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RESEARCH

Tail dependence in emerging ASEAN-6 equity markets: empirical evidence from quantitative approaches

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Abstract

This study contributes a rich set of quantitative methodologies including a non-parametric approach (Chi-plots and K-plots) as well as copulas (traditional and time-varying with Student's t-copulas) to the existing literature in terms of determining the dependence structure in ASEAN stock markets. Drawing on the emerging ASEAN equity returns of six countries from January 2001 to December 2017, we found that Student's t-copulas under time-varying approach is the most appropriate approach to explain these co-movements. Among all research return pairs, the dependence between Vietnam and other ASEAN equity indices has the lowest value. Meanwhile, all couples show left- and right- tail dependence by each pair for pre- and post-financial shocks. Hence, diversification across these pairs of equity markets from ASEAN is still adequate for international investors, though it might trigger contagion risks.

Keywords: ASEAN, Stock indexes, Chi-plots, K-plots, T-copulas, Time-varying copulas

Introduction

Following the 2007 financial crisis, studies on co-movements among financial asset returns have penetrated every aspect of risk management models. There are several financial risk management models in existence, such as Value-at-Risk (introduced by J.P. Morgan in 1980), Expected Shortfall, Spectral Risk Measures, and others. However, these concepts are supposed to be specialized constructions that do not integrate external shocks such as spillover phenomenon and non-linear dependence. Recently, the application of the multivariate copulas approach has attracted scholars' attention because this technique exhibits asymmetric tail dependence.

When it comes to linear dependence, the research data should carefully test its shape as well as the clearly known distribution. Nevertheless, some financial data are entirely different in certain periods including 'hot' growth, crisis, or abnormal return for any reason. Therefore, using popular distribution in single-variate has some disadvantages in validating risk models. For instance, correlation (or Pearson parameter) is usually used for linear dependence, but the estimation is criticized for being biased. Jin and Lehnert (2018) indicate that copulas would result in consistent results, robustness, and flexibility for these kinds of risk models.

In the context of the growth of emerging stock markets, the strong linkage among markets such as Europe and Asia attracts many scholars' attention. Therefore, there are many questions that are continuously raised by international investors when choosing the appropriate portfolios for investment. Additionally, in ASEAN countries, some equity markets draw attention because in relation to emerging markets such as Singapore, Thailand, Malaysia, and Vietnam. For the reasons stated above, we employed non-parametric and parametric statistics to estimate the dependence structure of ASEAN stock markets during the period from 2001 to 2017. Specifically, Vietnam is one of the countries that have potential growth in terms of equity market (Huynh 2019). Of course, challenges as well as risks are involved (Huynh et al. 2020a, b). It is worth investigating a region involving such expansive opportunities and challenges. The three main questions in this research as follows are focused on contributing new empirical evidence: (i) was there any dependence structure, particularly spillover risk, among ASEAN nations during the period from 2001 to 2017? (ii) If possible, what was the absolute magnitude of this dependence? (iii) Is it possible to simulate the dependence trend in these estimated parameters?

Most of the ASEAN nations have experienced a significant financial crisis between 1997 and 1999, during which period Thailand has its first crisis. In the mere 10 years since then, these economies have faced the global financial crisis instigated by subprime mortgage interconnected with structured investment vehicles from the United States. One of the ASEAN countries that applied effective policies to control the impact of the spillover phenomenon on equity markets is Malaysia. Mahathir Mohamad, then Prime Minister of Malaysia, applied capital control measures, which were conscientiously opposed by the International Monetary Fund at that time (Lim and Goh 2012). The primary policy purposes were to stabilize domestic economies and to discourage speculative short-term financial instruments. In general, the isolation of Malaysia from other economies, which is what low interdependence refers to, supported management regimes to avoid large capital withdrawal from foreign investors in portfolio investment. Therefore, we examine the dependence structure among ASEAN economies to confirm the level of contagion risk transmitted through equity markets, which is theorized as one of the main causes of the financial crisis. By employing time-varying copulas to construct our hypothesis testing, we indicate whether the spillover risk transmission is higher or not by the determined level of parameters. Additionally, using non-parameters based on plotting the dependence, we re-evaluate our findings from another perspective.

In the second section, we acknowledge the currently existing literature and define what our contributions are. This research is mainly driven by two motivations: firstly, it aims to model the structural dependence of several markets and the interactions between them at the time in order to build a portfolio based on those markets. Secondly (and more importantly) it has been empirically tested in the ASEAN region (especially in emerging markets such Malaysia, Vietnam, etc.), where such research is quite limited. To summarize, our contributions are to (i) fill a gap in the literature on modelling dependence structures by employing an integration of different quantitative econometrics by the use of time-varying copulas under Student's t-copulas, which will capture the left-tail dependence over a specific period; (ii) focus on the ASEAN region and some emerging economies on which limited research has been conducted; and (iii) propose practical applications for the financial community including investors and policymakers.

The paper proceeds in five sections: a brief reprise of standard theory of dependence structure in the financial aspect ("Literature review" section), methodology and data ("Data and methodology", section, "Data sample and explanation" section), analysis and findings ("Copulas approaches" section), and policy implications ("Non-parametric approach" section).

Literature review

Bekaert et al. (2014) contributes an understanding of the fundamental concept of spillover volatility as well as contagion risk across economies through global stock markets. It is clear from this that stock markets are interdependent. As such, Mun and Brooks (2012) and Burggraf et al. (2019) evaluate that risks could be incurred by transmission by higher movements from stock prices. This can be easily understood from the financial crisis, which enlarged risk through contagion possibilities: the more volatility, the more transmission. In the previous perspectives, linear methods have been employed to articulate this matter. However, it is necessary to address the nonlinear shape of data and marginal risks under left-tail dependence. Genest and Favre (2007) emphasize that copulas approach not only captures ordinary correlation but also deals with tail dependence in any random variable.

There are many studies regarding modeling dependency by copulas. Charfeddine and Benlagha (2016) investigate the dependence structure between twelve kinds of commodities and four main stock indexes such as SP500, CAC40, DAX30, and FTSE100 from 1992 to 2015. By employing different copulas modeling including Gaussian copulas, Rotated Clayton copulas, Plackett copulas, Student's t-copulas, Symmetrized Joe-Clayton copulas, and Frank copulas, this paper concludes that Student's t-copulas are the most appropriate for verifying the vast majority of estimated regimes in different economies. However, instead of emerging markets, this research's scope mainly focuses on the US stock market, which sometimes involves very high return as well as volatility. Furthermore, most of the recent studies concentrate on explaining the dependence modeling in developed countries, such as Liu et al. (2013) or Righi et al. (2015). Furthermore, commodities and energy sources are also important factors for estimation, as in studies from Masters and White (2011), Tang and Xiong (2012), and Adams and Glück (2015). Interestingly, Huynh et al. (2018) conduct updated research on copulas estimation for risk validation in the cryptocurrency market. However, a primary limitation of the study is the use of non-dynamic copulas, which is a popular copulas approach used in estimation along with wavelet-based copulas, employed by Aloui et al. (2011) to define the dependence structure between agricultural commodity products and other financial instruments. Many previous studies mainly employ multivariate GARCH to determine the dynamic correlation; afterward, these findings are used to interpret implications for the level of dependence between these kinds of assets. Therefore, the main problem is the emergence of results that are biased and misleading as indicated by Füss et al. (2012). This calls attention to correlation patterns being unstable under conditional regimes, and inconsistency through erratic behavior. Delatte and Lopez (2013) indicate definitively that there is a dependence structure among many pairs of commodity futures and return on equity indexes in the asymmetric model with the time-varying copula. It is worth noting that Patton (2006) extends time-varying copulas with conditional joint distribution to rank the dependence structure under tail between Chinese stock markets and others.

Regarding copula models for joint distributions, a large number of studies such as Poon et al. (2004), Longin and Solnik (2001), and Bae et al. (2003) conclude that stock markets seem to collapse together but reach their peak individually. Therefore, we focus on examining both tails of the return on ASEAN stock markets to investigate the spillover risks, which might be transmitted through any shock from one market. Employing copulas methodology, especially the time-varying approach, quantifies contemporaneous interdependence between univariate time series concerning the co-movements of other random variables. Bartram et al. (2007) and Ane and Labidi (2006) collect data from the European stock indices to measure dependence structure in copulas. Meanwhile, Patton (2006) extends the time-varying copulas to illustrate his hypotheses that data often moves dynamically. Interestingly, there is a paper by Jiang et al. (2017) concerning co-movement and the volatility fluctuation between stock markets in the ASEAN region. This paper employs the three-dimensional continuous wavelet transformation from 2009 to 2016. Conversely, Mun and Brooks (2012) evaluate that dependence structure, as well as risk, may emerge from this period. Nevertheless, this paper by Jiang et al. makes contributions through its empirical findings when it shows that Vietnam has the lowest level of dependence. In contrast, historical events proved that Malaysia employed policies to avoid withdrawal from capital flows, which might have a lower dependence too.

