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An Analysis of Contagion Effect on ASEAN Stock Market Using Multivariate Markov Switching DCC GARCH

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Abstract : Contagion effect is a transmission of volatility from shocks arising in one country to other countries. Volatility transmission particularly occurs in emerging countries like the ASEAN. In this study, we investigate the contagion effect in eight stock of the South East Asia stock markets (ASEAN), namely stock exchange of Thailand (SET), Indonesia stock exchange (IDX), Hanoi stock exchange (HNX), Kuala Lumpur Stock Exchange (KSX), Singapore Exchange Limited (STI), The Philippine Stock Exchange, Inc. (PSEi), Cambodia Securities Exchange (CSX) and Lao PDR stock exchange (LSX) (which call ASEAN stock markets). The contagion effect is investigated using correlation analysis, thus, we employ the MS-DCC-GARCH model. The result of this research shows that ASEAN stock markets usually stay in high correlation regime and the degree of volatility is high. This indicates a strong contagion among ASEAN stock markets.

Keywords : contagion; Markov switching model; DCC-GARCH model; ASEAN stock markets.
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1 Introduction

In the financial perspective, the contagion effect refers to the relationship among the financial assets, thus the shock of one asset can be transferred to other assets and the

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contagion effect is tested by correlation [1]. Thus, Investors or institutions should beware of this contagion effect. (See [2], [3] and [4]). In the past few years, the study of contagion effect has been rapidly grown. Mollah [5], Sibel [6], and Chiang et al. [7] have investigated the contagion effect in the developed country to emerging country by estimate dynamic conditional correlation. These studies confirmed the contagion effect between developed countries to emerging markets. There are several studies indicating the contagion effect among the group of countries. Fang et al. [8], Triaminic and Falianty [9] have found the contagion effect from China to 5 stock markets in ASEAN (Indonesia, Malaysia, Thailand, Singapore, and Philippines). Samitas et.al [10], Harkmann [11] and Alexakis et al. [12] have found the contagion effect in EU stock market during the crisis period. In case of in case of ASEAN, Chiang et al. [4], Rahman and Sidek [13] and Chunxiu [14] found that the distribution of volatilities during the 2007 economic crisis in five ASEAN countries

In the literature, the contagion effect can be investigated by four methods [15]. Firstly, the multiple equilibria approach which is the traditional method for testing the contagion effect. It basically tests the contagion effect between many countries. Fratzscher [16] and Jeanne and Masson [17] employed the multiple equilibria model to study currency crisis in twenty-four emerging economies during 1986 1998. Secondly, the unanticipated-shock model, Fry-McKibbin et al. [18] applied this method to study contagion effect Russian crisis in 1998, the US hedge fund Long-Term Capital Management (LTCM) in 1998, Brazil crisis in 1999 and Turkey in 1999. They found that result is not clear to approve the contagion effect. Thirdly, the co-movement analysis, Baig and Goldfajn [19] have studied the contagion effect in emerging economies during in the late 1990s. Finally, the asymmetric models, Eichengreen et al. [20] adopt this approach to study the currency crises in 20 industrialized economies.

In this study, we investigate the contagion effect in the ASEAN stock market using the co-movement method. The contagion effect in ASEAN stock markets (which include the Cambodia and Laos stock markets) is quite new in the literature and the investigation of the contagion effects in these markets could provide a great benefit to the investors and financial institutions in the ASEAN. In the methodology point of view, there are many models that used for measuring co-movement or correlation among the variables. For example, constant conditional correlation GARCH (CCC-GARCH) model of Bollerslev [21], dynamic conditional correlation GARCH GARCH (DCC-GARCH) model of Engle [22]. However, these two models were found to have a limitation on the regime shift in the correlation. Thus, the model was developed and extended to the Markov Switching approach and thus the Markov Switching DCC-GARCH model is introduced by Billo and Caporin [23]. They applied this model to test the contagion effect and compared with the conventional DCC-GARCH. They revealed that although the DCC-GARCH model allowed the correlation to change over time, the results from the Markov Switching DCC-GARCH model provide a clear state (upper or lower state) in the correlation. It can indicate the upward (upper) and downward (lower) condition of correlation and can detect the unobserved crisis or shock through Hidden Markov process [24].

As the success of the Markov Switching DCC-GARCH model in the investigation of contagion effect, in this study, we consider to include a new emerging ASEAN stock markets, which are Cambodia and Laos stock markets. To the best of our knowledge, this is the first attempt in a study the contagion in the ASEAN stock markets. This paper is organized as follows. Section 2 represents the methodology. Section 3 presents the data and models specifications. Then, section 4 presents result of our empirical result. The last section offers concluding remarks.

2 Methodology

2.1 GARCH Model

Time series analysis often assumes that the variance of the data is constant (Homoscedasticity). In fact, the variance of the data depends on historical error (Heteroscedasticity). So, the variance or the volatility of the data should not be constant. Thus, most researches estimated the mean and variance of time series data by GARCH model, proposed by Bollerslev [21], with the following equation:

$$r_t = \mu_t + \varepsilon_t \tag{2.1}$$

$$\varepsilon_t = z_t \sqrt{\sigma_t^2} \tag{2.2}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_t \varepsilon_{t-q}^2 + \sum_{i=1}^{p} \beta_t \sigma_{t-p}^2 \tag{2.3}$$

where z_t is the stock index return on time t, μ_t is constant term, ε_t is error term, z_t is white noise, σ_t^2 is the volatility of ε_t at the time t and α_t, β_t are parameter at the time t

