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Abstract This paper aims at analyzing the financial risk and co-movement of stock markets in three countries: Indonesia, Philippine and Thailand. It consists of analyzing the conditional volatility and test the leverage effect in the stock markets of the three countries. To capture the pairwise and conditional dependence between the variables, we use the method of vine copulas. In addition, we illustrate the computations of the value at risk and the expected shortfall using Monte Carlo simulation with copula based GJR-GARCH model. The empirical evidence shows that all the leverage effects add much to the capacity for explanation of the three stock returns, and that the D-vine structure is more appropriate than the C-vine one for describing the dependence of the three stock markets. In addition, the value at risk and ES provide the evidence to confirm that the portfolio may avoid risk in significant measure.

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1 Introduction

Southeast Asia has emerged as the new Asian tiger at a time when China's economic growth is on the wane. Even if the global economy takes a downturn, as before, the IMF has constantly forecast that the economic growth will be about 6.1% in 2013 for Indonesia, Malaysia, the Philippines, Thailand, and Vietnam.

Regardless of economic downturn or economic prosperity, the Southeast Asian countries maintain consistency for instance, the GDPs of Thailand, the Philippines, and Indonesia decreased by 40.0%, 83.4%, and 37.3%, respectively, during the Southeast Asian financial crisis. Even though in recent years, the growth in the Southeast Asian countries has been impressive for example, the GDPs of Thailand, the Philippines, and Indonesia was on a year-on-year increase of 5.9%, 6.6%, and 6.1%, respectively, in 2012. Southeast Asias booming economy has also led to the prosperity of the stock market. In 2012, the Philippine benchmark stock index rose 29.8%, Indonesias stock market rose 12.6%, and Thailands stock market was up 30%. In addition, the Thailand SET Index earnings per share forecast growth of up to 24%, and return on equity of up to 19.2%, higher than the 16.9% of India and 16.8% of China. Thus, the Southeast Asian countries have been growing according to, or above, expectations; in particular, Thailand, Indonesia, and the Philippines have been very strong over the past year, and they displayed a wave of strong co-movement and interdependence. Thus, it is evident that the study of the Southeast Asian stock market is of practical significance for investors, businesses, and governments.

In addition, a detailed survey of the ASEAN stock market is relevant because of the increased economic cooperation in accordance with the ASEAN agreement, the successful financial reforms, the current booming economy, and the distinguished structure of the emerging stock markets. Moreover, there is a dearth of research material and literature that focus on their dependence structure. A noteworthy exception to this is the study done by Sharma and Wongbangpo [1] who analyze the degree of the long-term and short-term co-movements in the stock markets of the five ASEAN countries, Indonesia, Malaysia, Singapore, Thailand, and the Philippines. Their results revealed that there exists a long-run relationship among the stock markets of Indonesia, Malaysia, Singapore, and Thailand, but the Philippine market does not share this relationship. Of course, in recent years, there has emerged some literature that focuses on the dependence patterns of the Asian stock market, as well. For example, Ning and Wirjanto [2] used the copula approach to examine the extreme returnvolume relationship in six countries, Taiwan, Singapore, Malaysia, Thailand, Indonesia, and Korea. The study applied Clayton, survival Clayton, Frank and Gumbel copulas to fit asymmetric returnvolume dependence at extremes for these markets. Lim et al. [3] applied a battery of nonlinearity tests to re-examine the weak-form efficiency of 10 emerging Asian stock markets that include China, India, Indonesia, South Korea, Malaysia, Pakistan, the Philippines, Sri Lanka, Taiwan, and Thailand. Sharma [4] studied the correlation between emerging Asian markets and the United States. The study found that the linear positive correlation between Malaysia and the

Philippines reaches up to 0.976. Although there are few researchers who studied the co-movement or correlations between ASEAN countries, they focus on pair dependences (see Sharma [4], Ning and Wirjanto [2]) and the degree of the long-term and short-term co-movement (see Sharma and Wongbangpo [1]). Or more accurately, there are not studies of multivariate dependence structure and tail dependence in ASEAN stock market so far to date.