Based on this literature review, we employ a rich set of quantitative techniques to bridge some gaps in previous research. First, the research period is expanded from 2001 to 2017, which covers the financial crisis in 2007 and 2008. Second, few studies cover ASEAN regions. Third, Jiang et al's study (Jiang et al. 2017) mainly focuses on wavelet function incorporated into traditional copulas rather than time-varying copulas. Hence, we choose to employ time-varying copulas with t-Student's distribution to illustrate the dependence structure. Finally, we would like to compare some historical events with the statistical results to affirm and critique some countries' policies regarding stock capital flows.

Furthermore, there are several empirical studies that have employed quantitative techniques to capture heavy tails and co-movements using Extreme value theory (EVT), Dynamic conditional correlation (DCC), and mixture and vine copulas, such as Al Rahahleh and Bhatti (2017); Al Rahahleh et al. (2017); Do et al. (2016) and Nguyen et al. (2016). The review by Do et al. (2016) expressly indicated that there is no study that employs time-varying under Student's t-copulas for examining tail dependence structure among 185 relevant research papers over 16 years. Noticeably, most studies come into an agreement that there is dependence structure, known as spillover risks, among ASEAN-6 countries. Moreover, the studies of Al Rahahleh and Bhatti (2017); Al Rahahleh et al. (2017), and Nguyen et al. (2016) look more deeply into co-movements as well as risk transmission from global perspectives through arguments on financial crises. Interestingly, these studies have addressed the underlying limitations of econometric models. Recently, Luu Duc Huynh (2019) employed the VAR-SVAR Granger Causality and Student's-t copulas to estimate the causal relationships in the cryptocurrency market. This study also indicates the role of joint distribution in terms of risk determination in spillover effects. It suggested the employment of further quantitative techniques such as copulas integrated with the most appropriate distribution for correcting the misspecified models. To summarize, we acknowledge these studies to establish a chain of quantitative evidence that copulas is considered the cutting-edge method to estimate the tail dependence structure.

By reviewing the current literature on ASEAN regions, we found that the study of Jiang et al. (2017) addressed co-movements in wavelet form structure, which relates to leading and lagging countries in cyclical business phases. Later, Maneejuk et al. (2018) studied structural dependence from the perspective of oil. Li and Zeng (2018) further contributed to the literature by estimating dependence structure among ASEAN countries, the United States, and China. Recently, Nguyen and Huynh (2019) constructed the portfolio of the ASEAN community through calculating the dependence structure. We have gathered that the previous results have contributed to the literature in terms of empirical methodologies and the variety of assets. Despite the extensive work being continuously conducted in this field, there is little investigation of dependence structure in stock markets in ASEAN areas, which are considered collectively as the emerging economic part of the world. More importantly, our research is the initial step for those who seek to establish international portfolios based on dependence structure during a different period. We will contribute to existing literature by using time-varying copulas under Student's t-copulas to estimate dependence structure, especially to examine the tail-left dependence, among ASEAN-6 equity markets.

Data and methodology

Data sample and explanation

We collected the data for our estimation from the stock index of ASEAN countries by Thomson Reuters in the period from January 2001 to December 2017. We used the equity indices VN Index, SET Index, FTSE Straits times Index, PSEi Index, FTSE Bursa Malaysia KLCI Index, and Jakarta SE Composite Index, which are representative of the stock markets of Vietnam, Thailand, Singapore, the Philippines, Malaysia, and Indonesia, respectively. The main reason for our choice of these countries was to ensure the availability of datasets from between 2001 and 2017. Additionally, these six stock markets occupy 80% the ASEAN regions, while the remaining ones are small and newly established, for example, Cambodia, Laos, Myanmar, etc. In addition, Do et al. (2016) found that most studies examining the capital market in the ASEAN region also use these 6 countries, such as Balli et al. (2014). Therefore, our results can be interpreted to relate to the ASEAN area. After streamlining our data by eliminating the missing data from the various holidays in these stock markets, we calculate the log-return as theorized by Fama and Miller (1972).[1] After calculating the ASEAN stock returns, we summarize the data based on some basic criteria such as mean, standard deviation, skewness, and kurtosis. By doing this, we can note some features from each economy in the ASEAN region.

As a result in Table 1 and Figure 1, we determined that the average return in Indonesia was notably higher than the other stock markets in the ASEAN area. The Indonesia index

[1] $r_t = \ln\left(\frac{I_t}{I_{t-1}}\right)$, in which the specific index returns rt. by the time t. I_t is the stock index of the specific country in period t, and I_{t-1} is the stock index of the specific country in the period (t-1)

Table 1 Statistics Description

Variables	Mean	Std. Dev.	Min	Max	Median	Skewness	Kurtosis	JB
Indonesia	0.0032	0.0302	−0.2330	0.1159	0.0046	−0.9487	9.0844	1501[a]
Philippine	0.0020	0.0282	−0.2015	0.1619	0.0025	−0.4197	8.3207	1072[a]
Singapore	0.0006	0.0254	−0.1647	0.1532	0.0017	−0.3851	9.5812	1623[a]
Thailand	0.0021	0.0282	−0.2666	0.1075	0.0041	−1.4041	14.0140	4775[a]
Vietnam	0.0020	0.0406	−0.2028	0.1570	0.0014	−0.3606	7.3113	706[a]
Malaysia	0.0011	0.0179	−0.1145	0.0665	0.0018	−0.7839	8.0092	1018[a]

Note that the total observation is 887 over our research period. JB is considered as Jarque-Bera asymptotic test for normality on the specified variable in level form. [a] indicate statistically significant 1% level. Noted that all p-values are zero. Therefore, all variables are not standard distribution form.

increased 15 times during the period from 2001 to 2017. This explains why many investors choose to earn their return from this market. Furthermore, the Indonesian Government has gradually developed its policies to build infrastructure as well as to attract foreign direct investment, which fosters this equity market to become one of the most rapidly growing emerging stock markets. In contrast, Singapore experiences the lowest average return in the ASEAN region, although Singaporean market capitalization is the largest. However, because Singapore has reached a saturation point, investors might not take opportunities to earn profits. Thus, the volatility in Singapore is the lowest, which presents stable movements as well as neutralizes volatile risks. When it comes to other risk factors such as skewness and kurtosis, Thailand has suffered from a higher absolute value with – 1.4041 and 14.0140, respectively. It can be interpreted that Thailand has negative skewness in the left tail. The standardized kurtosis, then, is over four, which means that the heavy tail is also a risk factor in this country. The monetary crisis was catalyzed by Thailand in 1997. Additionally, not long ago, Thailand's SET index decreased by 108.41 points, equivalent to the loss of 816 Baht (nearly 23 billion USD) (Sutheebanjard and Premchaiswadi 2010). The main reason for these statistics in Thailand is the failure to control the depreciation of Thai Baht, and the presence of risks associated with the country.

Copulas approaches

Huynh et al. (2018), Huynh and Burggraf (2020) assert that the intent of the copulas approach comes from Sklar (1959)'s theorem of generating joint multivariate probability-distribution functions. In our research, we refer to studies from Huynh et al. (2018), specifically the fundamental concept of joint density function H in Eq. (2) with C representing the copulas:

$$\exists C : [0,1]^d \rightarrow [0,1] \tag{1}$$

which satisfies the main condition for $x = (x_1, x_2, \ldots, x_d)$

$$H(x) = C\{F_1(x_1), \ldots, F_d(x_d)\}\ x \in R^d \tag{2}$$

The function 'C' here is called 'traditional copulas' (or vanilla copulas), with two main characteristics: (i) dividing into many sides and (ii) marginal distribution following a standard normal distribution.[2] This copula has a disadvantage in distribution. Hence, we would like to refer the other copulas' functions as follows. Among the variety of

[2]According to Sklar's theorem, for an n-dimensional random vector, the interdependence structure between random variables is defined by a copula, and is decomposed into a series of marginal distribution.