2.2 Dynamic Conditional Correlation GARCH (DCC-GARCH) Model

Bollerslev [21] introduced the concept to develop the constant conditional correlation GARCH (CCC-GARCH) model to estimate the correlation. Nevertheless, the restriction of the model is that the correlation is constant with no change through time (not time varying). Later, Engle [23] developed the dynamic conditional correlation GARCH (DCC-GARCH) model to solve this problem in the following way:

$$H_t = D_t R_t D_t, \tag{2.4}$$

where H_t is $n \times t$ matrix of conditional variances at time t, R_t is Conditional Correlation matrix at time t and D_t is Diagonal matrix of σ_t^2 at time t. As following:

$$D_t = diag\{\sqrt{\sigma_{1t}}, ..., \sqrt{\sigma_{nt}}\}. \tag{2.5}$$

After estimating the volatility from the GARCH model, the result is in the form of a vector. So, it's converted to a matrix [25].

$$D_t = \begin{bmatrix} \sqrt{\sigma}_{11} & 0 & \cdots & 0 \\ 0 & \ddots & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{\sigma}_{nt} \end{bmatrix} \tag{2.6}$$

The result will be in the form of a correlation matrix. The equation is as follows [25].

$$R_t = diag\,\{Q\}_t^{-1}\,Q_t diag\,\{Q\}_t^{-1}\,, \tag{2.7}$$

where R_t is conditional correlation matrix (which is a dynamic correlation or time varying correlation metrix) at time t and Q_t is conditional correlation matrix with time varying at time t.

Therefore, the Dynamic Conditional Correlation (GARCH) model [22] is expressed by:

$$Q_{i,t} = (1-\theta_{i,1}-\theta_{i,2})\,\bar{Q}_i + \theta_{i,1}Q_{i,t-1} + \theta_{i,2}\varepsilon^{'}_{i,t-1}\varepsilon^{2}_{i,t-1} \tag{2.8}$$

where Q_t is conditional correlation matrix with time varying at time t in condition $\bar{Q} = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{t-1}\varepsilon^{'}_{t-1}$, T is time, θ_1 and θ_2 are parameters in range $0 \leq \theta_1 + \theta_2 < 1$.

2.3 Markov Switching Dynamic Conditional Correlation GARCH (MS-DCC-GARCH) Model

A special feature of the Markov switching model is that it allows the parameter estimates from the equation to switch between states. By the Markov process, all parameters are controlled by the state variable (S_t) with probability (p_{ij}) [26]:

$$Pr(S_t = j\,|S_{t-1} = i) = p_{ij}, \sum_{j=1}^{k} p_{ij} = 1; i = 1,...,k \tag{2.9}$$

This study is based on the two-state Markov switching model (assumed to be an up and down state). The first step is as follows:

$$p_{ij} = Pr\,(S_t = j\,|S_t = i\,)\,; \sum_{j=1}^{2} p_{ij} = 1, i, j = 1, 2, \tag{2.10}$$

where p_{ij} is the probability of switching form regime i to j regime and $\sum_{j=1}^{2} p_{ij} = 1$ in order to separate the non-linear function into two states.

Billo and Caporin [23] proposed the Markov Switching DCC-GARCH model by combining the Markov Switching into DCC-GARCH model so it can be written as follows.

$$\begin{gathered} Q_{t,(S_t=i)} = \left(1-\theta_{1,(S_t=i)}-\theta_{2,(S_t=i)}\right)\bar{Q}_{t,(S_t=i)} + \\ \theta_{1,(S_t=i)}S_{it-1}Q_{t-1,(S_t=i)} + \theta_{2,(S_t=i)}S_{it-1}\varepsilon'_{t-1,(S_t=i)}\varepsilon^{2}_{t-1,(S_t=i)}, \end{gathered} \tag{2.11}$$

where Q_{t,S_t} conditional correlation matrix with time varying at time t in regime S_t and s_{it-1} is state variable of i at time $t-1$. So, we can write the equations as follows:

$$r_{S_t} = \mu + v_{s_t}\sqrt{\sigma^{2}_{s_t}} \tag{2.12}$$

$$H_{s_t} = D_{s_t} R_{s_t} D_{s_t} \tag{2.13}$$

$$R_{s_t} = diag\{Q\}_{s_t}^{-1} Q_{s_t} diag\{Q\}_{s_t}^{-1} \tag{2.14}$$

$$D_{s_t} = diag\left\{\sqrt{\sigma_{s_{1t}}}, ..., \sqrt{\sigma_{s_{nt}}}\right\}, \tag{2.15}$$

where s_t is the state variable under the probability of equation (2.10) and $\sigma_{s_t}^2$ is the volatility of ε_t at the time t in regime s_t. Assume $\Theta = (\mu, \alpha, \beta, \theta_{1,S_t}, \theta_{2,S_t}, p_{11}, p_{22})$ is the vector value of the parameters in Equations (2.12-2.15).Based on Engle's [22], the likelihood function of the dynamic volatility model (DCC-GARCH) is as follows:

$$L(\Theta_{s_t}) = L_v(\theta_{s_t}) \cdot L_Z(\mu, \alpha_s, \beta_s) \tag{2.16}$$

where $L_v(\theta_{s_t})$ is the volatility part from GARCH model and $L_Z(\mu, \alpha_s, \beta_s)$ is the correlation coefficient from the MS-DCC-GARCH model. Further, the likelihood function of the MS-DCC-GARCH model is as follows:

$$L(\Theta_{s_t}) = L_v(\theta_{s_t}) \cdot L_Z(\mu, \alpha_s, \beta_s) \tag{2.17}$$

$$L(\Theta_s) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{k/2}} \left\{-\frac{1}{2}\varepsilon^t \varepsilon\right\} \tag{2.18}$$

$$L_Z(\mu, \alpha_s, \beta_s) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{k/2} |R_{s_t}|} \exp\left\{-\frac{1}{2} e_{s_t}^T R_{s_t}^{-1} e_{s_t}\right\}. \tag{2.19}$$

