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Modeling Dependence Structure of Evidence from ASEAN-5 Stock Market Patterns

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ABSTRACT

This paper was proposed to focus on the dependence structure of economics cycles (economic booms and recessions) among ASEAN-5 stock indexes which were the Philippines stock market (The Philippines Composite index: PSEi), Indonesia Stock market (Jakarta Composite Index: JCI), Malaysia stock market (FTSE Bursa Malaysia KLCI: FTSE), Thailand stock market (SET Index: SET) and Singapore Stock Market (The Straits Time Index: SGX). The data was transformed to be standardized residuals and observed as monthly samples during 2001 to 2018. Technically, Markov Switching Bayesian Vector Autoregressive model (MSBVAR) and CD-Vine Copula approaches were applied to do econometrical estimations in this study. The MSBVAR model was used to determine regime switching of the data set. For CD-Vine copula models, they were employed to computationally seek dependence structures. To exemplify each state of regimes, the Elliptical copula model was chosen to structurally define the relation among ASEAN-5 stocks. Empirically, the result represented the dynamics co-movement of each stock. CD-Vine copula trees showed that the PSEi index and JCI contained the strongly structural dependence in economic booming situations of the pre-crisis period. On the other hand, in the post-crisis period, PSEi had the strongly dependence connection with FTSE Bursa Malaysia. Thus, capital flows between Philippines and Indonesia were financially changed from flowing between Philippines and Indonesia to Philippines and Malaysia after crises. However, in the case of economic recessions, the result showed that there was the independent structure among ASEAN-5 stocks, both in pre-crisis and post crisis.

JEL Classification: G15, G17

Keywords: ASEAN-5 stock exchanges; Bayesian inference; MSBVAR; CD-Vine copula approaches

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INTRODUCTION

The financial sector which was broadly known as "stock markets" was one of the most crucial components of the free-market economy since it enhanced companies to capably access on the ability to raise investing funds. As the sensible reason, investment flows could be monitored as the real-time update, offering stock shares were the predominant indicator .The stock market could not be roughly predicted since its volatilities .In fact, there were many stages of systematically econometric processes dealing with the time-varying trends of stock exchanges, but results seemed to be still doubtful for many cases .Additionally, facing the changing economy relied on real business cycles; the paper was conducted to clarify stakeholders for systematic structures to decide the sort of right aspects to financially invest in their targets. To sensibly understand the movements of financial indexes, the predictable cycles were provided for doing a decision-making in the different patterns of changing economic regimes . This was not beneficial only for individual investors or financial investment considerations, but it would be an alternatively advantage tool for other academic branches to provide an effective solution for their difficulties.

Historically, the 2008 financial crisis in US (called "Hamburger") was the evidence to significantly indicate the prediction by traditional econometric tools such as Granger (1992), Brooks (1998), and Liu et al. (2016) was a lack of preciseness. This was one of the great financial failure in the world strongly confirmed that volatilities were more prioritized rather than focusing predictable parameters of the significant levels in hypothesis testing .Moreover, its causality had a negative spread out to impact a structural damage in Europe and Asia economies during 2009. The keyword was "the structural effect" which was intensively mentioned as the clue to find solutions. The forecasting of stock markets around the world had been being inevitably reconstructed before aftershocks which were chronic and not easy to shortly cure came. To struggle to seek the solution, economists might go through the root of the problem – estimations and predictions in volatilities. Consequently, investment opportunities, economics cycles, stock market fluctuations, stock return variations, deeply structural relations, even stationary-trend checking were all included into a multi-analytic process.

The multi-analytic process applied to this paper contained two major components. The former section was the data classification, which carried the stationary testing and regime switching. The ADF unit-root test introduced by Dickey and Fuller (1979) and Markov Switching model were relied on the subjective statistical approach called "Bayesian inference". With the advanced simulation technique (MCMC simulations), the Bayesian inference was empowered to provide better solutions for hypothesis analyses. To assure the use of this alternative statistics for data classifications was widely highlighted in modern econometrics, Chaiboonsri and Wannapan (2019) investigated the data stationary and switching observations to prepare for machine learning analyses. Wannapan and Chaiboonsri (2018) applied Bayesian inference and simulations for understanding the fluctuations of macroeconomic variables. Also, Chaiboonsri and Wannapan (2018) used the full option of Bayesian inference in the data classification prepared for the extreme value forecasting in dynamic predictions of ASEAN-3 growth indicators. Moreover, Chaiboonsri et al. (2017) employed the Bayesian inference and MCMC approach to clarify the up-down trends of ICT segments in India. For others, Xia and Griffiths (2012) and Diniz et al. (2011) studied the unit root test based on Bayesian inference for data stationary in financial econometrics.