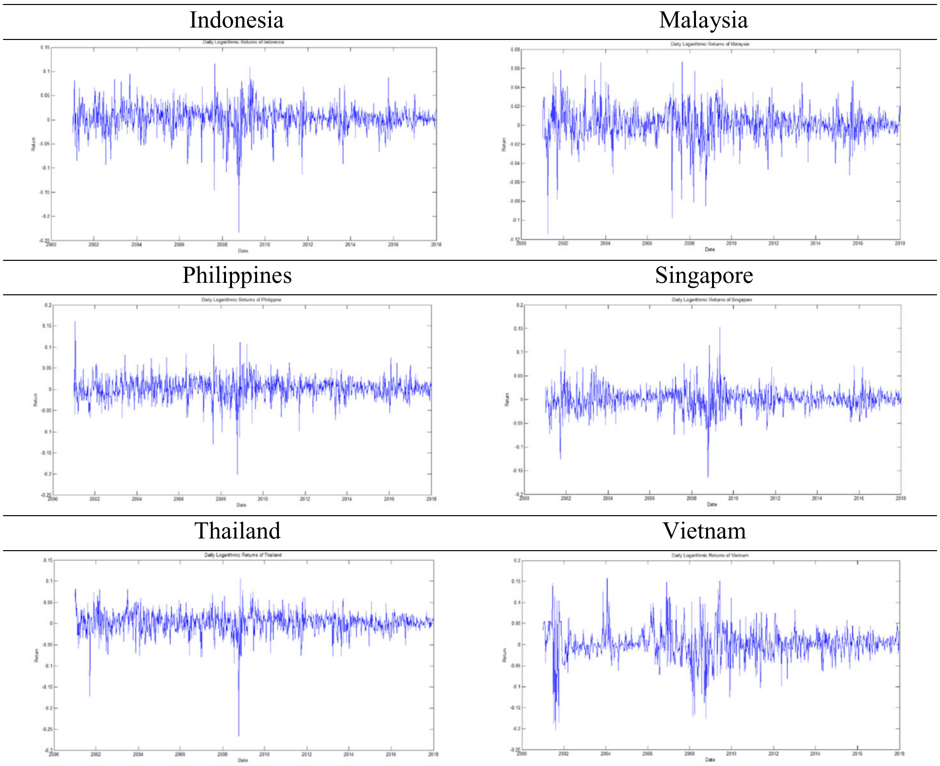

Fig. 1 Weekly Logarithmic Returns by country. Based on our plotted weekly logarithmic returns charts, we recognized that the volatility is quite high in the period of 2007. This represents the 2007 global financial crisis, which triggered the large gaps in stock return movements. This characteristic fulfilled our prediction at first glance, with further estimation required

copula families, we mainly focus on t-DCC copulas (t-student's distribution of Dynamic Conditional Correlation copulas), Gaussian DCC copulas (Gaussian Dynamic Conditional Correlation copulas), tv-copulas (time-varying copulas) and tv-SJC copulas (time-varying and static bivariate symmetrized Joe-Clayton copulas).

Nevertheless, Charfeddine and Benlagha (2016) conclude that t-student copulas allow us to estimate fat-tail shape. Additionally, it may increase the joint probability that results in the same events happening. Therefore, this study also indicates that t-student copulas will more applicable for dynamic data, whereas the Gaussian faces limitation. Thus, the t-student copulas (with u and v as uniform random variables obtained from the cumulative distribution function) are written as:

$$C(u, \mathrm{v}|\rho, \nu) = \int_{-\infty}^{t_{\nu}^{-1}(u)} \int_{-\infty}^{t_{\nu}^{-1}(\mathrm{v})} \frac{1}{2\pi(1-\rho^2)^{\frac{1}{2}}} \left\{1 + \frac{x^2 - 2\rho xy + y^2}{\nu(1-\rho^2)}\right\}^{-\frac{\nu+2}{2}} dsdt \tag{3}$$

Its components include parameter ρ, which represents a parameter of estimated copulas, and ν, which is the degree of freedom of t-student's distribution. Meanwhile, t_{ν}^{-1} is the inverse of the standard univariate (Charfeddine and Benlagha 2016). To be more specific, SJC copulas present both upper and lower tail with two parameters τ_U, τ_L, respectively. Clearly, the other copulas require symmetrical dependence of random variables for estimation. Thus, Static Bivariate Symmetrized Joe-Clayton copulas have an advantage over symmetrized data, and offers high precision in relation to the tail, calculating exactly the expected coefficient for interpretation. In particular, the Joe-Clayton copula is written as a function:

$$C_{JC}(u,v|\tau_U,\tau_L) = 1-\left(\left\{\left[1-(1-u)^k\right]^{-\gamma} + \left[1-(1-v)^k\right]^{-\gamma} - 1\right\}^{-\frac{1}{\gamma}}\right)^{\frac{1}{k}} \tag{4}$$

$$k = 1/\log_2(2-\tau_U) \tag{5}$$

$$where\ \gamma = -1/\log_2(\tau_L)$$

$$\tau_U \epsilon (0,1), \tau_L \epsilon (0,1)$$

Hotta et al. (2006) expands the approach mentioned earlier by symmetric $\tau_U = \tau_L$ by this formula:

$$C_{SJC}(u,v|\tau_U,\tau_L) = 0.5C_{JC}(u,v|\tau_U,\tau_L) + 0.5C_{JC}(1-u,1-v|\tau_U,\tau_L) + u + v - 1 \tag{6}$$

We develop this model by adding the time-varying factor then standardize it into tv-SJC copulas with the research of Charfeddine and Benlagha (2016) regarding dependence parameters:

$$\widehat{dep_t} = c_j + u_t, t = T_{j-1}+1, T_{j-1}+2, \ldots, T_j \tag{7}$$

where $j = 1, 2, \ldots, m+1$; $T_0 = 0$. $T_{m+1} = T$ and c_j is the conditional mean of estimated dependency parameters for each regime.

This is done under the assumption that the dependence parameter is calculated by past information and follows an ARMA (1,k). Hence, the Gaussian coefficient according to Nguyen and Bhatti (2012) is:

$$\rho_t = \Lambda\left(\beta_\rho \rho_{t-1} + \omega_\rho + \gamma_\rho \frac{1}{k}\sum_{i=1}^{k}|u_{t-i}-v_{t-i}|\right) \tag{8}$$

This means that parameter k is very wide and historical information is needed to choose the most appropriate one. We also propose the Gumbel and Clayton copulas here with the same assumption of ARMA (1,k)[3]:

$$\delta_t = \beta_U \delta_{t-1} + \omega_U + \gamma_U \frac{1}{k}\sum_{i=1}^{k}|u_{t-i}-v_{t-i}| \tag{9}$$

$$\theta_t = \beta_L \theta_{t-1} + \omega_L + \gamma_L \frac{1}{k}\sum_{i=1}^{k}|u_{t-i}-v_{t-i}| \tag{10}$$

After defining how to establish the tv-SJC copulas above, in the following equation by Nguyen and Bhatti (2012) is indicated the dynamics of the upper- and lower-tail dependences, respectively.

$$\tau^U = \Pi\left(\beta_U^{SJC}\tau_{t-1}^U + \omega_U^{SJC} + \gamma_U^{SJC}\frac{1}{k}\sum_{i=1}^{k}|u_{t-i}-v_{t-i}|\right) \tag{11}$$

$$\tau^L = \Pi\left(\beta_L^{SJC}\tau_{t-1}^L + \omega_L^{SJC} + \gamma_L^{SJC}\frac{1}{k}\sum_{i=1}^{k}|u_{t-i}-v_{t-i}|\right) \tag{12}$$

[3]We used Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion to choose the most appropriate lag-order for ARMA (1,k).

In order to interpret the level of dependency of the data structure, we utilized the literature as well as the empirical evidence of Meneguzzo and Vecchiato (2004), Mashal and Zeevi (2002), Breymann et al. (2003), and Galiani (2003).

The main method to estimate copulas parameters, therefore, is Inference-function-for-margins (IFM), which extracts the exact maximum likelihood (EML). Thus, these parameters are quite important to define the level of dependency.

$$\hat{\theta}_{it} = argmax\sum\nolimits_{t=1}^{T} \ln f_{it}\left(z_{i,t}|\Omega_{t-1},\theta_{it}\right) \tag{13}$$

$$\hat{\theta}_{ct} = argmax\sum\nolimits_{t=1}^{T} \ln c_t\Big(F_{1t}\left(z_{i,t}|\Omega_{t-1}\right), F_{2t}\left(z_{2,t}|\Omega_{t-1}\right), \ldots F_{nt}\left(z_{n,t}|\Omega_{t-1}\right), \hat{\theta}_{it}, \hat{\theta}_{ct}\Big) \tag{14}$$

This approach is derived from the study of Joe and Xu (1996), Joe (1997), and Joe (2005), in which F and c_t are the functions for unknown marginal parameter vectors and unknown copula parameter, respectively. This value is used under the assumption that the margins are correctly specified, and sample variables are unobservable, independent, and identically distributed random variables (i.i.d.).

Non-parametric approach

We used the study by Nguyen et al. (2016) and Huynh et al. (2020a) for plotting each point. We plotted on graphs of a wide area (λ_i, χ_i) for the movement of both variables (X_i, Y_i) with $i = 1, 2, \ldots, n$. In order to draw this pair (X_i, Y_i), the calculation was as follows:

$$\mathrm{X_i} = \frac{\mathrm{H_i - F_i G_i}}{\sqrt{\mathrm{F_i(1-F_i)G_i(1-G_i)}}} \tag{15}$$

$$\lambda_\mathrm{i} = 4\mathrm{S_i}\ \max\left\{\left(\mathrm{F_i}-\frac{1}{2}\right)^2, \left(\mathrm{G_i}-\frac{1}{2}\right)^2\right\} \tag{16}$$

Here, $S_i = sign\{(F_i-\frac{1}{2})(G_i-\frac{1}{2})\}$. The confidence interval lies in $\pm c_p/\sqrt{n}$ (approximately at C_p at the significance level 95%, which is nearly 1.78).