3 Data

The data used in this study are the daily return from eight stock closing price index of the South East Asia stock markets (ASEAN), namely stock exchange of Thailand (SET), Indonesia stock exchange (IDX), Hanoi stock exchange (HNX), Kuala Lumpur Stock Exchange (KSX), Singapore Exchange Limited (STI), The Philippine Stock Exchange, Inc. (PSEi), Cambodia Securities Exchange (CSX) and Lao PDR stock exchange (LSX). The data start from 20 April 2012 to 22 October 2018 totaling 1,679 observations and are obtained from Bloomsburg database. Next, we converted stock price index to a continuous rate of return (equation 3.1) in order to satisfy the stationary properties.

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100, \tag{3.1}$$

where $r_{i,t}$ is the rate of return of stock index i country at time t, $P_{i,t}$ is index of stock market i at time t and $P_{i,t-1}$ is the price of stock market i at time $t-1$.

Table 1 shows the descriptive statistics of the returns of the ASEAN-8 stock market. First, for mean, most of the data have positive return except for Cambodia and Laos have negative return. For Skewness, we found that all countries do not equal 0 [27], which means that the data mostly are negatively skewed (except Laos has positive skewness at 0.0881), and the Kurtosis is greater than 3 [28] called leptokurtic. According to the Jarque-Bera value, we transform the p-value of the test to be the Maximam Bayes Factor (MBF) and we find that it is strongly reject the normality data for all series. Thus, the data are not normally distributed. Finally, according to the ADF-test. The data series are stationary, as indicated by the MBF. Figure 1 shows daily index returns of each countrys stock market, converted into continuous return.

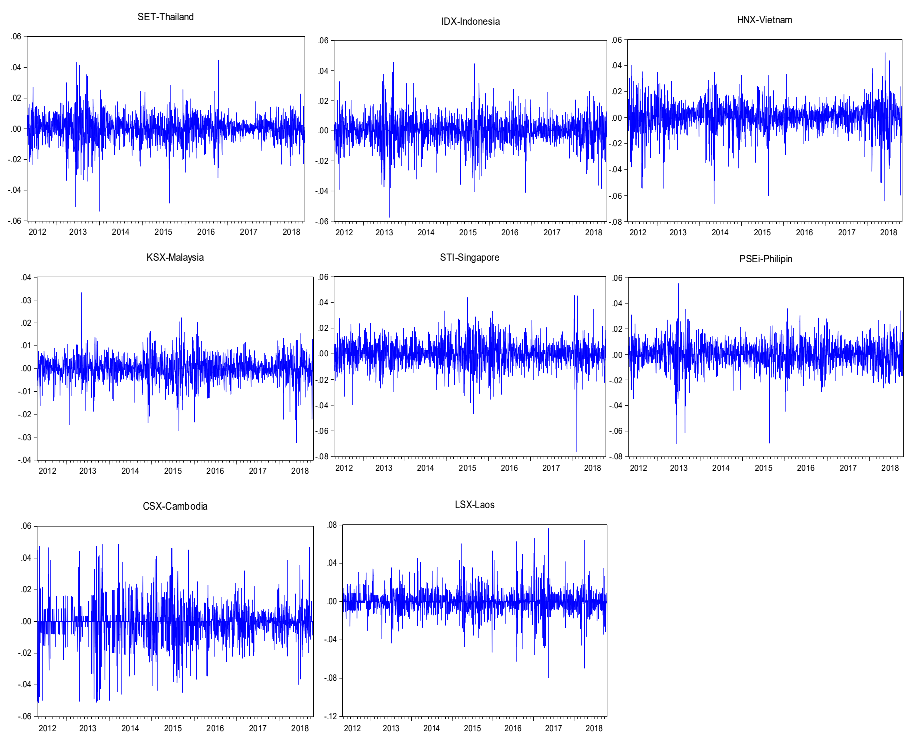

Figure 1: Daily log-return of ASEAN Stock Exchange, 2012-2018.

Table 1: Descriptive statistics

	SET	IDX	HNX	KSX	STI	PSEi	CSX	LSX
Mean	0.002	0.002	0.001	0.000	0.000	0.000	-0.006	-0.001
Median	0.002	0.000	0.001	0.000	0 .000	0.000	0.000	0.000
Maximum	0.044	0.045	0.050	0.033	0.045	0.055	0.048	0.076
Minimum	-0.053	-0.057	-0.066	-0.032	-0.076	-0.069	-0.051	-0.079
Std. Dev.	0.008	0.009	0.011	0.005	0.009	0.010	0.012	0.012
Skewness	-0.420	-0.436	-0.868	-0.421	-0.289	-0.628	-0.329	0.088
Kurtosis	7.674	6.679	7.760	6.941	7.033	7.998	7.550	10.018
J-B test	1594a	1011a	1820a	1148a	1173a	1878a	1494a	3485a
ADF Test	-40.03a	-26.18a	-43.21a	-37.79a	-43.35a	-39.71a	-40.75a	-34.32a

Note: a indicates the strong evidence support the alternative hypothesis.