Since Bedford and Cooke [19] [8] introduced pair-copula construction (PCC) of mutivariate distribution, vine copulas have been widely developed and used in econometrics and finance. Especially, Aas et al. [23] developed standard maximum likelihood (ML) estimation for Canonical vine (C-vine) and Drawable vine (D-vine) copulas, where the challenge was to provide a good starting point for the required high dimensional optimization. Compared vine copulas with standard multivariate copulas, standard multivariate copulas, such as multivariate normal and multivariate-t copulas, become inflexible in high dimensions because of never allowing for different dependency structures between pairs of variables. On the contrast, vine approach is more flexible, as we can select bivariate copulas from a wide range of (parametric) families. Additionally, copula approach may capture the upper and lower tail dependence, which is more precise to calculate value at risk (VaR) and expected shortfall (ES).

This paper applies the vine copula approach to study the stock return co-movement and tail dependence, especially to shed new light on the dependence between three countries: Indonesia, Philippine and Thailand. Moreover, on the basis of this approach, we investigate the value at risk (VaR) and the expected shortfalls (ES). The main contributions of the paper are as follows: (1) This paper describes the conditional volatility and the leverage effect in Indonesia, the Philippines, and Thailand; (2) The study makes use of vine copulas to analyze the co-movement and conditional dependences, and tail dependences; (3) The paper combines vine copula with the Monte Carlo simulation method, thus enabling the estimation of value at risk and expected shortfall.

The paper is organized as follows: Section 2 describes the methodology used in the investigation. Section 3 discusses the empirical results. Section 4 provides the results of economic application for risk measure. Lastly, Section 5 offers conclusions.

2 Methodology

Copulas are functions that join multivariate marginal distribution functions to form joint distribution functions. If $X = (X_1, X_2, \ldots, X_n)$ is a random vector with joint distribution function H and marginal distributions $F_1, F_2, \ldots, F_n$, then there exists a copula C, such that

$$H(x_1,x_2,\ldots,x_n) = C(F(x_1),F(x_2),\ldots,F(x_n)) \tag{1}$$

In the light of formula (1), the copula function can be expressed as:

$$C(u_1,u_2,\ldots,u_n) = H(F^{-1}(u_1),F^{-1}(u_2),\ldots,F^{-1}(u_n)) \tag{2}$$

So, we need to find the appropriate marginal distributions for the copula model. Taking into consideration the characteristics of stock returns, which are generally non-normal, volatility clustering, and asymmetric, we employ the Glosten-Jagannathan-Runkle (GJR) model with the skewed student-t and skewed generalized error distribution (SGED) to capture the time-varying volatility and leverage effect, and to fit the marginal distributions for the copula model.

2.1 A GJR model for marginal distributions

Glosten, Jagannathan, and Runkle [12] extended the Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model. Subsequently, it was named GJR-GARCH model; it includes leverage terms for modeling asymmetric volatility clustering. The form of the ARMA (P, Q)-GJR (K, L) model can be expressed as

$$r_t = c + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \varepsilon_i \tag{3}$$

$$\varepsilon_t = h_t \eta_t \tag{4}$$

$$h_t^2 = \omega + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{k} \gamma_i I[\varepsilon_{t-i} < 0]\varepsilon_{t-i}^2 + \sum_{i=1}^{l} \beta_i h_{t-i}^2 \tag{5}$$

where $\sum_{i=1}^{p} \phi_i < 1, \omega > 0, \alpha_i >= 0, \beta_i >= 0$, $\alpha_i + \gamma_i >= 0$, and $\sum_{i=1}^{k} \alpha_i + \sum_{i=1}^{l} \beta_i + \frac{1}{2}\sum_{i=1}^{k} \gamma_i < 1$. The formulas (3) and (5) are called mean equation and variance equation, respectively; the formula (4) describes the residuals ε_t is consist of standard variance h_t and standardized residuals η_t; the leverage coefficient γ_j is applied to negative standardized residuals, giving negative changes additional weight. In addition, the standardized residuals are assumed to be the skewed student-t or skewed generalized error distribution in this study, and the cumulative distributions of standardized residuals are formed to plug into copula model.

