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Asymmetric Risk Spillovers Between China and ASEAN Stock Markets

JIUSHENG CHEN AND XIANNING WANG
School of Economics and Management, Chongqing Normal University, Chongqing 401331, China
Corresponding author: Jiusheng Chen (jiusheng_chen@163.com)

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ABSTRACT This study attempts to investigate the interdependence and risk spillover effects between China and ASEAN-6 stock markets by using the Copula-TV-GARCH-CoVaR model and the MES model covering the period from January 04, 2010 to April 30, 2021. The results indicate that these stock markets, except the Vietnam stock market, experience a dependency structure. The pair of China and Singapore exhibited the highest dependence structure, whereas Vietnam was least likely to have dependence structures with China stock market. Upside and downside CoVaRs are symmetric and display similar temporal dynamics throughout the sample period for all the series. Moreover, the values of upside CoVaRs are systematically above the upside VaRs for all markets in the sample periods, while the values of downside CoVaRs are systematically below the downside VaRs. The MES and ΔCoVaRs are significantly positive and varied from one market to another, which indicates that there are bidirectional asymmetric risk spillover effects between China and the ASEAN-6 stock markets. Furthermore, the pairs of risk spillover between China and ASEAN stock markets identified using MES and ΔCoVaR may not be identical. Our results indicate that international portfolio managers and policymakers should consider the existence of asymmetric risk spillover effects between China and the ASEAN countries.

INDEX TERMS ASEAN, stock market, CoVaR, risk spillover, TV-GARCH, MES.

I. INTRODUCTION

The Belt and Road Initiatives and the establishment of the China-ASEAN Free Trade Area have strengthened the economic interconnection between China and ASEAN countries and also contribute to promoting the integrated development of economy and finance. In 2010, the bilateral trade volume was US$292.8 billion. By 2020, the bilateral trade volume roses up to US$684.6 billion, increasing 2.3 times during the 10 years. China's investment in ASEAN grew by more than 70% year on year, and ASEAN has become China's largest trading partner. Armed with this background, cross-border financial interconnection among China and ASEAN countries is growing through the trading effect [1]. China has stepped into the economic and financial networks composed of ASEAN countries. Furthermore, it may be easier influenced by AESAN countries in economic and, the more crucial field, finance. Consequently, it is important for us to exam the risk spillover and linkage between China and the ASEAN economies, to design macro-prudential policies to safeguard financial stability in case of potential shocks originating from the other economies. In addition, it also helps for portfolio diversification across different countries, since the performance of a portfolio depends on the interlinkage between them. Diversification benefits can be achieved when the portfolios display low or negative interconnection. Conversely, portfolios with high positive linkage may display a low performance.

There has been an increasing interest in investigating the linkage and dependence structure between China and ASEAN stock markets in recent years and a rich body of literature that documents the theme. Li and Zeng [2] show that the dependence between China and the ASEAN stock markets is very sensitive to the financial crisis and the coefficients are enhanced significantly during the US sub-prime mortgage crisis. The results were also supported

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by Kang *et al.* [3]. As for the region, the interdependence of the ASEAN countries is more vulnerable to the US shocks than that of those affected by the developed economies of East Asia [4]. Moreover, the financial integration of China and the ASEAN countries have gradually increased during the crisis [5] and the ASEAN Economic Community is more integrated with the Chinese stock market than with the United States stock market [6]. Nguyen and Elisabeta [7] find that financial integration in a moderate level before and after the recent crisis and a higher level during the crisis. Trading is an important determinant of financial integration in China and ASEAN countries [1].

Unlike the previous studies that focus on interconnections and integration among stock markets in China and ASEAN countries, we construct a new composite model named Copula-TV-GARCH-CoVaR model to evaluate the time-varying financial risk spillover effects between China and ASEAN stock markets. One of the key advantages of this model is the unconditional variance of the GARCH model evolves smoothly over time. This overcomes the main weaknesses of other GARCH models. Hence, this TV-GARCH model is superior to other GARCH models and produces the most accurate estimators. Moreover, the degree of risk spillover effect changes between the two countries could be captured by the CoVaR model introduced by Adrian and Brunnermeier [8] and the MES model introduced by Acharya *et al.* [9] in a time-varying manner.

Motivated by exploring the market risk contagion among China and ASEAN countries, we emphasize the risk spillover effects across China and ASEAN countries. Our study focuses on China's spillover because China has become the second-largest economy in the world, and the impact of the China market in the globe is increased rapidly [10] as described above. Risk contagion and volatility spillover between China stock markets and global markets have received rapidly increasing interest from academics, economists and investors in recent years [11]–[14]. This paper extends the existing body of literature in two ways. First, since the stock return series always contains various degrees of turbulence, the possibility of changes in the unconditional variance should be taken into account in modeling the GARCH model [15]. As a consequence, traditional models, such as APARCH, EGARCH, IGARCH and other GARCH models are not suitable for modeling time-varying unconditional variance for China and ASEAN stock indices. We, therefore, use the Time-Varying GARCH (TV-GARCH) model as a marginal model. In the TV-GARCH model, the variance of the return series decomposed into two components, a stationary and a nonstationary one. The nonstationary component is typically a deterministic function of time, whereas the stationary component follows a GARCH process [15]–[19]. Furthermore, the interdependence between China and ASEAN stock markets may demonstrate asymmetric behaviors. Therefore, we propose a conditional copula approach to model the dependence structure between these two markets. Additionally, we evaluate the dependence from another perspective by using non-parameters based on plotting the dependence.

Second, there are few studies conducted on the level of risk spillover effect between China and ASEAN countries. Therefore, this study also attempts to fill the gap in the literature and to provide recent empirical evidence in investigating the risk spillover effect between China and the ASEAN stock markets performance in a time-varying manner and to provides some noteworthy insights into the aspect of the risk spillover direction across stock markets in a multi-country context. We hope that our findings may have implications for investment in ASEAN and China and help to determine the appropriate portfolio for investors. Why we choose ASEAN countries is that they are the emerging markets and they have provided a significant number of opportunities for foreign investors in recent years [20]. As mentioned before, ASEAN has become China's largest trading partner in 2020, while trade openness is an important factor when risk transmission among countries and plays a significant role in predicting the risk of a stock market.

Our study derives several noteworthy findings. First, our empirical results indicate that there are bidirectional asymmetric risk spillover effects between China and ASEAN stock markets since the ΔCoVaR and MES of the stock series are significantly positive and vary slightly from one market to another. Second, the upside and downside CoVaRs are symmetric and display similar temporal dynamics throughout the sample period. Third, values of upside CoVaR are systematically above the upside VaRs for all markets in the sample periods, while the values of downside CoVaR are systematically below the downside VaRs. The findings of this study may have implications for constructing the optimal cross-board portfolio. It is also important for policymakers, financial supervisors and regulators to maintain financial stability in their countries.

The rest of this paper is organized as follows. Section II provides a review of past literature and Section III describes the methodology used, including the copula model, TV-GARCH model and CoVaR model as well as MES model. Data and descriptive statistics are presented in Section IV, while Section V presents and discusses the empirical results. Section VI summarizes our main findings and considers policy and practical implications.

II. LITERATURE REVIEW

Several methods have been used to evaluate the spillover effect between two different markets, namely, conditional Value-at-risk (CoVaR) [8], [21], [22], marginal expected shortfall (MES) [9], [23]–[26], Granger causality in risk [27], [28], principal component analysis [29], [30], SRISK [31], multivariate Extreme Value Theory [32] and network analysis [33]–[35]. Generally, the most commonly used methodology applied to address the issue is CoVaR which was introduced by Adrian and Brunnermeier [8] and generalized by Girardi and Ergün [21], CoVaR captures possible risk spillovers between markets by providing information on the value-at-risk (VaR) of a market conditional on the fact that another market is in financial distress. Girardi and Ergün generalized the model by considering the VaR of a market conditional on the fact that another market's returns take values less than or equal to its VaR. Reboredo *et al.* [22] extend the model to examine the downside and upside risk spillovers and find asymmetries in upside and downside risk spillovers between exchange rates and stock prices.

The second methodology investigates the spillover effect between two different markets by using the MES model. MES is defined as its expected equity loss when the market itself is in its left tail. Acharya *et al.* [9] calculate time-invariant MES measures. Idier *et al.* [24] and Song *t al.* [36] confirm that the MES can be regarded as a proxy of systemic risk or used as a standard indicator to reflect the bank fragility and systemic exposure, meanwhile, Idier *et al.* [24] argue that MES is worse than a simple balance-sheet ratio in predicting large equity losses when a true crisis comes.

There are ample empirical studies that have been conducted in the literature on the risk spillover effect between different markets, especially in global stock markets. Asgharian and Nossman [37] analyze the risk spillover from the U.S. market to European countries' equity markets. Ameur *et al.* [38] assess this risk contagion for the US, Europe and the Asia-Pacific region covering January 2004-December 2016. They find that the conventional European index (US stock market) shows the highest contribution to the world market's systemic risk at the downside CoVaR (upside CoVaR). Shen [39] investigates the international risk transmission mechanism between the US and major Asian stock markets and finds the cross-country risk linkages increase over time. They also show that the shocks in the US market significantly increase the risk in the Asian markets, except China and Russia. Hanif *et al.* [40] also examine the spillover between the US and Chinese equity sectors with the period of COVID-19. They find time-varying bidirectional asymmetric risk spillovers between US and China. The risk spillover from the US to China is higher before COVID-19 and from China to the US during COVID-19 spread.

Ji *et al.* [41] analyse the risk spillover effect among G7 stock markets and verified the magnitude of risk spillover from the remaining G7 countries to the US is significantly larger than that from the US to these countries. Su [42] proposes a quantile variance decomposition framework for measuring extreme risk spillover effects in G7 and BRICS stock markets and revealed how extreme risk spillover across developed and emerging stock markets. Yang *et al.* [43] find that the Stock Connect programs strengthen the downside risk spillovers between China and London markets in most cases and China stock markets are more likely affected by the London stock market. Yang *et al.* [44] investigate the asymmetric risk spillovers between Shanghai and Hong Kong stock markets by using the CoVaR mode and show that, the asymmetric risk spillovers between these two markets are significant and the importance of the Shanghai stock market gradually increase with the implementations of Stock Connect schemes. Boako *et al.* [45] find low positive significant dependencies between all African markets and their developed counterparts, except for Egypt.

Some empirical studies provide insights into the risk spillover effect between the crude oil market and the stock market. For instance, Mensi *et al.* [46] show that there exist up and down risk asymmetric spillovers from oil to stock markets and vice versa in the short and long-run horizons. But Wen *et al.* [47] hold different points of view, they indicate that the asymmetry spillover effect is significant at upside quantiles but not significant at downside quantiles. Ji *et al.* [48] and Jiang *et al.* [49] investigate the risk spillover between oil and BRICS stock markets, they find that there is significant risk spillover with heterogeneous characteristics from oil to BRICS stock markets. The degree of oil dependence, energy policy and risk management strategy plays an important role in the heterogeneity of risk spillovers among countries. Tiwari *et al.* [50] uses the CoVaR and MES model to capture the risk spillover effects between oil and stock market indices of G7 economies and indicates that oil price dynamics contribute significantly more to the G7 stock market returns during volatile times than during tranquil times. In particular, the Canadian stock market appears more sensitive and vulnerable to negative external shocks emerging from the crude oil market than the other markets. Du and He [27] investigate the extreme risk spillovers between WTI crude oil and S&P 500 stock index and reveal that there are significant risk spillovers between these two markets. They also find that risk spillovers from the stock market to the crude oil market are positive, and spillovers from the crude oil market to the stock market are negative before the recent financial crisis. The bidirectional positive risk spillovers are strengthened markedly after the financial crisis.

Some studies have investigated the risk of spillovers among other markets. For instance, Reboredo *et al.* [22] examined the downside and upside risk spillovers from exchange rates to stock prices and vice versa for emerging economies, such as Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey. Sun *et al.* [51] found that commodity markets exert spillover effects on maritime markets and the risk spillovers in oil-freight index pairs after the global financial crisis are different from before. Meng *et al.* [52] indicates that there exist asymmetric risk spillover effects between crude oil and China's commodity sectors. The degree of the downside spillover effect from crude oil price is larger than that of the upside spillover effect.

However, few research studies have examined the risk spillover effects of the Chinese and ASEAN stock markets. Some studies investigated the risk spillover effects between stock markets in China and Asian countries, for example, Xiao [53] estimates the direct and indirect risk spillovers of the Chinese stock market to major East Asian stock markets during turbulent and calm periods. They find that downside and upside spillovers are significantly different between the turbulent and calm periods. Jin [54] found that there exist asymmetries in upside and downside risk spillovers from China to ten Asian stock markets, with higher intensity in downside risk spillovers.

All the above-mentioned empirical research discussed interconnections and integration among stock markets in China and ASEAN countries. However, no study – as far as we know – has considered the risk spillover effect between China and the ASEAN stock market. To fill this gap, we discuss the risk spillover effect between China and the ASEAN stock market by using the MES model and Copula-TV-GARCH-CoVaR method, which takes the time-varying unconditional variance for seven countries into account. Most of the existing work uses the GARCH model with static unconditional variance to model the marginal distribution for return assets. Therefore, our current work has an important contribution to related research, in terms of research content and empirical methods.

III. METHODOLOGY

In this section, we use the TV-GARCH to model the marginal distribution. Then, the dependence between China and ASEAN stock markets is modeled by using a copula model and a non-parametric approach with Chi-plots and K-plots. The final step is to estimate the CoVaRs and delta CoVaRs through the joint distribution of the China and ASEAN stock markets, which are used to measure the risk spillover between them, and we also use the MES and LRMES model to compute the risk spillover between these markets.

