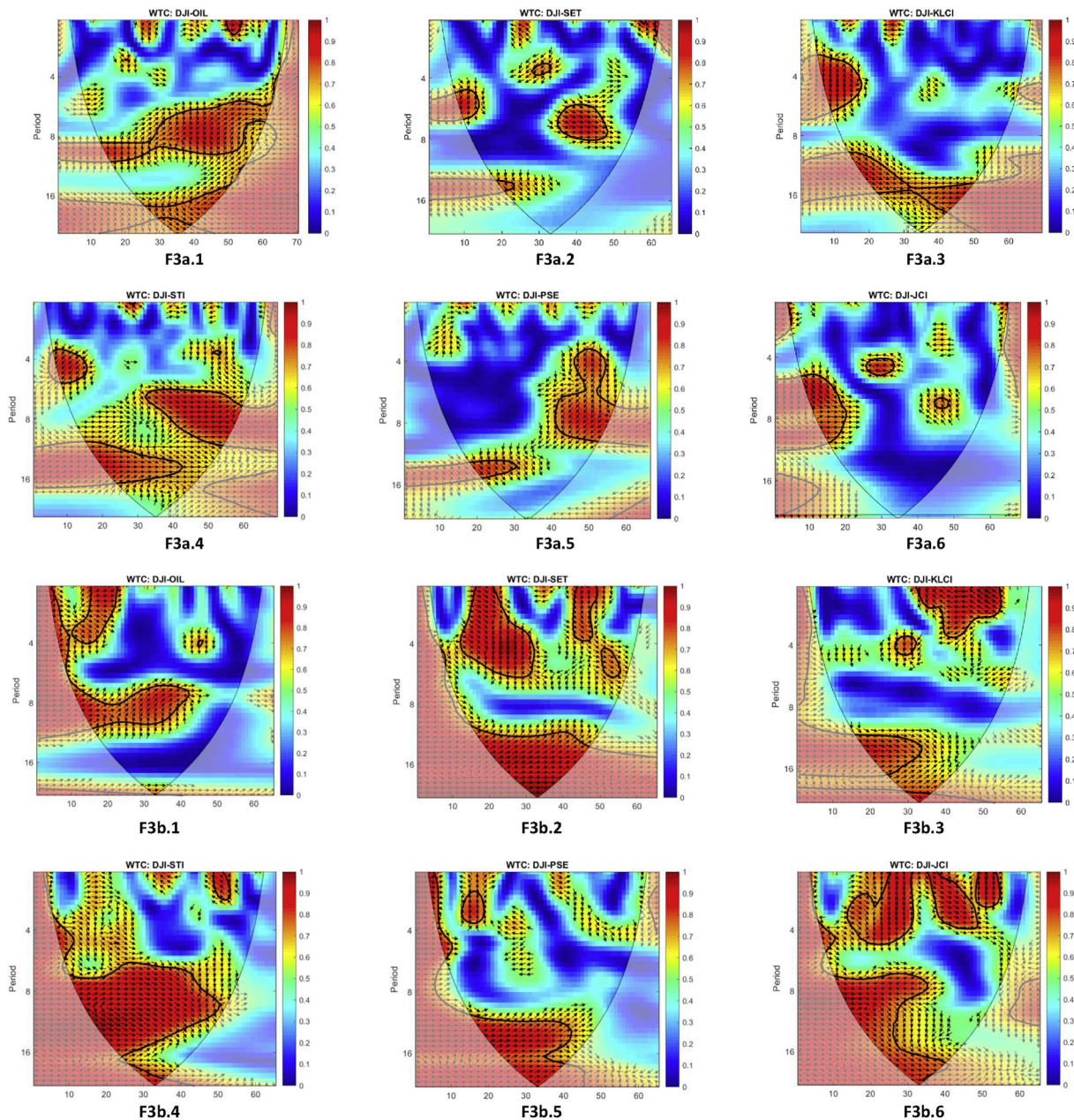
Figure 3. a. Continuous Wavelet Transformation Coherence Plots Pre-COVID-19 period. b. Continuous Wavelet Transformation COVID-19 period.

market with the US market between days 30–50 *(Mar 30 to Apr 28)*, over 0-4-days frequency bands. And strong coherence between days 30–45 *(Mar 30 to Apr 21)*, over a long-term period of more than 16-days.

There are many red-colored islands in F2.4a indicating of strong dependency between the Singaporean stock markets with the US markets throughout the sample period, except towards the end of the sample. Strong coherence is detected over a short, medium, and most long-term horizon. The biggest island in this CW plot indicates a very strong coherence between days 11–48 *(Mar 3 to Apr 24)*, over a medium to a long-term horizon of 6–17-days. There appears a mild coherence between days 22–30 *(Mar 18 to 30)* over a medium-term horizon of 4-5-days. A strong coherence over high-frequency bands of 0-2-days is detected for the sample periods of days 32–38 *(Apr 1 to 9)* and 48–56 *(Apr 24 to May 8)*. Last but not least, in the period between days 30–38

(Mar 30 to Apr 9), STI is strongly dependent on the DowJones over a long-term horizon of low-frequency bands of more than 17-days.