2.2 Vine copulas

Regarding vine copulas, it is worth taking a moment to understand the development process. Joe and Hu [5] gave the first pair-copula construction (PCC) of a multivariate copula, the construction of which is dependent on distribution functions. Bedford and Cooke [19] [8]expressed these constructions in terms of densities, and organized these constructions in a graphical way involving a sequence of nested trees, which are called regular vines. They also proposed two subclasses of the PCC: we call them C-vine and D-vine copulas. Furthermore, C-vine and D-vine copulas have been made use of in analyzing the conditional dependence for finance asset return, as they are more flexible than some multivariate copulas. For example, multivariate normal copula does not have tail dependence; multivariate t-copula has only a single degree of freedom parameter and symmetric tail dependence, while the nested Archimedian copulas and Hierarchical Archimedian copulas require additional parameter restrictions and thus result in reduced flexibility for modeling dependence structures (see Joe [15]; Savu and Trede [16]; Czado [22]). Various studies demonstrate the properties, classifications, structures, and merits of vine copulas (Nikoloulopoulos et al. [5]; Kurowicka and Cooke [9]; Joe et al. [10]; Joe [29]; Aas et al. [23]).

Compared to the above-mentioned multivariate copulas, the vine copulas are more flexible in high dimensions because vine copulas allow for different dependency structures between the pairs of variables. C-vine and D-vine copulas are subclasses of the vine copula. They possess all the characteristics of the vine copula, and find applications far and wide. Let us consider the three-dimensional structures of the C-vine and D-vine copulas, the trivariate distribution, and the density function, which can be expressed as

$$F_{123}(x_1,x_2,x_3) = \int_{-\infty}^{x_1} C_{23|1}(F_{2|1}(x_{2|z}),F_{3|1}(x_{3|1}))dF_1(z) \tag{6}$$

$$f_{123}(x_1,x_2,x_3) = c_{12}(F_1,F_2) \times c_{13}(F_1,F_3) \times c_{23|1}(F_{2|1},F_{3|1})) \times \prod_{i=1}^{3} f_i(x_i) \tag{7}$$

and

$$F_{123}(x_1,x_2,x_3) = \int_{-\infty}^{x_2} C_{13|2}(F_{1|2}(x_{1|z}),F_{3|2}(x_{3|z}))dF_2(z) \tag{8}$$

$$f_{123}(x_1,x_2,x_3) = c_{12}(F_1,F_2)) \times c_{23}(F_2,F_3) \times c_{13|2}(F_{1|2},F_{3|2})) \times \prod_{i=1}^{3} f_i(x_i) \tag{9}$$

respectively. The formulas (6) and (7) reflect the structure of the three-dimensional C-vine copula, and the formulas (8) and (9) reflect that of the D-vine copula. In formulas (6) and (7), $C_{23|1}(\cdot,\cdot)$ and $C_{13|2}(\cdot,\cdot)$ are the dependency structure of the bivariate conditional distribution, while $c_{ij}(\cdot,\cdot)$ is a bivariate copula density in formulas (7) and (9). The marginal conditional distribution in the C-vine and D-vine is in the form $F(r_t \mid \upsilon)$, which can be written as

$$F(r_t \mid \upsilon) = \frac{\partial C_{r,\upsilon_j|\upsilon_{-j}}(F(r \mid \upsilon_{-j}), F(\upsilon_j \mid \upsilon_{-j}))}{\partial F(\upsilon_j \mid \upsilon_{-j})} \tag{10}$$

where $C_{r,\upsilon_j|\upsilon_{-j}}$ is the dependency structure of the bivariate conditional distribution of r and υ_j conditioned on υ_{-j}, and the vector υ_{-j} is the vector υ excluding the component υ_j (see Aas et al. [23]). For a univariate υ, we use the function $h(r,\upsilon;\theta)$ to represent the conditional distribution function when r and υ are uniform, i.e. $f(r) = f(\upsilon) = 1$, $F(r) = r$ and $F(\upsilon) = \upsilon$. This special marginal conditional distribution is given by