A. THE TV-GARCH MODEL

In this paper, we use the time-varying GARCH model of Amado and Teräsvirta [19], [55] in which the unconditional variance evolves smoothly over time. Let the return series $\{y_t\}$ be given as

$$y_t = E(y_t\,|F_{t-1}) + \varepsilon_t \tag{1}$$

where F_{t-1} contains the historical information available at time t-1. For simplicity, it is assumed that $E(y_t\,|F_{t-1}) = 0$. The innovation sequence ε_t has a conditional mean $E(\varepsilon_t\,|F_{t-1}) = 0$, and variance σ^2. Let $\varepsilon_t = \zeta_t\sigma_t$, where $\{\zeta_t\} \sim iid(0,1)$, $E\zeta_t^3 = 0$, and $E\left|\zeta_t^2\right|^{2+\phi} < \infty$, $\phi > 0$. Furthermore, σ_t^2 is assumed to have a time-varying representation measurable with respect to a multiplicative decomposition

$$\sigma_t^2 = h_t g_t \tag{2}$$

where h_t describes the short-run dynamics of the variance of the returns and g_t is a positive-valued deterministic component. h_t is modeled as the GARCH(p, q) process of

$$h_t = \alpha_0 + \sum_{t=1}^{p} \alpha_i \varepsilon_{t-i}^{*2} + \sum_{t=1}^{q} \beta_i h_{t-j} \tag{3}$$

where $\varepsilon_t^* = \varepsilon_t / g_t^{1/2}$. Equation (3) is assumed to satisfy the set of conditions for positivity and stationarity of the conditional variance of ε_t^*. This implies $\alpha_0 > 0$, $\alpha_i \geq 0$. The unconditional variance component is smooth and time-varying, introducing nonstationarity into σ_t^2. It is a linear combination of bounded transition functions defined as follows:

$$g_t(\theta_1, t^*) = g_t = \delta_0 + \sum_{l=1}^{r} \delta_l G(t^*; \gamma_l, c_l) \tag{4}$$

where $\theta_1 = (\delta', \gamma', c_1', \ldots, c_r')' \in \Theta_1 = (\Delta \times \Gamma \times C)$, with $\delta = (\delta_0, \delta_1, \ldots, \delta_r)'$, $\gamma = (\gamma_1, \ldots, \gamma_r)'$, $c_l = (c_{l1}, \ldots, c_{lr})'$, $l = 1, \ldots, r$, is an element of the parameter space of Our transition function is the general logistic transition function:

$$G_l(t^*; \gamma_l, c_l) = \left(1 + \exp\left\{-\gamma_l \prod_{k=1}^{K_l} t^* - c_{lk}\right\}\right)^{-1} \tag{5}$$

The transition function (5) is a continuous and non-negative function bounded between zero and one. Equation (5) satisfying the identification restrictions $\gamma_l > 0$ and $c_{l1} \leq c_{l2} \leq \ldots \leq c_{lk}$, $l = 1, \ldots, r$. The parameters, c_{lj} and γ_l, determine the location and the speed of the transition between different regimes. Furthermore, the calendar time $t^* = t/T$, where T is the number of observations.

Equations (1)-(5) define the time-varying GARCH (TV-GARCH) model. The unconditional variance in this model is time-varying and equals $E_t(\varepsilon_t^2) = E(\zeta_t^2 h_t g_t) = g_t E h_t$. This means that when $\delta_1 = \ldots = \delta_r = 0$, the unconditional variance $E_t(\varepsilon_t^2) = \delta_0^* E h_t$ (constant). When $r = 1$ and $k = 1$, g_t increases (decreases) monotonically over time from δ_0 to $\delta_0 + \delta_1$ when $\delta_1 > 0$ ($\delta_1 < 0$), with the location centered at $t = c_1 T$. The slope parameter γ_1 in (5) controls the degree of smoothness of the transition: the larger γ_1, the faster the transition is between the extreme regimes. When $\gamma_1 \to \infty$, g_t collapses into a step function. When $\delta_l \neq 0$ for r>1 and k>1, equations (4) and (5) form a very flexible parameterization capable of describing nonmonotonic deterministic changes in the unconditional variance. The Model Specification and Estimation of parameters are discussed in detail by Amado and Teräsvirta [15], [19], [55].

B. COPULA MODELS

We modeled the dependence structure between China and ASEAN-6 stock returns using copula functions. It provides the flexibility to consider the complexity of the dependence structure by using the copula function, as it can model the marginal distribution individually and combines these marginal into a joint distribution. Moreover, by employing a wide array of copula functions, dependence structures of the marginal distributions can be described more adequately and accurately. The Sklar's Theorem [56] indicates that for any d-dimension joint distribution function $H(z_1, z_2, \ldots, z_n)$ with marginal distribution function $F_1, F_2, \ldots, F_d$, there exists a d-dimension copula function.

$$H(z_1, \ldots, z_d) = C(F_1(z_1), \ldots, F_d(z_d)) = C(u_1, \ldots, u_d) \tag{6}$$

If $F_1, F_2, \ldots, F_n$ are continuous, then the copula C associated with H is unique and may be obtained by

$$C(u_1, u_2, \ldots, u_d) = H(F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_d^{-1}(u_d)), \quad \forall(u_1, u_2, \ldots, u_d) \in (0, 1)^d \tag{7}$$

where $u_1 = F_1^{-1}(u_1), u_2 = F_2^{-1}(u_2), \ldots, u_d = F_d^{-1}(u_d)$, F_i^{-1} is the quantile function of F_i, $i = 1, \ldots, d$, that is, $F_i^{-1}(p) = \inf\{x \,|F_i(x) \geq p\}, p \in (0, 1)$.

If we use the density function to express the copula function, Eqn. (7) can be written by

$$h(z_1, z_2) = c(F_1(z_1), F_2(z_2)) \prod_{i=1}^{2} f_i(z_i) \tag{8}$$

where h in Eqn. (8) is the density function associated with H, fi is the density function for each marginal, and the copula density c is obtained by differentiating Eqn. (8) and can be expressed as:

$$c(F_1(z_1), \ldots, F_2(z_2)) = \frac{h(F_1^{-1}(u_1), F_2^{-1}(u_2))}{\prod_{i=1}^{2} f_i(F_1^{-1}(u_i))} \tag{9}$$

In this paper, we use 16 copulas to examine whether they suit the return series or not. The copula family studied in this paper includes Normal copula, Student-t copula, eight Archimedean copula (Frank, Kimeldorf Sampson Copula (Clayton), Joe, BB1, BB2, BB3, BB6, BB7), one Archimax copula (BB4) and five EV copula (Galambos, Gumbel, Husler-Reiss copula, Tawn, BB5). The Gaussian copula is related to the multivariate Gaussian distribution. In the bivariate case, this copula function for a random vector (Z_1, Z_2) is defined by:

$$C(u_1, u_2; \rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left[\frac{-(r^2 - 2\rho rs + s^2)}{2(1-\rho^2)}\right] drds \tag{10}$$

with $u_i = \Phi(z_i)$; i = 1, 2 and Φ represents the univariate standard Gaussian density function. ρ is the Pearson correlation coefficient $(-1 < \rho < 1)$.

The Student-t copula is defined as

$$C(u_1, u_2; \rho, v) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \times \exp\left[1 + \frac{(r^2 - 2\rho rs + s^2)}{v(1-\rho^2)}\right]^{-\frac{v+2}{2}} drds \tag{11}$$

where $t_v^{-1}(\cdot)$ denote the quantile function of the standard t-student distribution with v degrees of freedom. The advantage of this copula is that it captures tail dependence, while the Gaussian copula does not [57], [58]. The parameter ρ describes the dependence structure between u_1 and u_2, in both Gaussian and Student-t copulas.

The BB1 copula [59] is given by

$$C(u_1, u_2; \theta, \delta) = \left(1 + \left[(u_1^{-\theta} - 1)^{\delta} + (u_2^{-\theta} - 1)^{\delta}\right]^{-1/\theta}\right) \tag{12}$$

with $\theta > 1$, $\delta \geq 1$, and generator function is $\phi(t) = (t^{-\theta} - 1)^{\delta}$.

The BB2 copula [59] has the form

$$C(u_1, u_2; \theta, \delta) = \left[1 + \delta^{-1} \ln(e^{\delta u_1^{-\theta}} + e^{\delta u_2^{-\theta}} - 1)^{\delta}\right]^{-1/\theta} \tag{13}$$

with $\theta > 1, \delta > 0$ and generator function $\phi(t) = e^{(t^{-\theta}-1)} - 1$.

The BB3 copula [59] is defined as

$$C(u_1, u_2; \theta, \delta) = \exp\left\{-\left[\delta^{-1} \ln\left(e^{\delta \tilde{u}_1^{\theta}} + e^{\delta \tilde{u}_2^{\theta}} - 1\right)\right]^{1/\theta}\right\} \tag{14}$$

with $\theta > 1$, $\delta > 0$, $\tilde{u} = -\ln u$ and $\tilde{v} = -\ln v$. The generator function is $\phi(t) = \exp\left\{\delta(-\ln t)^{\theta}\right\} - 1$. The other copulas are listed in Table 7.

Here we use the Maximum Likelihood (ML) method to estimate copula functions since the data used in this paper is two-dimensional and the ML is simple and flexible compared to other methods. Let $h(z_1, z_2, \ldots, z_n)$ is the density function of $F(z_1, z_2, \ldots, z_n)$, then we can obtain

$$h\,(z_1, z_2, \ldots, z_n) = c(F_1(z_1), F_2(z_2), \ldots, F_n(z_n)) \prod_{i=1}^{n} f_i(z_i) \tag{15}$$

where $c(\cdot)$ is the density function of the Copula function $C(\cdot)$ and $f_i(z_i)$ the density function of the marginal distribution $F_i(z_i)$. The density function of Copula function can be expressed as

$$c(u_1, u_2, \ldots, u_n; \rho) = \frac{\partial C(u_1, u_2, \ldots, u_n; \rho)}{\partial u_1 \partial u_2 \ldots \partial u_n} \tag{16}$$

According to the maximum likelihood estimation principle, the log-likelihood function is given by

$$l(V, \alpha) = \sum_{t=1}^{T} \ln c(F_1(z_1; \nu_1), \ldots, F_1(z_n; \nu_n); \alpha) + \sum_{i=1}^{n} \sum_{t=1}^{T} \ln f_i(z_{it}; \nu_i) \tag{17}$$

where $V = (\nu_1, \ldots, \nu_n)'$ is the parameter vector of the marginal distribution $F_1, \ldots, F_n$. α is the parameter vector in the Copula function. Given a set of marginal distributions and a copula, the previous log-likelihood may be written, and by maximization $l(V, \alpha)$ the value of the parameter vector $(\hat{V}, \hat{\alpha})$ can be obtained: $(\hat{V}, \hat{\alpha}) = \arg\max_{V,\alpha} l(V, \alpha)$.

As indicated above, each of the copula functions captures the dependence from the joint distributions in their own manner. Here we present two dependence concepts, including Kendall's tau and Spearman Rho.

The Kendall's tau between two random variables X_1 and X_2 can be obtained from copula functions by the following expression:

$$\tau = \tau(X_1, X_2) = 4 \int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1 \quad (18)$$

While Spearman rho which is obtained from copula by the equation:

$$\rho = \rho(X_1, X_2) = 12 \int_0^1 \int_0^1 u_1 u_2 dC(u_1, u_2) - 3 \quad (19)$$

Although both τ and ρ are measures of concordance, their values can be quite different. Nelson [60] summarizes the relationship between τ and ρ with the following inequalities:

$$\frac{3\tau - 1}{2} \le \rho \le \frac{1 + 2\tau - \tau^2}{2}, \quad \text{for } \tau > 0 \quad (20)$$

$$\frac{\tau^2 + 2\tau - 1}{2} \le \rho \le \frac{1 + 3\tau}{2}, \quad \text{for } \tau < 0 \quad (21)$$

To choose the best fitting copula, we apply three information criteria for copula's goodness of fit, AIC [61], [62], BIC [63] and HQ [64]. Decreasing AIC, BIC and HQ values indicate improvement in the fitting quality of the model.

C. RISK SPILLOVER MEASURES

Two models are applied to obtain the risk spillover effects between China and ASEAN-6 stock markets, which are the conditional value-at-risk (CoVaR) measurement [8], [21] and Marginal Expected Shortfall (MES) [9], [65]. To obtain the CoVaR value of the stock market series, we need to calculate the Value-at-Risk (VaR) of the stock market series. The VaR is defined as the maximal loss for a given time and a confidence level $(1 - \alpha)$. For downside VaR can be expressed as $\Pr(r_t \le VaR_{\alpha,t}) = \alpha$, similarly, we can compute the upside VaR by considering $\Pr(r_t \ge VaR_{1-\alpha,t}) = \alpha$. The VaR also always be used by financial regulators to assess the risks at a given probability level during a period.

Here the VaR of China and ASEAN-6 stock markets can be estimated by

$$VaR_{t|t-1}^{1-\alpha} = \mu_t + z_{1-\alpha} h_{t|t-1}, \ \Pr(r_{t|t-1} < VaR_{t|t-1}^{1-\alpha}) = 1 - \alpha \quad (22)$$

where $z_{1-\alpha}$ represents the $(1 - \alpha)$ quantile of the standard normal distribution, $VaR_{t|t-1}^{1-\alpha}$ represents the maximal loss of long position. If we want to calculate the maximal loss of short position, use α substitute for $1 - \alpha$. In this section, α is set as 0.05, which can measure the fifth quantile of the return distribution.