Similar to Singapore, the Philippines' stock markets also showed high dependence on the US markets. In F5a, we observed several waves of very high coherence between PSEi and DowJones index from the inception up to 75% *(Feb 18 to Apr 30)* of the sample period over a medium-term horizon of 6–16-days. Within that period, days 22–41 *(Mar 23 to Apr 21)* we also observed a very high coherence over low-frequency bands of greater than 16-days. Over a short-term, very high coherence is observed in two occurrences, between days 11–19 *(Mar 4 to 16)* and 34 to 44 *(Apr 8 to 24)* with frequency bands of less than 4-days.

The Indonesian stock markets also indicate a strong coherence with the US stock markets over a short, medium, and long-term horizons throughout the sample period. The high coherence between JSI and Dow

Jones are observed in F2.6a between days 14–32 *(Mar 6 to Apr 2)* and 37 to 48 *(Apr 9 to May 6)* over a frequency band of 0-4-days respectively and days 50–54 *(Apr 29 to May 6)* over a frequency band of fewer than 2 days. A strong coherence is also evident for days 11–32 *(Mar 3 to Apr 2)* over frequency bands of 7–13-days. Mid-point *(Mar 30 to Apr 9)* of the sample period shows a high coherence with the US stock index over a long-term horizon of more than 16-days consistent with all other ASEAN-5 countries except for Thailand.

4.5. Coherence analysis between Covid-19 daily cases and country-specific equity indexes

The F2.2b WC plot shows a very high dependence between Thailand's financial markets with its daily number of Covid-19 cases in the mid-sample period of days 31–39 *(Mar 31 to Apr 14)* over high-frequency bands of less than 1-day. Another significant coherence is detected in days 29–31 *(Mar 27 to 31)* over a medium-term of 5-6-days. The strong coherence between the Malaysian stock markets and the daily number of Covid-19 infection in F2.3b is apparent in days 12–19 *(Mar 4 to 13)*, over a medium-term of 6–7 days. In Singapore, only mild coherence is observed between its stock market with its Covid-19 cases (F2.4b). And this coherence is detected in the early period briefly between days 5–7 *(Feb 24 to 27)*, over very high-frequency bands of 2-4-days. The Philippines' financial markets were also briefly affected by Covid-19 infection (F2.5b) between days 32–34 *(Apr 6 to 8)*, over a medium-term of 4-5-days. As for the Indonesian market, F2.6b showed very high dependence between JSI and the daily number of Covid-19 cases during the inception and towards the end of the sample period, between days 4–8 *(Feb 21 to 27),* and recurring at days 60–62 *(May 15 to 19)* over high-frequency bands of 1 – 3-days and less than 2-days respectively. In the medium term, we find strong coherence between the period of 16–20 *(Mar 10 to 16)* over the 11–13-days frequency bands.

Overall, the WC plots suggest that the financial markets of the ASEAN-5 countries are not greatly affected by the Covid-19 outspread. When there is evidence of coherence, it is over a short or medium-term period. By contrast, the ASEAN-5 financial markets are highly dependent on the US equity market movements, particularly for Singapore, Philippines, and Indonesia with dependency evident throughout the sample period over short, medium, and long-term periods. The findings of this study corroborate the fact that financial markets respond to global major events, including pandemic outbreaks and oil price volatility (Al-Awadhi et al., 2020; Sharif et al., 2020).

4.6. Further analysis: coherence by different phases - beginning, mid and end of the study periods

We further examined the wavelet coherence (WC) plots based on three different phases emerging from the sample periods; the beginning, mid, and end of the periods. In the *first phase (beginning)*, when it is still an epidemic (February) (Ali et al., 2020a, b), the effects on the equity markets are localized, where patterns of dependency are detected in line with the local occurrences or spread of the Covid-19 in the respective countries under study (Indonesia, Malaysia, and Singapore).

In the *second phase (mid),* (the month of March and April) strong dependency with the US stock markets is evident for all the ASEAN countries except for Malaysia. Notable important events took place during this phase that affects the global financial markets (Ali et al., 2020b). The first one is the week leading to March 9th where stock markets worldwide nosedived to its lowest since the 2008 Financial Crisis. This occurs due to the oil prices dispute between Saudi Arabia and Russia. The second significant event during that week was when WHO declared the novel coronavirus as a pandemic affecting more than 100 countries worldwide (Mar 11) (WHO). Third, Europe was declared as the epicenter of the pandemic with cases rising rapidly and new cases became greater than those in China (Mar 13). Acknowledging this, the United States imposed a travel ban to and from the Schengen area (Mar

13). Throughout March and April, many countries worldwide took strict measures to contain Covid-19 widespread with `stay-at-homes', quarantines and lockdowns, resulting to closures of businesses, schools and higher learning institutions and cancellation of many events and travels (Ali et al., 2020b; Zaremba et al., 2020). The pandemic-induced recession causes many people to be furloughed, unemployed, and in extreme poverty worldwide.

