Analyzing the Contribution of ASEAN Stock Markets to Systemic Risk

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Abstract In this paper, seven stock markets from six countries (Thailand, Malaysia, Indonesia, Vietnam, the Philippines, and Singapore) and their risk contribution to ASEAN stock system are investigated using the Component Expected Shortfall approach. Prior to computing this systemic risk measure, we need to compute a dynamic correlation, thus the study proposes a Markov Switching copula with time varying parameter to measure the dynamic correlation between each pair of stock market index and ASEAN stock system. The empirical results show that Philippines stock index contributed the highest risk to the ASEAN stock system.

Keywords Markov switching model copula · Time varying dependence · CES · ASEAN stock markets

1 Introduction

Although economic growth in ASEAN countries has been quite favorable in general, it can be disrupted or even reversed by various factors as we have witnessed from such situation as the financial crisis in 2008–2009 in Thailand or the political disorders elsewhere. These situations can be referred as a risk that might occur in the future.

After the establishment of the Association of Southeast Asian Nations (ASEAN), it is crucial to observe the roles and impacts of the seven leading ASEAN financial markets which consist of the Stock Exchange of Thailand, Bursa Malaysia, Ho Chi Minh Exchange, Hanoi Stock Exchange, the Philippine Stock Exchange, Singapore Stock Exchange, and Indonesia Stock Exchange. These stock markets can potentially

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stimulate the ASEAN economic growth for functioning as the large source of capital investment. After the formal establishment of the ASEAN Community in 2015, ASEAN countries become more integrated and thereby leading to fewer trade barriers and more collaboration among the various stock markets of ASEAN. Although cross-border collaboration of ASEAN countries can promote ASEAN stock markets and offer more opportunities to investors across the region, it can also bring a large financial risk to a country as well as across the ASEAN countries. Therefore, it will be a great benefit to the ASEAN if we can quantify the contribution of each stock market to the overall risk of the ASEAN stock system. To achieve our goal, this study considers Component Expected Shortfall (CES) concept proposed by Banulescu and Dumitrescu [1]. This new approach provides several advantages like that it can be used to assess the contribution of each stock market to the overall risk of the system at a precise date. In the real application, the study of Liu et al. [9] examined the volatility and dependence for systemic risk measurement using copula model with CES. Their work found that CES can explain the financial crisis risk in 2009 and that the risk contribution was lower in pre-crisis period when compared to the post crisis time. Hence, we expect that CES becomes a good candidate tool for policy makers to select which stock markets to monitor, with a view to discourage the accumulation of systemic risk.

Prior to measuring one-period-ahead, the time-varying correlations of ASEAN and individual stock market need to be computed. Banulescu and Dumitrescu [1] and Liu et al. [9] proposed a Dynamic conditional correlation (DDC) GJR-GARCH(1,1) model to compute conditional volatility, standardized residuals for the ASEAN and each country. However, the linear correlation and normality assumption of the model might not be appropriate and accurate for measuring the correlation between two financial markets. In reality, finance asset return has the presence of heavy tails and asymmetry correlation thus implementing DCC-GJR-GARCH may lead to inadequate CES estimation. To overcome these problems, the study proposed an alternative model, a Markov Switching dynamic copula as advanced by Silva Filho et al. [4] to compute the dynamic correlation of market pair. This model takes an advantage of the copula approach of Sklar theorem to construct the joint distribution of the different marginal distribution with different copula structure. Hence, the model becomes more flexible to capture both linear and nonlinear and both symmetric and asymmetric correlation between ASEAN and individual stock market. In addition, we also take into account the non-linearity and asymmetric dependence of the financial data since financial markets are likely to be more dependent in market downturn than in market upturn, see Chokethaworn et al. [3], Fei et al. [5], Filho and Ziegelmann [6], Pathairat et al. [12].

The rest of this paper is organized as follows: Sects. 1, 2 and 3 present the approaches that we employ in this study. In Sect. 4, we explain the data and the empirical results and Sect. 5 provides a conclusion of this study.

2 Methodology

2.1 ARMA-GARCH Model

The log-difference of each stock index (y_t) is modeled by univariate $ARMA(p, q)$ with $GARCH(1, 1)$. This study used $GARCH(1, 1)$ since it is able to reproduce the volatility dynamics of financial data, while leading to no autocorrelation in the ARMA process. In our case, the $ARMA(p, q) - GARCH(1, 1)$ (where p is the order of AR and q is the order of MA) is given by

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = h_t z_t \tag{2}$$

$$h_t^2 = \varpi + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{3}$$

where μ, ϕ_i, ψ_i, ϖ, α_1 and β_1 are the unknown parameters of the model, ε_t is the white noise process at time t, h_t^2 is the variance of error at time t, z_t is standardized residuals and it must satisfy the condition of being independently and identically distributed. We also assume that ε_t has a student-t distribution with mean 0, variance σ^2, and degree of freedom ν, i.e., $\varepsilon_t \sim t(0, \sigma^2, \nu)$. Some standard restrictions on the GARCH parameters are given such that $\varpi > 0, \alpha_1 > 0, \beta_1 > 0$ and $\alpha_1 + \beta_1 < 1$.