The latter section was in terms of deeply modeling relations. The mathematical application called "copula models" was employed to seek the rare structural connection in financial data. With working on residual terms, the structural dependences provided by copula analyses could more deeply explain predictive parameters could not be found from a multi-linear model. From literatures, Mendes and Souza (2004), Bellini (2010), and Razak and Ismail (2016) used copula models to extend the explanatory ability of linear and nonlinear regression, and copula models resulted the efficiency of the portfolio risk computation. Moreover, copula models were not applied only in financial econometrics. Romyen et al. (2019) employed the CD-Vine copula approach to investigate the structural dependences of foreign direct investments in ASEAN countries. For agricultural economics, Somboon et al. (2019) applied the Vine copula to explore rare structures of natural rubber imports in ASEAN countries. For tourism economics, Wannapan et al. (2018) used the bivariate copula approach to understand extreme structural connections among tourism demands, the financial market, and economic growth in Thailand.

THE OBJECTIVE AND SCOPE OF RESEARCH

This paper aimed to consider into dependence structures of ASEAN 5 stock markets .The collected data was chosen as monthly samples during 2001 to 2018. The ASEAN-5 stock exchanges were Philippines stock market (The Philippines Stock Exchange Composite index: PSEi), Indonesia Stock market (Jakarta Composite Index: JCI), Malaysia stock market (FTSE Bursa Malaysia KLCI: FTSE), Thailand stock market (SET Index: SET) and Singapore Stock Market (The Straits Time Index: SGX).

METHODOLOGIES

Bayesian statistics and inference

In terms of technical processes, the part of statistical inference is the introduction of the alternative called “Bayesian inference”. This subjective statistics is employed to deal with random parameters for econometric models. With randomly provide the variety of parameters parallel to random trends in financial time-series data, this will potentially give the sensitivity of predictive results relied on real situations, making a substantial conclusion based on a solid background by prior settings.

Specifying the Bayesian inference, “the prior”, an identical solution is given for *w* as a least-squares function, maximum likelihood estimation will also present an over-fitting calculation. To solve the complex model, we specified earlier a “prior distribution” which explains our “belief levels” over values that *w* might take before the weight penalty is regularized. The prior equation is explained in the equation (1),

$$p(w \mid \alpha) = \prod_{m=1}^{M} (\alpha / 2\pi)^{\frac{1}{2}} \exp\left[-\frac{\alpha}{2} w_m^2 \right] \tag{1}$$

After setting the prior, errors are measured and computed a single point estimate of WLS for the weight. The likelihood and prior are specified. Thus, the “posterior distribution” over *w* via Bayes’ rule is calculated as follows;

$$p(w \mid t, \alpha, \sigma^2) = \frac{likelihood \times prior}{nornalised \quad factor} = \frac{p(t \mid w, \sigma^2)\, p(w \mid \alpha)}{p(t \mid \alpha, \sigma^2)} \tag{2}$$

From Equation (1) and (2), { $p(t \mid w, \sigma^2)$ } cannot be analytically performed. Bayesian modelling, as mentioned, requires a joint distribution, which is conveniently factored into a prior distribution for the parameters, and the completed data likelihood function is expressed in Equation (3) (Shalizi and Gelman, 2013; Wannapan et al. 2018),

$$L\big(y \mid (p(t \mid w, \sigma^2))\big) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{y_t^2}{2\sigma_t^2} \right), \tag{3}$$

where *y* refers to the time-series data of n observations, $y = (y_1, y_2, \ldots y_n)$ and θ stands for the estimated parameters. Considering Equation (3), the parameters in the log-likelihood function can be maximized, which is written as Equation (4),

$$LnL\big(y \mid (p(t \mid w, \sigma^2))\big) = -\frac{1}{2} \sum_{i}^{n} \ln\big(2\pi\sigma_t^2\big) - \sum_{i}^{n} \frac{y_t^2}{2\sigma_t^2} \tag{4}$$

For the model validation in Bayesian inference, the study of Kass and Wasserman (1995), data *D* is assumed to be one of two hypotheses (H_0 and H_1) regarding the probability density which is $pr(D|H_0)$ or $pr(D|H_1)$, assuming the prior probabilities $pr(H_0)$ and $pr(H_1)$ = 1 – $pr(H_1)$ and the posteriori probabilities $pr(H_0|\mathrm{D})$ and $pr(H_1|D)$ = 1 – $pr(H_0|D)$. The posterior probabilities are transformed to the odds scale (odds = probability / (1 – probability)), and the transformation can be defined as a simple form based on Bayes’s theorem. The Bayes’factor is derived as Equation (5):

$$pr(H_k \mid D) = \frac{pr(D \mid H_k)pr(H_k)}{pr(D \mid H_0)pr(H_0) + pr(D \mid H_1)pr(H_2)}, (k = 0, 1) \tag{5}$$

Then

$$\frac{pr(H_0 \mid D)}{pr(H_1 \mid D)} = \frac{pr(D \mid H_0)}{pr(D \mid H_1)} \frac{pr(H_0)}{pr(H_1)}.$$

The transformation is calculation by

$$B_{01} = \frac{pr(D \mid H_0)}{pr(D \mid H_1)}.$$

It is the *Bayes factor*. Thus, the posterior odds = Bayes factor $\times$ prior odds. The Bayes factor is a synopsis of the evidence provided by a statistical model, which is proposed by Jeffrey's scales (Kass and Raftery, 1961). The interpretation of B_{01} in half-units on Jeffrey's scales is simply described as two categories, hence, there are:

Bayesian Factor	Evidence against H_0
BF < 1/10	Strong evidence for H_1
1/10 < BF < 1/3	Moderate evidence for H_1
1/3 < BF < 1	Weak evidence for H_1
1 < BF < 3	Weak evidence for H_0
3 < BF < 10	Moderate evidence for H_0
10 < BF	Strong evidence for $H_{0.}$

ADF unit root testing

The ADF test analyzes the null hypothesis that a time-series index is stationary against the alternative (non-stationary data), assuming that dynamics in data have the autoregressive moving average model (ARMA) (Said and Dickey, 1984). The ADF test is based on estimating the regression test, which is expressed by the equation (6),

$$\Delta y_t = c + \alpha' D_t + \varphi y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t. \tag{6}$$

The prior density of φ is factorized and shown in the equation (7),

$$p(\varphi) = p(\phi) p(a^* \mid \phi) \tag{7}$$

The Markov Switching Bayesian Vector Autoregressive model (MSBVAR)

To estimate market regimes, the market is divided into bull market and bear market through Markov switching Bayesian VAR model by the following equation,

$$z_t = \alpha_0 + \beta z_{t-1} + u_t \tag{8}$$

where $s_t = 0$ and u is IID random variables contains zero means and variance σ_t^2. When s_t is changed from 0 to 1, The stationary AR (1) processed with mean $\alpha_0/(1-\beta)$ will switch to another stationary AR (1) process with mean $(\alpha_0 + \alpha_1)/(1-\beta)$.Then ,$\alpha_1 \neq 0$. Therefore, the dynamic structures at different levels will depend on the value of state variables s_t .

The first-order Markov chain condition with constant transition probabilities generates the latent variable which leads to regime switching. The transaction probabilities can be denoted that

$$P(S_t = j \mid S_{t-1} = i) = P_{ij}, (i, j = (0,1)) \tag{9}$$

and the probabilities in a Markov process can be expressed in a matrix form;

$$\begin{bmatrix} P(S_t = 0) \\ P(S_t = 1) \end{bmatrix} = \begin{bmatrix} P_{00} & P_{10} \\ P_{01} & P_{11} \end{bmatrix} \begin{bmatrix} P(S_{t-1}) = 0 \\ P(S_{t-1}) = 1 \end{bmatrix} \tag{10}$$

The ARMA-GJR model

To find the marginal distribution for copula model, the ARMA-GJR model is commonly used. In the paper, the ARMA(p,q)-GJR(1,1) model (where p is the order of the autoregressive (AR) and q is the order of the moving-average model (MA)) is given by

$$y_1 = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \varphi_i \varepsilon_{t-i} + \varepsilon_t, \tag{11}$$

$$\varepsilon_t = h_t z_t, \tag{12}$$

$$h_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2, \tag{13}$$

where $\mu, \phi, \varphi, \omega, \alpha_1$, and β_1 are unknown parameters of the model. They are derived as follows;

ε_t : while noise processes at time t,
h_t^2 : variances at time t,
z_t : standardized residuals.

Copula Models

Sklar' s theorem) Sklar, 1959 (introduced the copula formula, and this concept can be explained by the following equation;

$$H(x_{1,\ldots,} x_d) = c(F_1(x_1), F_2(x_2), \ldots, F_d(x_d)) \tag{14}$$

H :n-dimensional distribution with marginal F_i , i=1,2,..,d .

$x_1, \ldots, x_d$: random vectors.
C :d-copula for all $x_1, \ldots, x_d$.

Sklar's Theorem with bivariate copula can be shown in the equation (15);

$$C(u_1; u_2) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2)\right) \tag{15}$$

Defined that :

$u_1, u_2 \in (0,1)$,
F : the distribution function of invertible margins F_1 and F_2,
C.),(. : the elliptical copula model if F is a symmetrical joint distribution.

Vine copula models (C-vine and D-vine copulas)

The major stock exchanges of ASEAN5 countries such as, PSEi, JCI, FTSE, SET and STI are defined to be $x_1, \ldots, x_5$ with marginal distribution functions, $F_1, \ldots, F_5$ referred to corresponding densities .Thus, this can be expressed in the equation (16) .

$$f\,)x_1,\, x_2,\, x_{3,}x_{4,}x_5 = (f_1)x_1(\,f\,)x_2|x_1\ (f)\ x_3|x_1,\, x_2(\,f)\ x_4|x_1,\, x_2, x_3\ (\,f)\ x_5|x_1,\, x_2, x_3, x_4.(\tag{16}$$

Computationally, the dimensional joint density can therefore be represented in terms of bivariate copula trees, $C_{1,2}$, $C_{1,3}$, $C_{1,4}$, $C_{1,5}$, $C_{2,3|1}$, $C_{2,4|1}$, $C_{2,5|1}$, $C_{3,4|12}$, $C_{3,4|12}$ and $C_{4,5|123}$ with densities $C_{1,2}$, $C_{1,3}$, $C_{1,4}$, $C_{1,5}$, $C_{2,3|1}$, $C_{2,4|1}$, $C_{2,5|1}$, $C_{3,4|12}$, $C_{3,4|12}$ and $C_{4,5|123}$, which are alternatively called “pair-copulas” . Based on the graphical presentation of canonical)C (-and D-vines copula, these are shown by Figure 1.