However, VaR cannot reflect systemic risk when the whole financial system stability is under threat. To emphasize the systemic risk measurement, we introduce CoVaR to measure the risk spillover between ASEAN-6 stock market returns and China stock market returns. CoVaR has some advantages in capturing the tail dependence and extreme risk spillover, which has been widely applied in the financial fields [21], [22], [46], [66], [67]. Therefore, in this paper, downside and upside CoVaR is formally defined as the α quantile of the conditional distribution for one return series conditional on the α quantile of the conditional distribution for another return series. Here we just give the downside CoVaR equation:

$$\Pr(r_{1,t} \le CoVaR_{1,t}^{\alpha} \,\big|\, r_{2,t} \le VaR_{2,t}^{\beta}) = \alpha \quad (23)$$

where $\Pr(r_{2,t} \le VaR_{2,t}^{\beta}) = \beta$, $r_{1,t}$ and $r_{2,t}$ denote the ASEAN stock market and China stock market returns at time t, respectively. αg and βg represent the corresponding quantile of the estimated GPD. Upside CoVaR is similar to downside CoVaR. Eqn. (23) is a conditional probability formula, which can be expressed as an unconditional bivariate distribution probability form:

$$\frac{\Pr(r_{1,t} \le CoVaR_{1,t}^{\alpha}, r_{2,t} \le VaR_{2,t}^{\beta}) = \alpha}{\Pr(r_{2,t} \le VaR_{2,t}^{\beta})} \quad (24)$$

Given $\Pr(r_{2,t} \le VaR_{2,t}^{\beta}) = \beta$, the CoVaR in Eqn. (24) can be expressed as:

$$\Pr(r_{1,t} \le CoVaR_{1,t}^{\alpha}, r_{2,t} \le VaR_{2,t}^{\beta}) = \alpha\beta \quad (25)$$

According to Sklar's [56] theorem, the joint distribution function of two continuous variables can be expressed in terms of a copula function. CoVaR in Eqn. (25) can be represented in terms of copulas by solving the following equation:

$$C(F_{1,t}(CoVaR_{1,t}^{\alpha}), F_{2,t}(VaR_{2,t}^{\beta})) = \alpha\beta \quad (26)$$

where $F_{1,t}$ and $F_{2,t}$ are the marginal distribution of the China and ASEAN stock market returns, respectively, and Eqn. (26) can be reduced as:

$$C(u, v) = \alpha\beta \quad (27)$$

where $C(\cdot, \cdot)$ is a copula function, $u = F_{1,t}(CoVaR_{1,t}^{\alpha})$ and $v = F_{2,t}(VaR_{2,t}^{\beta})$. Given its copula representation in Eqn. (27), the CoVaR can be computed by the following two-step procedure(see Reboredo and Ugolini [66], Mensi *et al.* [46] and Ji *et al.* [68]):

Given α, β and the specific forms of the copula function $C(\cdot, \cdot)$, we can obtain the value of $u = F_{1,t}(CoVaR_{1,t}^{\alpha})$ by solving Eqn. (26) or Eqn. (27), since $VaR_{2,t}^{\beta}$ can be obtained by Eqn. (22).

Taking u, we can obtain the CoVaR value as the quantile of the distribution of $r_{1,t}$, with a cumulative probability equal to u, by inverting the marginal distribution function of $r_{1,t}$: $CoVaR_{1,t}^{\alpha} = F_{1,t}^{-1}(u)$.

To capture the marginal contribution of the spillover risk from the ASEAN-6 stock market to China, here we introduce the measurement of delta CoVaR (ΔCoVaR). Referring to Adrian and Brunnermeier [8], Girardi and Ergün [21], Reboredo and Ugolini [66], Mensi *et al.* [46], Ji *et al.* [68]

and Juan Meng *et al.* [52], the ΔCoVaR is defined as the difference between the VaR for stock returns in China conditional on the distressed state of ASEAN stock market, and the VaR for China stock returns conditional on a benchmark state of ASEAN stock market, considering it as the median of the return distribution of ASEAN stock market. Thus, we can obtain $\Delta CoVaR_{1,t}^{\alpha}$ as follows:

$$\Delta CoVaR_{1,t}^{\alpha} = \frac{(CoVaR_{1,t}^{\alpha} - CoVaR_{1,t}^{\alpha,\beta=0.5})}{CoVaR_{1,t}^{\alpha,\beta=0.5}} \tag{28}$$

where $CoVaR_{1,t}^{\alpha,\beta=0.5}$ satisfies that $\Pr(r_{1,t} \leq CoVaR_{1,t}^{\alpha} \left| F_{2,t}(r_{2,t}) = 0.5\right) = \alpha$ with $F_{2,t}(\cdot)$ being the distribution function of a variable $r_{2,t}$.

To test whether the spillover effect of risk is significant, we use the Kolmogorov-Smirnov (K-S) bootstrapping test [69] to compare the CoVaR and VaR values, the KS statistic is defined as follows:

$$KS_{mm} = (\frac{mn}{m+n})^{\frac{1}{2}} \sup_{x} |F_m(x) - G_n(x)| \tag{29}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR and VaR distribution functions, respectively, and m and n are the sizes of the two samples. The null hypothesis of there being no risk spillover effects is designed as $H_0^1 : CoVaR_{1,t}^{\alpha} = VaR_{1,t}^{\alpha}$. This means that there is no significant difference between CoVaR and VaR, indicating no risk spillover effect between ASEAN stock market returns and China stock returns. We again rely on the bootstrap KS test of Abadie [69] to compare the cumulative CoVaRs distribution functions in 0.05 quantile and 0.5 quantiles, respectively. The null hypothesis $H_0^2 : CoVaR_{1,t}^{\alpha} = CoVaR_{1,t}^{0.5}$, means no significant difference between $CoVaR_{1,t}^{\alpha}$ and $CoVaR_{1,t}^{0.5}$.

Another financial risk spillover measurement is MES. Following Acharya *et al.* [9] and Idier *et al.* [24], we define the MES of a stock market as its short-run expected equity loss conditional on the ASEAN-6 stock markets taking a loss greater than its Value-at-Risk at $\alpha\%$. Let us denote $r_{i.t}$ the daily stock return of the China stock market and $r_{ASEAN.t}$ the daily ASEAN-6 stock markets return. Then the MES can be expressed as

$$\mathrm{MES}_{i,t}^{\alpha} = E_t(r_{i,t} \left| r_{ASEAN,t} \leq VaR_{ASEAN}^{\alpha} \right.) \tag{30}$$

Higher levels of MES imply that the China stock market is more likely to be exposed to bad states of the ASEAN-6 markets and vice versa. This MES model permits the assessment of daily equity loss and is also named short-run MES. To measure the expected loss over a six-month horizon, we can use the long-run MES (denoted by LRMES) which is deduced from the short-run MES. For the threshold value $C = -2\%$, Acharya *et al.* [70] proposed an approximation of the LRMES as $\mathrm{LRMES}_{i,t}^{\alpha} \simeq 1 - \exp(-18 \times \mathrm{MES}_{i,t}^{\alpha})$. This approximation represents the expected loss over a six-month horizon, obtained conditionally on the ASEAN stock market falling by more than 40% within the next six months.

IV. DATA AND DESCRIPTIVE STATISTICS

A. DATA

The data for our estimation from the stock indices of China and ASEAN countries were collected daily from January 04, 2010 to April 30, 2021 by Wind Financial Database and Yahoo Finance. We used the equity indices VNINDEX Index, SET Index, FTSE Straits times Index (STI), PSEI Index, FTSE Bursa Malaysia KLCI Index (KLCI) and Jakarta SE Composite Index (JKSE), which are representative of the stock markets of Vietnam, Thailand, Singapore, the Philippines, Malaysia and Indonesia, respectively. To eliminate the spurious correlation generated by holidays, we eliminate the observations which occurred on holidays. Therefore, 2384 observations were achieved for each time series. We use these six countries as the ASEAN regions, since these six stock markets occupy most of the ASEAN regions, while the remaining ones are small and newly established [71] and most studies about the stock markets in the ASEAN region also use these 6 countries [72]–[74].

Figure 1 plots the historical evolution of price trends for ASEAN-6 and China stock market indices. As can be seen from Figure 1, JKSE, PSEI and SET have some similar trends from 2010 to 2020, and we can also find some periods of significant price fluctuations in Figure 1. The first significant period is that both the Chinese stock market and the Singapore stock market experienced a big fall during 2015-2016. The second significant period is after the COVID-19 outbreak and all the ASEAN-6 stock market indices experienced declines. However, as can be observed in Figure 1, China stock market index dropped 13.78.5% during the COVID-19 period, which is less than ASEAN stock markets fell. The stock markets of ASEAN countries have been severely affected by COVID-19. The FTSE Bursa Malaysia KLCI Index declined by 23.89% from the start of the year 2020. Jakarta SE Composite Index fell more than 37.34%, the FTSE Straits Times Index down a massive 31.32%, the PSEI Index lost 38.74%, the SET Index fell by over 35.8% and the VNINDEX Index fell 31.81%, respectively. These facts imply that there are inseparable potential relationships among these stock markets.

Returns are computed by the formula $R_t = 100 \times \log(P_t/P_{t-1})$, where P_t is the closing price index for China and ASEAN-6 stock markets at time t. Figure 1 also depicts the time series of stock market returns. By viewing this figure, we can see that all the time series showing stylized facts about financial returns such as volatility cluster and volatility persistence, with higher volatility around the onset of the COVID-19 in 2020 and the period of 2015-2016.

B. SUMMARY OF DESCRIPTIVE STATISTICS

Table 1 provides the descriptive statistics of the return series. As demonstrated in Table 1, the mean of the return series varies between 0.0025 and 0.0367. The vulnerable mean return occurs in SSEC, followed by STI and KLCI, while the highest mean return is found in relation to the

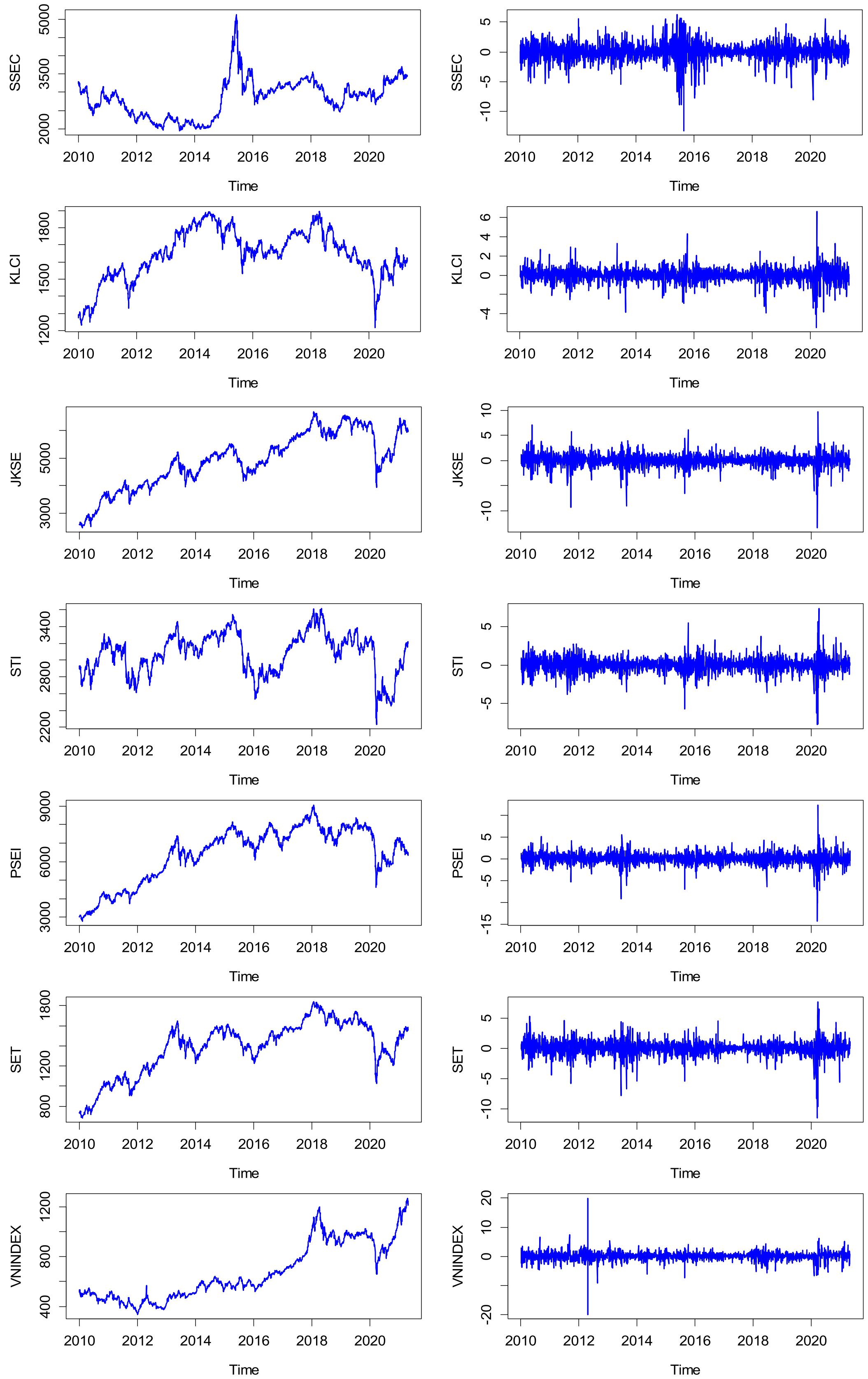

FIGURE 1. The index prices and daily returns for each series.

TABLE 1. Summary statistics for returns on daily SSEC and ASEAN-6 stock returns.

	SSEC	KLCI	JKSE	STI	PSEI	SET	VNINDEX
Minimum	-13.2292	-5.4047	-13.3265	-7.6917	-14.3224	-11.4282	-19.9180
Maximum	6.2665	6.6263	9.7042	7.3645	12.3450	7.6531	19.9030
Mean	0.0025	0.0095	0.0355	0.0044	0.0315	0.0324	0.0367
Std.dev.	1.4591	0.7228	1.2183	0.9427	1.2945	1.1427	1.4119
Skewness	-0.9498	-0.3990	-1.0379	-0.4474	-0.9331	-1.1252	-0.4586
Kurtosis	7.5947	9.3390	13.1759	9.1685	15.2599	12.7490	35.6603
Jarque-Bera	6099.3***	8742.5***	17702***	8444.8***	23514***	16675***	126579***
ADF	-12.576***	-13.327***	-13.463***	-13.265***	-13.502***	-12.735***	-13.585***
PP	-2233.7***	-2263.3***	-2136.7***	-2559***	-2307.9***	-2500.6***	-2621.1***
PKSS	0.114*	0.2065*	0.1785*	0.0299*	0.3938*	0.2442*	0.1356*
Q(20)	51.754***	35.598**	63.871***	44.763***	64.301***	49.02***	23.745***
Q^2 (20)	1174.9***	1461.3***	479.49***	2018.3***	964.87***	1315.7***	489.64***
ARCH (20)	380.03***	633.03***	247.37***	720.04***	459.97***	550.82***	650.16***

Notes: The standard errors reject the null hypothesis of normal distribution according to Jarque-Bera statistics. Q^2 (20) is the Ljung-Box Q-statistics of order 20 on the square return series. ARCH (20) is the Lagrange Multiplier test for lags 20 on heteroskedasticity. ***, ** and * is statistically significant at 1%, 5% and 10%, respectively.