$$h(r,\upsilon;\theta) = F(r|\upsilon) = \frac{\partial C_{r,\upsilon}(r,\upsilon)}{\partial \upsilon} \tag{11}$$

where θ is the parameter set of $C_{r,v}$. We employ different methods to order the sequences of variables in the C-vine and D-vine models. For C-vine, we calculate the sum of empirical Kendall's tau $S_\tau^i = \sum_{j=1,i\neq j}^{n} \tau_{i,j}$ for each variable i, and select the maximum one as the first variable. After that, we record the remainder of the variables and repeat the process of calculating the sum of Kendall's tau, thus finding out the second and third variables. For example, there are three variables in our study. So,$S_\tau^1 = \tau_{12} + \tau_{13}$, $S_\tau^2 = \tau_{21} + \tau_{23}$ and $S_\tau^3 = \tau_{31} + \tau_{32}$, if S_τ^2 is the biggest value, then the order should be 2, 1, 3 or 2, 3, 1. For D-vine, we determine the order that satisfies the maximization of the sum of empirical Kendall's tau $S_\tau = \sum_{i=1}^{n-1} \tau_{i,i+1}$, e.g., the S_τ of the order 2, 1, 3 is the biggest, then the preferable order should be 2, 1, 3 or 3, 2, 1.

2.3 Parameter estimation method

Generally, we use the two-stage estimation method that is called inference function margins (IFM) to estimate our model. This point means that we first estimate GJR-GARCH model thereby getting the marginal distributions, and then plug the marginal distributions into copula model for estimated parameters of vine copulas. Joe [15] [18] showed that this estimator is close to and asymptotically efficient to the maximum likelihood estimator under some regularity conditions. Hence, the two-stage estimation method can efficiently compute the estimator without losing any real information. In the process of parameter estimation of vine copulas, we turn to sequential maximum likelihood estimation method for obtaining initial values of vine copulas, and then use maximum likelihood estimation to estimate the parameters of C- and D-vine copulas. Aas et al. [23], Czado et al. [8] introduced detailed calculate process. A brief process of sequential maximum likelihood estimation can be described as follows.

First, using maximum likelihood estimation to estimate parameters of each non-conditional copula; second, computing observations by using conditional distribution function (formula (11)) and known non-conditional copulas in the first step; third, we estimate the parameters of the copulas conditional on one variable; fourth, computing observations for copulas given two variables by using formula (10); at last, we estimate copulas given two variables using observations from the fourth step. Through these five steps we can get initial values of 4 dimensional vine copulas. If there are more 4 dimensional variables, observations may be gotten by using formula (10) again. We only use the first three steps for getting starting values of each copula in our study.

In this paper, we use Gaussian copula, T copula, Clayton copula, Frank copula, Gumbel copula, Joe copula, BB1 copula, BB6 copula, BB7 copula, BB8 copula, and the rotate copulas to analyze the co-movement. Further details regarding this, which include their properties and characteristics, are discussed in Liu and Sriboonchitta [19], Sriboonchitta et al. [1] and Brechmann and Schepsmeier [15]. We should note is that this study applies Akaike information criterion (AIC) and Bayesian information criterion (BIC) to select a fitting pair-copula family, where both information criteria correspond to the results of sequential maximum likelihood estimation.

3 Empirical results

We investigate, in this, study, the interactions between three major stock market indices, namely, the Philippine SE (Composite Index in the Philippines), Jakarta SE (Composite Index in Indonesia), and SET (SET Index in Thailand). Our sample covers the period from January 2, 2008, to April 30, 2013. The index returns are calculated by using the differences between the logarithms of the close prices of each index.

The data description and statistics for three index returns are detailed in Table 1. Obviously, the three series are very similar. They all have heavy tails, are skewed to the left, especially the Philippines, and have kurtosis greater than three. In addition, they do not follow normal distribution. So we assume that the margins are skewed student-t and skewed GED, which are appropriate.