2.2 Conditional Copula Model

Sklar theorem showed a way to construct a joint distribution function using copula approach. By the theorem, let H be the joint distribution of random variable $(x_1, x_2, ..., x_n)$ with marginals $F_1(x_1), F_2(x_2), ..., F_n(x_n)$, then the joint cumulative distribution function (cdf) can be represented according to

$$H(x_1, x_2, ..., x_n) = C(F(x_1), F_2(x_2), ..., F_n(x_n)) \tag{4}$$

when $F_i(x)$ are continuous functions, then Eq. (1) provides a unique representation of cdf for any random variables or Copula is unique. In this study, we aim to analyze the dynamic dependence of two dimension copula, therefore, according to Pattan (2006), we can rewrite (Eq. 4) in the form of conditional copula such that

$$H(x_1, x_2 |\omega) = C(F_1(x_1 |\omega), F_2(x_2 |\omega)) \tag{5}$$

where ω is a 1 dimension conditioning variable of x_1 or x_2 and F_1 and F_2 become the conditional distribution of $x_1 \,|\omega$ and $x_2 \,|\omega$, respectively. Thus, we can obtain the conditional density function by differentiating (Eq. 5) with respect to x_1 and x_2.

$$\begin{aligned} h(x_1, x_2 \,|\omega) &= \frac{\partial^2 H(x_1, x_2 \,|\omega)}{\partial x_1, x_2} \\ &= \frac{\partial F_1(x_1 \,|\omega)}{\partial x_1} \cdot \frac{\partial F_2(x_2 \,|\omega)}{\partial x_2} \cdot \frac{\partial^2 C(F_1(x_1 \,|\omega), F_2(x_2 \,|\omega) \,|\omega)}{\partial u_1 \partial u_2} \\ &= f_1(x_1 \,|\omega) \cdot f_2(x_2 \,|\omega) \cdot c(u_1, u_2 \,|\omega) \end{aligned} \tag{6}$$

where $u_1 = F_1(x_1 \,|\omega)$ and $u_2 = F_2(x_2 \,|\omega)$ and these marginal distributions (u_1, u_2) are uniform in the [0, 1]. In this dynamic case, Patton (2006) suggested allowing the dependence parameter (θ_t) to vary over time in the ARMA (1,10) process, as follows:

$$\theta_t = \Lambda(a + b\theta_{t-1} + \varphi \Gamma_t) \tag{7}$$

where $\Lambda(\cdot)$ is the logistic transformation for each copula function, a is the intercept term, b is the estimated coefficient of AR and Γ_t is the forcing variable which is defined as

$$\Gamma_t = \begin{cases} \frac{1}{10} \sum_{j=1}^{10} F_1^{-1}(u_{1,t-j}) F_2^{-1}(u_{2,t-j}) & elliptical \\ \frac{1}{10} \sum_{j=1}^{10} \left| u_{1,t-j} - u_{2,t-j} \right| & Archimedean \end{cases}$$

In the Copula model, there are two main classes of the copulas namely, Elliptical class and Archimedean class. Both classes contain copula families that are used to join the marginal distribution. In the case of Elliptical copula, there are two symmetric copula families consisting Gaussian and the Student-t copulas. Both families have a similar structure except for their tail dependence. The Student-t copula has shown to be generally superior to the Normal copula since it has tail dependence. As for the Archimedean case, it is an alternative class of copulas with asymmetric tail dependence, meaning that dependence in lower tail can be larger than dependence in upper tail and vice-versa.

In the most recent development, there are many copula functions being proposed to join the marginal distribution; see, e.g., [2, 8]. In this study, we consider 5 conditional copula families consisting Gaussian copula, Student-t copula, Gumbel copula, Clayton copula, and Symmetrized JoeClayton (SJC) copula to analyze the structure of dependence between each stock market and ASEAN market (see the copula functions in Tofoli et al. [15].

2.3 Regime-Switching Copula

There are many evidences regarding financial returns tending to exhibit different patterns of dependence such as those from the works of Silva Filho et al. [4], Tofoli et al. [15], and Pastpipatkul et al. [12]. These studies arrived at similar conclusion that stock markets exhibit the different degree of dependence over time and Tofoli et al. [15] specifically mentioned that stock returns tend to be more dependent during crisis period or high volatility period while likely to be less dependent in the market upturn or low volatility period. For these reasons, the dependence structure of the variables may be determined by a hidden Markov chain with two states (Tofoli et al. [15]). Hence, in this study, it is reasonable to extend the time varying copula of Patton [14] to the Markov Switching of Hamilton [7] and thus we have a Markov-switching copula with time-varying dependence (MS-Cop) to model dependence parameter (θ_t). The study allows the (θ_t) to vary across the economic regime, say the upturn market (regime 1) and downturn market (regime 2). Thus, θ_t is assumed to be governed by an unobserved variable (S_t).

$$\theta_t = \theta_{t(S_t=1)} + \theta_{t(S_t=2)} \tag{8}$$

where $\theta_{t(S_t=1)}$ and $\theta_{t(S_t=2)}$ are time varying dependence parameter for regime 1 and regime 2, respectively. Thus, when the regime switching is taken into account in dependence parameter, then we can rewrite the dynamic function with ARMA(1,10) process Eq. (7) for two regimes as

$$\begin{aligned}
\theta_{(S_t=1),t} &= \Lambda(a_{(S_t=1)} + b\theta_{(S_t=1),t-1} + \varphi\Gamma_t) \\
\theta_{(S_t=2),t} &= \Lambda(a_{(S_t=2)} + b\theta_{(S_t=2),t-1} + \varphi\Gamma_t)
\end{aligned} \tag{9}$$

where there is only intercept term of time varying (Eq. 9) $a_{(S_t=i)}, i = 1, 2$, that is governed by state. In this study, the unobservable regime ($S_t = 2$) is governed by the first order Markov chain, meaning that the probability of this time t is governed by $t - 1$, hence, we can write the following transition probabilities (P):

$$p_{ij} = Pr(S_t = j | S_{t-1} = i) \quad and \quad \sum_{j=1}^{2} p_{ij} = 1 \qquad i, j = 1, 2 \tag{10}$$

where p_{ij} is the probability of switching from regime i to regime j, and these transition probabilities can be formed in a transition matrix P, as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} = 1 - p_{11} \\ p_{21} = 1 - p_{22} & p_{22} \end{bmatrix} \tag{11}$$