The *third phase (end)* is during May onwards, where the financial markets of the ASEAN-5 countries did not show any dependence to the US stock market and economy nor the Covid-19 daily cases as the outbreak seems to be under control in this region and easing of strict measures are slowly being lifted in most countries. Referring to Figure 1, we can see that each financial market is in the recovery mode, and the lines are diverging rather than converging with each other, an indication of respective national efforts to revamp their economies.

4.7. Wavelet coherence analysis

4.7.1. Lead-lag relationships between DowJones and oil price before and during the pandemic

In 4.4 and 4.5, our findings indicate that while the COVID-19 pandemic may have adversely affected global economies, its actual effect on the ASEAN-5 equity market was rather low (only in the beginning of the outbreak). The bigger part of the ASEAN-5 equity markets' movement was dependent on the US equity markets. To ascertain this initial inference, we further analysed the relationships between the US equity markets with the ASEAN-5 equity markets using the wavelet transform coherence analysis. In particular, we analysed both the coherence and phase lag between, DowJones and oil prices, and Dow Jones and ASEAN five equity markets respectively, to see the effect of the US equity markets on ASEAN-5 domestic equity markets. To ensure that this relation is not temporary or unique to the pandemic era, we included the pre-pandemic time-period to further reaffirm our conclusion. The following section describes the relationships between two time-series, notably the DowJones and the ASEAN-5 domestic equity markets.

During the pre-COVID-19 period, the WTC plot of F3a.1 indicates very significant coherence between DowJones and oil prices throughout short, medium and long-term horizons. Strong in-phase coherence is observed between days 49–53, over 0-1-days frequency bands between DowJones and the oil price. However, the largest island on the plot, between days 12–65 over the medium-term horizons indicates that oil price is leading the US equity market, with initial movement showing oil price leading at 90°. Over the long-term, (>15-days frequency bands), days 25–40 DowJones appears leading but approaching days 40–50, oil price is leading the relationships. Overall, DJI and oil-price have lead-lag relationships, with the oil prices predominantly leading the US equity market, throughout the sample period.

Similar observation is also found during the COVID-19 pandemic period as depicted by Figure 3b.1. Strong coherence is observed during the short and medium-term horizons. In particular, between *Feb 20 to Mar 2*, DJI and oil prices are in phase over 0-2-days frequency bands. Between *Mar 2 – 18*, over 2-4-days frequency bands, both indexes are moving together but at some stage DJI is leading. However, between *Mar 2 – April 16*, over the medium-to-long-term horizons (8-13-days frequency bands), the oil price is leading the equity market. As such, similar to the pre-COVID period, the lead-lag relationships between DJI and oil-prices appear to occur in turns, with the oil prices predominantly leading the US equity market. As both plots, pre and during the pandemic showed strong coherency between the oil prices and the US equity market, the subsequent WTC plot analysis will only compare the ASEAN-5 equity markets with DowJones assuming that DowJones have strongly embedded the effects of oil prices in its equity market movements. Our finding depicting strong coherency between the US stock market and oil prices movement has also been reported by Sharif et al. (2020) in their analyses of the wavelet coherence plot, indicating a strong dependency

between the two with the oil prices predominantly leading the US market.

4.7.2. Lead-lag relationships between ASEAN-5 stock market indexes with DowJones before and during the pandemic

Before the pandemic, in F3a.2, we observed several small islands of high coherency between the US and Thailand's equity markets over the short, medium and long-term horizons between days 8–13, 18 to 23, 28 to 33, and 34 to 48. Almost all coherence plots indicate that the US market is leading Thailand's equity market except during the mid-period (days 28–33) where Thailand appears to be leading the relationships.

During the pandemic, a larger and more intense coherence plots can be observed between the US and Thailand equity markets compared to the pre-pandemic period. The biggest island covering days 12–32 (*Mar 4 to Apr 1*) over the short-to-medium term horizons (0-6-days frequency bands), indicates that the US is leading the equity markets. In particular, between days 20–32 (*Mar 16 to Apr 1*), the US is leading the Thailand's market by 90°. Similarly, over the short-term horizons, between days 42–49 (*Apr 17 to 28*) and 50 to 55 (*Apr 29 to May 11*), both islands indicate a strong relationship led by the US equity market. Over the long-term horizons, some parts of the island indicate an in-phase relationships, however for the most parts of days 15–48 (*Mar 9 to Apr 27*), Thailand equity market appears to be leading the relationships.

The Malaysian equity market pre-pandemic reveals several large islands of coherence led by or in-phase with the US equity market over the short to medium-term and long-term horizons. In particular, over 2-6-days frequency bands, between days 4–18, the arrows downward indicate that the US equity market is leading the Malaysian market by 90°. Between days 14–32, DowJones is leading the Malaysian market over relatively medium-frequency bands and both markets become in phase after days 32–50 over the long-term.