VNINDEX. On the other hand, SSEC yields the highest standard deviation, indicating that the volatility of China stock market was greatly affected by some of the major events during the period under investigation. The standard deviation of KLCI and STI is the smallest compared to other indices, suggesting that the fluctuation in these two markets is milder, which is exactly in line with Figure 1. The kurtosis and skewness showed that the returns had patterns of high-peak and the fat-tail phenomenon, which in turn implies that the extreme returns may have occurred frequently. SSEC and ASEAN returns are significantly left-skewed, which implies the implied volatility distribution has an asymmetric tail extending to the left (i.e., toward more negative values). The kurtosis value is greater than 3, indicating that all returns present significant leptokurtic, and the Vietnam stock market return series display larger Kurtosis than the other return series. Meanwhile, the maximum and minimum values reflect the presence of larger extreme returns.

The Jarque-Bera test shows that the null of normality is strongly rejected for all returns. Figure 2 also confirmed that all return series reject normality. The weaknesses of Jarque-Bera is that the test is relevant only for the unconditional distribution of return series, therefore, the Ljung-Box Q statistic is applied to test the serial correlation or autocorrelation of return series, and the null hypothesis of the Ljung-Box test is no serial correlation or no autocorrelation. The Ljung-Box statistics of each return and squared return reject the null hypothesis, showing the significant autocorrelations in both returns and squared returns. Furthermore, we employed three popular tests, namely the Augmented Dickey-Fuller (ADF) test [75], Phillips-Perron (PP) unit root test [76] and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [77] to explore the stationarity for the return series. The null hypotheses of ADF and PP tests are that the return series has a unit root, while that of the KPSS test is the opposite. The results of ADF and PP tests reject the null hypotheses of a unit root at a significance of 1%, and the KPSS test accepts the null hypotheses for each return series, which identifies that all return series used in this paper were stationary. To confirm the presence of heteroskedasticity (nonlinear dependence), the Lagrange Multiplier (LM) test for 20 lags on autoregressive conditional heteroscedasticity (ARCH) is applied. The results rejected the null hypothesis of no ARCH effects, reveals the presence of ARCH effects in all of the index series. These findings support the use of a GARCH-type model.

In brief, the preliminary analysis shows that these time series are characterized by non-normal distribution, left-skewed and fat tails. Moreover, these series also exhibit autocorrelation and ARCH effects. These findings confirm the appropriateness of the TV-GARCH model for the data.

Figure 3 depicted the linear correlation between ASEAN-6 and China stock markets. In Figure 3, the level of dependency of China and these ASEAN-6 countries' stock markets varies from 0.17 to 0.59. The correlation between China and Vietnam is the lowest and the value is 0.17, and what is interesting is that Vietnam experienced a lower correlation with other ASEAN stock markets than that of China with other ASEAN stock markets except for Vietnam. This can be explained by the fact that the internationalization of Vietnam is lower than that of other ASEAN countries. The correlation between other ASEAN-5 stock markets is relatively high, and the value varies from 0.45 to 0.59. This shows that other ASEAN countries are more connected with each other except Vietnam.

To test the interdependent structure of stock markets further, we employ a non-parametric approach with Chi-plots [78] and K-plots [79], the results presented

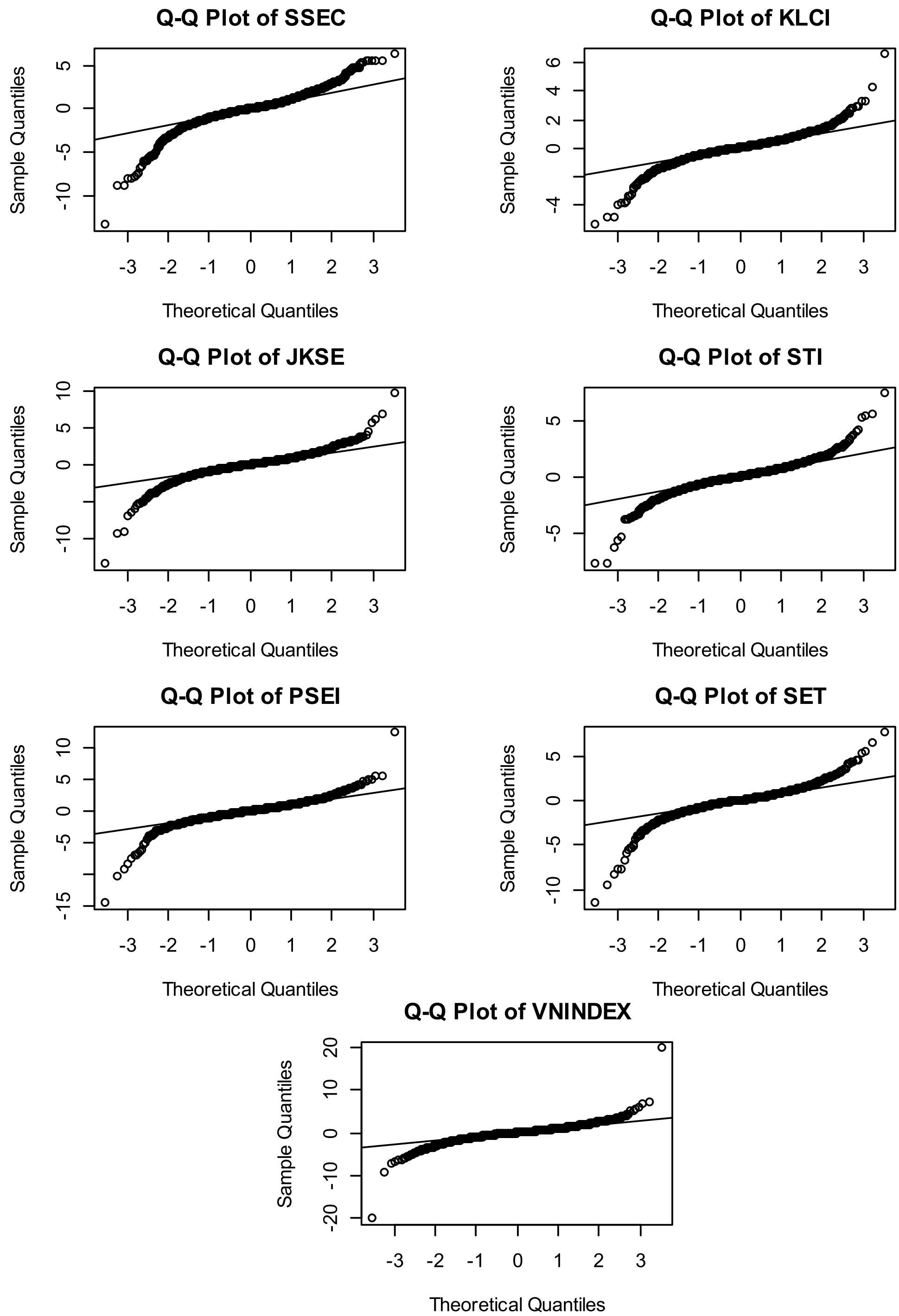

FIGURE 2. Q-Q plot of the return series.

in Figure 4. We conclude that these stock market series, except Vietnam, experience a dependency structure, the results support the view mentioned above. In the Chi-plots estimation, most graphs lay out of the controlling line (−0.05; 0.05), except Vietnam. As we can see that the Vietnam index is very close to the controlling line. This means that these stock indices except VNINDEX are interdependent together at a significance level of 5%, and the Vietnam stock market is relatively independent compared to the other stock exchanges.

In regards to K-plots, Figure 5 showed that except VNINDEX, the points on the graphs are not linearly distributed along the 45-degree line, which means that these stock index series are confirmed as dependence structures.

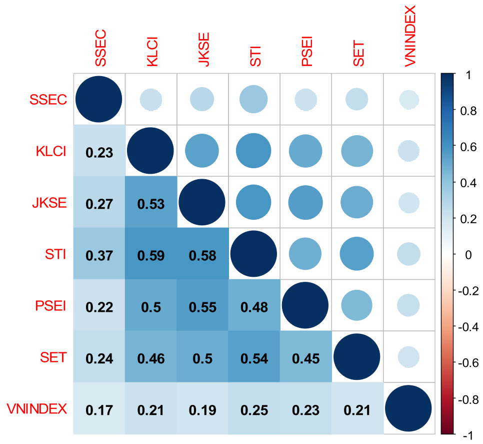

FIGURE 3. **The matrix of linear correlation by Pearson.**

These findings are similar to the previous tests based on Chi-plots.

V. RESULTS AND DISCUSSION

A. MARGINAL ESTIMATION RESULTS

In order to estimate the marginal distribution, eight GARCH family models including the TV(1)-GARCH(1,1), TV(2)-GARCH(1,1), GARCH(1,1), SGARCH(1,1), EGARCH(1,1), APARCH(1,1), IGARCH(1,1) and GJR-GARCH(1,1) models were utilized to fit the stock market return series. The selected models were chosen, based upon the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and log-likelihood values (LogLike). Table 2 provides the results of the GARCH models and the Loglike, AIC and BIC values for all the stock market series. According to AIC and BIC minimum principle and LogLike maximum principle, the TV(1)-GARCH(1,1) model is the best fit model for SSEC, JKSE, PSEI, SET, since the AIC and BIC are minimum and LogLike is maximum. For KLCI and STI, APARCH(1,1) is the best fit model, and the TV(2)-GARCH(1,1) model is the best fit for VNINDEX.