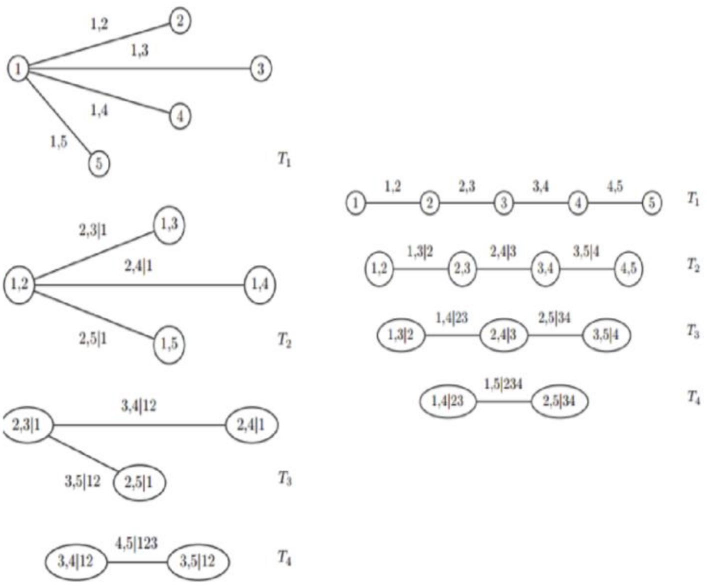

Figure 1 The graphical details of canonical)C (-and D-vines

DATA DESCRIPTION

First of all, the data set which has the major stock indexes in ASEAN contains transformed standardized residual of monthly log-return trends during 2001 to 2018 (210 collected samples). Considering into Figure 2, it provided the descriptive fluctuation details of the data. This can be evidently stated the fluctuations are not normal linearity. With the special condition of financial indexes which is dramatic swing, it seemed linear modelling approaches cannot satisfy to achieve the real structural relations among indexes. Moreover, Table 1 represented the general statistic data.

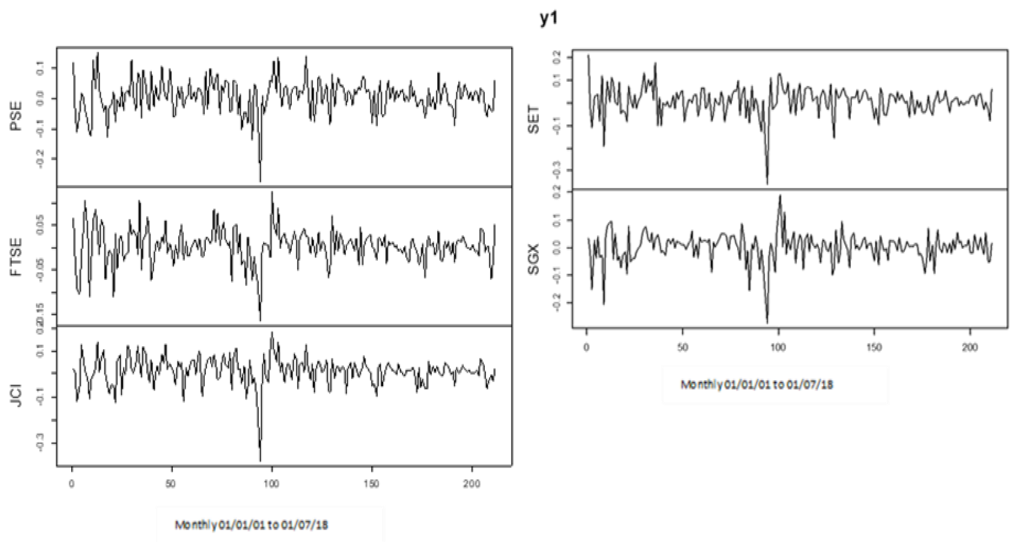

Figure 2 The descriptive index returns of monthly data for ASEAN-5 stock exchanges during 2001 to 2018

Table 1 The descriptive statistic information of ASEAN-5 major stock indexes during 2001 to 2018

Statistics/Indexes	PSEi	JCI	FTSE	SET	SGX
Min	-0.275382	-0.37720	-0.165142	-0.359188	-0.273640
Median	0.011958	0.01734	0.007432	0.013073	0.010600
Mean	0.007753	0.01259	0.004574	0.008739	0.002578
Max	0.153549	0.18342	0.127032	0.212034	0.193002

Source: authors

EMPIRICAL RESULTS

Bayesian ADF unit-root testing

The alternative way to verify the stationary of collective data by employing Bayesian inference interpreting was descriptively explained in Table 2. The stationary testing based on the model conducted by Dickey and Fuller (1979) was set to be the framework for the hypothesis comparison. To test unit roots, the result showed that the data is totally stationary in each collected index. Computed Bayes' factors are larger than 10. The summary result shown in Table 2 provided by the comparison of the Bayes factor strongly supported the evidence that factors are not suspicious when they are moved to econometrically compute.