2.4 Copula Likelihood Estimation

Since the computation of the ML estimate may be difficult to find the optimal solution for a large number of unknown parameters, the two-stage maximum likelihood (ML) approach, as proposed by Patton [14] and Tofoli et al. [15], is conducted in this study to estimate the MS-Cop model. In the first step, we estimate and select the parameters of the best fit marginal distributions for individual variables from ARMA(p,q)-GARCH process. In the second step, we estimate the dependence structure of the MS-Cop. According to (Eq. 6), let $\Theta = \{\omega_1, \omega_2, \theta_t\}$ we can derive the likelihood function of a single regime conditional copula as

$$L(\Theta\, |x_1, x_2) = f_1(x_1\, |\omega_1) \cdot f_2(x_2\, |\omega_2) \cdot c(u_1, u_1\, |\theta_t)$$

where $f_1(x_1\, |\omega_1)$ and $f_2(x_2\, |\omega_2)$ are the density function of the marginal distribution which are assumed to be fixed obtaining from ARMA(p,q)-GARCH process in the first step. $c(u_1, u_2\, |\theta_t)$ is the density function of the conditional copula. Note that the study is considering two-regime MS-Cop, thus we can rewrite the single regime conditional copula to be two-regime MS-Cop as:

$$\begin{aligned} & L(\Theta_{S_t}\, |x_1, x_2) \\ & = \sum_{t=1}^{T} \log\left[\sum_{S_t=1}^{2} [f_1(x_1\, |\omega_1) \cdot f_2(x_2\, |\omega_2) \cdot c(u_1, u_2\, \left|\theta_{(S_t=i),t}\right.)] \cdot \Pr(S_t = i\, |\xi_{t-1})\right] \end{aligned} \quad (12)$$

where $Pr(S_t = i\, |\xi_{t-1})$ is the filtered probabilities and ξ_{t-1} is the all information up to time $t-1$, $\Phi_{S_t,t-1}, x_{1,t-1}, x_{2,t-1}$. To compute the $Pr(S_t = i\, |\xi_{t-1})$, we employ a Kims filter as described in Kim and Nelson [11]. The estimation in this second step is performed by maximizing the copula log-likelihood Eq. (12).

3 Component Expected Shortfall

In this section, we introduce a Component Expected Shortfall (CES) which is proposed in Banulescu and Dumitrescu (2012). We apply the MS-Cop to CES in order to assess the contribution of an individual stock in ASEAN to the risk of the ASEAN stock system at a precise date. Let r_{it} denote the return of stock index i at time t and r_{mt} denote the aggregate return of the ASEAN stock index at time t.

$$r_{mt} = \sum_{i=1}^{n} w_{it} \cdot r_{it} \quad (13)$$

where w_{it} is an individual weight the value-weighted of stock index i, $i = 1, ..., n$, at each date under analysis. These weights are given by the relative of stock index i capitalization to ASEAN stock system. And CES is defined as the part of Expected Shortfall (ES) of the ASEAN stock index due to ith stock index

$$\begin{aligned} CES_{it} &= \frac{w_{it}\partial ES_{m,t-1}(C)}{\partial w_{it}} \\ &= -w_{it}E_{t-1}(r_{it}\,|r_{mt} < C) \end{aligned} \tag{14}$$

where $E_{t-1}(r_{it}\,|r_{mt} < C) = \partial ES_{m,t-1}(C)/\partial w_{it}$ is the Marginal Expected Shortfall (MES) which measures the marginal contribution of individual stock index to the risk of the ASEAN stock index.

$$\begin{aligned} MES_{mt} &= \left[h_{it} \cdot \kappa_{it} \frac{\sum_{t=1}^{T} \Upsilon_{mt} \Phi(\frac{C-\Upsilon_{mt}}{h_{mt}})}{\sum_{t=1}^{T} \Phi(\frac{C-\Upsilon_{mt}}{h_{mt}})} \right] \\ &+ \left[h_{it} \cdot \sqrt{1-\kappa_{it}} \frac{\sum_{t=1}^{T} e_{it} \Phi(\frac{C-\Upsilon_{mt}}{h_{mt}})}{\sum_{t=1}^{T} \Phi(\frac{C-\Upsilon_{mt}}{h_{mt}})} \right] \end{aligned} \tag{15}$$

where $\Upsilon_{mt} = r_{mt}/h_{mt}$ and $e_{it} = (r_{it}/h_{it}) - \kappa_{it}$ are standardized ASEAN market return and stock index i, which h_{mt} and h_{it} are the variance of error at time t. $C = 1/h_{mt}$ is the threshold value which is assumed to depend on the distribution of the r_{mt}. Φ is the cumulative normal distribution function and κ_{it} is the time varying Kendall s tau which can be tranformed from the expected dependence parameter $(E\kappa_t)$,

$$E\kappa_t = \sum_{j=1}^{2} [\kappa_{(S_t=j),t}] \cdot [Pr(S_t = j\,|\xi_{t-1}) \times P]$$

