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The risk spillovers from the Chinese stock market to major East Asian stock markets: A MSGARCH-EVT-copula approach

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ABSTRACT

This paper studies the risk spillovers of the Chinese stock market to major East Asian stock markets during turbulent and clam periods. We employ the Markov regime-switching model, the extreme value theory (EVT) and the vine copula function to model their multivariate dependence structures and compute the corresponding conditional Value-at-risk (CoVaR) in direct and indirect ways. In the case of the direct CoVaR, we find some interesting results that downside and upside spillovers are significantly different between the turbulent and calm periods, except for the China-Japan and the China-South Korea for the turbulent period. The evidence on the indirect results indicates the differences between the turbulent and calm periods do exist. The other results indicate the spillovers measured ignore the special nature of the different periods when the whole sample is used to model the dependence structure among the stock markets.

1. Introduction

In recent years, stock investors are difficult to optimize their portfolio strategies, due to volatility dynamics and complex dependence in stock markets. Making an effective decision is also hard, especially in extreme events. Therefore, studying complicated characteristics in stock portfolios is of vital significance for investors, regulators and risk managers. After the launch of the Shanghai-Hong Kong Stock Connect program,[1] Chinese stock market experienced a massive crisis that the Chinese stock index prices fell abruptly from June 2015 to early 2016 after the previous bullish impetus. Considering these aspects, we in this paper mainly study whether the Chinese extreme stock price changes affect Asian stock markets in two ways. One is called direct spillovers that the Chinese stock returns spill over to Asian stocks, and the other is called indirect spillovers that the Chinese stock returns conditional on the Hong Kong stock market spill over to Asian stock markets.

With Asian economy and finance development, Asian stock markets are more and more influential in the world. In particular, China has become the world's second economy, so its stock market exerts increasing impacts on Asian economy and trade. Although the Chinese stock market grows fast, it still belongs to an emerging market. Meanwhile, China owns close financial links with a global financial center, Hong Kong, which tightly connects Asian stock markets with the Chinese stock market. Furthermore, the Shanghai-Hong Kong Stock Connect program boosts stock trades between the Chinese stock market and the Asian. As a consequence, the Asian stock markets are susceptible to the Chinese stock market, especially in extreme events. If the extreme risks in the Chinese stock market arise, they will impair near stock markets through the direct and indirect risk spillovers. The Chinese stock market with the

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[1] This program provides foreign investors access to trade A share stocks (Shanghai Stock Exchange 180 Index and 380 Index) in the Shanghai Security Exchange via the Hong Kong Security Exchange, and mainland investors access to trade stocks (Hang Seng Composite index LargeCap Index and MidCap Index) in the Hong Kong Security Exchange.

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above-mentioned features makes this study more interesting and challenging. These characteristics the Chinese stock market show can be depicted through capturing stylized facts (heteroskedasticity, volatility clustering, asymmetric effects, nonlinear and dynamic dependence) in its return series. Based on these aspects, spillover effects of the Chinese stock market to Asian stock markets are computed.

Since Engle (1982) introduced autoregressive conditional heteroskedasticity (ARCH), a seminal contribution was made by Bollerslev (1986) who generalized ARCH to GARCH which is ease to investigate conditional heteroskedasticity and volatility clustering in financial return series. Nevertheless, the GARCH model just takes into account symmetric price changes. In further studies, more and more researchers considered asymmetric effects on volatility in financial markets and their studies provided new sights for asymmetric volatility (Bollerslev, Litvinova, & Tauchen, 2006; Campbell & Hentschel, 1992; Chkili, Hammoudeh, & Nguyen, 2014; Ewing & Malik, 2017; French, Schwert, & Stambaugh, 1987; Kristoufek, 2014; Salisu & Fasanya, 2013). On the other hand, conventional GARCH-type models belong to single-regime models, which are hard to elaborate volatility dynamics in economic cycles. Considering this case, some scholars came up with regime-switching models and later these models were proven to be more robust than the single-regime GARCH (SGARCH) models on measuring volatility (Gray, 1996; Marcucci, 2005). Meanwhile, the presence of switching regimes is in accordance with financial stylized facts (Gray, 1996; Haas, Mittnik, & Paolella, 2004; Marcucci, 2005). An original Markov Regime Switching ARCH model, introduced by Cai (1994) and Hamilton and Susmel (1994), is used to investigate volatility dynamics in financial markets. Gray (1996) developed the model introduced by Hamilton and Susmel (1994) to Markov regime-switching GARCH (MSGARCH) by defining innovations integrated with time-varying mixing weights to circumvent path dependence problems when translating GARCH parts. Subsequently, Klaassen (2002) made uses of the posterior probability of conditional variance to modify this method of upgrading regimes. Although MSGARCH becomes feasible to account for GARCH effects after the above-mentioned modifications, this approach still has a drawback of intractable analysis for its dynamic properties. Haas et al. (2004) introduced a new approach to solving the intractable interpretation by preserving each regime GARCH parameters only depending on its own variance process. Recent substantial literatures have focused on the fitting and forecasting performances between Markov regime-switching GARCH-type models and single-regime counterparts (Chang, 2012; Di Sanzo, 2018; Herrera, Hu, & Pastor, 2018; Marcucci, 2005; Zhang, Yao, He, & Ripple, 2019). Almost all of them confirmed the Markov regime-switching GARCH models outperform the single-regime ones on modeling financial return series. In this paper, we adopt the specification of Haas et al. (2004) to model stylized facts shared by stock returns.