4 Empirical Result

This section consists of three parts including (1) Empirical result of MS-DCC-GARCH (1,1), (2) Dynamic conditional correlation result and (3) Contagion result and explanation.

4.1 Empirical Result of MS-DCC-GARCH (1, 1)

Table 2 presents the results of two-regime MS -DCC-GARCH (1, 1). This model provides a regime 2 dependent variance equation. The value of the ω is constant. $(\alpha_t$ and $\beta_t)$ are the coefficient of the arch and GARCH terms at time $t-1$ period. The parameter values are more than zero indicating that the error term and the volatility in the past have positive effect on the volatility at time t. The shape and skew parameters show whether or not the data have symmetric distribution. The estimated shape parameter not equal one and estimated skew value between minus one to one will confirm that ASEAN stock index returns are asymmetrically distributed.

The unconditional volatility in each regime can be measured by the sum of ARCH and GARCH estimates $(\alpha_t + \beta_t)$. and the value of volatility persistence shows the degree of volatility in each country and the higher level means stock market has higher level of volatility and the result is provided in Table 3. We found that Thailand has the highest volatility at 0.999, followed by Singapore at 0.9948, Indonesia at 0.9842, while Laos has the lowest volatility at 0.937 because Laos has few companies listed in the stock market . We find that all markets of ASEAN have high fluctuation attributable to two major factors: 1. Internal factors in ASEAN which is the Malaysia currency crisis and 2. External factors such as USA election and QE tapering. Both of them affected ASEAN stock markets through financial linkage.

Table 2: Estimation result of MS -DCC-GARCH (1,1)

	SET	IDX	HNX	KSX	STI	PSEi	CSX	LSX
ω	0.073	0.000	0.000	0.000	0.001	0.001	0.001	0.000
α	0.073	0.097	0.120	0.086	0.070	0.089	0.224	0.672
β	0.92	0.88	0.858	0.894	0.925	0.877	0.746	0.265
$\alpha+\beta$	0.999	0.9842	0.9781	0.9807	0.9948	0.9663	0.9696	0.937
Skew	0.913	0.883	0.905	0.936	0.981	0.932	0.949	0.980
Shape	4.998	4.22	5.020	4.904	4.673	6.637	2.742	2.444
$\theta_{1,(s_t=1)}$	0.0554	$\theta_{1,(s_t=2)}$	0.0424		$\theta_{1,(s_t=1)}+\theta_{1,(s_t=2)}$.	0.9836	p_{11}	0.9392
$\theta_{2,(s_t=1)}$	0.9281	$\theta_{2,(s_t=2)}$	0.7985		$\theta_{2,(s_t=1)}+\theta_{2,(s_t=2)}$	0.8409	p_{22}	0.5457
Models			Skew-DCC-GARCH			MS-Skew-DCC-GARCH		
AIC			-725.987			$-11,398.35$		

The sum of $\theta_{1(s_t=1)}+\theta_{2(s_t=1)}$ in Table 2 is 0.9836 while the sum of $\theta_{1(s_t=2)}+\theta_{2(s_t=2)}$ is 0.8409. According to Chodchuangnirun.et.al [24], this summation referes to the correlation persistence. Therfore, we interpret regime 1 and regime 2 as high and low correlation regime, respectively.

Furthermore, in this section, the performance of our model MS-DCC-GARCH(1,1) is compared with the single regime DCC-GARCH. The results indicate that MS-DCC-GARCH model is the better model than DCC-GARCH on the basis of AIC information criteria (MS-DCC-GARCH has $-11,398.35$ and DCC-GARCH has -798.987).

Table 3: Transition probability matrix

	Regime 1	Regime 2	Duration
Regime 1	0.9329	0.0192	14.90313
Regime 2	0.453	0.5457	2.201189

Table 3 presents the transition probability matrix of the model. The empirical result presents the regime switching probability from regime 1 (which is a high correlation regime) to regime 2 (which is an low correlation regime) which is 0.0192, while regime 1 is still 0.9329. In contrast, the probability of regime switching from regime 2 to regime 1 is 0.453, while remaining in this regime is 0.5457. Thus, this result suggests a higher probability for regime 1 when compared to regime 2. The duration of staying in the lower regime is about 14 days and 2 days in upper regime. Therefore, ASEAN stock market has high probability to be in high correlation regime.

The estimated MS-DCC-GARCH (1, 1) model also produces the probabilities of two regimes for the period from 2012 to 2018. The plot of regime probabilities for all the returns is presented in Figure 2. The results show that ASEAN stock markets mostly experienced the lower regime except for the period from 2016 (the blue-dashed line). This period corresponds to the global event such as Donald Trump winning USA presidency, and Federal Reserves decision to smooth canceling QE (QE tapering) which caused huge capital from foreign investors flowing into ASEAN.

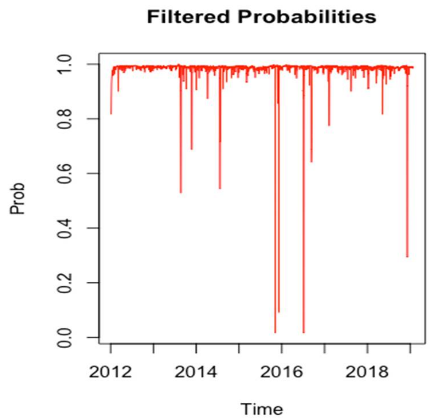

Figure 2: Filtered probabilities of ASEAN Stock index returns.