However, our study aims to assess the contribution of risk of each stock market to the ASEAN stock system, thus it is better to measure the risk in terms of percentage by

$$CES_{it}\% = (CES_{it}/\sum_{i=1}^{n} CES_{it}) \times 100$$

4 Data and Empirical Results

In this study, we use the data set comprising the Stock Exchange of Thailand index (SET), Indonesia Stock Exchange index (IDX), the Philippine Stock Exchange (PSE), Bursa Saham Kuala Lumpur Stock Exchange (BURSA), Straits Times stock index (STI), Ho Chi Minh Stock Index (HOC) and Hanoi Stock Exchange index(HN). The data set consists of weekly frequency collected from the period of January 1, 2009 to June 8, 2016, covering 388 observations. All the series have been transformed into the difference of the logarithm. And the ASEAN market index is based

Table 1 Descriptive statistics on ASEAN index

	SUM ASEAN	SET	IDX	BURSA	STI	HOC	HN	PSEI
Mean	0.0029	0.0032	0.0035	0.0016	0.0015	0.0025	0.0026	0.0037
Med	0.004	0.0059	0.004	0.002	0.0024	0.0022	0.0034	0.0047
Max	0.0975	0.0994	0.099	0.0568	0.1639	0.1202	0.1066	0.0913
Min	−0.0738	−0.1	−0.108	−0.0694	−0.104	−0.1633	−0.1498	−0.1287
Std.	0.0189	0.025	0.0238	0.015	0.0228	0.0335	0.0322	0.0251
Skew	−0.0991	−0.3708	−0.2792	−0.3585	0.6942	−0.1913	−0.1327	−0.5563
Kurtosis	6.3125	4.7446	5.9074	5.3807	10.8985	5.1584	5.0532	6.0172
JB	174.360*	56.895*	138.774*	97.8811*	1018.303*	76.082*	67.861*	163.742*
ADF-test								
None	−17.561*	−19.097*	−19.446*	−19.042*	−18.391*	−17.837*	−17.780*	−20.475*
Intercept	−17.935*	−19.396*	−19.854*	−19.261*	−18.456*	−17.904*	−17.867*	−20.927*
Intercept and Trend	−18.331*	−19.742*	−20.403*	−19.738*	−18.782*	−17.943*	−17.924*	−21.135*

Source Calculation
Note: * is significant at 1% level

on the stocks in only the seven stock markets of our interest. The computation of this index is defined as the value-weighted average of all stock index returns.

4.1 Modeling Marginal Distributions

For the first state, we use each ASEAN indexes prices to calculate the natural log returns defined as $r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1})$ where $P_{i,t}$ is the ith index price at time t, and $r_{i,t}$ is the ith log return index price at time t. The descriptive statistics of ASEAN returns are shown in Table 1 which is clear that mean of each ASEAN variable is positive with the highest mean returns being PSEI (0.0037), the lowest mean return being STI (0.0015), and that the standard deviation in HOC is the highest (0.0335) and that in BURSA the lowest (0.0150). In terms of skewness and kurtosis, the values of skewness are small but the values of kurtosis are large. So these mean that the distributions of ASEAN returns have fatter tail instead of normal distribution and Jaque-Bera test rejected the null hypothesis, thus the return series has non-normal distribution.

Moreover, in order to check unit roots in the series, the Augmented Dickey-Fuller (ADF) tests are applied. The test results at 0.01 statistical significance level 0.01 indicated that all series of ASEAN returns are stationary. Table 2 presents the coefficient for the ARMA(p,q)-GARCH(1,1) with student-t distribution for each ASEAN return series. The optimum lag for ARMA(p,q)-GARCH(1,1) is selected by the minimum Akaike information criterion (AIC) and Bayesian information criterion (BIC) value. The estimated equations of SUM ASEAN, SET, and IDX are

Table 2 Estimate of ARMA(q,p)-GARCH(1,1) in student-t distribution

	SUM ASEAN	SET	IDX	BURSA	STI	HOC	HN	PSEI
μ	0.004***	0.001	0.002	0.002***	0.002*	0.001	0.001*	0.005
	(−0.001)	(−0.001)	(−0.001)	(−0.001)	(−0.001)	(−0.001)	(−0.001)	(−0.001)
AR(1)	0.391***	0.562***	0.603***	−1.353***	−0.909***	0.911***	0.905***	−1.066***
	(−0.033)	(−0.045)	(−0.059)	(−0.014)	(−0.023)	(−0.029)	(−0.024)	(−0.055)
AR(2)	0.328***	−0.256***	0.522***	−0.958***	−0.891***	–	–	−0.117**
	(−0.044)	(−0.049)	(−0.054)	(−0.014)	(−0.021)			(−0.049)
AR(3)	−0.904***	0.657***	−0.155***	–	–	–	–	–
	(−0.034)	(−0.044)	(−0.054)					
MA(1)	−0.398***	−0.575***	−0.708***	1.395***	0.974***	−0.951***	−0.950***	0.974***
	(−0.025)	(−0.016)	(−0.016)	(−0.011)	(−0.003)	(−0.027)	(−0.024)	(−0.018)
MA(2)	−0.336***	0.291***	−0.454***	0.982***	0.990***	–	–	–
	(−0.033)	(−0.014)	(−0.005)	(−0.011)	(−0.002)			
MA(3)	0.957***	−0.710***	0.173***	–	–	–	–	–
	(−0.024)	(−0.020)	(−0.004)					
ω	0.000*	0.000**	0.000*	0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α	0.154**	0.219***	0.138**	0.115**	0.098**	0.048**	0.026*	0.073**
	(−0.062)	(−0.082)	(−0.058)	(−0.056)	(−0.041)	(−0.023)	(−0.015)	(−0.036)
β	0.790***	0.643***	0.809**	0.802***	0.861***	0.936***	0.971***	0.879***
	(−0.073)	(−0.113)	(−0.067)	(−0.095)	(−0.044)	(−0.032)	(−0.016)	(−0.055)
ν	5.009***	9.892***	4.554***	4.360***	4.637***	7.205***	7.139***	5.191***
	(−1.305)	(−5.053)	(−1.208)	(−1.195)	(−1.021)	(−2.319)	(−2.480)	(−1.335)
AIC	−5.3193	−4.689	−4.843	−5.722	−5.076	−4.102	−4.246	−4.677
BIC	−5.2046	−4.575	−4.729	−5.628	−4.982	−4.029	−4.174	−4.594
$Q^2(10)$	0.4154	0.2548	0.2478	0.2448	0.5784	0.9854	0.8845	0.5946
KS-test	0.5757	0.6584	0.5447	0.9871	0.9844	0.4354	0.8841	0.6844