Quantile-Quantile-plot (QQ-plot) was used, and the value of H_i is defined as follows:

$$\mathrm{K_0}(\omega) = \mathrm{P}\Big(\mathrm{UV}\le\omega = \mathrm{P}\Big(\mathrm{U}\le\frac{\omega}{\vartheta}\Big)\mathrm{d}\vartheta\Big) = \mathrm{I}\mathrm{d}\vartheta + \frac{\omega}{\vartheta}\mathrm{d}\vartheta = \omega - \omega\log(\omega) \tag{17}$$

$$\mathrm{W_i : n} = \omega \mathrm{k_0}(\omega)\{\mathrm{K_0}(\omega)\}^{\mathrm{i-1}}\{1-\mathrm{K_0}(\omega)\}^{\mathrm{n-i}}\mathrm{d}\omega \tag{18}$$

Therefore, $\mathrm{k_0}$ is the relative density. This is the main approach of the K-plot (or Kendall-plot). Furthermore, we also refer to the studies by Dastgir et al. (2019a, b) and other performance measures from Saito (2019) and Eom et al. (2019) for recent literature incorporating new research methodologies of copula Causality.

Findings

Test of stationary

Primarily, we employed Dickey-Fuller and the Autocorrelation Function (ACF) to test whether our return series is stationary or not. The results show that all return variables from each country are stationary at the original level from Table 2 and Figure 2. Its finding is appropriate for the following test, which we carry out.

Table 2 Test of stationary by Dickey-Fuller

Variables	Original value t-statistics
Indonesia	−30.579***
Malaysia	−27.437***
Philippines	−31.200***
Singapore	−28.430***
Thailand	−29.469***
Vietnam	−24.208***

*, **, *** significant at 10%, 5% and 1% levels, respectively

Test of dependence structure by linear correlation

In Table 3, the level of dependency of these ASEAN countries varies from 0.13577 to 0.5655. Interestingly, the pair of Singapore and Malaysia experiences high correlation whereas the relationships between Vietnam and the other economies are quite weak. This can be explained by the fact that Vietnam is one of the countries that has limited instruments in financial markets. Therefore, the internationalization of ASEAN stock markets is limited in Vietnam. Additionally, Thailand started to use derivatives from 2006 while Vietnamese investors have only used future derivatives for trading since 2017.

It is worth mentioning that the criteria for being officially listed in stock exchange, including the number of exchangeable stocks or minimum shareholders in the company, etc., lead to the various levels of dependency structures. In addition, Malaysia, Singapore, Indonesia, the Philippines, and Thailand share similarities regarding geography, religion, and economic growth. Therefore, these characteristics contribute to the interdependency among these stock markets.

The non-parametric approach by chi-plots and K-plots

One of the contributions of this paper is employing a non-parametric approach with Chi-plots and K-plots for testing the dependence structure in different ASEAN stock markets. Based on the results shown in Figure 3 in Appendix and Figure 4 in Appendix, we determine that ASEAN countries, except Vietnam, experience a dependency structure. In the Chi-plots estimation, most graphs lay out of the controlling line (– 0.05; 0.05). This means that these random variables are interdependent together at a significance level of 5%. In contrast, the Vietnam index keeps staying in line with the controlling line, which demonstrates that the Vietnam stock market is a separate interaction from the other stock exchanges.

In regards to K-plots, the Kendall-plots method from the literature of Nguyen and Bhatti (2012) showed that, as the points are not linearly distributed along the 45-degree line of most graphs, these random variables are confirmed as dependence structures. Concomitantly, the findings in this section complement the ones obtained by the aforementioned traditional tests. These findings are similar to the previous tests based on Chi-plots.

Therefore, based on two methodologies, we investigate the existence of dependent structures among ASEAN stock markets. A notable point is the separate status of Vietnam's interdependence. It is clear that Vietnam is a 'child' stock market with simple financial products, which restricts its interaction with the other economies through equity capital flows.

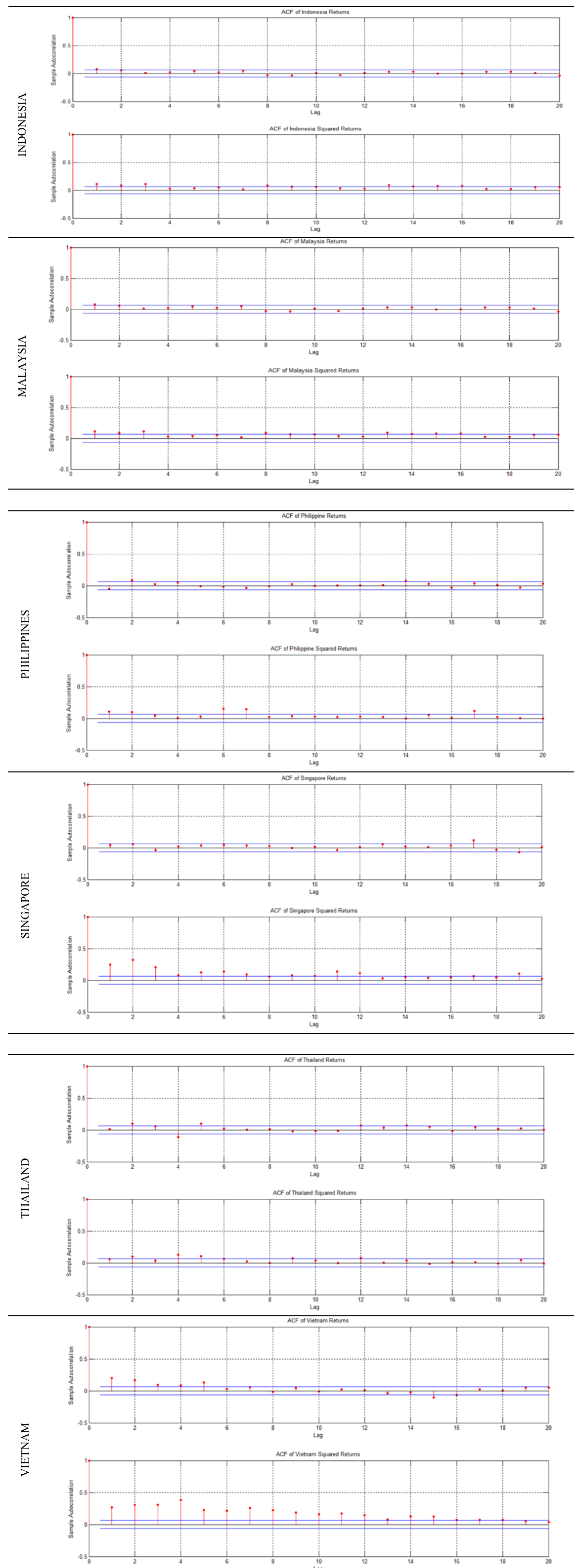

Fig. 2 Autocorrelation Function by one stock market for stationary testing

Table 3 The matrix of linear correlation by Pearson

	Indonesia	Philippine	Singapore	Thailand	Vietnam	Malaysia
Indonesia	1					
Philippine	0.5307	1				
Singapore	0.5191	0.4891	1			
Thailand	0.4966	0.4738	0.5064	1		
Vietnam	0.1722	0.1759	0.1774	0.1595	1	
Malaysia	0.5284	0.4635	0.5665	0.4717	0.1357	1

Copulas approach for estimation

In our research, we employ four main families of copulas including Clayton copulas, Gumbel copulas, Gaussian copulas (Normal copula) and t-copulas, which demonstrate the left tail, right tail, and no tail, respectively. In order to maintain robustness, we also perform goodness of fit for testing whether our random variables fit with each copula family or not. Our hypothesis for testing is $H_0 : C = C_0 = 0$, which considers which copulas family is represented for the level of dependency by each pair. Based on our statistical results in Table 4, 100% of t-copulas' p-value rejects the null hypothesis above; 87% of Gaussian copulas' p-value also fits rejection. Only 27% p-value under Clayton and Gumbel copulas does not fit rejection. Therefore, we conclude that most estimation appropriately fits with Gaussian and t-copulas, although Embrechts (2009) indicates 99.99% of copulas estimations and their applications fail this test. Thus, we do not rely only on this finding but also interpret the parameters from Log-likelihood to choose the best-fit model for structure explanation.