To characterize financial return series, the distribution selection is very significant to model return series in the financial field. However, it is still not unanimous for a proposed distribution whose performances can vary with the financial assets. Considerable researchers turned to a student-*t* distribution or a skewed student-*t* distribution to capture features of the fat tail and the skewness (Azzalini & Capitanio, 2003; Branco and Dey, 2001; Hansen, 1994; Jones & Faddy, 2003). Whereas the distributions can capture nature of the financial return to some extent, they mistakenly estimate the possibility of the extreme events because of their specification of the double fat tails. For this reason, some researches that focused on the tail distribution of the financial return series used an Extreme Value Theory (EVT) method (Bhattacharyya & Ritolia, 2008; Chan & Gray, 2006; Marimoutou, Raggad, & Trabelsi, 2009; McNeil & Frey, 2000; Youssef, Belkacem, & Mokni, 2015). Their empirical results on the distribution tail fits indicate this method is better than most of the parametric approaches. In the light of its accuracy in tail and flexibility in whole distribution, we in this paper divide the whole distribution into tail distributions based on the EVT and a middle distribution based on the empirical distribution to describe return series together.

Another question is how to model nonlinear dependence of the multivariate return series. Marginal distributions just capture stylized facts of the univariate return series, while multivariate distributions can display complex relationships of the financial assets. Thus, the joint distribution is concerned by investors and risk management sectors so forth. Since Sklar (1959) gave copula functions to model the joint distribution on the multivariate framework, one strand of literatures (Hu, 2010; Hussain & Li, 2018; Wang, Chen, & Huang, 2011) studied two-dimensional relationships between major stock markets by copula functions with different features. Although multivariate copulas can capture complicated multivariate systems among variables, they are hard to be estimated when variables gradually increase. In considering this issue, Joe (1996) decomposed a multivariate copula into a set of bivariate copulas. Meanwhile, Bedford and Cooke (2002) presented a graphic decomposition of the multivariate system which is called a “Vine” structure. However, the decomposition algorithm is too tricky to select suitable vine structures. Aas and Berg (2009) introduced two special forms, texitcanonical (C-) and drawable (D-) vines, to estimate multivariate systems. In financial markets, Zhang (2014) adopted the two vines to forecast value-at-risk (VaR) of major stock indexes. Reboredo and Ugolini (2015a) used them to study conditional value-at-risk (CoVaR) between European sovereign debt and financial systems. Furth studies, Diβmann et al. (2013) proposed R-vine matrix (RVM) to construct more regular dependence structures. Some scholars began to use the R-Vine copula to measure and forecast portfolio VaR of the financial assets. Koliai (2016) argued that the EVT combined with the R-Vine copula can test financial stress well as the specifications are flexible and consistent. Yu, Yang, Wei, and Lei (2018) also consented that the EVT combined with the R-Vine copula can accurately measure and forecast VaR of the crude oil portfolios. Sahamkhadam, Stephan, and Östermark (2018) employed GARCH-EVT-Copula based on three weight approaches to measure how much of a reduction in portfolios risk. These scholars all confirmed the R-Vine copula can be viewed as an effective method to capture complicated dependence structures of the portfolios and measure the portfolio risks. In this paper, we consider scarce literatures on multivariate dependence structures among East Asian stock markets, especially after the launch of the Shanghai-Hong Kong Stock Connect. In the light of the China’s particularity in this region, we think its extreme stock price changes have meaningful influences on Asian stock markets. This paper endeavors to fill this gap and contribute to existing literatures in several ways.