4.2 Dynamic Conditional Correlation Result

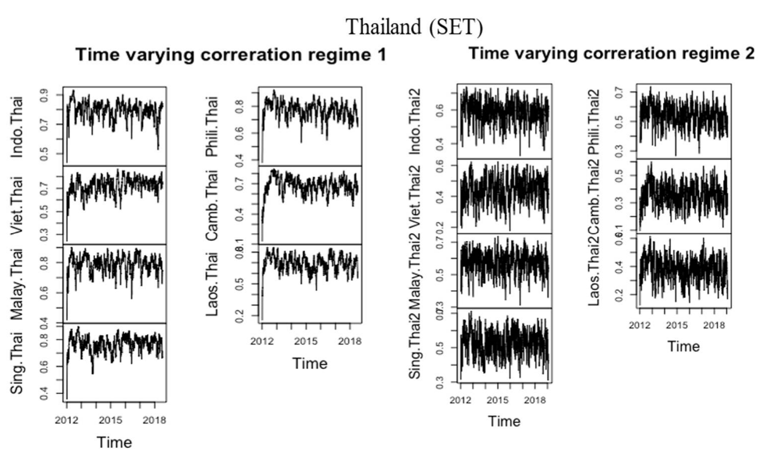

Figure 3: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Thailand.

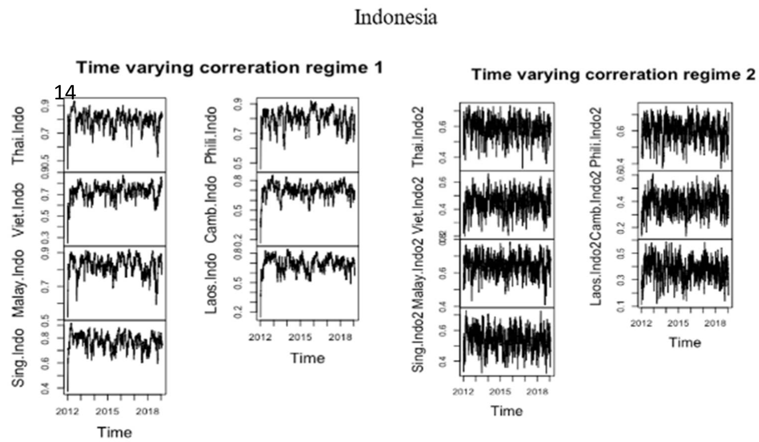

Figure 4: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Indonesia.

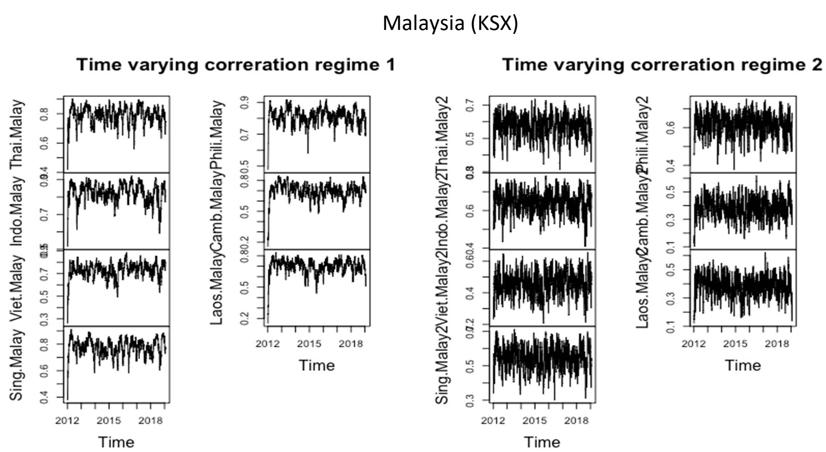

Figure 5: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Malaysia.

Vietnam (HNX)

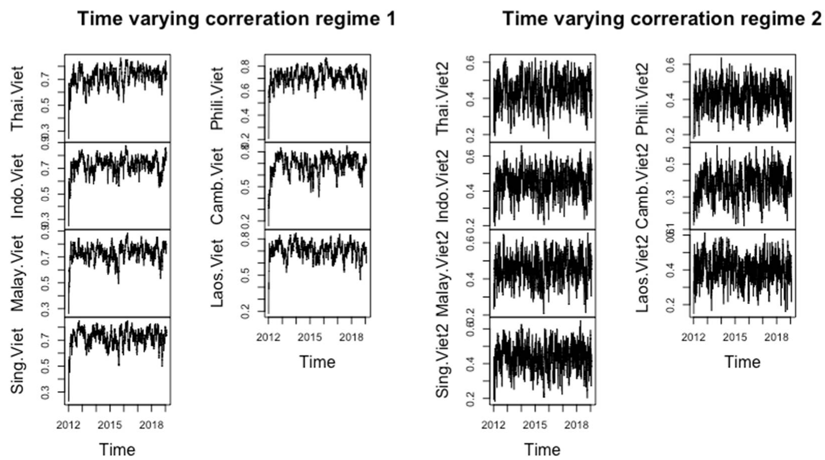

Figure 6: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Vietnam.