We estimated the parameters based on the Log-likelihood function to choose the best-fit model. The most significant value of Log-likelihood was our basis for choosing the most appropriate copulas function for interpretation. From the results shown in Table 5, we confirmed that most of the stock index pairs stayed in t-copulas. Thus, it reflected the data visualization in the description of the statistics (mostly the kurtosis phenomenon). Traditional approaches have shown limitations in accounting for those random variables of previous studies with normal distribution and linear correlation. By conducting a test with copulas, we can observe the simultaneous distribution of random variables without indicating their exact shapes.

Our findings on the copulas approach are quite similar to the results shown in the Pearson correlation parameters. The pair of Malaysia and Singapore exhibited the highest dependence structure, whereas Vietnam was less likely to have dependency structures with the remaining stock exchanges in ASEAN. To control for shifts in the market, we recorded results from when the Indonesia stock exchange moved, which led to the co-movement of the Philippines stock index by 0.491 (based on copulas approaches). To summarize, we estimated and calculated the copulas function in order to choose t-copulas for all random variables. Interestingly, it was advantageous to allow the t-copulas parameters to interpret the level of interdependence among the stock indexes over the periods of research. Based on empirical evidence, many studies indicate that the time series of stock indexes vary over such periods. Patton (2001, 2004, 2006), Jondeau and Rockinger (2003), Berkowitz et al. (2011), and Creal et al. (2011) suggest that using dynamic copulas will compensate for the limitations of previous studies in that this approach can adapt to time lag as well as changes in information. In order to

Table 4 The results of Goodness-of-fit

Pair	Data	Normal	Clayton	Gumbel	t-copulas
Indonesia-Philippine	Gof_Statistic	0.029404	0.099322	0.099448	0.019918
	Gof_param	0.48716	0.79443	1.4387	0.4912
	P-value	**0.1134**	0.0004995	0.0004995	**0.3791**
Indonesia-Singapore	Gof_Statistic	0.024674	0.13975	0.089544	0.017133
	Gof_param	0.50132	0.80877	1.4666	0.50854
	P-value	**0.2293**	0.0004995	0.0004995	**0.51**
Indonesia-Thailand	Gof_Statistic	0.023446	0.12957	0.048184	0.011607
	Gof_param	0.45391	0.84746	1.4014	0.45911
	P-value	**0.2632**	0.0004995	0.007493	**0.9116**
Indonesia-Vietnam	Gof_Statistic	0.029888	0.031696	0.026152	0.021016
	Gof_param	0.12738	0.1584	1.0779	0.09955
	P-value	**0.1304**	**0.1424**	**0.2203**	**0.3242**
Indonesia-Malaysia	Gof_Statistic	0.030041	0.12067	0.088685	0.019581
	Gof_param	0.49883	0.8007	1.4589	0.50017
	P-value	**0.1014**	0.0004995	0.0004995	**0.4071**
Philippine-Singapore	Gof_Statistic	0.03868	0.1003	0.12466	0.026504
	Gof_param	0.468	0.77517	1.4222	0.48651
	P-value	**0.03147**	0.0004995	0.0004995	**0.1494**
Philippine-Thailand	Gof_Statistic	0.021942	0.083165	0.086918	0.022012
	Gof_param	0.43398	0.7906	1.3462	0.42124
	P-value	**0.3092**	0.001499	0.0004995	**0.2672**
Philippine-Vietnam	Gof_Statistic	0.065087	0.062279	0.055113	0.04018
	Gof_param	0.12116	0.18273	1.0647	0.081323
	P-value	0.0004995	0.007493	0.006494	**0.01848**
Philippine-Malaysia	Gof_Statistic	0.035631	0.059861	0.092769	0.022916
	Gof_param	0.43849	0.76973	1.3546	0.4254
	P-value	**0.04146**	0.004496	0.0004995	**0.2313**
Singapore-Thailand	Gof_Statistic	0.016328	0.15587	0.05485	0.0078838
	Gof_param	0.47503	0.73941	1.4235	0.47906
	P-value	**0.6678**	0.0004995	0.001499	**0.9955**
Singapore-Vietnam	Gof_Statistic	0.034138	0.018871	0.052699	0.024377
	Gof_param	0.16341	0.23648	1.1057	0.16774
	P-value	**0.07143**	**0.5639**	0.005495	**0.1833**
Singapore-Malaysia	Gof_Statistic	0.048451	0.12037	0.10266	0.031779
	Gof_param	0.54804	0.92907	1.5337	0.5467
	P-value	0.005495	0.0004995	0.0004995	**0.04745**
Thailand-Vietnam	Gof_Statistic	0.02546	0.015541	0.038322	0.02129
	Gof_param	0.12491	0.18517	1.0724	0.12151
	P-value	**0.2323**	**0.7777**	**0.05245**	**0.2882**
Thailand-Malaysia	Gof_Statistic	0.028121	0.13323	0.050293	0.014174
	Gof_param	0.45308	0.84455	1.3975	0.45063
	P-value	**0.1364**	0.0004995	0.004496	**0.7308**
Vietnam-Malaysia	Gof_Statistic	0.02974	0.032195	0.0302	0.016429
	Gof_param	0.11931	0.15552	1.0887	0.11677
	P-value	**0.1174**	**0.1384**	**0.1284**	**0.5999**

The test for Goodness-of-fit is inherited from the Eq. 12 and Eq. 13. Furthermore, our hypothesis for testing is $H_0 : C = C_0 = 0$, $H_A : C \neq C_0 \neq 0$. However, Embrechts (2009) indicates 99.99% Copulas estimations and its applications fail to this test
Entries set in bold can clearly see the 'Goodness-of-fit'of Copulas

Table 5 The parameters for each Copulas family

Pair	Data	Normal	Clayton	Gumbel	t-Copulas
Indonesia-Philippine	Loglikelihood	117.900	117.000	111.000	**136.400**
	Param	0.487	0.794	1.439	0.491
	λ_U		0.418		
	λ_L			0.381	
Indonesia-Singapore	Loglikelihood	126.000	120.500	121.400	**146.700**
	Param	0.501	0.809	1.467	0.509
	λ_U		0.424		
	λ_L			0.396	
Indonesia-Thailand	Loglikelihood	100.300	88.580	98.250	**118.400**
	Param	0.454	0.848	1.401	0.459
	λ_U		0.441		
	λ_L			0.360	
Indonesia-Vietnam	Loglikelihood	7.067	9.109	8.058	**14.870**
	Param	0.127	0.158	1.078	0.100
	λ_U		0.013		
	λ_L			0.098	
Indonesia-Malaysia	Loglikelihood	124.600	121.300	118.100	**141.900**
	Param	0.499	0.801	1.459	0.500
	λ_U		0.421		
	λ_L			0.392	
Philippine-Singapore	Loglikelihood	107.500	112.400	102.900	**132.100**
	Param	0.468	0.775	1.422	0.487
	λ_U		0.409		
	λ_L			0.372	
Philippine-Thailand	Loglikelihood	90.690	86.660	75.980	**94.390**
	Param	0.434	0.791	1.346	0.421
	λ_U		0.416		
	λ_L			0.326	
Philippine-Vietnam	Loglikelihood	6.389	12.370	5.470	**13.940**
	Param	0.121	0.183	1.065	0.081
	λ_U		0.023		
	λ_L			0.083	
Philippine-Malaysia	Loglikelihood	92.810	92.180	81.040	**102.200**
	Param	0.439	0.770	1.355	0.425
	λ_U		0.406		
	λ_L			0.332	
Singapore-Thailand	Loglikelihood	111.300	104.300	104.700	**128.900**
	Param	0.475	0.739	1.423	0.479
	λ_U		0.392		
	λ_L			0.372	
Singapore-Vietnam	Loglikelihood	11.700	16.750	11.530	**24.260**
	Param	0.163	0.237	1.106	0.168
	λ_U		0.053		
	λ_L			0.129	

Table 5 The parameters for each Copulas family *(Continued)*

Pair	Data	Normal	Clayton	Gumbel	t-Copulas
Singapore-Malaysia	Loglikelihood	155.700	148.500	148.400	**175.500**
	Param	0.548	0.929	1.534	0.547
	λ_U		0.474		
	λ_L			0.429	
Thailand-Vietnam	Loglikelihood	6.794	11.290	6.862	**14.760**
	Param	0.125	0.185	1.072	0.122
	λ_U		0.024		
	λ_L			0.091	
Thailand-Malaysia	Loglikelihood	99.900	81.890	95.960	**111.900**
	Param	0.453	0.845	1.398	0.451
	λ_U		0.440		
	λ_L			0.358	
Vietnam-Malaysia	Loglikelihood	6.194	8.190	9.088	**19.890**
	Param	0.119	0.156	1.089	0.117
	λ_U		0.012		
	λ_L			0.110	

The robustness checks for our results are based on the loglikelihood value. The highest value of loglikelihood suggested us to choose the t-Copulas for interpreting our results. Moreover, the parameters (param) demonstrate how strong two equity markets commit

Entries set in bold can clearly see the 'Goodness-of-fit'of Copulas

utilize the dynamic copulas, we needed to run the model AR-GJR-GARCH (1,1) to extract its residual for time-varying copulas such as T-DCC, G-DCC, time-varying Clayton, and time-varying SJC. Our results are presented in Table 6. The main difference between t-copulas and time-varying copulas is to change the residual from the AR-GJR-GARCH (1,1) approach to the cumulative t-skew (skew t-CDF) for estimating dynamic parameters and plotting them in the graphs. This means further employing time-varying copulas under Student's t-distribution to investigate the dependence structure. To be more detailed, we refer to a study by Zhang et al. (2014) to alternate between GARCH estimation and copulas. This model shows that the adjustable parameters in model GJR-GARCH and t-copulas accurately capture the level of dependence structures.