Table 2 Stationary testing for the log-return forms of ASEAN-5 stock indexes

Indexes	Bayesian Factor Model	Hypothesis	Bayes Factor Ratio	Result	Interpretation
PSE	Model 1 Model 2	H_0 (M_i): Stationary model H_1 (M_j): Non-stationary data	BF > 10 (2.56e+14)	Strong evidence for M_i (Select $H_0(M_i)$)	Stationary data
FTSE	Model 1 Model 2	H_0 (M_i): Stationary model H_1 (M_j): Non-stationary data	BF >10 (4.6e+14)	Strong evidence for M_i (Select $H_0(M_i)$)	Stationary data
JCI	Model 1 Model 2	H_0 (M_i): Stationary model H_1 (M_j): Non-stationary data	BF >10 (4.67e+13)	Strong evidence for M_i (Select $H_0(M_i)$)	Stationary data
SET	Model 1 Model 2	H_0 (M_i): Stationary model H_1 (M_j): Non-stationary data	BF > 10 (1.23e+17)	Strong evidence for M_i (Select $H_0(M_i)$)	Stationary data
SGX	Model 1 Model 2	H_0 (M_i): Stationary model H_1 (M_j): Non-stationary data	BF > 10 (1.22e+11)	Strong evidence for M_i (Select $H_0(M_i)$)	Stationary data

Note: computing by the package "MCMCpack"

The empirical results from the Markov Switching Bayesian VAR model

Because of extreme fluctuations in financial indexes, regime classification was one of the major points to precisely visual this chaos. The switching-regime calculation based on Bayesian statistics indicated that there were different frequencies between Bull and Bear situations. Details were presented in Table.3. In bull periods, there were 67 months were belonged to pre-crises durations, which were more than the recession times, referring as 29 months. This implied the ASEAN-5 stocks were active and attractive. In other words, the positive trends in ASEAN financial markets were confirmed by the comparison between bull and bear periods during the post financial crisis (after 2008). The switching model resulted 100 months were expansion, which were vastly higher than the bear periods (13 months) during the post crisis.

Table 3 The result of switching regimes for ASEAN-5 stocks between the period before and after crisis

Bull period	Durations (Months)
Pre-crises	67
Post-crises	100
Bear period	**Durations (Months)**
Pre-crises	29
Post-crises	13

Source: authors

The estimation results of the dependence structure toward among financial markets in ASEAN-5 countries

Economic boom (Bull market)

a) The Elliptical t-copula of C-vine in Pre-crises periods (2001-2008)

Following Figure 3, it was experimentally fixed the Philippines stock market to be the market which was the oldest financial market in ASEAN (the exchange has been in operation since 1927) and the centre of capital flows. During the boom-situational periods, the result indicated that capital flows mostly transfer between Philippines and Indonesia because the strongly dependent structure (143.3649) is obviously displayed by the copula tree (C-vine t-copula model). On the other hand, the stock exchange in Thailand had the weakest dependence with the Philippines financial market during the pre-crises periods. However, there was not the conclusion that between both two countries are nearly perfect competitive. This should be alternatively explained that these two stock exchanges are linked by funding from neighbour countries, not direct investing funds.

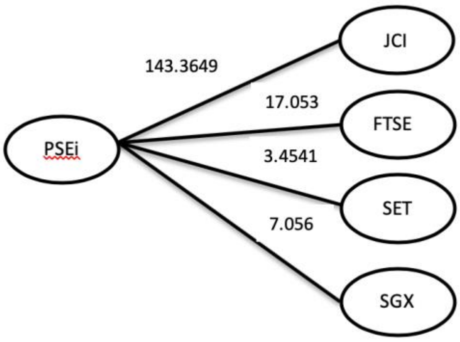

Figure 3 The estimation results of dependence structure in Bull markets in the elliptical (t-copula) C-vine model during the pre-crises periods (2001-2008)

b) The Elliptical t-copula of D-vine in pre-crises period (2001-2008)

According to Figure 4, starting from the dependence structure of the Philippines financial market and Indonesia financial market, there was confirmed the strongly structural connection and it was obviously stronger than the other pairs as shown by the estimation results of the D-vine tree from the D-vine copula. Therefore, this could be implied capital flows mostly transferred between Philippines and Indonesia financial markets during 2001 to 2008.