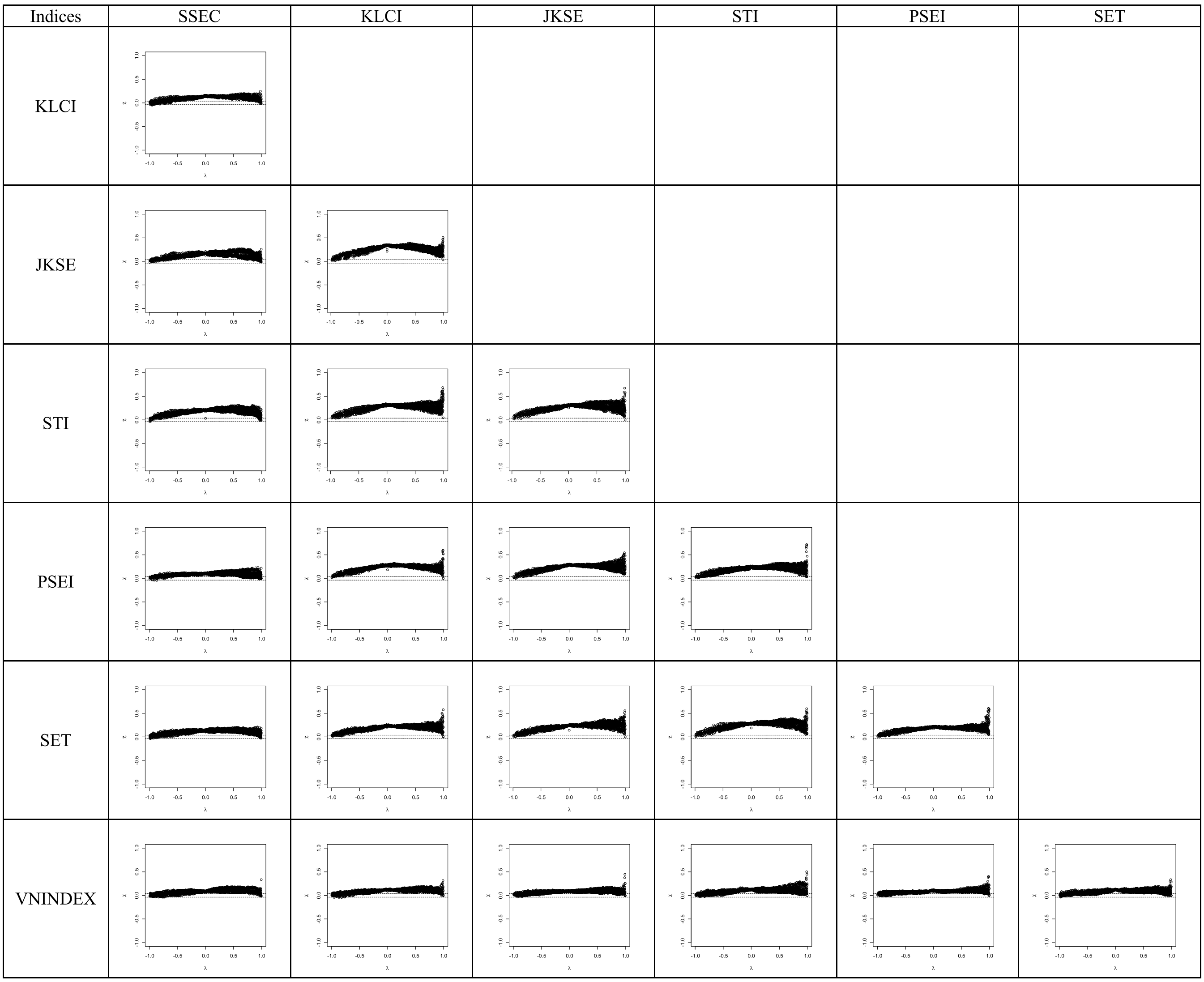

FIGURE 4. **Chi-plots estimation for stock index series.**

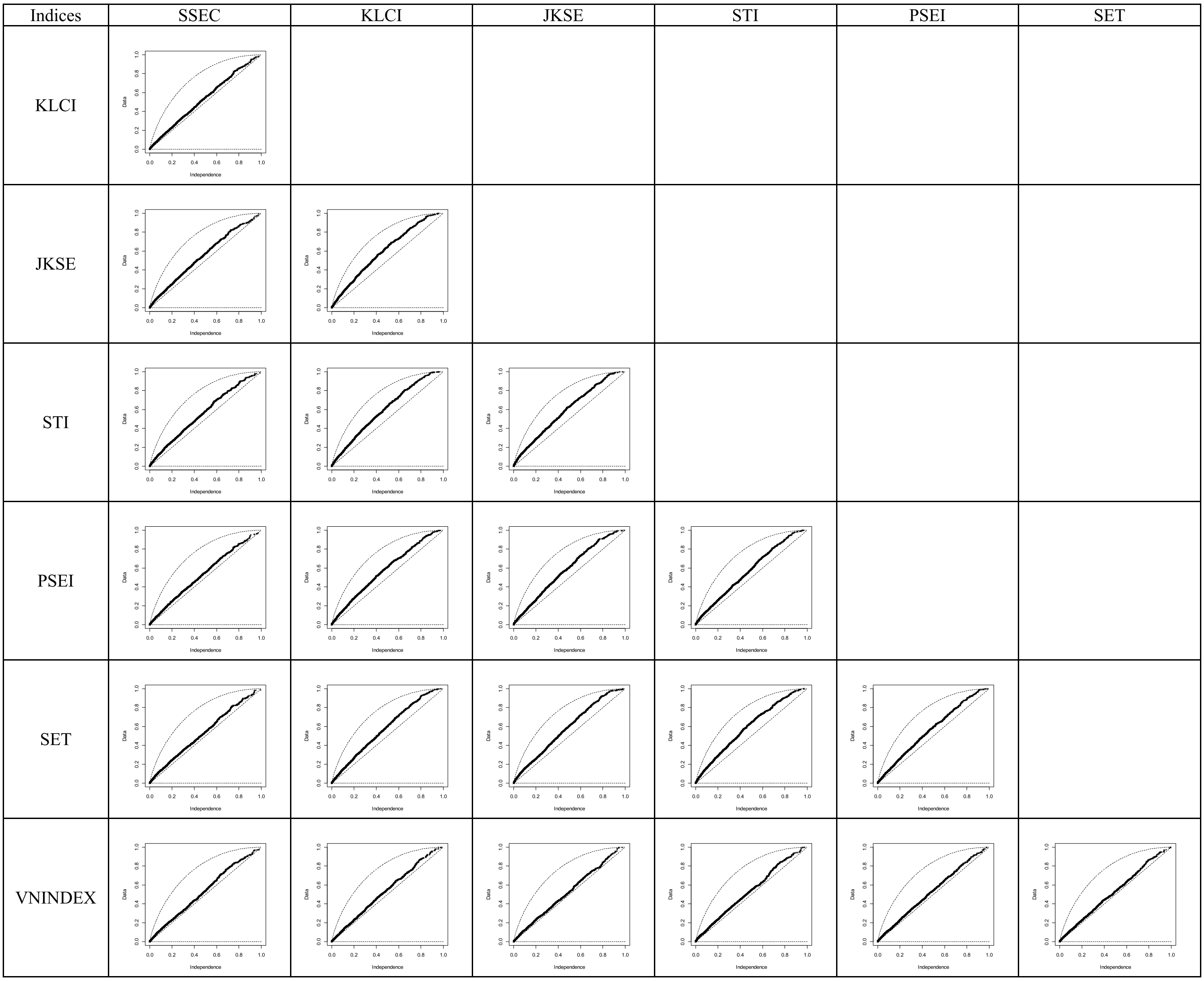

FIGURE 5. K-plots estimation for stock index series.

For consistency, we choose the TV(1)-GARCH(1,1) model to estimate the marginal distribution for each series, and the results are shown in Table 3.

Table 3 depicts that the unconditional variance $E_t(\varepsilon_t^2) = \delta_0^* Eh_t$ is time-varying for all the stock market series, since the value of δ_0 is not equal to 0. The g_t decreases monotonically over time for SSEC and VNINDEX return series and increases monotonically over time for the rest of the ASEAN return series since the value of δ_1 is negative for SSEC and VNINDEX and the value of δ_1 for the rest of the ASEAN return series is positive. The slope parameter γ_1 shows that the ASEAN-6 stock return series has a faster transition between the extreme regimes compared to the China stock index series.

After estimate by the TV-GARCH model for each return series, the standardized residual sequences and volatility series can be obtained. Figure 6 exhibits the daily time-varying volatility for each time series. We can find that the level of volatility is varying. For the China stock market, most of the volatility occurred during the period of the 2015 stock market crash which was caused by too much leverage, and the steepest volatility rises occurred in 2012 in Vietnam. However, for the rest of the ASEAN-6 countries, the highest return volatility happened after the COVID-19 outbreak. As mentioned earlier, the degree of volatility in the Malaysia and Singapore stock markets is less significant than that of in Thailand, Philippines and Indonesia stock markets during the period of COVID-19.

B. COPULA MODEL RESULTS

In the next step, we use the PIT data to capture dependence structures between China stock market and ASEAN stock markets. 16 kinds of bivariate copulas are adopted for fitting the stock index pairs including Normal copula, t copula, Frank copula, Clayton copula, Joe copula, BB1 copula, BB2 copula, BB3 copula, BB4 copula, BB5 copula, BB6 copula, BB7 copula, Galambos copula, Gumbel copula, Husler-Reiss copula and Tawn copula, the results can be

TABLE 2. GARCH model fitting results for each series.

Index	Model	Loglike	AIC	BIC
SSEC	TV(1)-GARCH(1,1)	**-3050.422**	**6114.844**	**6155.276**
	TV(2)-GARCH(1,1)	-3150.271	6316.543	6362.752
	GARCH(1,1)	-3948.19	7902.38	7919.707
	SGARCH(1,1)	-3949.62	7907.24	7930.344
	EGARCH(1,1)	-3945.975	7901.95	7930.831
	GJR-GARCH(1,1)	-3949.486	7908.972	7937.853
	APARCH(1,1)	-3946.649	7905.298	7939.955
	IGARCH(1,1)	-3950.936	7909.872	7932.976
KLCI	TV(1)-GARCH(1,1)	-3219.805	6453.611	6494.043
	TV(2)-GARCH(1,1)	-3433.059	6882.118	6928.327
	GARCH(1,1)	-2291.344	4588.688	4606.015
	SGARCH(1,1)	-2292.054	4592.108	4615.212
	EGARCH(1,1)	-2272.025	4554.05	4582.931
	GJR-GARCH(1,1)	-2271.887	4553.774	4582.655
	APARCH(1,1)	**-2268.3**	**4548.6**	**4583.257**
	IGARCH(1,1)	-2299.172	4606.344	4629.448
JKSE	TV(1)-GARCH(1,1)	**-3145.96**	**6305.919**	**6346.352**
	TV(2)-GARCH(1,1)	-3225.597	6467.194	6513.403
	GARCH(1,1)	-3552.502	7111.004	7128.331
	SGARCH(1,1)	-3547.502	7103.004	7126.108
	EGARCH(1,1)	-3501.733	7013.466	7042.347
	GJR-GARCH(1,1)	-3512.375	7034.75	7063.631
	APARCH(1,1)	-3495.65	7003.3	7037.957
	IGARCH(1,1)	-3556.632	7121.264	7144.368
STI	TV(1)-GARCH(1,1)	-3214.181	6442.362	6482.795
	TV(2)-GARCH(1,1)	-3180.675	6377.35	6423.558
	GARCH(1,1)	-2918.63	5843.26	5860.587
	SGARCH(1,1)	-2917.524	5843.048	5866.152
	EGARCH(1,1)	-2882.065	5774.13	5803.011
	GJR-GARCH(1,1)	-2882.603	5775.206	5804.087
	APARCH(1,1)	**-2880.56**	**5773.12**	**5807.777**
	IGARCH(1,1)	-2922.831	5853.662	5876.766
PSEI	TV(1)-GARCH(1,1)	**-3256.219**	**6526.437**	**6566.87**
	TV(2)-GARCH(1,1)	-3267.521	6551.042	6597.251
	GARCH(1,1)	-3676.58	7359.161	7376.488
	SGARCH(1,1)	-3672.792	7353.584	7376.688
	EGARCH(1,1)	-3648.283	7306.566	7335.447
	GJR-GARCH(1,1)	-3646.588	7303.176	7332.057
	APARCH(1,1)	-3642.76	7297.52	7332.177
	IGARCH(1,1)	-3678.798	7365.596	7388.700
SET	TV(1)-GARCH(1,1)	**-3145.583**	**6305.166**	**6345.599**
	TV(2)-GARCH(1,1)	-3340.098	6696.196	6742.405
	GARCH(1,1)	-3323.617	6653.235	6670.562
	SGARCH(1,1)	-3320.189	6648.378	6671.482
	EGARCH(1,1)	-3293.458	6596.916	6625.797
	GJR-GARCH(1,1)	-3299.312	6608.624	6637.505
	APARCH(1,1)	-3291.613	6595.226	6629.883
	IGARCH(1,1)	-3321.729	6651.458	6674.562
VNINDEX	TV(1)-GARCH(1,1)	-3377.883	6769.766	6810.199
	TV(2)-GARCH(1,1)	**-3114.101**	**6244.203**	**6290.412**
	GARCH(1,1)	-3953.476	7912.952	7930.279
	SGARCH(1,1)	-3955.501	7919.002	7942.106
	EGARCH(1,1)	-3940.93	7891.86	7920.741
	GJR-GARCH(1,1)	-3955.322	7920.644	7949.525
	APARCH(1,1)	-3948.393	7908.786	7943.443
	IGARCH(1,1)	-3957.469	7922.938	7946.042

found in Appendix Table 8. According to the likelihood maximum and AIC value, BIC value and HQ minimum principle, the optimal Copula for these group series is BB3 Copula. On this basis, the parameters θ and δ of BB3, Kendall's τ correlation coefficients, Spearman ρ_s correlation coefficients of two groups in the three periods are shown in Table 4.

According to Table 4, all the correlation coefficients are positive with dependence structure differed across different stock markets, which are in line with Jin's results [54].

TABLE 3. TV(1)-GARCH(1,1) model estimates for different stock returns.

Index	δ_0	δ_1	γ_1	c_1	α_0	α_1	β_1
SSEC	4.2024	-4.2024 (1.9854)	-0.6248	0.5518 (1.7346)	0.0084 (0.0040)	0.0624 (0.0138)	0.9307 (0.0144)
KLCI	0.3878	1.0358 (0.1761)	5.5215	0.8864 (0.0032)	0.0683 (0.0255)	0.1071 (0.0265)	0.8246 (0.0450)
JKSE	1.2681	1.5492 (0.4791)	5.5215	0.8849 (0.0039)	0.0489 (0.0199)	0.1339 (0.0394)	0.8233 (0.0501)
STI	0.7043	0.9292 (0.2548)	5.5215	0.8863 (0.0031)	0.0211 (0.0081)	0.0757 (0.0153)	0.9043 (0.0195)
PSEI	1.2619	2.1005 (0.4541)	5.5215	0.8851 (0.0029)	0.0610 (0.0219)	0.1245 (0.0290)	0.8206 (0.0399)
SET	1.0303	1.6635 (0.4397)	5.5215	0.8839 (0.0026)	0.0183 (0.0074)	0.0912 (0.0189)	0.8950 (0.0208)
VNINDEX	3.6922	-2.5108 (0.0759)	5.5215	0.2429 (0.0048)	0.0665 (0.0323)	0.0929 (0.0319)	0.8522 (0.0474)

Notes: The table reports parameter estimates for the TV(1)-GARCH(1,1) model and their standard errors (in brackets) for different stock price returns.

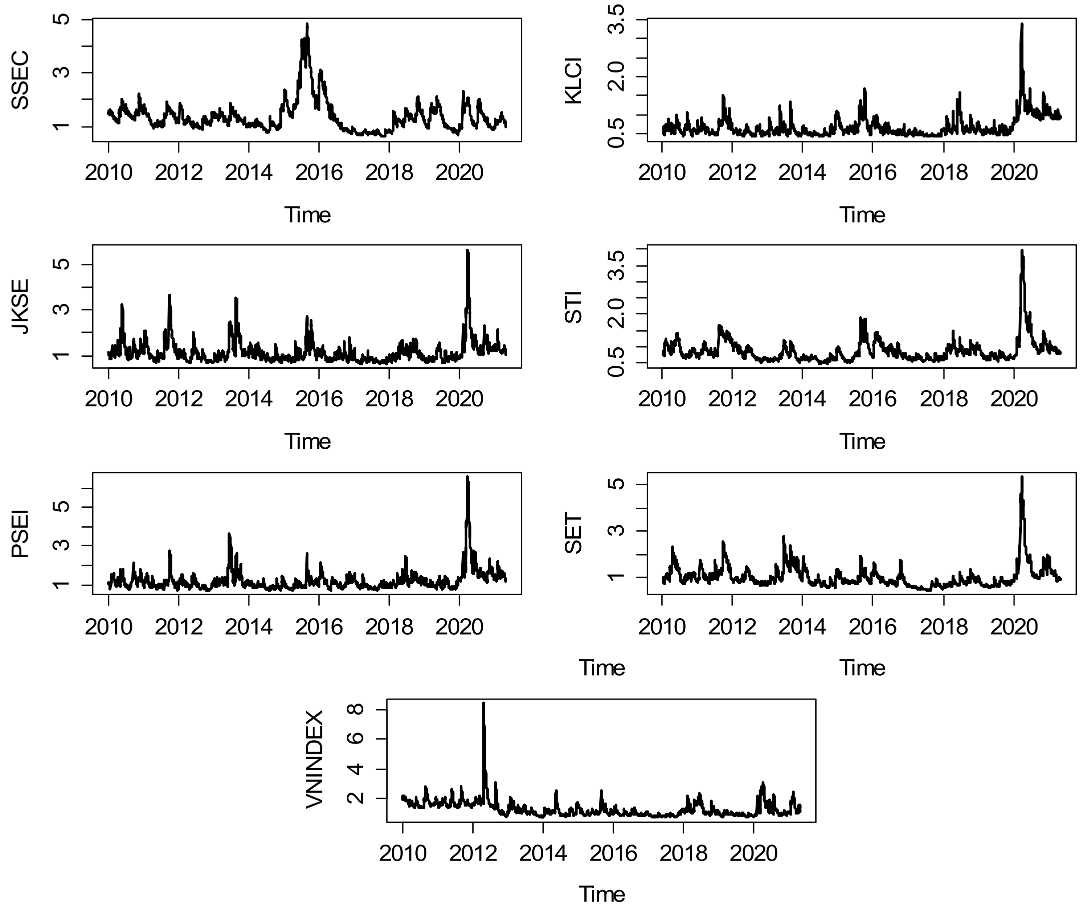

FIGURE 6. Time-varying conditional volatility of the returns.