Table 2 shows the results of the marginal assumption of the skewed student-t distribution performed with the GJR-GARCH model for the three stock returns. First, it can be concluded that all the leverage effects add much to the capacity for explanation of the three stock returns, since each leverage effect parameter γ is significant. Second, this paper calculates the AIC and BIC when the margin is the skewed GED,

Table 1 Data Description and Statistics on Daily Returns

	Indonesia	Philippines	Thailand
Mean	0.0005	0.0006	0.0005
Median	0.0013	0.0008	0.0013
Maximum	0.1032	0.0706	0.0861
Minimum	-0.1095	-0.1309	-0.1109
Std. Dev.	0.0169	0.0147	0.0153
Skewness	-0.5488	-0.9897	-0.4079
Kurtosis	11.0660	11.6427	9.2490
Jarque-Bera	3249	3855	1947
Probability	0.0000	0.0000	0.0000

Table 2 Results of ARMA-GARCH Model

	Indonesia		Philippines		Thailand
C	0.0007*	—	—	—	—
	(0.0004)				
Ar1	0.1122***	—	—	Ar1	0.0348
	(0.0311)				(0.0287)
ω	0.831e-05***	ω	0.7e-05**	ω	0.7e-05**
	(0.3e-06)		(0.2e-05)		(0.2e-05)
α	0.0601*	α	0.0435*	α	0.0475**
	(0.0254)		(0.0193)		(0.0182)
β	0.8185***	β	0.8496***	β	0.8454***
	(0.0341)		(0.0283)		(0.0304)
γ	0.1675***	γ	0.1847***	γ	0.1645***
	(0.0472)		(0.0529)		(0.0482)
Skew	0.9433***	Skew	0.8509***	Skew	0.9018***
	(0.0412)		(0.0320)		(0.0370)
ν	7.1698***	ν	5.0109***	ν	7.2489***
	(1.3808)		(0.7243)		(1.4606)
LM-test	0.3958	LM-test	0.8162	LM-test	0.6271
LogL	3527.4720	LogL	3445.0980	LogL	3473.1870
AIC	-5.9804	AIC	-5.8438	AIC	-5.8899
BIC	-5.9459	BIC	-5.8180	BIC	-5.8597

Note: Signif. codes are as follows: 0 *** 0.001 ** 0.01 * 0.05 0.1. The numbers in the parentheses are the standard deviations.

and the AIC and BIC are -5.9702 and -5.9357, -5.8278 and -5.8020, -5.8839 and -5.8537, respectively, for the Philippines, Indonesia, and Thailand. When compared with the skewed student-t distributions assumption, the AIC and BIC are smaller, as shown in Table 2. Therefore, the GJR-GARCH model with the skewed student-t marginal distribution is the better performing in terms of AIC and BIC.

There exists a precondition for using any copula, which is that the marginal distribution must be uniform (0, 1); if it is not, the wrongly specified model for the marginal distribution may cause incorrect fit copulas. We use Box-Ljung and Kolmogorov-Smirnov (KS) tests to test the validity of the models, and the test results obtained are given in Table 3. None of the KS tests rejects the null hypothesis, and at 5% level, none of the Box-Ljung tests rejects the null hypothesis. Therefore, it can be clearly seen that all the series satisfy the condition of iid uniformity (0, 1).

Table 3 KS Test for Uniform and Box-Ljung Test for Autocorrelation

KS Test			
	Statistic	P value	Hypothesis
$u_{1,t}$	0.0167	0.8969	0 (acceptance)
$u_{2,t}$	0.0239	0.5099	0 (acceptance)
$u_{3,t}$	0.0330	0.1538	0 (acceptance)
Box-Ljung Test			
	Moments	X-squared	P-value
$u_{1,t}$	First moment	5.5303	0.3546
	Second moment	7.2354	0.2037
	Third moment	5.8187	0.3243
	Fourth moment	5.8543	0.3207
$u_{2,t}$	First moment	10.5864	0.0602
	Second moment	2.5125	0.7746
	Third moment	8.7818	0.1181
	Fourth moment	1.0282	0.9603
$u_{3,t}$	First moment	2.4138	0.7894
	Second moment	9.4736	0.0916
	Third moment	10.5063	0.0621
	Fourth moment	9.1190	0.1044