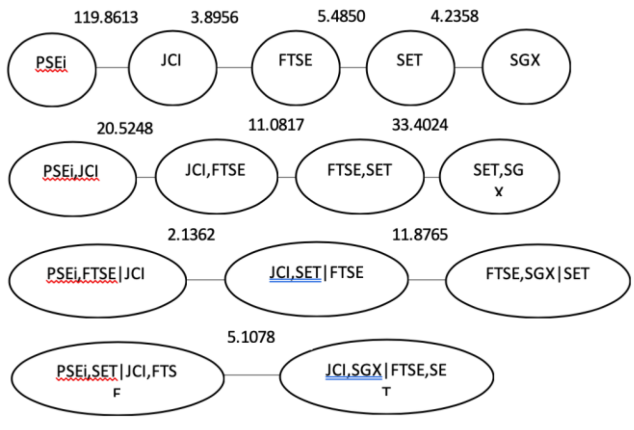

Figure 4 The estimation results of dependence structure in Bull markets in Elliptical (t-copula) from -Vine during the pre-crises periods (2001-2008)

c) The Elliptical t-copula of C-vine in post-crises period (2009-2018)

Following Figure 5, after financial crisis, the estimated results showed that capital flows changed from flowing between Philippines and Indonesia financial markets to transfer between Philippines and Thailand financial markets because of the strongly structural parameter between these two countries (18.4975). On the

other hand, Singapore financial market has weakly dependence structure with Philippines financial market in periods 2009 to 2018.

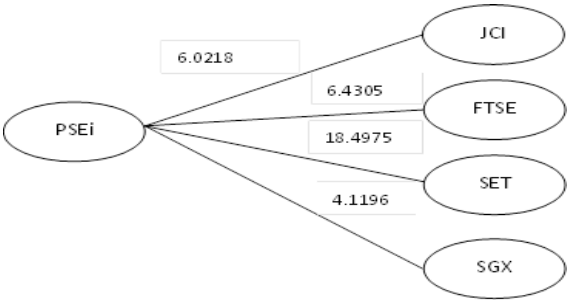

Figure 5 The estimation results of dependence structure in Bull markets in Elliptical (t-copula) from C-Vine during the post-crises periods (2009-2018)

d) The Elliptical t-copula of D-vine in post-crises period (2009-2018)

According to Figure 6, the estimation results from the D-vine tree by the elliptical copula model differed from the C-vine model, and the direction was changed to flow in economic booms between pre-crisis and post-crisis. The structural dependence between the Philippines and Indonesia financial markets were weak. Interestingly, the Singaporean financial market is the strong dependence related to the stock exchange of Thailand. This was obviously stronger than other pairs. As a result, it can be understandable that capital flows mostly transfer between Singapore and Thailand financial markets during 2009 to 2018 since these two countries were not enormously caused by the crisis. They were well-known as the hub of financial cooperation in this continent.

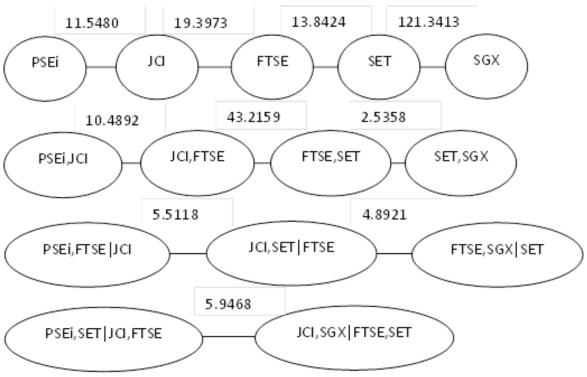

Figure 6 The estimation results of dependence structure in Bull markets in Elliptical (t-copula) from D-Vine during the post-crises periods (2009-2018)

Economic recession (Bear market)

a) The Clayton copula of C-vine in Pre-crises periods (2001-2008)

Following Figure 7, in economic recessions (the period during 2001 to 2008), the result indicated that every financial market had the weakly dependent structure with the Philippines financial market, especially Thailand financial market. Besides, it was weaker if the situations in the bear market were getting worst. This could be stated that the financial markets in ASEAN-5 countries were sensitive to uncontrollable shocks, which were not simply and inevitably needed to make an appropriate protection.

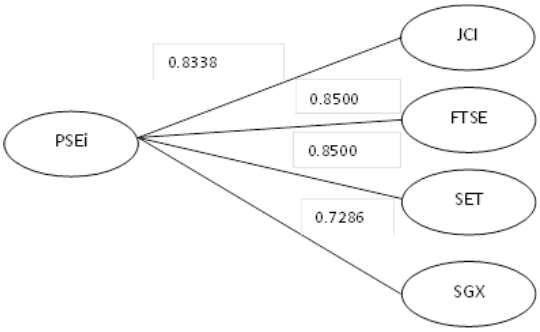

Figure 7 The estimation results of dependence structure in Bear markets in Elliptical (Gaussian copula) from C-Vine during the pre-crises periods (2001-2008)

b) The Clayton copula of D-vine in pre-crises period (2001-2008)

According to Figure 8, the estimation results from D-vine copula model was resembled from the C-vine tree by the t-copula model. Empirically, the Thai financial market is a weak dependence connecting with the Philippines financial market and others. Additionally, the results were different from in the situations regarding economics booms. This confirmed that downsizing in ASEAN stocks was one of potential causes indicating to the beginning of the financial crisis during 2008.