Kendall's τ correlation coefficients between China stock index series and ASEAN stock market returns varying from 0.1887 to 0.2829. The pair of China and Singapore exhibited the highest dependence structure, whereas Vietnam was least likely to have dependence structures with China stock market according to Kendall's τ correlation coefficients. These findings are consistent with the results of the non-parametric method in Figure 3 to Figure 5. Kendall's τ correlation coefficients between China stock index series and Vietnam stock index returns is 0.1887, and the coefficient of Kendall's τ between China and Singapore is 0.2829. Table 4 also shows the Spearman ρ_s correlation coefficients and the results are a little bit different compared to Kendall's τ, but it also shows that China experienced dependence with ASEAN-6 countries, which verified that China has stepped into the economic and financial networks composed by

TABLE 4. **BB3 Copula parameter estimates.**

	θ	δ	τ	ρ_s	Loglike
SSEC-KLCI	1.1284 (0.0130)	0.2165 (0.0221)	0.2022	0.2964	119.2
SSEC-JKSE:	1.1414 (0.0132)	0.2749 (0.0234)	0.2319	0.2495	165.8
SSEC-STI	1.1795 (0.0137)	0.3554 (0.0249)	0.2829	0.2583	275
SSEC-PSEI	1.1141 (0.0127)	0.2087 (0.0220)	0.1888	0.2775	102.8
SSEC-SET	1.1337 (0.0129)	0.2203 (0.0221)	0.2074	0. 2454	129.6
SSEC-VNINDEX	1.1191 (0.0127)	0.1986 (0.0219)	0.1887	0.2774	101.1

Notes: The table reports the parameters of BB3 Copula and Std. Error (in parentheses).

TABLE 5. **Descriptive statistics of VaR and VaR backtests.**

	SSEC	KLCI	JKSE	STI	PSEI	SET	VNINDEX
Panel A:VaRdownside							
Minimum	-7.9894	-5.5966	-9.2298	-6.5432	-10.7861	-8.7709	-13.7949
Maximum	-1.0036	-0.6650	-1.0213	-0.7790	-1.1343	-0.7232	-1.2241
Mean	-2.2318	-1.0850	-1.8349	-1.4256	-1.9306	-1.6962	-2.1418
Median	-2.0271	-0.9334	-1.6231	-1.2772	-1.7281	-1.4927	-1.8607
Variance	0.9024	0.2009	0.6369	0.3508	0.6904	0.6713	0.8230
Stdev	0.9500	0.4482	0.7981	0.5923	0.8309	0.8193	0.9072
Kupiec test	0.3397 (0.5560)	0.00634 (0.9364)	0.1296 (0.7188)	0.2052 (0.6506)	0.1539 (0.6949)	0.0301 (0.8623)	0.2376 (0.6260)
Christoffersen test	0.3670 (0.8323)	1.4185 (0.4920)	0.5728 (0.7510)	6.0802 (0.0478)	2.1780 (0.3365)	5.0026 (0.0820)	3.6625 (0.1602)
Panel B:VaRupside							
Minimum	1.0087	0.6841	1.0922	0.7879	1.1974	0.7879	1.2974
Maximum	7.9945	5.6156	9.3007	6.5521	10.8491	8.8356	13.8683
Mean	2.2369	1.1041	1.9058	1.4345	1.9937	1.7609	2.2151
Median	2.0322	0.9525	1.6941	1.2861	1.7912	1.5574	1.9341
Variance	0.9024	0.2009	0.6369	0.3508	0.6904	0.6713	0.8230
Stdev	0.9500	0.4482	0.7981	0.5923	0.8309	0.8193	0.9072
Kupiec test	0.4605 (0.4974)	0.0117 (0.9138)	0.9357 (0.3334)	0.2052 (0.6506)	1.3485 (0.2455)	0.3397 (0.5600)	2.1148 (0.1459)
Christoffersen test	0.4755 (0.7884)	1.6544 (0.4373)	2.6508 (0.2657)	6.0802 (0.0478)	3.3195 (0.1902)	7.2576 (0.0265)	4.5069 (0.1050)

Notes: The table reports the descriptive statistics of VaRs and the conditional and unconditional coverage test Likelihood Ratio statistic and p-value (in parentheses).

ASEAN countries. To summarize, we estimated and calculated the copulas function to choose BB3 copulas for all return series.

C. SPILLOVER EFFECT RESULTS

Before estimating the risk spillover effect between SSEC and ASEAN-6 stock market series, the VaR of these return series was calculated according to equation (22). Figure 7 exhibits the daily time-varying upside and downside VaRs at the 5% significance levels as well as the daily time-varying volatility using the TV-GARCH fitted parameters. We can see that upside and downside VaR values are symmetric and displayed similar temporal dynamics throughout the sample period. In particular, VaR changes with the fluctuation of the returns and timely reflect the change of the market. High VaR values (in absolute value) occurred associated with high volatility. In a comparison of dynamic VaRs for these stock series, averagely speaking, KLCI has the most steady and the lowest upside and downside VaRs, followed by the STI, while SSEC has the most volatile and the largest upside and downside VaRs most of the time. In addition, most of the ASEAN stock returns follow a similar pattern for volatility and VaRs changing over the sample period. These results can provide us a preliminary idea about the direction of the

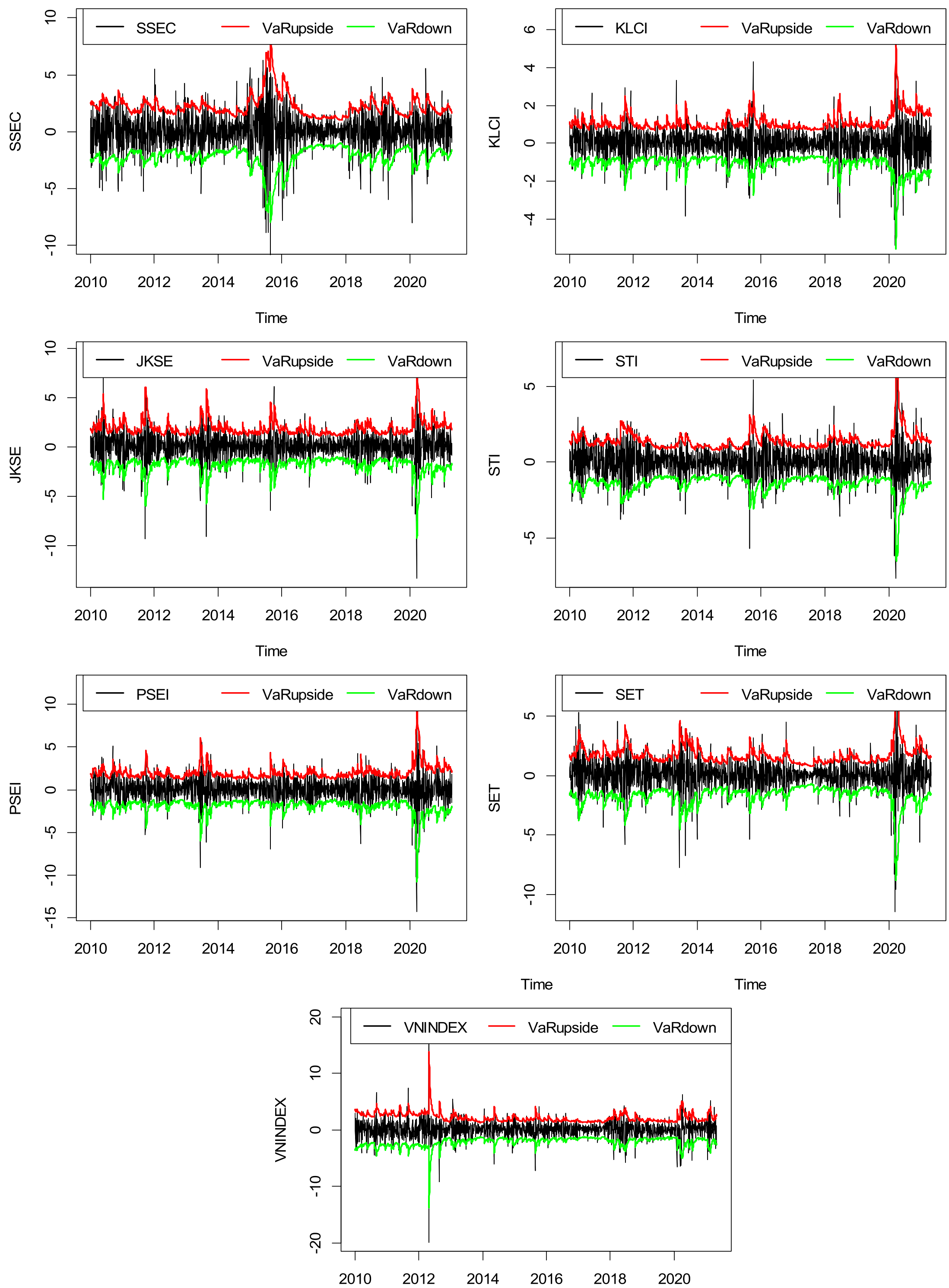

FIGURE 7. Time-varying VaR of the return series in the period of 2010-2021.

risk spillovers, either from the ASEAN economy to a China market set or from the China market set to the ASEAN economy.

Table 5 illustrates the descriptive statistics of VaRs and the conditional and unconditional coverage test Likelihood ratio statistic and p-value. Descriptive statistics of VaRs display that the mean and variance of the KLCI are the smallest, while the mean and variance of the SSEC are the largest. The mean and variance of the KLCI are −1.0850 and 0.2009 for the downside VaRs, and that is 1.1041 and 0.2009 for the upside VaRs, respectively. The mean and variance of the SSEC are −2.2318 and 0.9024 for the downside

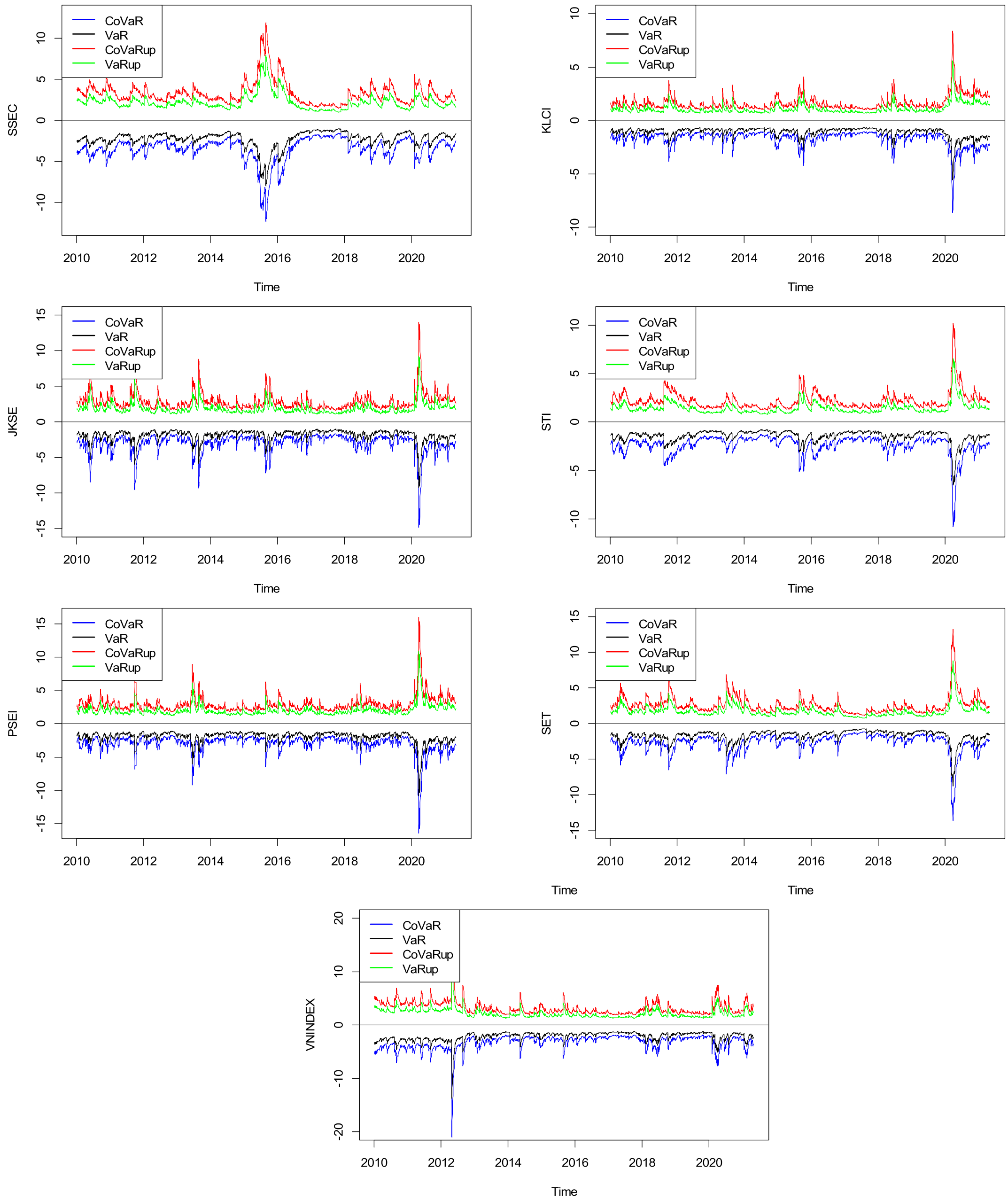

FIGURE 8. CoVaR for each stock market series.