First, we employ the MSEGARCH to model return series of the East stock markets. The R-vine copula allows us to model marginal distributions and multivariate systems of the financial return series separately, so we adopt the EVT and the empirical distributions to model return series filtered by the MSEGARCH model. The R-vine copula that is a hierarchical structure can characterize dependence structures among the East Asian stock markets. We use data inversed by the marginal distribution to estimate the R-vine copula.

Consequently, the relationships with the Chinese stock market can be captured through the estimated multivariate structures. Meanwhile, we consider the Chinese market experienced a massive crisis so we also employ the R-vine copula to capture dependence structures for different periods. Second, we use the estimated dependence structures to compute spillovers (Chinese stock markets to other stock markets) based on previous literatures on the CoVaR approach. Adrian and Brunnermeier (2011) measured VaR of one market conditional on the other market in financial distress, and later Girardi and Ergün (2013) generalized this method by comparing CoVaR of one market with its VaR. Finally, Reboredo and Ugolini (2015a) extended it to multivariate CoVaR setting. Referring to the above-mentioned literatures, we compute the upward and downward CoVaR to measure the direct and indirect spillovers of the Chinese stock market to the East Asian stock markets. At the same time, we implement the bootstrap Kolmogorov-Smirnov test developed by Abadie (2002) and used by Bernal, Gnabo, and Guilmin (2014) and Reboredo and Ugolini (2015b) to check whether the spillover effects do exist. Finally, we analyze the differences of the CoVaR.

The reminder of this paper is organized as follows: Section 2 illustrates Econometric methods adopted. Section 3 provides the description of the characteristics of the East Asian stock indexes. Section 4 shows the empirical results. Section 5 concludes this paper.

2. Econometric methodology

2.1. The EGARCH model[2]

The EGARCH model introduced by Nelson (1991) captures existing asymmetric shocks to volatility. The EGARCH (1, 1) is defined as follows:

$$r_t = \mu_t + \varepsilon_t = \mu_t + h_t z_t \tag{1}$$

$$\ln\left(h_t^2\right) = \omega + \alpha[|z_{t-1}| - E|z_{t-1}|] + \gamma z_{t-1} + \beta \ln\left(h_{t-1}^2\right) \tag{2}$$

where μ_t is conditional mean and h_t is conditional variance. z_t is an independent random variable. α denotes the magnitude effect which implies a significant effect on volatility, and γ tests for the sign effect which highlights asymmetric impacts on volatility. Good news shocks to volatility are represented by the sum $\alpha + \gamma$ depending on whether the innovation ε_t is bigger than zero, the bad news $\alpha - \gamma$ otherwise.

2.2. The MSEGARCH model

An EGARCH model belongs to the single-regime model, while a MSEGARCH model is a more effective approach to capturing structural transmission in financial movements. The switching probability is defined as:

$$\Pr(s_t = i | s_{t-1} = j) = p_{ij} \tag{3}$$

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix} \tag{4}$$

where s_t is subjective to a Markov process. p_{ij} denotes the switching probability from state j at time $t-1$ to state i at time t. P means the transition matrix which contains the probability of the two states where p and q stand for switching probability under the state 1 and 2, respectively. MSEGARCH is estimated as follows:

$$f\left(r_t | \psi, I_{t-1}\right) = \sum_{i=1}^{K} \sum_{j=1}^{K} p_{ij} \phi_{i,t-1} f_D(r_t | s_t = j, \psi, I_{t-1}\right) \tag{5}$$

$$L(\psi | I_{t-1}) = \prod_{t=1}^{T} f(r_t | \psi, I_{t-1}) \tag{6}$$

where $f_D(r_t | s_t = j, \psi, I_{t-1})$ denotes conditional density function given regime-switching model parameters ψ and information sets I_{t-1}.$f(r_t | \psi, I_{t-1})$ integrates discrete conditional ones. $\phi_{i,t-1}$ is filtered probability of the state i at time $t-1$. The likelihood function is obtained according to Eq. (5). In this respect, this model can adjust the corresponding specifications which depend on the various regimes. Thus, the MSEGARCH is defined as:

$$r_{s,t} = \mu_{s,t} + h_{s,t} z_{s,t} \tag{7}$$

$$\ln\left(h_{s,t}^2\right) = \omega_s + \alpha_s[|z_{s,t-1}| - E|z_{s,t-1}|] + \gamma_s z_{s,t-1} + \beta_s \ln\left(h_{s,t-1}^2\right) \tag{8}$$

where conditional variance $h_{s,t}^2$ denoted in the above variance equation varies over the different states at time t. This is to say, the

EGARCH model takes different values depending on when the stock is in a high or a low volatility state. The other parameters and variables also follow this specification. z_t is an independent random variable with the skewed-student-t distribution[3] proposed by Hansen (1994) and Reboredo and Ugolini (2015a, 2015b).