We refer to the study of Patton (2006) to estimate the parallel parameters in tail dependence as follows:

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U \tau_{t-1}^U + \alpha_U \cdot \frac{1}{m}\sum_{j=1}^{m}\left|u_{t-j} - v_{t-j}\right|\right) \tag{19}$$

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L \tau_{t-1}^L + \alpha_L \cdot \frac{1}{m}\sum_{j=1}^{m}\left|u_{t-j} - v_{t-j}\right|\right) \tag{20}$$

In which $\Lambda(x) \equiv (1 + e^{-x})^{-1}$ is the changing logistics function so $\tau_t^U, \tau_t^L \in (0,1) \forall t$. Simultaneously, $\beta_U \tau_{t-1}^U$ and $\beta_L \tau_{t-1}^L$ are the limits of auto-regression with $|u_{t-j} - v_{t-j}|$, which is the compulsory variable in the function. The dependence parameter is determined with the following equation:

Table 6 Estimation for AR–GJR–GARCH (1,1) model

	Indonesia	Malaysia	Philippines	Singapore	Thailand	Vietnam
c_0	0.0037	0.0009	0.0026	0.0008	0.002	0.0004
	(0.001)	(0)	(0.001)	(0.001)	(0.001)	(0.001)
c_1	−0.0356	0.05	−0.0419	0.0387	−0.0393	0.2315
	(0.044)	(0.038)	(0.039)	(0.033)	(0.037)	(0.041)
ω	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)
α	0.1631	0.0711	0.0411	0.0253	0.0724	0.3483
	(0.076)	(0.06)	(0.03)	(0.024)	(0.023)	(0.11)
β	0.7984	0.8798	0.8911	0.8696	0.9254	0.6704
	(0.15)	(0.123)	(0.064)	(0.054)	(0.029)	(0.086)
γ	0.0328	0.057	0.0698	0.1705	0.0048	0.0676
	(0.104)	(0.072)	(0.043)	(0.061)	(0.03)	(0.106)
υ	4.6782	5.3685	6.5995	6.122	5.8375	4.8907
	(0.715)	(1.036)	(1.302)	(1.236)	(1.095)	(0.788)
λ	−0.1022	− 0.0942	− 0.1004	− 0.1038	− 0.2007	− 0.0331
	(0.052)	(0.056)	(0.064)	(0.043)	(0.047)	(0.047)

Our estimation of model AR–GJR–GARCH (1,1) model is to obtain the estimated coefficients for further following estimation. Therefore, we go through some main characteristics of this model that long run persistence of shocks exists. Moreover, the risk model is consistent and asymptotically normal

$$\rho_t = \tilde{\Lambda}\left(\omega_\rho + \beta_\rho.\rho_{t-1} + \alpha.\frac{1}{m}\sum_{j=1}^{m}\Phi^{-1}\left(u_{t-j}\right).\Phi^{-1}\left(v_{t-j}\right)\right) \tag{21}$$

Then, $-1 < \rho < 1$ is our prerequisite condition whereas Φ^{-1} is the inversed function for the cumulative distribution function. Therefore, these assumptions are strictly used to build up Eq. 16. In order to keep $\rho_t \in (0, 1)\ \forall\, t$, our estimation must choose $\Lambda(x) \equiv (1 - e^{-x})(1 + e^{-x})^{-1} = \tanh(x/2)$, which follows the rules of the logistics function. Thus, we can determine any pair of variables between $\Phi^{-1}(u_{t-j})$ and $\Phi^{-1}(v_{t-j})$ to define dependence structure in ARMA (1,0). Zhang et al. (2014) refined the correlation as mentioned earlier with the matrix for time-varying copulas

$$\mathcal{Q}_t = (1-\alpha-\beta)S + \alpha\left(\varsigma_{t-1}\varsigma_{t-1}^{'}\right) + \beta\mathcal{Q}_{t-1} \tag{22}$$

Then, S is a covariance matrix of ς_t, $\alpha, \beta > 0$, $\alpha + \beta < 1$. Thus, we can interpret that

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$$

In which $q_{i,\ j,\ t}$ is a component for matrix; $\mathcal{Q}_t$ and i, j is a component for a correlation matrix with condition R_t. By employing this methodology, we can calculate the related parameters for time-varying copulas in terms of DCC copulas (t-student's distribution of Dynamic Conditional Correlation copulas), Gaussian DCC copulas (Gaussian Dynamic Conditional Correlation copulas), tv-copulas (time-varying copulas), and tv-SJC copulas (time-varying and static bivariate symmetrized Joe-Clayton copulas).

Table 7 above shows that the level of dependence structure increases after decreasing shocks. Our findings are relevant to Hansen (1994). Based on our results, there are 12

Table 7 Estimation for parameters in Time-varying Copulas model

	tDCC	GDCC	tvC	tvSJC	
Indonesia - Philippines					
v	10.776				
	(4.503)				
ω			0.0482	1.0553	1.6476
			(0.109)	(2.165)	(1.255)
α	0.0577	0.0587	−0.9909	−10	−7.5073
	(0.017)	(0.017)	(0.428)	(18.114)	(4.875)
β	0.8694	0.8689	0.6846	−0.2586	−0.5145
	(0.041)	(0.04)	(0.229)	(1.255)	(0.278)
Indonesia - Singapore					
v	14.2384				
	(8.144)				
ω			0.1018	0.2173	1.8095
			(0.048)	(0.201)	(1.423)
α	0.0408	0.0372	−0.7269	−1.2259	−9.9997
	(0.021)	(0.02)	(0.269)	(1.375)	(5.698)
β	0.9407	0.946	0.9035	0.9392	−0.8999
	(0.04)	(0.038)	(0.037)	(1.423)	(0.089)
Indonesia - Thailand					
v	13.2707				
	(5.802)				
ω			−0.9126	0.8537	1.4176
			(0.468)	(4.23)	(2.82)
α	0.0628	0.0665	−0.6241	−9.9999	−9.9996
	(0.024)	(0.025)	(0.701)	(18.601)	(13.294)
β	0.8117	0.7891	−0.2557	−0.8535	−0.575
	(0.086)	(0.095)	(0.401)	(2.82)	(0.534)
Indonesia - Vietnam					
v	20.9213				
	(13.291)				
ω			−5.1766	1.692	−9.8017
			(1.105)	(0.835)	(97.353)
α	0.034	0.0316	1.1724	−8.1776	−9.8526
	(0.016)	(0.016)	(2.839)	(4.578)	(27.844)
β	0.9022	0.9013	−0.7011	0.8758	−0.9932
	(0.047)	(0.053)	(0.716)	(97.353)	(0.071)
Indonesia - Malaysia					
v	8.8425				
	(3.124)				
ω			0.0673	0.5398	0.5078
			(0.057)	(1.047)	(1.215)
α	0.0484	0.0393	−0.6181	−6.3802	−4.7909
	(0.024)	(0.028)	(0.331)	(3.912)	(5.083)
β	0.9106	0.9224	0.886	−0.2229	− 0.9256