Note: $u_{1,t} = F_{skt}(x_{phi,t})$, $u_{2,t} = F_{skt}(x_{indo,t})$, and $u_{3,t} = F_{skt}(x_{thai,t})$

In the light of the maximum value of the empirical Kendall's tau, the sequence for the C-vine copula is Indonesia, the Philippines, and Thailand, and the sequence for the D-vine copula is Thailand, Indonesia, and Philippines. Thus, we see that C-vine and D-vine have the same structure, both of which calculate the dependence between the Philippines and Thailand, conditional to Indonesia. Since there are only three variables, it is easy to implement, and comprehensive analysis is possible to study the dependences conditional to each variable. Therefore, we use C-vine to estimate the dependence conditional to Indonesia under maximum empirical Kendall's tau, and for others, we make use of D-vine. Table 4 and Table 5 present the estimated parameters of the C-vine and D-vine copulas, respectively. According to the minimum AIC and BIC principle, the optimal choices of the C-vine copula are BB1, Survival BB1, and BB7 copula, in that order, while the same for the D-vine copula are Survival BB1, BB1, and T copula when the selected in the order Indonesia, Thailand, and the Philippines; the other best choices of the D-vine copula are survival BB1, BB1, and T copula. First and foremost, it is evident that the D-vine structure for Thailand is more appropriate than the C-vine one because the sum values of the AIC and BIC are the smallest for D-vine. Second, all the market pairs have significant co-movement and tail dependence especially so for the Indonesian and Thailand markets which possess the greatest dependence, which includes their upper tail (0.6013) and lower tail (0.3369), among these three country markets. Third, the Kendall's tau of $C_{PT|I}$ and $C_{T,P}$ are 0.1147 and 0.2709, and their upper tail and lower tail dependence are 0.1234 and 0.0080, and 0.2035 and 0.1591, respectively. So, if the Indonesian market is given as the condition, the Kendall's tau falls by 57.66%; the lower tail dependence almost becomes independent, while the upper tail dependence decreases 39.36%. In addition, if we compare $C_{I,T}$ with $C_{IT|P}$, the dependence structure can be observed to undergo a change, when the Philippine market is given as the condition. Moreover, the Philippine market has been seen to have a more profound effect on the tail dependence of Indonesia and Thailand. Last, when the Philippine market is given as the condition, the lower and upper tail dependences between the Thailand and Indonesian markets are seen to become symmetric and tiny. From the above-mentioned results, we can conclude that the information of Indonesia stock market has the effective influence to the lower dependence between Philippine and Thailand, which means the information make investors reduce the probability of high loss simultaneously. On the contrast, the information of Philippine stock market contributes to reduce the possibilities of high loss and profitability at the same time. The information of Thailand plays the same role as Philippines.

4 Economic application of risk measures

Copulas have attracted much attention in the computation of value at risk, expected shortfall for risk measure, as pointed out by Kole et al. [22], Junker and May [23], Ouyang et al. [24], etc. In order to strengthen the practical applicability of the empirical results, we make use of the Monte Carlo simulation and the estimation results of the vine copula to calculate the VaR and ES of equally weighted portfolio. The detailed procedures that we propose to evaluate the risk consist of four steps: first, we

Table 4 Results of C-vine Copulas and Kendalls tau

Copulas	parameters	standard error	Lower and upper tail dependence	Kendall'tau	AIC	BIC
BB1 ($C_{I,P}$)	0.3164***	0.0563	0.1574	0.2712	-245.1503	-235.0088
	1.1847***	0.0337	0.2049			
Survival BB1($C_{I,T}$)	0.2573***	0.0555	0.3369	0.3498	-389.3588	-379.2173
	1.3627***	0.0448	0.6013			
BB7($C_{T,P\|I}$)	1.1011***	0.0304	0.0080	0.1147	-51.9699	-41.8285
	0.1436***	0.0389	0.1234			
sum					-686.479	-656.0546