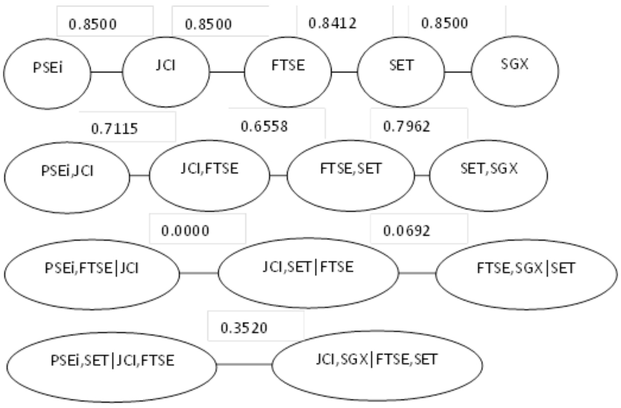

Figure 8 The estimation results of dependence structure in Bear markets in Elliptical (Gaussian copula) from D-Vine during the pre-crises periods (2001-2008)

c) The Clayton t-copula of C-vine in post-crises period (2009-2018)

Graphically displayed in Figure 9, the case of economic recession results indicated that the financial stock exchange in Philippines has the weak structural dependence with others during the post-crisis period. Recession was unfavourable. This confirmed that ASEAN-5 stocks struggled to survive in this situation by reducing international investments. Structural money flows were inevitably affected. Even though these five were strongly bonded by active multi-cultural submissions, the financial movements flowed around the continent were still slightly moved.

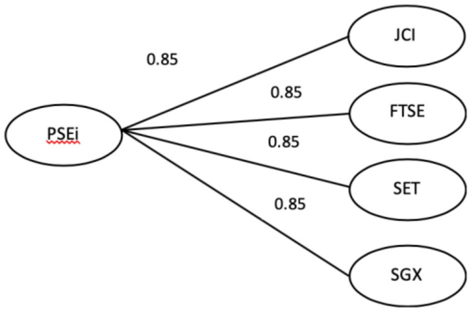

Figure 9 The estimation results of dependence structure in Bear markets in Elliptical (Gaussian copula) from C-Vine during the post-crises periods (2009-2018)

d) The Clayton copula of D-vine in post-crises period (2009-2018)

According to Figure 10, the estimation results from the D-vine tree by the t-copula model confirmedly showed the direction of flowing investment funds slightly moved between economic booms and economic recessions since there were quite independent in economic recessions. Each country trended to be protected and recovered in the economic system. With this unfavourable situation, ASEAN stocks seemed to be useless when economies needed the certain national incomes and outcomes.

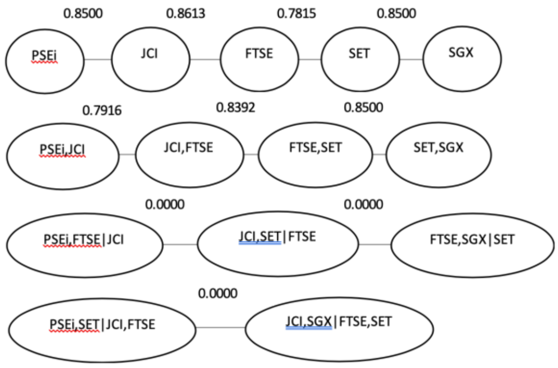

Figure 10 The estimation results of dependence structure in Bear markets in Elliptical (Gaussian copula) from D-Vine during the post-crises periods (2009-2018)

CONCLUSION

This paper contained the multi-analytic process in the financially econometric model. The employment of the alternative statistics called “Bayesian inference” was also introduced. The financial movements in South East Asia were one of the most emerging economies. The continent is dynamically growing up. Studying deeply on the structural connection among five major countries such as Philippines, Indonesia, Malaysia, Thailand, and Singapore was always the highlight to be the sign of financial visualization in this continent.

Empirically, this study found that there was a contagion among ASEAN-5 financial indexes and two types of copula models (Elliptical and Archimedean) were quite different since the symmetrical condition of joint distributions. There were the dynamics co-movement connection and conversed relations among capital markets in ASEAN-5 countries. Moreover, the Elliptical copula was computationally fitted model when it worked with the case of the pre-crisis period before 2008, which everything was unprepared for financial shocks. The symmetrical condition could be used to explain this kind of situation. However, the condition interestingly differed in terms of post-crisis periods. In economic boom and recessions after the subprime crisis in 2008, the stock exchanges were not structurally depended on each other. The dependent structure seemed to be an asymmetric joint distribution. The t-copula model could not be suitable to describe the dependence structure for financial markets because changing in the stocks or financial sectors were the kind of the uncontrollable factor. Relied on the chaos theory, realistically, these trends were not the normal distribution. The asymmetric copula (Clayton copula) was strongly recommended to employ to verify the dependent structure among stocks in ASEAN countries. In conclusion the result represented in this paper was the solution to point out the cause of the failure of financial economic predictions before the crisis existed. One of the huge mistakes was to deal with volatilities. The data classification and structural dependent estimation were the efficient tool to empower the understanding of correlations in financial indexes.