Table 7 Estimation for parameters in Time-varying Copulas model *(Continued)*

	tDCC	GDCC	tvC	tvSJC	
	(0.056)	(0.073)	(0.074)	(1.215)	(0.115)
Philippines - Singapore					
v	12.1766				
	(5.389)				
ω			−0.5822	−0.0496	1.1642
			(0.358)	(0.043)	(1.059)
α	0.009	0.0218	−0.7041	−9.9995	−5.0406
	(0.006)	(0.019)	(0.476)	(2.786)	(4.515)
β	0.9889	0.9593	−0.2969	−0.9022	−0.6408
	(0.012)	(0.047)	(0.468)	(1.059)	(0.432)
Philippines - Thailand					
v	39.7454				
	(33.605)				
ω			0.0041	−1.5307	1.183
			(0.065)	(1.17)	(0.646)
α	0.0096	0.01	−0.8443	1.3923	− 6.5031
	(0.006)	(0.006)	(0.368)	(2.443)	(3.028)
β	0.9869	0.9864	0.7433	0.1798	0.0854
	(0.011)	(0.011)	(0.123)	(0.646)	(0.221)
Philippines - Malaysia					
v	15.9193				
	(8.571)				
ω			−0.5876	−0.8893	0.6422
			(0.213)	(3.359)	(1.777)
α	0.0161	0.015	−0.5648	−3.5354	−4.805
	(0.007)	(0.006)	(0.62)	(14.29)	(8.759)
β	0.9741	0.9769	0.1172	−0.1835	−0.2511
	(0.013)	(0.01)	(0.159)	(1.777)	(0.749)
Philippines - Vietnam					
v	28.5507				
	(23.732)				
ω			−2.6645	−9.9998	1.6231
			(1.065)	(6343.733)	(139.05)
α	0.0135	0.0135	1.5003	9.9997	−10
	(0.008)	(0.007)	(1.72)	(16,144.394)	(652.5)
β	0.9728	0.9744	0.1475	4.3826	0.6776
	(0.017)	(0.015)	(0.201)	(139.05)	(5.633)
Singapore - Thailand					
v	9.0856				
	(3.045)				
ω			−0.404	−1.083	1.4928
			(0.299)	(1.035)	(1.001)
α	0.0211	0.0162	−2.1804	−1.6226	−9.9961
	(0.014)	(0.01)	(0.707)	(3.749)	(4.38)

Table 7 Estimation for parameters in Time-varying Copulas model *(Continued)*

	tDCC	GDCC	tvC	tvSJC	
β	0.9696	0.9786	−0.2267	−0.8683	−0.9302
	(0.03)	(0.016)	(0.268)	(1.001)	(0.039)
Singapore - Vietnam					
v	199.8059				
	(8777.354)				
ω			−4.1932	0.8938	−2.6044
			(0.687)	(0.688)	(3.556)
α	0.0194	0.0193	−1.2939	−6.1077	−8.4366
	(0.014)	(0.011)	(0.76)	(4.435)	(9.21)
β	0.9691	0.9693	−0.8946	0.7639	−0.3521
	(0.028)	(0.022)	(0.028)	(3.556)	(0.55)
Singapore - Malaysia					
v	9.4262				
	(3.191)				
ω			0.0709	1.4373	1.9502
			(0.058)	(1.236)	(1.299)
α	0.0432	0.0347	−0.6044	−9.9998	−9.0747
	(0.018)	(0.017)	(0.247)	(5.774)	(5.759)
β	0.9079	0.9161	0.8647	−0.5537	− 0.9309
	(0.042)	(0.049)	(0.049)	(1.299)	(0.054)
Thailand – Vietnam					
v	42.8752				
	(22.979)				
ω			−0.1177	−2.231	−2.6358
			(0.18)	(2.499)	(4.768)
α	0.0278	0.0275	−0.4673	−1.819	3.824
	(0.029)	(0.034)	(0.364)	(4.558)	(20.7)
β	0.9277	0.9275	0.8798	3.4432	3.1172
	(0.122)	(0.147)	(0.063)	(4.768)	(1.964)
Thailand - Malaysia					
v	8.4662				
	(2.829)				
ω			−0.9144	0.3341	1.0142
			(0.406)	(0.496)	(1.26)
α	0.0566	0.0484	−0.8585	−3.1716	−9.9998
	(0.022)	(0.021)	(0.487)	(1.937)	(5.012)
β	0.8023	0.8194	−0.2653	0.4911	−0.8431
	(0.043)	(0.046)	(0.404)	(1.26)	(0.063)
Vietnam - Malaysia					
v	18.4456				
	(10.407)				
ω			−4.2061	−1.6873	−1.7468
			(0.566)	(22.524)	(12.396)
α	0.0099	0.0097	−0.7419	−0.6685	−0.7096

Table 7 Estimation for parameters in Time-varying Copulas model *(Continued)*

	tDCC	GDCC	tvC	tvSJC	
	(0.006)	(0.006)	(0.412)	(26.549)	(7.449)
β	0.9834	0.9843	−0.8844	3.0697	2.3942
	(0.011)	(0.01)	(0.049)	(12.396)	(7.565)

Standard errors of the corresponding coefficients are reflected in square brackets. We employed the Eq. 14, 15, 16 and 17 to estimate the parameters from our existing literature

pairs over 15 couples of variables, which have t-copulas dependence structures (we make our comparisons among the three central figures Akaike, BIC, and Log-likelihood for the maximum value). There are three objectives, Indonesia – Vietnam, the Philippines – Vietnam, and the Philippines – Singapore, that share the dynamic SJC copulas trait. We can deduct in particular the probabilities of increasing or decreasing indexes.

In the period from 2001 to 2006, with the decreasing trend by time, when the Philippines index went up, the Singapore stock exchange had the probability of increasing its position by 42% initially. However, the probability of increasing was still 31% at the end of 2006. Interestingly, in the early period of the 2007 financial crisis, the level of dependence structure among these stock indexes were quite high. As regards the pair of the Philippines and Singapore, two markets were interconnected through the dynamic SJC model both in the lower and upper tails.

We also observed that the parameters in traditional copulas moved around the average value of time-varying copulas. Importantly, stock exchanges in the ASEAN region saw co-movements in each pair by time-varying copulas with the left tail (risks) and right tail. As a result, Malaysia shared a lower dependence on the other ASEAN stock indexes. In general, most pairs of stock indexes had a tail-dependence structure, which meant that when one exchange moved the other might have experienced higher probability of one side of two-side movement (increasing or decreasing).

Conclusion and implications

This study employed various methodologies such as the non-parametric (Chi-plots and K-plots) as well as copulas parametric (traditional copulas and time-varying copulas with t-student's distribution) to estimate the dependence structure of all couples of stock indexes in ASEAN countries. With the covered data from January 2001 to December 2017, our study contributes further empirical evidence for contagion risks (or spillover risks) in the transmission mechanism through equity capital flows.

Our results indicate that the level of interconnection of these indexes ranges from 0.4 to 0.5 in the different tests. However, Vietnam experienced the lowest dependence with the other economies. Therefore, during the financial crisis, the mutual influence of these regions on Vietnam was less likely to be harmful to its stock market. The main reason is that Vietnam is a child economy with monotonous financial instruments. Without derivatives and securitization development, Vietnam is isolated on the playing field of risks transmission. It is typical that independence helps Vietnam survive after financial crisis whereas Singapore, Thailand, and Malaysia have a strong relationship together with a tremendous amount of wherewithal in a difficult period.

Additionally, Malaysia represents another case of blocking capital flow in a financial crisis, which supports the country in overcoming contagion risks. The government of

Malaysia defined its structural dependence along with the other ASEAN countries; therefore, it can potentially trigger the spillover phenomenon to this economy. Although the International Monetary Fund opposes its policy due to it threatening the free flow of capital, this limitation avoids the flooding of withdrawals from foreign investors, which causes the biggest shock to this market. Recently, Chao et al. (2019) emphasized the role of the supervision process to avoid the possibility of financial crisis, which is associated with macro and micro prudential regulation. Therefore, our contribution also refers to the theoretical framework from Chao et al. (2019) to explain how Malaysia impacted financial capital flows with high dependence structure.

Furthermore, we evaluated structural interdependence by different methodologies, using both non-parametric and parametric copulas (traditional and time-varying). We come to a conclusion that copulas models with t-student's distribution are well fitted for our datasets, similarly to Hansen's study (Hansen 1994). This illustrates how there can be a small increase in the stock index after the minor shock during the financial crisis. We also present empirical findings that time-varying copulas allow users to predict the future trends of dependence structure. Thus, it constitutes premises for those who would like to foresee the co-movements from each pair in ASEAN equity markets. ASEAN countries also pertain to the theoretical and empirical works of Li et al. (2016), Zhang et al. (2019), and Kou et al. (2016) in terms of group decision-making. In particular, these countries could minimize the information losses by using a ranking formula with heterogeneous techniques for order preference by similarity. In doing so, the spillover effects could be detected before they become more severe. Therefore, we would like to employ another perspective by using copulas to capture spillover as in the published study of Kou et al. (2016).