Source Calculation
Note: (1) *, **, and *** denote significant at 90, 95 and 99%, respectively
(2) In the bracket is standard error

ARMA(3,3)-GARCH(1,1), BURSA and STI are ARMA(2,2)-GARCH(1,1), VI and VAI are ARMA(1,1)-GARCH(1,1), and PSEI is ARMA(2,1)-GARCH(1,1). Furthermore, the coefficient of each equation is statistically significant at 1% in most cases which means that the t distribution assumption for ARMA-GARCH model is reasonable.

In addition, the autocorrelation test (LjungBox test) and the KolmogorovSmirnov test (KS-test) are also shown in this table. The p-value of the KS-test suggests that the probabilities of the integral transform of the standardized residuals are uniform in the [0, 1] interval. Additionally, the p-value of the LjungBox-test of autocorrelation on standardized residuals with 10 lags, $Q^2(10)$, confirms that we cannot reject the 5% significance level; thus, there is no autocorrelation in any of the series.

4.2 Model Fit

MS-Cop models are estimated by different copula functions, and selection of the most appropriate structure dependence between each pair in this section is based on the lowest Akaiki information criterion (AIC) and Bayesian information criterion (BIC). Table 3 presents various copula functions of MS-Cop model. It contains the AIC and BIC for each copula model. These are evaluated at the highest value of copula log likelihood. The result showed that Clayton copula yields the lowest AIC and BIC for IDX-ASEAN pair, STI pair, and PHI-pair; while for SET-ASEAN, BURSA-ASEAN, HOC-ASEAN, and HN-ASEAN pairs, Gumbel copula provides the best structural fit.

Table 3 Family selection of each pair copula

AIC BIC	SET ASEAN	IDX ASEAN	BURSA ASEAN	STI ASEAN	HOC ASEAN	HN ASEAN	PHI ASEAN
Gaussian	225.2815	374.7991	212.0398	313.8305	56.7444	53.3816	536.4979
	248.8749	398.3925	235.6333	337.424	80.3379	76.9751	560.0914
Student- t	236.8088	382.0257	218.9943	336.3531	56.6692	56.6692	542.4576
	268.2667	413.4837	250.4523	367.811	88.1271	88.1271	573.9156
Clayton	211.3228	305.5207	187.2049	282.9581	46.2591	45.8371	439.9532
	234.9163	329.1142	210.7983	306.5516	69.8526	69.4306	463.5466
Gumbel	192.52	333.1427	180.1803	297.4253	51.0105	45.0553	447.7723
	216.1134	356.7362	203.7738	321.0088	74.604	68.6487	471.3658
SJC	255.0907	381.9507	226.8514	342.2112	69.2851	63.4991	527.4651
	294.4132	421.2731	266.1739	381.5336	108.6076	102.8216	566.7876

Source Calculation

4.3 Results of Estimated Parameters

Table 4 reports the estimated parameters of the MS-Cop for seven pairs of market returns. The models present a dynamic copula equation and the result showed that all stock pairs provide an evidence of the lower value of intercept coefficient in regime 1, $a_{(S_t=1)}$, than the value of the regime intercept coefficient in regime 2 $a_{(S_t=2)}$. Thus, we can interpret regime 1 as the low dependence regime, while regime 2 as the high dependence regime. Moreover, many recent studies, such as the studies by Tofoli et al. [15] and Karimalis and Nimokis [10], suggested that the degree of dependence during market upturns is less than that during market downturns. Thus, we will indicate the high dependence regime as the market downturn regime and the low dependence regime as the market upturn regime. Furthermore, we take into consideration the estimated coefficient, b, which is related to the autoregressive parameter component in the dynamic equation. Different results have been obtained from these coefficients. We found that the autoregressive parameter components of $c_{set,Asean}$, $c_{bursa,Asean}$, $c_{hoc,Asean}$, $c_{hn,Asean}$, and $c_{psi,Asean}$ have a negative sign, indicating that those pair relations are persistent over time, while the autoregressive parameter components of $c_{idx,Asean}$ and $c_{sti,Asean}$ have a positive sign, indicating that those pair relations are not persistent over time. As for the distance from the perfect correlation in the dependence dynamics co-movement, φ, the results also provide a different sign for each pair return. We found that the φ of $c_{set,Asean}$, $c_{idx,Asean}$, $c_{bursa,Asean}$, $c_{sti,Asean}$, and $c_{psi,Asean}$ has a negative sign, indicating that the greater distance from the perfect correlation can decrease their dependence, while the φ of $c_{hoc,Asean}$ and $c_{hn,Asean}$ has a positive sign, indicating that the greater distance from the perfect correlation can increase their dependence.