VaRs, and that is 2.2369 and 0.9024 for the upside VaRs, respectively.

To verify that the results acquired from VaR calculations are consistent and reliable, two methods are used to evaluate the quality of the VaR estimates in this paper: the unconditional (Kupiec) and conditional (Christoffersen) coverage tests. Kupiec's test [80], also known as the proportion of failure test, measures whether the number of exceptions is synchronized with the confidence level. Kupiec's test is conducted as a likelihood-ratio (LR) test and the test statistic takes the form

$$LR = -2\ln\left(\frac{(1-p)^{T-x}p^{x}}{[1-(\frac{x}{T})]^{T-x}(\frac{x}{T})^{x}}\right)$$

Under the null hypothesis that the model is correct, LR is asymptotically χ^2 (chi-squared) distributed with one degree of freedom. If the value of the LR statistic exceeds the critical value of the χ^2 distribution, the null hypothesis will be rejected and the model is deemed as inaccurate. The results in Table 5 accept Kupiec's test at 95% confidence level, the P-values of the return series are all larger than 0.05.

Kupiec's test considers only the frequency of losses and not the time when they occur. As a result, it may fail to reject a model that produces clustered exceptions [81]. So we introduced the conditional coverage test which calls Christoffersen's test. Christoffersen's test [82], [83] allows examining whether the reason for not passing the test is

TABLE 6. Risk spillover effect analysis summary and hypothesis test results.

Spillover path	Average MES	Average LRMES	Average ΔCoVaR	$KS_1(H_0$:CoVaR=VaR)	$KS_2(H_0:CoVaR_{0.05}=CoVaR_{0.5})$
Panel A: ASEAN→China					
KLCI→SSEC	0.5390	0.9991153	9.5614	0.5204 [0.0000]	1 [0.0000]
JKSE→SSEC	1.0281	0.9999937	8.5164	0.5523 [0.0000]	1 [0.0000]
STI→SSEC	0.9396	0.9999851	8.8471	0.5812 [0.0000]	1 [0.0000]
PSEI→SSEC	0.8302	0.9999563	8.0723	0.5082 [0.0000]	1 [0.0000]
SET→SSEC	0.8149	0.9999491	8.2277	0.5258 [0.0000]	1 [0.0000]
VNINDEX→SSEC	0.6786	0.9997973	8.0294	0.5023 [0.0000]	1 [0.0000]
Panel B: China→ASEAN					
SSEC→KLCI	0.2746	0.984519	10.1449	0.6622 [0.0000]	1 [0.0000]
SSEC→JKSE	0.8738	0.9999911	7.5170	0.6274 [0.0000]	1 [0.0000]
SSEC→STI	0.7011	0.9999336	5.7903	0.6521 [0.0000]	0.99916 [0.0000]
SSEC→PSEI	0.6364	0.9998858	7.6479	0.6269 [0.0000]	1 [0.0000]
SSEC→SET	0.65478	0.9997221	6.6023	0.5246 [0.0000]	0.99329 [0.0000]
SSEC→VNINDEX	0.7287	0.9999458	8.5570	0.5338 [0.0000]	1 [0.0000]

Notes: We use the KS test to find the CoVaR and VaR differences. KS_1 test results with a null hypothesis of $CoVaR_{0.05}=VaR_{0.05}$ and KS_2 test results with a null hypothesis of $CoVaR_{0.05}=CoVaR_{0.5}$. p values are reported in square brackets.

caused by inaccurate coverage, clustered exceptions, or even both. The results of Christoffersen's test show that most of the series passed the test except STI and SET. Therefore, we conclude that the VaRs are accurate and VaR models are useful.

In the next step, we computed the downside and upside CoVaRs and MES by equation (26) and equation (30). Figure 8 shows a graphical characterization of the upside and downside CoVaR for all the stock return series. In a graphical aspect, they reflect existing spillovers between China and ASEAN-6 stock markets. The figures illustrate that the upside and downside CoVaRs are symmetric and display similar temporal dynamics throughout the sample period. We can also find that the values of upside CoVaR are systematically above the upside VaRs for all markets in the study periods, while the values of downside CoVaR are systematically below the downside VaRs. The results implied that the risk from foreign countries' stock markets will amplify the risk of the domestic market.

The results of average ΔCoVaR in Table 6 indicate that the value of average ΔCoVaR is significantly positive and much larger than that of others (i.e., short-run MES and LRMES measures). Panel A of Table 6 illustrated the direction of risk spillover from ASEAN-6 countries to the China stock market. In panel A, we can see that the ASEAN-6 stock market had a spillover effect on China stock market, albeit in different magnitude. The highest average ΔCoVaR occurs from Malaysia to China, followed by Singapore to China, while the lowest average ΔCoVaR is found from Vietnam to China, which indicates that the China stock market appears more vulnerable to shocks from the Malaysia stock market and Singapore stock market, the reason may be that Singapore and Malaysia are the top two investors in China and Singapore is well known for being an international financial and commercial hub. In addition, the Malaysian stock market is the hub of the ASEAN stock markets and it is the main source of the contagion effect in ASEAN [84]. China stock market received the least impact from Vietnam because Vietnam stock market is a small-capitalization stock market compared to other ASEAN stock markets and it has barely effect on other countries. In other words, the risk of contagion from Malaysia to China is relatively strong and the risk of contagion from Vietnam to China is relatively weak compared to other ASEAN countries. Panel B of Table 6 illustrated the direction of risk spillover from China to ASEAN-6 countries' stock market.

The results in Panel B of Table 6 show that China stock market also had a spillover effect on ASEAN-6 stock markets. We could corroborate that the highest average ΔCoVaR occurs from China to Malaysia, followed by China to Vietnam and from China to the Philippines, while the lowest average ΔCoVaR is found from China to Singapore. The results indicated that Malaysia and Vietnam stock markets, compared to other ASEAN-6 stock markets are more vulnerable to shocks from China stock market, while the Singapore stock market received the least impact from the

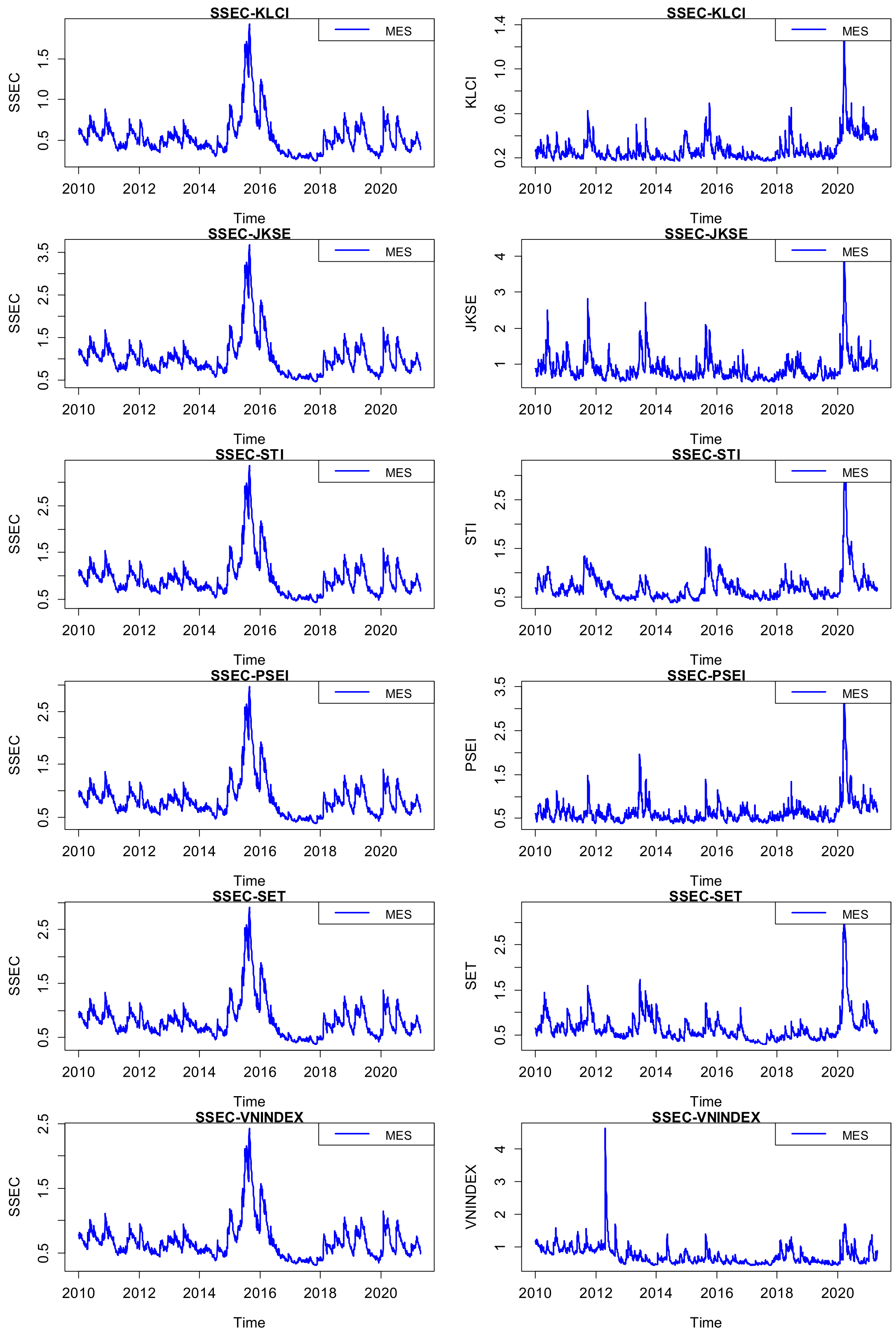

FIGURE 9. **MES for each stock market series.**

China stock market. This is because Vietnam and Malaysia are China's top two trading partners in ASEAN and the small-capitalization stock markets of Vietnam and Malaysia are vulnerable to financial risk from other stock markets,

TABLE 7. Copula functions.

Copula	Function
Archimedean Copula	
Frank	$C(u_1,u_2;\delta)=-\delta^{-1}\log\left(\left[\eta-(1-e^{-\delta u_1})(1-e^{-\delta u_2})\right]/\eta\right),\quad \eta=1-e^{-\delta}$
Joe	$C(u_1,u_2;\delta)=1-(\bar{u}_1^{\delta}+\bar{u}_2^{\delta}-\bar{u}_1^{\delta}\bar{u}_2^{\delta})^{1/\delta}$
BB6	$C(u_1,u_2;\theta,\delta)=1-\left(1-\exp\left\{-[(-\log(1-\bar{u}_1^{\theta}))^{\delta}+(-\log(1-\bar{u}_2^{\theta}))^{\delta}]^{1/\delta}\right\}\right)^{1/\theta}$
BB7	$C(u_1,u_2;\theta,\delta)=\delta^{-1}\left[1-\left\{1-[1-(1-\delta)^{\theta}]^{-1}[1-(1-\delta u_1)^{\theta}][1-(1-\delta u_2)^{\theta}]\right\}^{1/\theta}\right]$
Clayton	$C(u_1,u_2;\delta)=(u_1^{-\delta}+u_2^{-\delta}-1)^{-1/\delta}$
Archimax Copula	
BB4	$C(u_1,u_2;\theta,\delta)=(u_1^{-\theta}+u_2^{-\theta}-1-[(u_1^{-\theta}-1)^{-\delta}+(u_2^{-\theta}-1)^{-\delta}]^{-1/\delta})^{-1/\theta}$
EV Copula	
Gumbel	$C(u_1,u_2;\delta)=\exp\left\{(\tilde{u}_1^{\delta}+\tilde{u}_2^{\delta})^{1/\delta}\right\}$
Tawn	$C(u_1,u_2)=\exp\left[\log(u_1u_2)A\left(\frac{\log(u_1)}{\log(u_1u_2)}\right)\right]$ $A(t)=1-\beta+(\beta-\alpha)t+[\alpha^{\theta}t^{\theta}+\beta^{\theta}(1-t)^{\theta}]^{1/\theta}$
Husler-Reiss	$C(u_1,u_2;\delta)=\exp\left\{-\tilde{u}_1\Phi(\delta^{-1}+\frac{1}{2}\delta\log[\tilde{u}_1/\tilde{u}_2])-\tilde{u}_2\Phi(\delta^{-1}+\frac{1}{2}\delta\log[\tilde{u}_2/\tilde{u}_1])\right\}$
Galambos	$C(u_1,u_2;\delta)=u_1u_2\exp\left\{(\tilde{u}_1^{-\delta}+\tilde{u}_2^{-\delta})^{-1/\delta}\right\}$
BB5	$C(u_1,u_2;\theta,\delta)=\exp\left\{-[\tilde{u}_1^{\theta}+\tilde{u}_2^{\theta}-(\tilde{u}_1^{-\theta\delta}+\tilde{u}_2^{-\theta\delta})^{-1/\delta}]^{1/\theta}\right\}$

Note: $\bar{u}=1-u$, $\tilde{u}=-\log u$, $\eta=1-e^{-\delta}$.

while the market capitalization for Singapore is the largest and less vulnerable to financial risk from China compared to other ASEAN countries. Table 6 also reports the KS statistics and the associated p values. KS_1 tests under the null hypothesis of no difference between the CoVaR and VaR and KS_2 tests under the null hypothesis of no difference between $CoVaR_{0.05}$ and $CoVaR_{0.5}$. We can see that the probability is equal to 0, lower than 1% significance level which provides strong evidence that we can reject the null hypothesis. This indicates that there is a risk spillover effect between China stock market and ASEAN stock markets.