During the COVID-19 pandemic, the Malaysian market appears to be leading the US equity market over the short-term horizons (0-4-days frequency bands) notably between days 32–55 (*Apr 1 to May 6*). The small island during the mid-period (*Mar 25 to Apr 1*) reveals downward arrows suggesting that DowJones is leading by 90°. Over the long-term horizons (12-16-days frequency bands), between days 15–33 (*Mar 9 to Apr 2*), the DowJones is also leading the Malaysian market.

During the pre-pandemic period, the Singaporean market in F3a.4 showed high coherence with the US market over short, medium and long-term horizons. In the beginning of the sample period, between days 5–15 (*Feb 12 to 26*), STI appears to be leading the US market. During the mid- and end-periods, days 15–42 and 32 to 60, over the long and medium-term horizons respectively, both equity markets are in phase with one another.

During the pandemic, the biggest island in F3b.4 plot indicates a very high coherence between DowJones and Singaporean equity market, with DowJones leading market movements over the medium and long-term horizons almost throughout the sample period; days 4–50 (*Feb 21 to Apr 28*). Only over the short-term, briefly, between days 49–52 (*Apr 27 to 30*) that the STI is leading DJI.

The Philippines equity markets in F3a.5 also showed significant coherence with the US market during the pre-pandemic over the medium and long-term horizons. In particular, between days 18–30, the US market is leading over 13-16-days frequency bands, and between days

40–58, the Philippines market is leading the relationships over 3-10-days frequency bands.

In F3b.5, a very high coherence can be observed over the short, medium and long-term horizons between DowJones and PSEi. The significant coherence appears at the beginning of the sample period with high-frequency bands of 0-6-days notable between *Feb 19 to Mar 3*. Another significant coherence was detected between days 12–19 (*Mar 5 -16*), over a high frequency bands of 1-4-days. This island has arrows upward suggesting that PSEi is leading by 90° in these relationships. Similarly, over the long-term horizons, between days 15–42 (*Mar 10 to Apr 22*), the largest island on this WTC plot indicates an in phase relationships between PSEi and DJI. However, at lower frequency bands that is greater than 16-days, PSEi seems leading the relationships.

During the pre-pandemic period, some islands of coherence are visible on F3a.6 between the Indonesian and US equity markets over the short and medium-term horizons. During the beginning sample period, between days 8–20, the US equity market appears to be leading the Indonesian market until both markets are in phase with each other. During the mid-sample period, between days 27–32 and 44 to 49, over the short and medium-term horizons, the Indonesian market is leading the relationships.

During the pandemic, the CWT plot of the US and Indonesia equity markets also provided strong coherency over short, medium and long-term horizons revealing the dependency of the Indonesian market to the US market. Over the short-term horizons, between days 13–32 (*Mar 5 to Apr 2*), initial market movement indicates that DowJones is leading the relationships and at half-way through DJI is strongly leading by 90°. Similarly, between days 36–50 (*Apr 8 to 29*), the US market is leading the relationships and between days 49–55 (*Apr 28 to May 8*) it is leading by 90°. Over the medium and long-term horizons, between days 5–11 (*Feb 24 to Mar 3*) and days 10–40 (*Mar 2 to Apr 15*) also revealed strong coherency, with the US leading the equity markets.

4.7.3. Summary of the lead-lag relationships pre and during COVID-19 pandemic

Overall, Figures 3a and 3b indicate very strong co-movements between ASEAN-5 equity markets and DowJones, predominantly led by the US market. Another significant observation during the pandemic period is that the islands on the WTC plots appear larger with persistent red color indicating high coherency between 0.9 to 1 signalling longer duration of significant market co-movements between the domestic equity markets with the international financial market. While the phase relationships are clearly led by the US equity markets for most occurrences (pre- and during the COVID-19 periods), there are several instances where the ASEAN-5 equity markets are leading the markets. Arguably, some domestic occurrences (Ibrahim et al., 2020) may have impacted these domestic financial markets movement. Table 3 summarizes the lead-lag relationships of the ASEAN-5 equity market indexes with DowJones at different time-horizons.

4.8. The wavelet packet Shannon entropy

Our final wavelet analysis uses the Wavelet packet Shannon entropy (WSPE) method to identify the content of randomness or disorder of market indexes pre- and during the COVID-19 period. Figure 4a and b

Table 3. Summary lead-lag relationships of ASEAN-5 equity market indexes with DowJones at different time-horizons.