Singapore

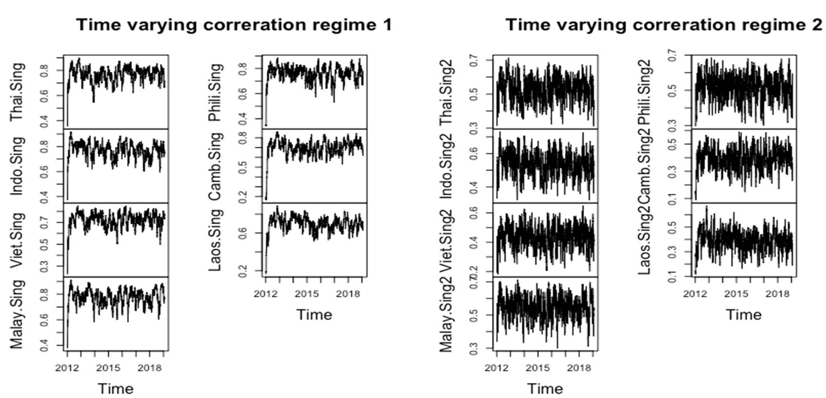

Figure 7: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Singapore.

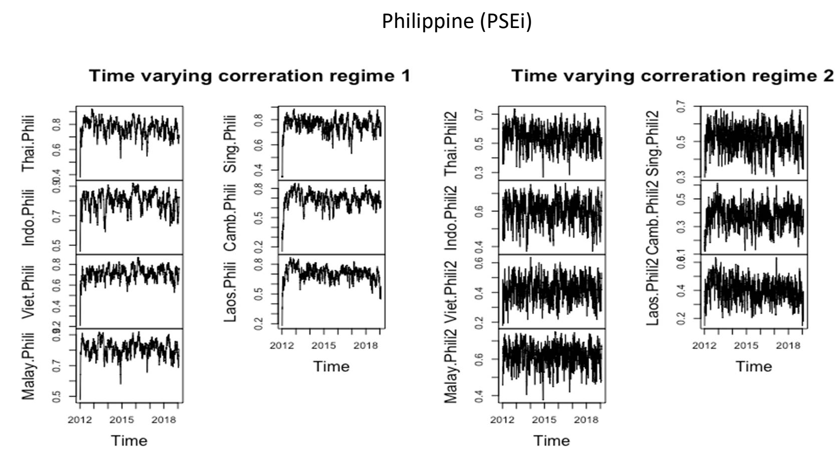

Figure 8: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Philippine.

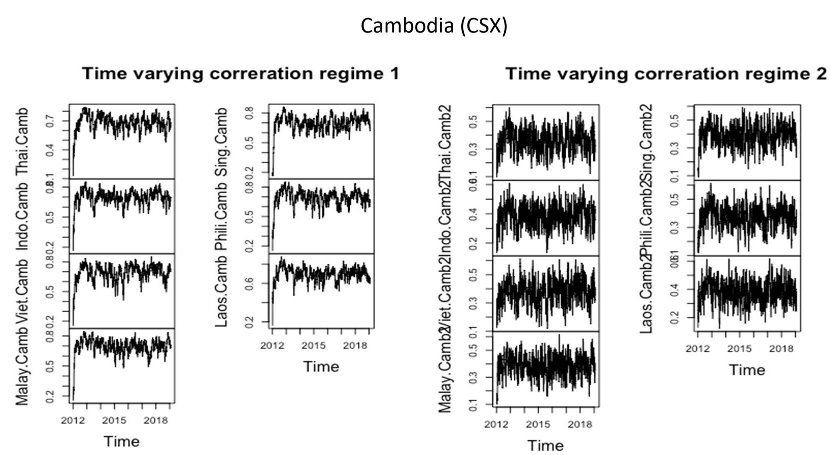

Figure 9: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Cambodia.

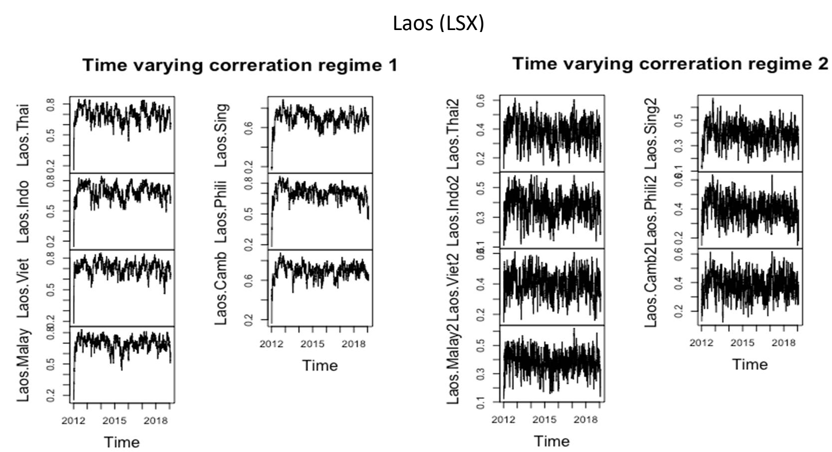

Figure 10: The Dynamic correlation with 2 regimes estimated by MS -DCC-GARCH of Laos.

Figure 3 shows the dynamic correlation between countries within ASEAN stock market using MS-DCC-GARCH model. The left-hand side is dynamic conditional correlation of low correlation regime and the right one is the high correlation regime. We observe that the conditional correlation in high correlation regime is less varying and swinging than in low correlation regime for all ASEAN stock markets.

4.3 The Mean of Dynamic Conditional Correlation

To make a simple interpretation, the average of the dynamic correlation of ASEAN stock markets is computed. The range of correlation is between to which correlation value close to or indicates a strong positive or negative relationship [29]. Table 4 shows the mean of dynamic conditional correlation in a high correlation regime. All mean correlation values are more than 0.9 and close to 1 meaning that they are moving in the same direction in a high correlation regime.