In short, the results of ΔCoVaR in Table 6 report that there exist asymmetric risk spillovers from China to ASEAN-6 stock markets and vice versa, albeit in different magnitude. The degree of risk spillover between China and Malaysia exhibited the highest value, which indicates that Malaysia is more integrated with the China stock market than other ASEAN-6 stock markets. The difference of spillover effect from China to ASEAN-6 stock market is more pronounced than that of from ASEAN-6 to China stock market.

The results of MES, shown in Table 6, suggest that the estimated average of MES is significantly positive and varies slightly from one market to another. The results of MES in panel A show that the highest average MES occurs from Indonesia to China, followed by Singapore to China and from the Philippines to China, while the lowest average MES is found from Vietnam to China. The results of MES in Panel B show that the highest average MES occurs from China to Indonesia, followed by China to Vietnam and from China to Singapore, while the lowest average MES is found from China to Malaysia. This result is slightly different from the results of ΔCoVaR, but they all reveal that there are significant loss returns in these markets on days when another market experiences a loss in the 5% left-hand tail within the sample period.

TABLE 8. Copula function fitting results of SSEC and ASEAN.

Copula	loglike	AIC	BIC	HQ
Panel A: SSEC-KLCI				
T Copula	45.49069	-84.98139	-67.65304	-78.67504
Gumbel Copula	43.35085	-84.70169	-78.92557	-82.59958
Joe Copula	24.94169	-47.88339	-42.10727	-45.78128
Normal Copula	54.4686	-106.9372	-101.16109	-104.83509
Frank Copula	49.70077	-97.40154	-91.62542	-95.29942
Tawn Copula	45.49069	-84.98139	-67.65304	-78.67504
Galambos Copula	38.23647	-74.47293	-68.69682	-72.37082
Kimeldorf Sampson Copula	62.33199	-122.66398	-116.88787	-120.56187
BB1 Copula	67.10528	-130.21056	-118.65833	-126.00634
BB2 Copula	62.33173	-120.66345	-109.11122	-116.45923
BB3 Copula	119.22161	-234.44323	-222.89099	-230.239
BB4 Copula	65.30222	-126.60444	-115.05221	-122.40022
BB5 Copula	43.35085	-82.70169	-71.14946	-78.49746
BB6 Copula	24.94169	-45.88339	-34.33116	-41.67916
BB7 Copula	66.76964	-129.53928	-117.98705	-125.33505
Husler Reiss Copula	35.1236	-68.24719	-62.47108	-66.14508
Panel B: SSEC-JKSE				
T Copula	61.43848	-116.877	-99.54862	-110.57063
Gumbel Copula	60.26555	-118.5311	-112.75499	-116.42899
Joe Copula	31.0531	-60.1062	-54.33009	-58.00409
Normal Copula	84.25386	-166.5077	-160.73161	-164.40561
Frank Copula	76.64241	-151.2848	-145.50871	-149.18271
Tawn Copula	61.43848	-116.877	-99.54862	-110.57063
Galambos Copula	55.90777	-109.8155	-104.03943	-107.71343
Kimeldorf Sampson Copula	100.02425	-198.0485	-192.27238	-195.94638
BB1 Copula	103.18504	-202.3701	-190.81786	-198.16586
BB2 Copula	100.01043	-196.0209	-184.46863	-191.81663
BB3 Copula	165.76025	-327.5205	-315.96828	-323.31628
BB4 Copula	102.37595	-200.7519	-189.19967	-196.54768
BB5 Copula	60.26555	-116.5311	-104.97888	-112.32688
BB6 Copula	31.0531	-58.1062	-46.55397	-53.90198
BB7 Copula	102.78769	-201.5754	-190.02315	-197.37115
Husler Reiss Copula	52.76114	-103.5223	-97.74616	-101.42016
Panel C: SSEC-STI				
T Copula	122.78047	-239.5609	-222.2326	-233.2546
Gumbel Copula	120.55258	-239.1052	-233.3291	-237.0031
Joe Copula	69.46113	-136.9223	-131.1461	-134.8201
Normal Copula	156.93662	-311.8732	-306.0971	-309.7711
Frank Copula	136.48456	-270.9691	-265.193	-268.867
Tawn Copula	122.78047	-239.5609	-222.2326	-233.2546
Galambos Copula	115.91918	-229.8384	-224.0622	-227.7362
Kimeldorf Sampson Copula	175.29464	-348.5893	-342.8132	-346.4872
BB1 Copula	184.7712	-365.5424	-353.9902	-361.3382
BB2 Copula	175.27907	-346.5581	-335.0059	-342.3539
BB3 Copula	274.95628	-545.9126	-534.3603	-541.7083
BB4 Copula	183.41819	-362.8364	-351.2841	-358.6322
BB5 Copula	120.55258	-237.1052	-225.5529	-232.9009

TABLE 8. ***(Continued.)*** **Copula function fitting results of SSEC and ASEAN.**

BB6 Copula	69.46113	-134.9223	-123.37	-130.718
BB7 Copula	184.24823	-364.4965	-352.9442	-360.2922
Husler Reiss Copula	109.19539	-216.3908	-210.6147	-214.2887
Panel D: SSEC-PSEI				
T Copula	28.74019	-51.48038	-34.15204	-45.17404
Gumbel Copula	28.73972	-55.47943	-49.70332	-53.37732
Joe Copula	15.03532	-28.07064	-22.29452	-25.96852
Normal Copula	41.30909	-80.61819	-74.84207	-78.51607
Frank Copula	32.44935	-62.8987	-57.12258	-60.79658
Tawn Copula	28.74019	-51.48038	-34.15204	-45.17404
Galambos Copula	27.61739	-53.23478	-47.45867	-51.13267
Kimeldorf Sampson Copula	55.71758	-109.43516	-103.65904	-107.33305
BB1 Copula	57.66112	-111.32223	-99.77	-107.118
BB2 Copula	56.52744	-109.05489	-97.50266	-104.85066
BB3 Copula	102.75036	-201.50071	-189.94848	-197.29648
BB4 Copula	57.89124	-111.78247	-100.23024	-107.57825
BB5 Copula	28.75428	-53.50855	-41.95632	-49.30432
BB6 Copula	15.03532	-26.07064	-14.51841	-21.86641
BB7 Copula	58.05085	-112.10171	-100.54948	-107.89748
Husler Reiss Copula	26.56327	-51.12653	-45.35041	-49.02442
Panel E: SSEC-SET				
T Copula	56.98701	-107.97401	-90.64567	-101.66767
Gumbel Copula	51.91565	-101.8313	-96.05518	-99.72918
Joe Copula	33.04515	-64.0903	-58.31419	-61.98819
Normal Copula	62.61054	-123.22109	-117.44497	-121.11898
Frank Copula	53.5722	-105.1444	-99.36829	-103.04229
Tawn Copula	56.98701	-107.97401	-90.64567	-101.66767
Galambos Copula	49.38821	-96.77643	-91.00031	-94.67431
Kimeldorf Sampson Copula	65.53016	-129.06033	-123.28421	-126.95822
BB1 Copula	74.06537	-144.13074	-132.57851	-139.92651
BB2 Copula	65.53	-127.06	-115.50777	-122.85578
BB3 Copula	129.61143	-255.22287	-243.67063	-251.01864
BB4 Copula	73.08535	-142.1707	-130.61846	-137.96647
BB5 Copula	51.91565	-99.8313	-88.27907	-95.62707
BB6 Copula	33.04515	-62.0903	-50.53807	-57.88607
BB7 Copula	74.21068	-144.42135	-132.86912	-140.21713
Husler Reiss Copula	46.62506	-91.25012	-85.47401	-89.14801
Panel F: SSEC-VNINDEX				
T Copula	35.39563	-64.79127	-47.46292	-58.48493
Gumbel Copula	32.9096	-63.8192	-58.04308	-61.71708
Joe Copula	19.85938	-37.71875	-31.94264	-35.61664
Normal Copula	37.60781	-73.21562	-67.4395	-71.1135
Frank Copula	32.86674	-63.73347	-57.95736	-61.63136
Tawn Copula	35.39563	-64.79127	-47.46292	-58.48493
Galambos Copula	28.05371	-54.10741	-48.3313	-52.0053
Kimeldorf Sampson Copula	49.81152	-97.62303	-91.84692	-95.52092
BB1 Copula	53.94693	-103.89387	-92.34164	-99.68964
BB2 Copula	50.16321	-96.32643	-84.7742	-92.1222

TABLE 8. *(Continued.)* **Copula function fitting results of SSEC and ASEAN.**

BB3 Copula	101.09791	-198.19583	-186.6436	-193.9916
BB4 Copula	51.80644	-99.61288	-88.06065	-95.40866
BB5 Copula	32.9096	-61.8192	-50.26697	-57.61497
BB6 Copula	19.85938	-35.71875	-24.16652	-31.51452
BB7 Copula	54.40681	-104.81362	-93.26139	-100.6094
Husler Reiss Copula	24.85233	-47.70466	-41.92854	-45.60254

The average value of LRMES is larger than that of MES, because LRMES measures the long-run shortfall condition on the long-run tail events, while MES measures the short-run shortfall and short-run tail events. Figure 9 shows the dynamic MES of the return series in the sample period. It is found that MES is a positively time-varying and considerable high value of MES occurred in the period of COVID-19 for most of the ASEAN countries, indicating that COVID-19 has increased the risk to the stock markets of ASEAN countries. This appears in line with our analysis of Figure 6 and Figure 7.

Overall, our results on MES and ΔCoVaRs indicate that there are bidirectional asymmetric risk spillover effects between China and ASEAN stock markets. These findings suggest that investors should utilize asymmetric hedging strategies between China and ASEAN stock markets.

VI. CONCLUSION

Interlinkage between China and ASEAN countries has been strengthening over time based on the Belt and Road Initiatives and the establishment of the China-ASEAN Free Trade Area. The partial opening of the China financial markets to foreign participation also increased interactions among China and ASEAN stock markets. How have these developments affected the risk spillover effects between China and ASEAN countries? To investigate, we construct a new composite model named Copula-TV-GARCH-CoVaR model to evaluate the time-varying financial risk spillover effects between China and ASEAN stock markets. We examined features such as fluctuation aggregation, fat tail distribution and time-varying unconditional variance of stock series, and so on by using the TV-GARCH model as the marginal model and obtaining standard residuals and volatility sequences. According to the marginal analysis, we find that all return series exhibit fat-tail distribution, conditional skewness and fluctuation aggregation. Then we estimated the dependence structure between seven stock markets (China, Vietnam, Thailand, Singapore, Philippines, Malaysia and Indonesia) using a non-parametric approach with Chi-plots and K-plots and BB3 copula model. The results conclude that these stock market series, except Vietnam, experience a dependency structure. The pair of China and Singapore exhibited the highest dependence structure, whereas Vietnam was least likely to have dependence structures with China stock market.

Finally, we assessed the risk spillover effects between them by computing the MES and LRMES as well as the CoVaR measure composed by BB3 copula and VaR model. The results depict that the upside and downside CoVaRs are symmetric and display similar temporal dynamics throughout the sample period. Moreover, values of upside CoVaR are systematically above the upside VaRs for all markets in the sample periods, while the values of downside CoVaR are systematically below the downside VaRs. The average ΔCoVaR and average of MES in Table 6 are significantly positive and vary slightly from one market to another, which indicates that there are bidirectional asymmetric risk spillover effects between China and ASEAN stock markets.

This analysis is of interest for investors whose stock portfolios include the ASEAN and China stocks with the aim of hedging and safeguarding against extreme co-movements in financial markets. In this context, a construction strategy of transnational investment portfolios crucially depends on the dependence structure between different stock markets and on how price shocks in one market may be transmitted to other markets. We suggest that market participants should be recognized that the bidirectional risk spillovers between China and the ASEAN markets, whether in the short position or a long position. They need to use hedging strategies to reduce the impact of stock price shocks on the other stock markets, especially for investors who invest in the stock in China and Malaysia. For the portfolio managers, they should consider the time horizons and adjust their positions, and hedge according to the investment cycle. When making a portfolio, they should increase positions of the stock in low correlation and reduce the stock positions in high correlation in a bear market. In a bull market, they should increase the stock positions which performed well in high linkage and decrease the stock positions in low linkage. As for policymakers, they should remain vigilant of extreme volatility in both China stock market and the ASEAN markets and intervene when is required, to keep the stock markets stable and reduce risks [46]. For Chinese policymakers and regulators, they should pay close attention to the countries which highly risk spillover effects to China stock market, such as Malaysia and Singapore.

In future research, we may include more risk spillover effect models and volatility models and consider whether different models can affect the results. For this purpose, the design of the corresponding simulation experiments and the method of empirical analysis can be further studied.

APPENDIX

See Tables 7 and 8.

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JIUSHENG CHEN received the B.S. degree in chemistry from Northeast Forest University, China, in 2009, the M.S. degree in biology and the Ph.D. degree in applied economics from Chongqing University, Chongqing, China, in 2013 and 2016, respectively. Since 2016, he has been a Lecturer with Chongqing Normal University, Chongqing. He has received the Research Grant from the Social Science Foundation of Chongqing and the Social Science Foundation of Chongqing Education Commission on the financial risk study. His research interests include financial systemic risk and financial risk spillover.

XIANNING WANG received the B.S. degree in economics from Xinyang Normal University, China, in 2009, the M.S. degree in quantitative economics from Chongqing Normal University, Chongqing, China, in 2012, and the Ph.D. degree in applied economics from Chongqing University, Chongqing, in 2016. From 2016 to 2019, he was a Lecturer with Chongqing Normal University, where he is currently an Associate Professor. His research interests include economic forecasting, decision-making optimization, and spatial mixing prediction. He has received the Research Grant from the Social Science Foundation of Chongqing and the Natural Science Foundation of Chongqing on the spatial mixing prediction study.