	Pre-Pandemic period					Pandemic period				
	Singapore	Malaysia	Indonesia	Philippines	Thailand	Singapore	Malaysia	Indonesia	Phillipines	Thailand
Short-term	Domestic	US	US	Domestic	US	Domestic	Domestic	US	Domestic	US
Medium-term	In phase	US	Domestic		US	US		US		US
Long-term	In phase	In phase		US	US	US	US	US	In phase	Domestic

Note: Domestic/US refer to either domestic or US market leading the market movement. In phase denotes that both markets are moving together.
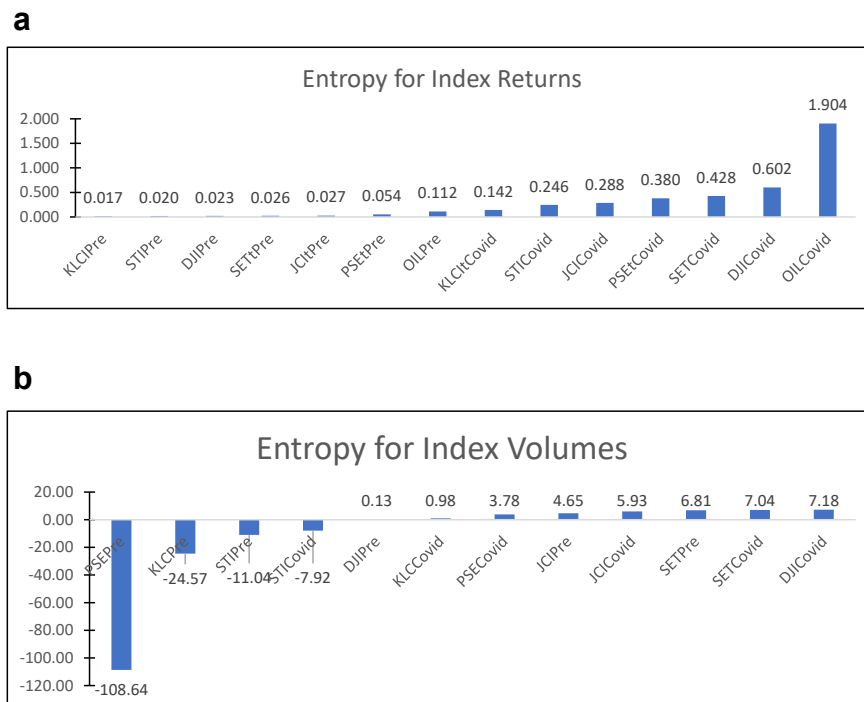
a

b

Figure 4. a. Wavelet packet Shannon entropy pre and during COVID-19 pandemic measured through index returns. b. Wavelet packet Shannon entropy pre and during COVID-19 pandemic measured through index volumes.

above show the estimated values of the WSPE pre- and during the COVID-19 pandemic period measured using the index returns and volumes respectively. Using the index returns measure, Figure 4a shows an increasing value during the COVID-19 period for all of the market indexes under study suggesting a condition of greater disorder and randomness during the COVID-19 period than the pre-COVID-19 period. Our findings are in line with Lahmiri and Bekiros (2020a) who also found a significant increase of WSPE value during the pandemic period compared to prior period, particularly, for the S&P 500 equity market which had been most affected by pandemic compared to other markets in their study.

Using the index volume measurement, the estimated value of the WSPE ranges from -108.64 to 7.18. The negative value indicates less disorder (or randomness) whereas the positive value indicates condition of more disorder. Philippines and Malaysia showed negative entropy during the pre-period and positive entropy during the pandemic period. Jakarta and Thailand have both positive estimates pre-and during the COVID-19 period whereas, Singapore has negative estimates pre-and-during the COVID-19 period. Interestingly, DowJones has positive entropy values pre- and during the COVID-19 period recording the least positive randomness (WSPE = 0.13) during the pre- and highest positive randomness (7.18) during the COVID-19 period.

Overall, we find that Singapore appears to maintain its stability before and during the COVID-19 period, whereas, other equity markets demonstrate some level of disorder and randomness during the pandemic period, whereby, higher entropy estimates are apparent during the COVID-19 period compared to its pre-period.

4.9. Robustness test

4.9.1. Granger causality

This section provides tests of robustness to support our earlier findings from the wavelet methods. The Granger causality tests are conducted for up to six lag orders and the results are presented in Table 4 below. Panel A provides the results for the pre-COVID-19 period and panel B during the COVID-19 period. During the pre-COVID-19 period, all relationships showed that DowJones helps to predict change in index

price for the Malaysian, Philippines, Thailand and Singaporean equity markets, and change in volume traded for the Indonesian market. Interestingly, during the COVID-19 period, all relationships (with the exception of JCI) appear bi-directional between DowJones and ASEAN-5 domestic equity markets at different lag orders.

4.9.2. Descriptive statistics of dynamic conditional correlation (DCC Bi-GARCH (1,1) for DowJones and ASEAN-5 equity market indexes (2015-25/9/2020 data)

Our second test of robustness reports the results of the dynamic conditional correlation (DCC Bi-GARCH (1,1) of the ASEAN-5 equity market indexes and oil prices, with DowJones before and during the COVID-19 pandemic period. The results in Table 5 indicates that before the COVID-19 period, Indonesia, the Philippines and Singapore reported a positive conditional correlation with Dow Jones, whereas, Malaysia and Thailand have a negative conditional correlation with DowJones. This suggests that during the pre-COVID-19 period, the volatilities of respective Indonesian, Philippines and Singaporean equity markets move together with DowJones. However, during the pandemic period, all of the ASEAN-5 equity markets and oil prices showed a negative conditional correlation with DowJones. Such dramatic correlation changes pre- and during the COVID-19 period implies a financial market turbulence during the pandemic period, to some extent, supporting our entropy results. Our t-test for the differences of the means of the conditional correlations are all significant.