Lastly, we identify implications for both policymakers and investors in the ASEAN region. By supervising the level of interconnection through time-varying copulas, the authorities could immediately intervene in equity markets to maintain their stable movements. This approach allows users to predict future dependence with the past and present dataset. As regards investors, this research could contribute to their techniques in constructing the optimal portfolios based on dependence parameters to define the specific weights. This also constitutes an implication for further research in the future. However, our paper has limitations that could be addressed by those who would like to expand this field, such as the omission of the United States of America and Europe stock markets as well as the other methodologies for testing including vine-copulas, Extreme Value Theory, etc. In particular, we omitted studies using more advanced quantitative techniques such as copula causality as in Dastgir et al. (2019a, b) or other performance measures such as those of Saito (2019) or Eom et al. (2019). More interestingly, the follow-up studies also employ the alternative techniques from Jiang et al. (2017) and Kou et al. (2012) such as wavelet and VMD-based copula tests and classification algorithms using MCDM and rank correlation for risk model construction. By doing this, further research could bring many contributions to the existing literature and methodology for tail dependence structure. Moreover, in order to increase the reliability of the statistical results, we also suggest that further research employ Bayesian confident interval or Bayesian methods (Maximum Bayes factor). More importantly, further work could be done with the theoretical framework from Kou et al. (2014) and Kou et al. (2019), which used clustering algorithms and machine learning to estimate systematic risk in their financial models, respectively. These methods will bridge the current gap in traditional statistical models in risk management research.

Appendix

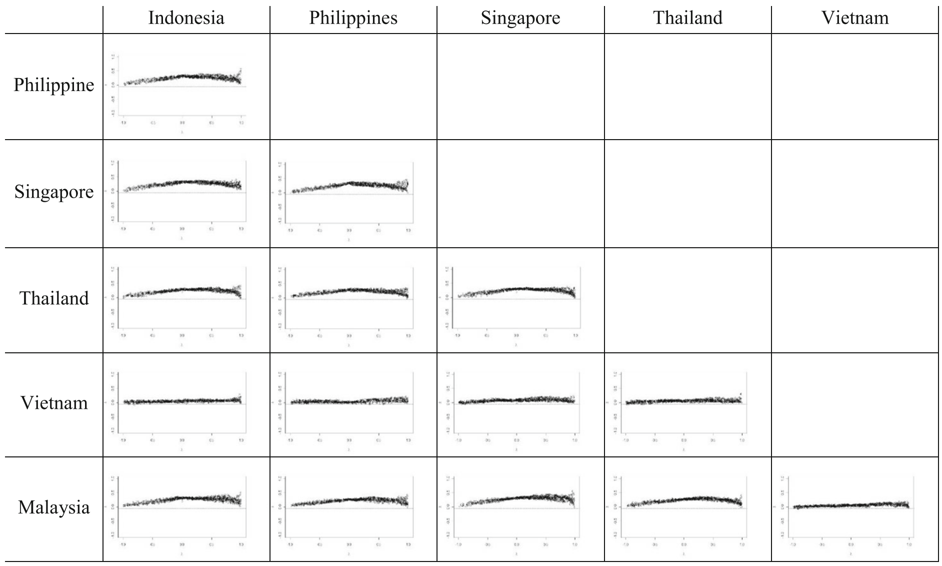

Fig. 3 Chi-plots estimation for dependency structure. In the Chi-plots, we analyze the tail dependence based on the density of plotted points on the marginal line. In case they lie more on the outside, we conclude they will depend on this side

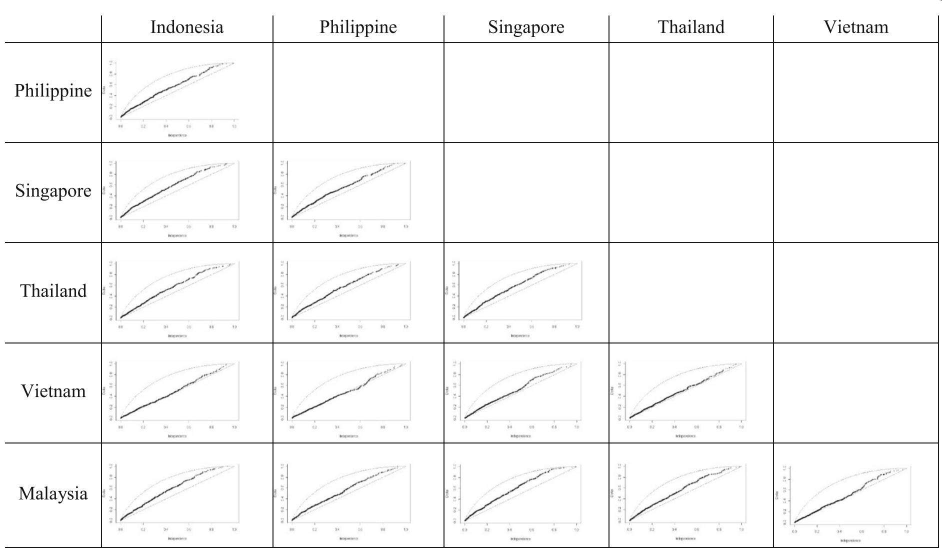

Fig. 4 K-plots estimation for dependency structure. The K-plots indicate that there is an inter-relationship between two random and continuous variables, in specific to the subject case, stock index. This can be noticed if the illustrated points do not lie along the 45-degree diagonal line at the tail of the graph, so one can conclude that these variables have mutual structural dependence

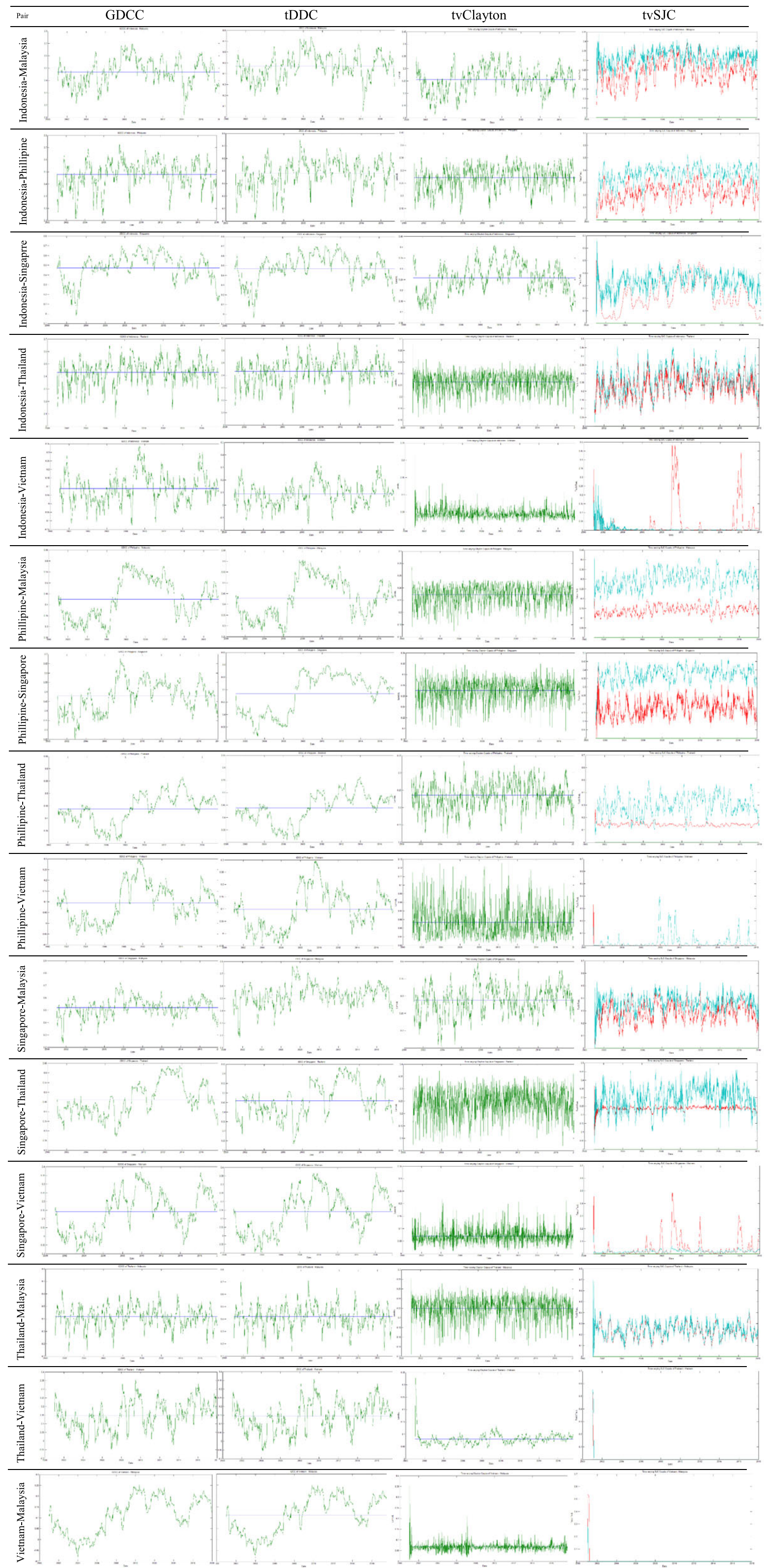

Fig. 5 Graphs for simulation Copulas with GDCC, tDDC, tvClayton, and tv-SJC for the dependence structure

Abbreviation
ASEAN: Association of South East Asian Nations

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Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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