Table 5 Results of D-vine Copulas Conditional to Thailand and the Philippines

Copulas	parameters	standard error	Lower and upper tail dependence	Kendall'tau	AIC	BIC
Survival BB1 ($C_{I,T}$)	0.2651***	0.0559	0.3314	0.3478	-389.3458	-379.2044
	1.3538***	0.0441	0.5993			
BB1($C_{T,P}$)	0.3187***	0.0565	0.1591	0.2709	-245.1539	-235.0124
	1.1831***	0.0331	0.2035			
T($C_{I,P\|T}$)	0.1958***	0.0292	0.0010	0.1255	-47.3063	-37.1648
	20.4644	14.1012	0.0010			
sum					-681.806	-651.3816
BB1($C_{T,P}$)	0.2644***	0.0539	0.1023	0.2319	-181.6724	-171.531
	1.1499***	0.0309	0.1728			
BB1 ($C_{P,I}$)	0.3695***	0.0625	0.2330	0.3446	-384.3979	-374.2564
	1.2878***	0.0390	0.2870			
T($C_{I,T\|P}$)	0.2854***	0.0290	0.0686	0.1843	-116.2577	-106.1162
	6.9649***	1.5714	0.0686			
sum					-682.328	-651.9036

generate 1117 random numbers of $C_{I,P}$ (BB1) and $C_{I,T}$ (Survival BB1); second, the standardized residual can be got from the inverse function of the skewed student-t distribution which is an assumption of the marginal distribution in the GJR-GARCH model; third, the next period stock returns can be forecasted through the mean equations of the GJR-GARCH models; fourth, we distribute equal weights to each stock return, and then we get the returns after the weighting; finally, the VaR and ES can be calculated at the 5%, 2%, and 1% levels. The four processes can be repeated

1000, 2000, and 5000 times to get the convergence values.

Table 6 presents the results of the VaR and ES of equally weighted portfolio. As can be seen in Table 6, the VaR converges to -1%, -1.35%, and -1.61% at the 5%, 2%, and 1% levels, respectively, and -1.41%, -1.78%, and -2.08% for the ES. Table 7 provides the VaR and ES of each stock market and the average value at the 5%, 2%, and 1% levels. First, there is no doubt that portfolio may successfully avoid risk, as can be seen by comparing the results as given in Table 6 with those in Table 7. The VaR and ES of Thailand are the least, which means that the Thailand stock market is at more risk. At the same time, this illustrates that Indonesia is at less risk, and that the Philippines is at medium risk.

Table 6 VaR and ES of Equally Weighted Portfolio

VaR	5%	2%	1%
1000 times	-0.01002	-0.01353	-0.01607
2000 times	-0.01004	-0.01349	-0.01608
5000 times	-0.01003	-0.01351	-0.01608
ES			
1000 times	-0.01412	-0.01777	-0.02081
2000 times	-0.01408	-0.01778	-0.02082
5000 times	-0.01408	-0.01777	-0.02080

Table 7 VaR and ES for Each Stock Market

VaR (5000 times)	Indonesia	Philippines	Thailand	Average
5%	-0.0138	-0.0159	-0.0167	-0.0155
2%	-0.0194	-0.0217	-0.0225	-0.0212
1%	-0.0238	-0.0260	-0.0270	-0.0256
ES (5000 times)				
5%	-0.0205	-0.0225	-0.0234	-0.0221
2%	-0.0269	-0.0287	-0.0295	-0.0284
1%	-0.0324	-0.0336	-0.0344	-0.0335

5 Conclusions

This paper depicts a model for estimating conditional volatility, dependency, VaR, and ES through a vine copula based GJR-GARCH model, in which the empirical evidence shows that there do exist leverage effects in these three country stock markets, and that all appropriate margins are skewed student-t distributions; given these, the optimal choices of the C-vine copula are BB1, Survival BB1, and BB7 copula, in that order, while the same for the D-vine copula are Survival BB1, BB1, and T copula. Another significant observation is that the D-vine structure is more appropriate than the C-vine one, as a whole. In addition, the Indonesian and Thailand markets show the greatest dependence, which includes their upper tail (0.6013) and lower tail (0.3369) in these three country markets. Also, the Philippine market has a significant effect on the tail dependence between Indonesia and Thailand. As a final note, it needs to be emphasized that the vine copula based GJR-GARCH model captures the VaR and ES successfully.

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