5. Discussion

Our study suggests several main findings; first, the overall coherency between the ASEAN-5 equity market and DowJones is relatively larger than the coherence with the number of COVID-19 cases. Second, from a phase-wise perspective, there are three different scenarios; phase 1 shows slight coherence between Covid-19 cases and domestic equity market movements, phase 2 shows high coherence between DowJones and domestic equity market movements whilst phase 3 does not show any coherence.

Table 4. Granger Causality of market index price and volume before and during the COVID-19 period.

Panel A: Pre-COVID-19 period

A does not Granger Caused B		F-stat, lag order					
A	B	1	2	3	4	5	6
Change in index price							
JCI	DJI	0.391	0.805	0.724	0.350	0.301	0.601
DJI	JCI	0.001	0.475	0.356	0.540	0.538	0.438
KLCI	DJI	0.223	0.874	1.724	0.939	1.388	1.266
DJI	**KLCI**	**10.261****	**5.492****	**3.304***	**2.353***	1.874	1.575
OIL	**DJI**	1.824	1.169	**2.990***	**2.240***	**2.449***	**2.776***
DJI	OIL	0.274	0.920	1.433	1.229	1.206	0.842
PSEi	DJI	0.027	0.404	0.996	0.678	0.605	0.591
DJI	**PSEi**	**13.061***	**7.012***	**5.645***	**4.231***	**4.096***	**3.421****
SET	**DJI**	1.845	2.117	**2.646***	**3.035***	**2.644***	**1.918***
DJI	**SET**	1.320	**2.487***	1.598	1.302	0.971	0.866
STI	DJI	0.031	0.174	0.761	0.872	0.933	0.853
DJI	**STI**	**9.378***	**5.595***	**3.330***	**2.612***	**1.966***	1.743
Change in Volume Traded							
JCI	DJI	1.501	0.656	0.729	0.611	0.411	0.361
DJI	**JCI**	**8.670***	**3.112***	**3.220***	**2.768***	**2.323***	1.753
KLCI	DJI	2.684	1.784	1.151	1.133	0.842	0.650
DJI	KLCI	0.002	0.067	1.729	1.296	0.942	1.685
OIL	DJI	0.142	0.050	0.075	0.077	0.163	0.166
DJI	OIL	0.092	0.329	0.269	0.408	0.786	0.421
PSEi	DJI	1.596	0.674	0.901	0.691	0.543	0.692
DJI	PSEi	0.732	0.643	0.437	0.661	0.661	0.556
SET	DJI	0.035	0.302	0.241	0.203	0.405	1.681
DJI	SET	0.324	0.497	0.243	0.311	0.321	0.453
STI	DJI	1.025	0.686	0.558	0.700	0.486	0.443
DJI	STI	0.001	0.296	1.086	0.857	1.144	1.424
Panel B: COVID-19 pandemic period							
Change in index price							
JCI	DJI	0.316	0.543	0.385	0.604	0.702	0.474
DJI	**JCI**	**8.883***	**10.556***	**7.780***	**5.552***	**4.912***	**3.982***
KLCI	**DJI**	9.052	**4.735***	**2.570***	**3.057***	**2.479***	**2.214***
DJI	**KLCI**	1.093	**7.062***	**4.937***	**4.113***	**3.672***	**7.937***
OIL	**DJI**	2.445	**7.182***	**4.001***	**2.869***	**2.521***	1.780
DJI	**OIL**	**10.290***	**5.845***	**3.906***	**3.488***	**2.679***	**2.305***
PSEi	**DJI**	0.641	**4.157***	**3.042***	**3.341***	**3.236***	**4.322***
DJI	**PSEi**	1.654	1.527	**4.143***	**2.981***	**3.713***	**2.944***
SET	**DJI**	**8.535***	**4.865***	**3.188***	**5.819***	**4.837***	**5.498***
DJI	**SET**	**15.392***	**19.382***	**11.100***	**9.200***	**6.909***	**7.782***
STI	**DJI**	**4.613***	1.451	0.356	1.075	0.890	0.528
DJI	**STI**	**12.701***	**34.991***	**21.187***	**16.641***	**16.133***	**14.875***
Change in Volume Traded							
JCI	DJI	0.224	0.055	0.406	0.336	0.853	0.730
DJI	JCI	1.855	1.002	0.822	0.942	1.652	2.060
KLCI	**DJI**	1.761	1.155	**3.003***	**2.999***	**3.669***	**3.089***
DJI	**KLCI**	**16.172***	**14.148***	**8.174***	**5.916***	**5.180***	**3.226***
OIL	DJI	0.074	0.311	0.123	0.189	0.209	0.426
DJI	OIL	1.880	0.972	0.886	0.697	0.547	0.451
PSEi	DJI	0.113	0.811	0.597	0.457	0.668	0.500
DJI	PSEi	0.052	0.105	0.174	0.428	0.679	0.647
SET	DJI	0.241	0.956	0.914	0.875	0.598	0.530
DJI	**SET**	**4.961***	**3.440***	**2.686***	**2.315***	1.893	1.351
STI	DJI	0.321	0.504	0.678	0.713	0.763	0.698
DJI	**STI**	2.527	**7.940***	**6.377***	**4.919***	**4.416***	**3.452***

*p<0.10; **p<0.05; ***p<0.01.