In addition, the transition probabilities p_{11} and p_{22} of all pair dependences are also reported in Table 4. We denote the probabilities p_{11} and p_{22} as the probabilities of

Table 4 Estimated parameters from Markov-switching dynamic copula

	$c_{set,Asean}$	$c_{idx,Asean}$	$c_{bursa,Asean}$	$c_{sti,Asean}$	$c_{hoc,Asean}$	$c_{hn,Asean}$	$c_{psi,Asean}$
$a_{(S_t=1)}$	1.7228	1.5386	1.599	1.282	0.2374	0.4255	1.8777
	(−0.0673)	(−0.4746)	(−0.0698)	(−0.0737)	(−0.4384)	(−0.0539)	(−0.583)
$a_{(S_t=2)}$	4.53	2.6278	4.9678	3.3328	6.801	10.6893	6.0509
	(−0.0001)	(−0.9729)	(−0.0002)	(−2.769)	(−22.582)	(−0.0001)	(−6.7414)
b	−0.3592	0.047	−0.3904	0.0773	−0.1345	−0.0857	−0.0289
	(−0.0001)	(−0.1854)	(−0.0001)	(−0.0826)	(−0.4144)	(−0.0041)	(−0.1807)
φ	−1.2757	−1.8663	−0.5262	−0.7013	0.1472	0.5014	−1.4553
	(−0.0001)	(−0.4534)	(−0.0045)	(−0.8727)	(−0.9533)	(−0.4512)	(−0.1541)
Transition probabilities							
p_{11}	0.9992	0.9999	0.9799	0.9999	0.9999	0.9999	0.9999
p_{22}	0.9987	0.9999	0.9984	0.9999	0.9999	0.9999	0.9999

Source Calculation
Note: In the bracket is standard error

staying in their own regime. We can observe that both regimes are persistent because of the high values obtained for the probabilities p_{11} and p_{22}.

4.4 Risk Measure

To achieve our goal of study, in this section, we extend our results obtained from the MS-Cop to assess the contribution of individual stock market to systemic risk at time. The study employed CES approach as a tool to assess the percentage of each stock markets contribution to the risk of the ASEAN stock system. The analysis is performed for almost eight years of samples from 2009 to 2016, coinciding with the period of Hamburger crisis of the United States of America (USA) (2009) and European debt crisis (2002-present). The study of Pastpipatkul et al. [13] investigated and found the effect of these crises on some countries in the ASEAN. Therefore, it is reasonable to measure the contribution of risk under these periods in order to check whether CES can identify the systemic financial risk or not.

As we mentioned in the introduction, the main purpose of the study is to access to contribution of each stock index to the ASEAN stock system. We also aim to identify the riskiest of the seven stock markets in the ASEAN by directly ranking the markets according to their CES%. According to Figs. 1, 2, 3, 4, 5, 6 and 7, these figures display the expected dependence (measured by Kendall tau) between individual stock index and the ASEAN stock system (upper panel); and the percentage of each