Malaysia and Indonesia stock markets have the highest value of conditional correlation at 0.9638 which means they have a strongest relationship in lower regime (when a country melt down, other countries fall too). Raman and Sidek [13], Chaiphat [30] explained this phenomenon as attributable to many factors as such: geographic factors: they have adjacent territory making it easy for trade and investment, market interdependence.

Table 5 shows the dynamic conditional correlation in low correlation regime. Apparently, the ASEAN correlations are positive but rather low ranging from 0 to 0.5 with the

Malaysia and Indonesia pair having the highest value of conditional correlation while the lowest conditional correlation is Laos and Cambodia stocks market pair (0.2756).

Table 4: Mean of dynamic conditional correlation of ASEAN stock markets in regime 1 (High correlation regime)

	SET	IDX	HNX	KSX	STI	PSEi	CSX	LSX
SET	1	0.954	0.9412	0.9547	0.9524	0.9459	0.9354	0.938
IDX	0.954	1	0.9441	0.9638	0.9536	0.9536	0.9444	0.9379
HNX	0.9412	0.9441	1	0.9451	0.9459	0.9417	0.9332	0.9418
KSX	0.9547	0.9638	0.9451	1	0.955	0.961	0.9415	0.9406
STI	0.9524	0.9536	0.9459	0.955	1	0.9483	0.942	0.9393
PSEi	0.9459	0.9536	0.9417	0.961	0.9483	1	0.9356	0.9403
CSX	0.9354	0.9444	0.9332	0.9415	0.942	0.9356	1	0.9404
LSX	0.938	0.9379	0.9418	0.9406	0.9393	0.9403	0.9404	1

Table 5: Mean of dynamic conditional correlation of ASEAN stock markets in regime 2 (Low correlation regime)

	SET	IDX	HNX	KSX	STI	PSEi	CSX	LSX
SET	1	0.5105	0.3427	0.4947	0.4431	0.46	0.2756	0.2733
IDX	0.5105	1	0.3486	0.5785	0.4557	0.5275	0.278	0.2612
HNX	0.3427	0.3486	1	0.3603	0.3327	0.3143	0.2698	0.2908
KSX	0.4947	0.5785	0.3603	1	0.4619	0.5451	0.5105	0.2711
STI	0.4431	0.4557	0.3327	0.4619	1	0.4295	0.2823	0.2796
PSEi	0.46	0.5275	0.3143	0.5451	0.4295	1	0.2663	0.2923
CSX	0.2756	0.278	0.2698	0.5105	0.2823	0.2663	1	0.2464
LSX	0.2733	0.2612	0.2908	0.2711	0.2796	0.2923	0.2464	1

4.4 Contagion Result

The next step, we investigate the contagion effect based on the definition of correlation. In this study, the estimated conditional correlation is applied to detect the contagion effect. Table 6 presents that the average conditional correlation from each column in Tables 4 and 5. In the high correlation regime (regime 1), all ASEAN markets have correlation values more than 0.9 and close to 1 meaning when the one stock market falls, other stock markets will fall in the same direction too.

We observe that Malaysia stock market has highest average conditional correlation in both two regimes, indicating that Malaysian stock market is the hub of the ASEAN stock markets and it is the main source of the contagion effect in ASEAN. In lower correlation regime (regime 2), we observe that the correlation values are quite different the average correlation of each country against other countries are relatively small and positive relationship. This is to say that the contagion effect in this regime is low when compared to regime 1. We also find that Malaysia stock market has the highest contagion effect in this regime, while Laos has a small contagion effect on other country. This finding supports the notion that the small capitalization stock market has barely effect on other countries.

In conclusion, we confirm that the huge capitalization of stock market is associated with higher probability to affect other stock markets than small capitalization. The results lead to the conclusion that ASEAN stock markets have a contagion effect in both regimes. In addition, the Malaysia stock market is the major country which transfers the volatility or high effect to other countries because it has the highest correlation value.

Table 6: The average mean of conditional correlation of ASEAN stock markets in 2 regimes

	SET	IDX	HNX	KSX	STI	PSEi	CSX	LSX
Regime 1	0.9527	0.9564	0.9491	0.9577	0.9546	0.9533	0.9466	0.9473
Regime 2	0.4713	0.495	0.4074	0.5277	0.4606	0.4794	0.3911	0.368

5 Conclusion

In this paper, we aim to study the ASEAN stock market relationship in different regime and examine the contagion effect. We apply the MS-DCC-GARCH model using 2 steps: 1. Estimate the volatility from GARCH and 2. MS-DCC-GARCH model is estimated for estimating the dynamic conditional correlation and investigate the contagion effect in ASEAN stock markets. The ASEAN stock markets are the ones of emerging country group including Thailand (SET), Indonesia (IDX), Vietnam (HNX), Malaysia (KSX), Singapore (STI), Philippines (PSEi). In addition, we include the new stock markets which are Cambodia (CSX) and Laos (LSX) in period of 2012 to 2018 with data of 1,679 observations.

In this study, we consider the dynamic conditional correlation to test the contagion effect in ASEAN stock markets. From the dynamic conditional correlation result, we separate the correlation into 2 regimes (High correlation and Low correlation regime) by applying Markov switching model. First, we compare this model to DCC-GARCH. The MS-DCC-GARCH model is better than DCC-GARCH in term of the AIC value. We compute the volatility persistence $(\alpha_t + \beta_t)$ which showed that Thailand has the highest constant volatility and compute the regime dependent correlation $\theta_{1(s_t=i)} + \theta_{2(s_t=i)}$. The results present that the data (ASEAN stock index returns) exhibit a regime shift in the correaltion. We find that there exhibit the positve correaltion of ASEAN stock markets in two differnt regimes.