Table 5. Descriptive statistics of DCC Bi-GARCH (1,1) for DowJones and ASEAN-5 equity market indexes before and during the COVID-19 pandemic and t-test of differences of means.

Panel A: Pre-COVID-19 period

	Oil	JCI	KLCI	PSEi	SET	STI
Mean	0.168	0.876	-0.853	0.290	-0.202	0.784
Median	0.605	0.991	-0.987	0.846	-0.525	0.983
Maximum	0.991	0.993	0.834	0.983	0.961	0.993
Minimum	-0.970	-0.660	-0.991	-0.943	-0.974	-0.903
Std. Dev.	0.840	0.351	0.425	0.816	0.745	0.503
Skewness	-0.244	-3.242	3.216	-0.587	0.408	-2.485
Kurtosis	1.223	12.778	11.800	1.498	1.444	7.619
Jarque-Bera	9.897	401.486	346.536	10.594	9.005	134.250
Probability	0.007	0.000	0.000	0.005	0.011	0.000
Panel B: COVID-19 period						
Mean	-0.971	-0.958	-0.977	-0.966	-0.976	-0.978
Median	-0.973	-0.962	-0.981	-0.977	-0.979	-0.982
Maximum	-0.952	-0.904	-0.913	-0.818	-0.954	-0.943
Minimum	-0.979	-0.967	-0.990	-0.983	-0.983	-0.986
Std. Dev.	0.006	0.011	0.015	0.028	0.007	0.009
Skewness	1.134	2.802	2.243	3.328	1.602	2.050
Kurtosis	3.936	11.859	8.295	15.727	4.889	7.196
Jarque-Bera	17.551	320.541	140.464	601.598	40.361	100.384
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: Parametric Test of Difference in Means (Mean Pre-COVID-19 – Mean COVID-19 period)						
Mean Differences	1.139	1.834	0.124	1.256	0.774	1.762
t (Observed value)	11.350	43.672	2.436	12.875	8.693	29.329
$\|t\|$ (Critical value)	1.977	1.977	1.977	1.977	1.977	1.977
df	138	138	138	138	138	138
p-value (two-tailed)	<0.0001	<0.0001	0.016	<0.0001	<0.0001	<0.0001
alpha (α)	0.05	0.05	0.05	0.05	0.05	0.05

This suggests that, when the outbreak is a local phenomenon (an epidemic), the equity market showed high coherency with the local occurrences of the outbreak. The investors' reaction may have been attributed to the number of new cases and the corresponding measures undertaken by the respective governments to control the outbreak (Ashraf, 2020) as it was being seen more of a country-specific problem. This is consistent with Zaremba et al. (2020) that suggest government intervention in curbing Covid-19 is instrumental in equity market volatility. At the beginning of the epidemic, investors are monitoring the government's response by way of the number of daily cases which results in the coherence between the equity market indexes and daily infected cases in these countries. Similarly, Al-Awadhi et al. (2020) study also finds China's stock markets showing negative performance as the daily number of confirmed Covid-19 cases in China increases, suggesting a strong correlation between the country's equity market with the country's epidemic phenomenon.

However, when it was declared as a pandemic, investors' sentiment showed high coherency and dependency with the global stock markets, specifically the DowJones. The pandemic induces uncertainty and volatility on global markets (Ali et al., 2020b). The wide media coverage builds negative investors' sentiments worldwide which caused the market to react adversely (Ali et al., 2020a, b). Occurrences such as elderly patients in Italy succumbing to the virus[9], worldwide collaboration in the development and deployment of diagnostics, treatments, and vaccines against coronavirus[10], and sharing of knowledge, skills, and expertise to win over this terror[11] left investors in a limbo as to the future direction of the equity market. Thus, such existences and deliberations could have underwritten the strong coherence and dependency at a global scale as it is seen as a global crisis, a threat to humankind[12] and a huge possibility of unprecedented financial turmoil. Indeed, our analysis of randomness and disorder before and during the pandemic period indicates that the pandemic period instigates a period of financial turbulence.

It is noteworthy that most investors in these ASEAN-5 countries took the cue or signal of future market movement from the DowJones, thus contributing to the high coherence between DowJones and country-specific equity market movements (Arshanapalli et al., 1995; Masih and Masih, 1999; Yang et al., 2014). The financial market volatility during this period was further exacerbated by the oil price disaster.