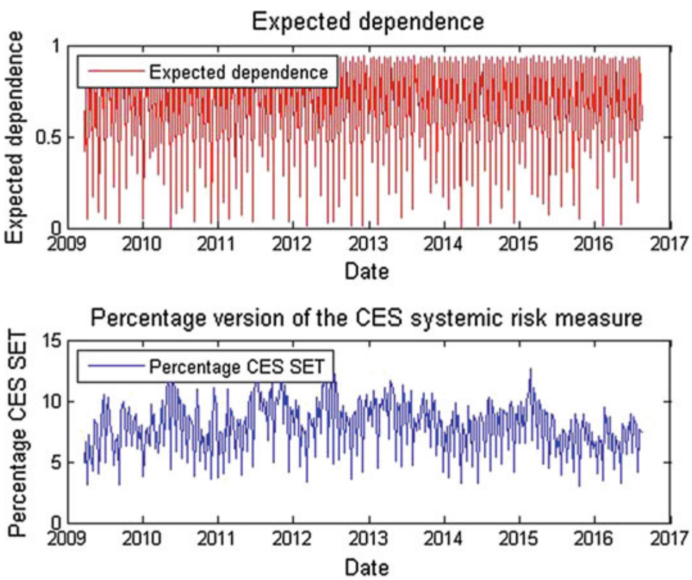

Fig. 1 CES SET

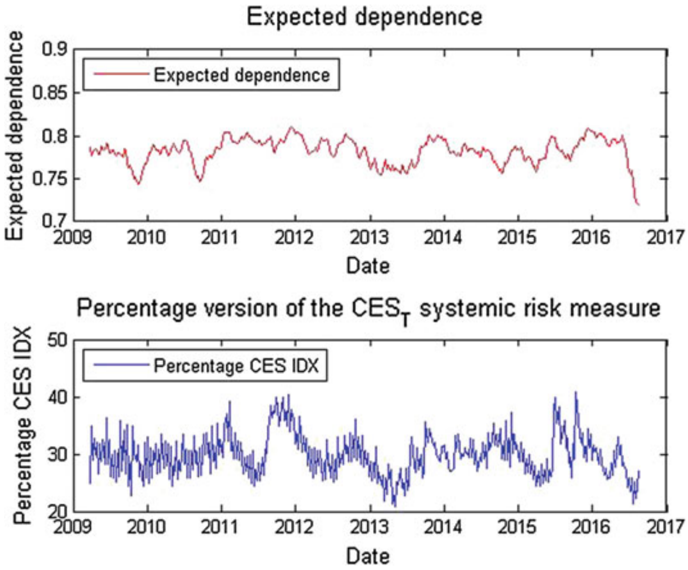

Fig. 2 CES IDX

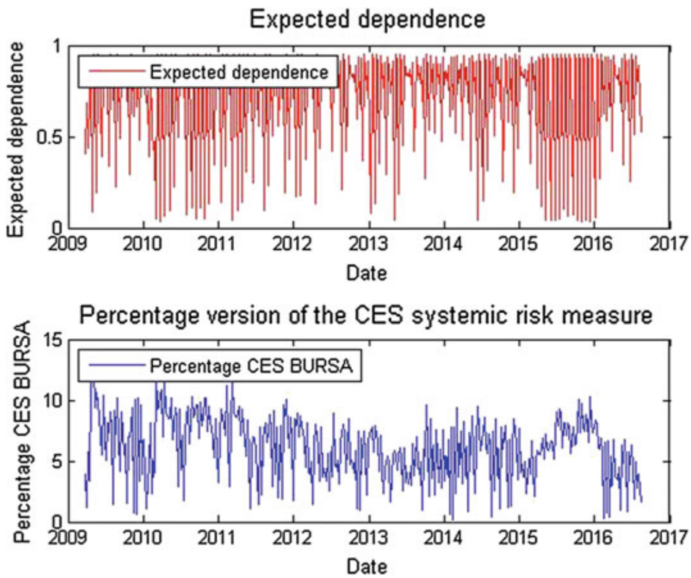

Fig. 3 CES BURSA

individual stock index in the risk of the ASEAN market system (measured by CES). Let consider the upper panel of all pairs, the results show that the expected dependencies are varying over time and provide an evidence of positive dependence. These

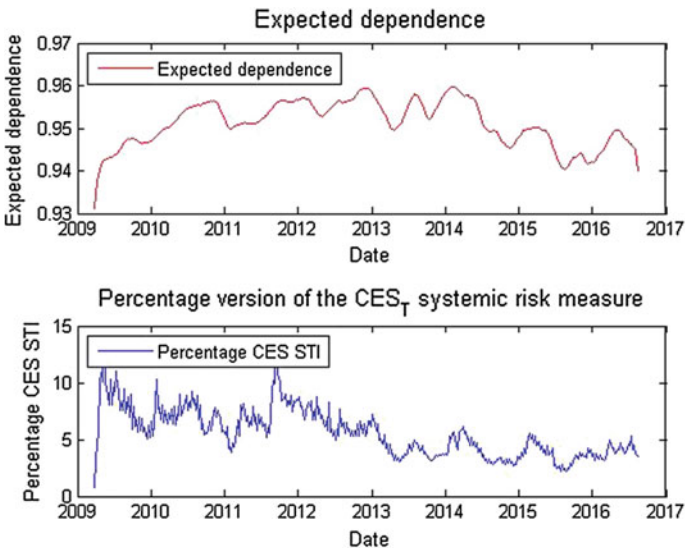

Fig. 4 CES STI

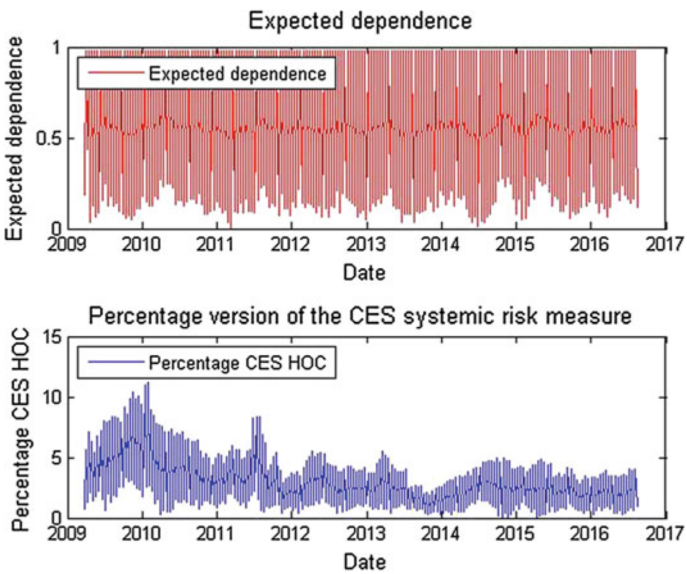

Fig. 5 CES HOC

indicate that ASEAN stock markets have the same movement direction throughout the sampling period. However, we can obviously notice that the time varying Kendalls tau, which was obtained from the estimated bivariate time varying dependence copula parameters, shows different results regarding correlation. The results of