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APPENDIX

Table 4 C-vine copula testing in bull markets during pre-crisis and post-crisis periods

Canonicals (C-vine)	2000-2008				2009-2018			
	t-copula		clayton		t-copula		clayton	
Bull markets	Parameters	S.E.	Parameters	S.E.	Parameters	S.E.	Parameters	S.E.
$c_{1,2}$	143.3649	212.470	0.3654	0.042	6.0218	0.0301	0.3232	0.051
$c_{1,3}$	17.0539	87.722	0.3118	0.063	6.4305	0.0310	0.2198	0.045
$c_{1,4}$	3.4541	0.000	0.3265	0.059	18.4975	0.2655	0.3815	0.045
$c_{1,5}$	7.0561	10.991	0.3582	0.050	9.4116	3.6474	0.3143	0.048
$c_{2,3\|1}$	4.1518	3.341	0.1547	0.066	4.1196	0.0328	0.0921	0.046
$c_{2,4\|1}$	5.2148	0.002	0.1491	0.082	196.5004	1.3828	0.1081	0.052
$c_{2,5\|1}$	87.1884	1075.493	0.2403	0.047	3.7032	0.0390	0.1727	0.037
$c_{3,4\|12}$	184.6091	21.637	0.1468	0.059	199.8554	89.4980	0.0538	0.042
$c_{3,5\|12}$	42.6531	3790.452	0.2739	0.072	4.4987	0.9874	0.1655	0.063
$c_{4,5\|123}$	3.8606	4.322	0.0609	0.084	199.9298	207.0621	0.0288	0.035
AIC	-126.7660		-126.8458		-166.1402		-139.0252	
BIC	-104.7190		-104.7989		-140.0885		-112.9735	
Log-likelihood	73.383		73.423		93.070		79.513	

Source: authors

Table 5 C-vine copula testing in bear markets during pre-crisis and post-crisis periods

Canonicals (C-vine)	2000-2008	2009-2018
Bear markets	Parameters	Parameters
	Clayton	Clayton
$c_{1,2}$	0.8338	0.8500
$c_{1,3}$	0.8500	0.8500
$c_{1,4}$	0.8500	0.8500
$c_{1,5}$	0.8500	0.8500
$c_{2,3\|1}$	0.7286	0.7973
$c_{2,4\|1}$	0.6500	0.7821
$c_{2,5\|1}$	0.7519	0.7829
$c_{3,4\|12}$	0.0798	0.0440
$c_{3,5\|12}$	0.3641	0.2812

$c_{4,5\|123}$	0.0871	0.5399
AIC	-479.0030	-241.0546
BIC	-456.330	-235.4051
Log-likelihood	249.501	130.527

Source: authors

Table 6 D-vine copula testing in bull markets during pre-crisis and post-crisis periods

D-vine	2000-2008				2009-2018			
	t-copula		clayton		t-copula		clayton	
Bear markets	Parameters	S.E.	Parameters	S.E.	Parameters	S.E.	Parameters	S.E.
$c_{1,2}$	119.8613	0.00	0.3395	0.047	11.5480	0.075	0.3054	0.055
$c_{1,3}$	3.8956	367.352	0.3816	0.056	19.3973	228.360	0.1850	0.052
$c_{1,4}$	5.4850	0,212	0.3399	0.054	13.8424	10.151	0.1875	0.045
$c_{1,5}$	4.2358	7.213	0.3291	0.073	121.3413	42.489	0.2291	0.046
$c_{2,3\|1}$	20.5248	0.124	0.0855	0.080	10.4892	14.274	0.1262	0.066
$c_{2,4\|1}$	11.0817	0.442	0.1103	0.114	43.2159	73.790	0.2358	0.068
$c_{2,5\|1}$	33.4024	879.436	0.3001	0.064	2.5358	0.925	0.2320	0.062
$c_{3,4\|12}$	2.1362	41.058	0.1332	0.087	5.5118	6.318	0.1993	0.067
$c_{3,5\|12}$	11.8765	454.825	0.1792	0.065	4.8921	1.899	0.1805	0.063
$c_{4,5\|123}$	5.1078	18.289	0.1909	0.089	5.9468	6.433	0.1216	0.071
AIC	-104.7043		-128.4870		-167.3240		-133.3025	
BIC	-83.2730		-106.4401		-141.2723		-107.2508	
Log-likelihood	62.352		74.244		93.662		76.651	

Source: authors

Table 7 D-vine copula testing in bear markets during pre-crisis and post-crisis periods

D-vine	2000-2008	2009-2018
Bear markets	Parameters	Parameters
	Clayton	Clayton
$c_{1,2}$	0.8500	0.8500
$c_{1,3}$	0.8500	0.8163
$c_{1,4}$	0.8412	0.7815
$c_{1,5}$	0.8500	0.8500
$c_{2,3\|1}$	0.7115	0.7916
$c_{2,4\|1}$	0.6558	0.8392
$c_{2,5\|1}$	0.7962	0.8500
$c_{3,4\|12}$	0.0000	0.0000
$c_{3,5\|12}$	0.0690	0.0000
$c_{4,5\|123}$	0.3520	0.0000
AIC	-484.4816	-329.3582
BIC	-470.8087	-323.7087
Log-likelihood	252.241	147.679

Source: authors