In the final phase, when order and control have been found on local grounds, investors gain confidence, thus detaching themselves from relying on the Covid-19 issues per se and the international markets in general. Our findings, to a certain extent, is in line with Ashraf's (2020) analysis in which he finds equity market returns reaction to the number of Covid-19 cases in several phases. Ashraf finds a strong negative decline in the beginning (around the first 20 days) and at the end of his sample period (40–60 days after the initial confirmed cases). Likewise, our study finds strong coherence between the equity market returns with the number of daily Covid-19 cases for Indonesia, Malaysia, and Singapore at the beginning of our sample period. However, we do not find similar interaction towards the end of the sample period. At this point, other issues of concern may have triggered investors' sentiment, such as the number of recovered cases, government's initiatives, incentives and

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[9] https://edition.cnn.com/2020/05/21/europe/italy-nursing-homes-deaths -intl/index.html.

[10] https://ec.europa.eu/commission/presscorner/detail/en/ip_20_797.

[11] https://www.reuters.com/article/us-health-coronavirus-italy-respirators/ch ina-sends-medical-supplies-experts-to-help-italy-battle-coronavirus-idUS KBN2101IM.

[12] https://english.alarabiya.net/en/News/world/2020/04/04/UN-chief-sa ys-coronavirus-biggest-threat-to-humankind-renews-global-ceasefire-calls.

stimulus packages to revive and enhance economic growth to sustain the new normal. Our finding contradicted Ashraf's due to the differences in the timeline. Days 40–60 (end of March and April) are comparable to our middle period but at this point, we do not find coherence between the number of local Covid-19 cases with the country's stock market performance. Instead, we find very strong coherence with the US stock market suggesting a co-movement between the ASEAN-5 stock markets with the international financial markets.

6. Conclusion and contribution of the study

This study hopes to provide several important contributions to the emerging markets' equity market participants and regulators. First, it is noted that investors' sentiment tends to variate as the pandemic progresses. Though the market movement was strongly associated with the local occurrences at the beginning of the outbreak in the respective countries, as the pandemic progressed, investors become more concerned over the global events. Thus, during periods of such calamities, investors need to be extremely vigilant and maintain a rigorous and dynamic short-term portfolio balancing mechanism. Second, the study finds strong evidence that suggests Singapore and the Philippines have a relatively strong co-movement with the Dow-Jones Index. Thus, in highly risky and volatile conditions, investors may consider taking hedging positions in these markets (Huang et al., 2018). Third, understanding the co-movement over time and frequency domains between the local stock indexes with the international market during such pandemic or crises periods will assist policymakers to better comprehend the influences of international markets and oil price on local economies (Huang et al., 2018) and to strategize appropriate financial policies that could cushion the impact of any adverse effects. Fourth, evidence suggests investors' preferences for both short-term and long-term portfolio and investment strategies. Markets tend to react based on different elements of information and investors' sentiment across time and space depending on investors' preferences. Our coherence plot indicates huge red-islands are evident for Singapore, Philippines, and Indonesia's financial markets during the mid-period of our sample, suggesting that market participants are seeking intermediate to long-term investments, based on the movement of DowJones. This contributes to the high coherency of these markets with international financial markets (DowJones) as opposed to the local markets influencing their investment decisions. In this regard, it is suggested that investors design their investment strategies based on their time-period and risk preference. Lastly, the high coherency with international financial markets pervades the effects of the pandemics as investors are getting used to the new norms of dealing with pandemics, indicating the importance of portfolio diversification and re-balancing.

In conclusion, moving forward, it is predicted that the future market movements will be more dependent on the country-specific macro-economic fundamentals arising from the stimulus packages put forward by respective countries in their efforts to revive the economy, in addition to the global economic and financial climate and appetite. Capital flow movement and management may be part of a large policy framework amid the looming crisis but they cannot replace invulnerable country-specific sustainable economic transformation and fundamentals. As the emerging market economies overcome the challenges of the Covid-19 and interruptions to the global supply chain, it should emerge as a haven for sovereign funds looking for high yields. The government should initiate industrial corridors with a consistent policy network and ensure accessibility, transparency, and good governance. This will attract the current bulk shifting of industries from certain countries, ultimately impacting the domestic equity market and mitigate dependence on global market movements. This historic challenge requires a vigorous policy response at both national and international levels. Saving lives and introducing effective prevention strategies to prevent crippling health systems is

the focus but, policymakers ought to find a balance between protecting the country's well-being and protecting the economic sustainability and facilitating commercial activities. All equity market participants, including the regulators, will need to change the thinking, practices, and strategies, in line with the new norms post Covid-19 and the highly debated data-driven decision-making needs.

Declarations

Author contribution statement

Kamilah Kamaludin: Analyzed and interpreted the data; Wrote the paper.

Sheela Sundarasen: Analyzed and interpreted the data.

Izani Ibrahim: Conceived and designed the experiments; Performed the experiments.

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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