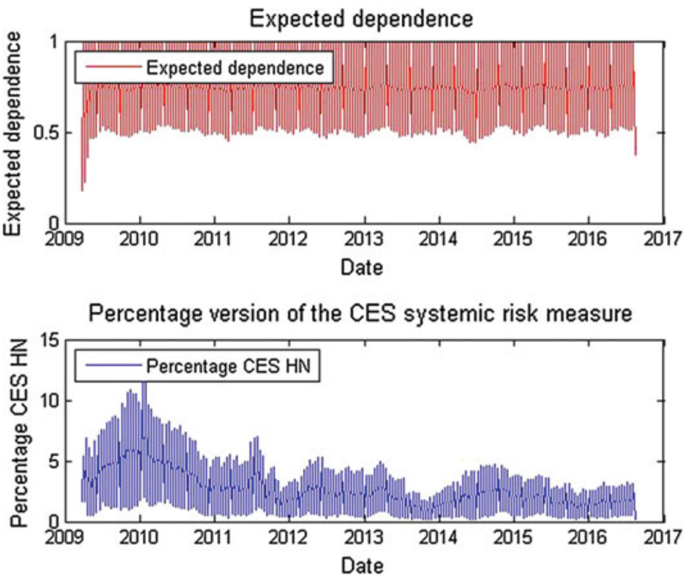

Fig. 6 CES HN

ASEAN-SET, ASEAN-BURSA, ASEAN-HOC, and ASEAN-HN pairs illustrate a highly fluctuating correlation over time where the values vary between 0.1–1, except for the ASEAN-HN where the value of time varying Kendalls tau varies between 0.5–1. Meanwhile ASEAN-IDX, ASEAN-STI, and ASEAN-PHI seem to have a lower fluctuating correlation where the values vary between 0.2–0.6, 0.93–0.96, and 0.2–0.5 for ASEAN-IDX, ASEAN-STI, and ASEAN-PHI, respectively. These evidences can be explained in various ways. Firstly, our results confirm that there exists a different degree of dependence between individual stock index and ASEAN stock system over time. Secondly, there is a positive co-movement between individual stock index and ASEAN stock system.

Then, let consider the lower panel of Figs. 1, 2, 3, 4, 5, 6 and 7 which presents the total loss of ASEAN stock system attributable to the seven stock markets for the period 2009–2016. There are several interesting findings that can be observed when we focus on the individual stock market results. We can observe that during 2008–2009 ASEAN-BURSA, ASEAN-STI, ASEAN-HOC, and ASEAN-HN seem to contribute a higher risk to ASEAN stock system when compared with their overall usual risk. This period coincides with the time of Hamburger financial crisis in USA. During 2009–2016, many emerging stock markets including ASEAN stock markets have experienced great growth after the crisis in 2008 since the Federal Reserve of USA introduced an unconventional Quantitative easing (QE) policy that led to a capital outflow from USA to the emerging markets. However, this large capital brought somewhat unwelcome pressure on stock price and a high volatility in the markets as well. In addition, we observe that CES% is also high in the periods of

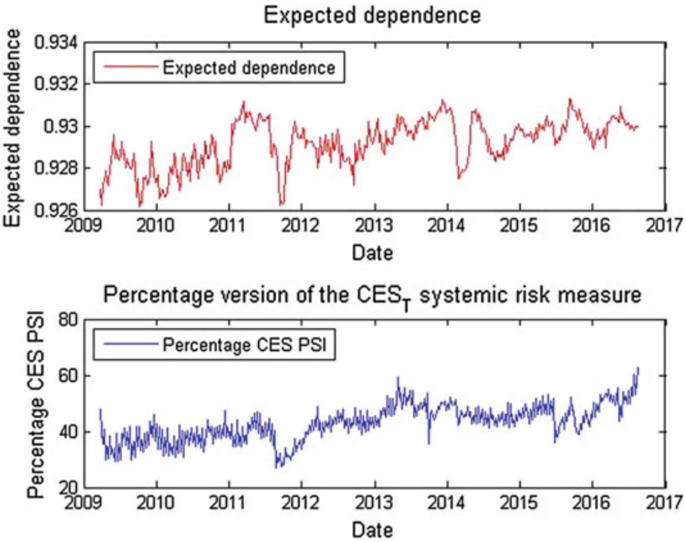

Fig. 7 CES PSI

2012 and 2014 in the cases of SET, IDX, PHI, and STI market indexes. We found that those two sub-periods are corresponding to the European debt crisis in 2012 and QE tapering in 2014. If we consider the amplitude of CES% in these two periods; in the first sub-period, we can see that PSI and IDX contribute the highest risk to the overall ASEAN stock system while HOC and HN contribute the lowest risk to ASEAN. In the second sub-period, we also observe that PSI is the highest risk contributor to the ASEAN stock system with the value of CES% more than 50%. The further interesting results of HOC and HN are also obtained. The evolution of CES% in these two markets perform similar level of contribution to the ASEAN financial risk. This can indicate that Vietnam stock markets seemed not affected by external factors or they had low interaction with global financial market as well as the ASEAN. Moreover, we notice that the evolution of CES% of these two countries took place very often and exhibited very high fluctuation. Consequently, decision about Vietnams stock regulations has to be made very often.

5 Conclusion

This study aims to assess the risk contribution of seven ASEAN stock markets to the aggregate ASEAN stock system. It is very important to analyze this issue because it may have significant implications for the development of ASEAN stock market and the regulation of the markets and their mechanisms. Thus, the study employed a

Component Expected Shortfall (CES) measure proposed by Banulescu and Dumitrescu [1] as a tool for assessing the contribution of each stock market to the overall risk of the ASEAN stock system. Instead of using the DCC-GARCH model to measure the dynamic correlation, the present study aims to relax the strong assumption of linear and normal correlation by using the copula approach. Thus, the study proposed to employ a Markov Switching copula with time varying parameter as a tool to measure the dependence between individual stock index and ASEAN stock system and the obtained best fit dependence parameters are used to compute the time varying correlation Kendall's tau.

Our findings on the degree of dependence are in line with previous findings in the literature. However, we clearly show that the degree of dependence can vary over time and the regime switching needs to be taken into account. In addition, the time varying risk contribution is considered here. We found that the Philippines stock index contributed the highest risk to the ASEAN stock system. Our results are very important to the policy makers or the regulators of each stock market since they can impose a specific policy to stabilize their stock markets when the financial risk is likely to occur. Moreover, our result will give a benefit to the investors by helping them to invest their money in the appropriate stock market.

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