Then, we compute the mean of dynamic conditional correlation. The results show that Malaysia and has strongest correlation in both regimes, while Laos stock market has lowest correlation. We thus suggest that the shock in the Malaysia stock market is highly affect to other markets.

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References

[1] Dornbusch, R., Park, Y. C., and Claessens, S. (2000). Contagion: understanding how it spreads. The World Bank Research Observer, 15(2), 177-197.

[2] Forbes, K. J., and Claessens, S. (2004, November). International Financial Contagion: The Theory, Evidence and Policy Implications. In conference" The IMF's role in emerging markets economies" in Amesterdam (p. 01).

[3] Kumar, V., Bisht, G. S., and Institu, S. B. S. P. G. (2010). An improved method for isolation of genomic DNA from filamentous actinomycetes. Journal of Sci. Engg. and Tech. Mgt. Vol, 2, 2.

[4] Mezghani, T., and Boujelbne, M. (2018). The contagion effect between the oil market, and the Islamic and conventional stock markets of the GCC country: Behavioral explanation. International Journal of Islamic and Middle Eastern Finance and Management, 11(2), 157-181.

[5] Mollah, S., Quoreshi, A. S., and Zafirov, G. (2016). Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. Journal of International Financial Markets, Institutions and Money, 41, 151-167.

[6] Sibel Celik (2012). The more contagion effect on emerging markets:The evidence of DCC-GARCH model. Econimic Modelling 29.1946-19

[7] Chiang, T. C., Jeon, B. N., and Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from ASEAN markets. Journal of International Money and finance, 26(7), 1206-1228.

[8] Yu, H., Fang, L., Sun, B., and Du, D. (2018). Risk contribution of the Chinese stock market to developed markets in the post-crisis period. Emerging Markets Review, 34, 87-97.

[9] Trihadmini, N., and Falianty, T. A. (2018). Interdependence and contagion in five ASEAN countries and five developed countries in the area of financial linkages. Competition and Cooperation in Economics and Business.

[10] Samitas, A., and Tsakalos, I. (2013). How can a small country affect the European economy? The Greek contagion phenomenon. Journal of International Financial Markets, Institutions and Money, 25.

[11] Harkmann, K. (2014). Stock market contagion from Western Europe to Central and Eastern Europe during the crisis years 2008-2012. Eastern European Economics, 52(3), 55-65.

[12] Alexakis, C., and Pappas, V. (2018). Sectoral dynamics of financial contagion in Europe-The cases of the recent crises episodes. Economic Modelling.

[13] Rahman, A. A., and Sidek, N. Z. M. (2011). Spill-over effect of us Sub-prime crisis on ASEAN-5 stock markets. In Business and social science research conference (p. 334). World Business Institute Australia Dubai, UAE.

[14] Chunxiu, M., and Masih, M. (2014). Contagion Effects of US Subprime Crisis on ASEAN-5 Stock Markets: Evidence from MGARCH-DCC Application.

[15] Cheung, L., Tam, C. S., and Szeto, J. (2009). Contagion of financial crises: A literature review of theoretical and empirical frameworks. Hong Kong Monetary Authority Research Paper 02.

[16] Fratzscher, M. (2003). On currency crises and contagion. International Journal of Finance and Economics, 8(2), 109-129.

[17] Jeanne, O., and Masson, P. (2000). Currency crises, sunspots and Markov-switching regimes. Journal of international economics, 50(2), 327-350.

[18] Fry-McKibbin, R., Martin, V., Gonzalez-Hermosillo, B., and Dungey, M. (2002). International Contagion Effects from the Russian Crisis and the LTCM Near-Collapse (No. 02/74). International Monetary Fund.

[19] Baig, T., and Goldfajn, I. (1999). Financial market contagion in the ASEAN crisis. IMF staff papers, 46(2), 167-195.

[20] Eichengreen, B., Rose, A. K., and Wyplosz, C. (1995). Exchange market mayhem: the antecedents and aftermath of speculative attacks. Economic Policy, 10(21), 249-312.

[21] Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. The Review of Economics And Statistics, 498-505.

[22] Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics, 20(3), 339-350.

[23] Billio, M., and Caporin, M. (2005). Multivariate Markov switching dynamic conditional correlation GARCH representations for contagion analysis. Statistical Methods and Applications, 14(2), 145-161.

[24] Chodchuangnirun, B., Yamaka, W., and Khiewngamdee, C. (2018, March). A Regime Switching for Dynamic Conditional Correlation and GARCH: Application to Agricultural Commodity Prices and Market Risks. Proceeding of In International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making (pp. 289-301). Springer, Cham.

[25] Elisabeth Orskaug. (2009). Multivariate DCC-GARCH Model-with Various Distributions. Norwegian University of Science and Technology.

[26] Hamilton J D, (1989) A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57 357384

[27] Hutchinson, M., and Gallagher, L. Skewness, kurtosis and convertible arbitrage hedge fund performance.

[28] Kallner, A. (2014). Laboratory statistics, handbook of formulas and terms. Chemistry International, 36(4), 23-23

[29] Hanson, B., Klink, K., Matsuura, K., Robeson, S. M., and Willmott, C. J. (1992). Vector correlation: review, exposition, and geographic application. Annals of the Association of American Geographers, 82(1), 103-116.

[30] Chaiphat, C. (2014). Cointegration of Capital Markets in ASEAN-5 Countries. Applied Economics Journal, 21(1), 42-58.

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