The more regimes will affect fitting performances in the short term because of possible intensive state switches among various volatility regimes. So we follow the regime selection from previous researches (Abounoori, Elmi, & Nademi, 2016; Crifter, 2013; Di Sanzo, 2018; Herrera et al., 2018) and adopt two regimes.

2.3. Extreme value theory

In our analysis, the POT (peaks over threshold) method of the EVT is applied to model. Excess distribution over the threshold η is defined as:

$$F_\eta(z) = P(Z-\eta \le z | Z > \eta) = \frac{F(z+\eta) - F(\eta)}{1 - F(\eta)} \tag{9}$$

Over a high threshold of the sequence innovations is an asymptotical generalized Pareto distribution (GPD). Meanwhile, we use empirical cumulative distribution function to complement the middle part of the whole distribution.

$$F_{\xi,\beta}(z) = \begin{cases} \frac{k^l}{n}\left(1 + \xi^l \frac{-z_t + \eta^l}{\beta^l}\right) & if \;\; z_t < \eta^l \\ \phi(z_t) & if \;\; \eta^l < z_t < \eta^u \\ 1 - \frac{k^u}{n}\left(1 + \xi^u \frac{z_t - \eta^u}{\beta^u}\right)^{\frac{-1}{\xi^u}} & if \;\; z_t > \eta^u \end{cases} \tag{10}$$

where ξ is the shape parameter and β is the local, and η^l and η^u denote lower and upper threshold, respectively. z_t is the innovation filtered by the MSEGARCH and $\phi(z_i)$ is the empirical distribution.

2.4. Copula models

Sklar (1959) proved that, for any d-dimension joint distribution function with marginal distribution function $F_1, F_2, \ldots, F_d$, there exists a d-dimension coupla function.

$$F(z_1, \cdots, z_d) = C(F_1(z_1), \cdots, F_d(z_d)) = C(u_1, \cdots, u_d) \tag{11}$$

where F is a multivariate distribution function with a set of marginal distribution functions $F_i, \; i = 1, \cdots, d$. Then, it can further be factorized into a pair-copula and a conditional marginal function.

$$F(z|v) = \frac{\partial C_{z,v_j|v_{-j}}\left(F\left(z|v_{-j}\right), F\left(v_j|v_{-j}\right)\right)}{\partial F\left(v_j|v_{-j}\right)} \tag{12}$$

Bedford and Cooke (2002) used graphic decomposition to elaborate the n-dimensional R-vine copula which consists of $n-1$ spanning trees whose T_{i-1} has $n-i+1$ nodes and $n-i$ edges. The last edges in the tree T_{i-1} will become nodes of the next tree T_i. In general, the R-Vine copula is different from the two particular R-Vine copulas (C-vine and D-vine) owing to more possible systems, and therefore it has more flexible structures.

Hierarchical tree structure is present in Fig. 1 which describes C-vine and D-vine copulas. Each tree in the C-vine copula (left panel) has one key node connected by the other nodes. Each nodes of the D-vine copula are tangled according to variable orders. The order in the previous tree determines the bivariate relationship in the next tree. On the other hand, the R-vine with more flexible features results in more complicated construction processes. This situation is improved since Dißmann et al. (2013) came up with the R-vine matrices (RVM) which construct the decomposition of the R-vine structure well. The RVM has the following properties:

$$\{m_{i,i}, \cdots, m_{d,i}\} \subset \{m_{j,j}, \cdots, m_{d,j}\}, 1 \le j \le i \le d \tag{13}$$

$$m_{i,i} \notin \{m_{i+1,i+1}, \cdots, m_{d,i+1}\}, i = 1, \cdots, d-1 \tag{14}$$

where for the triangular matrix $M = (m_{i,j})_{d \times d}$, each entry $m_{i,j}$ stems from it, and there are the following three conditions:

$$\{m_{k,i}, \{m_{k+1,i}, \cdots, m_{d,i}\}\} \in B_M(j) \;\; or \;\; B_{M}(j) \tag{15}$$

[3] We also consider student-distribution, but the evidence on the results indicates no significant effects on the conclusion.

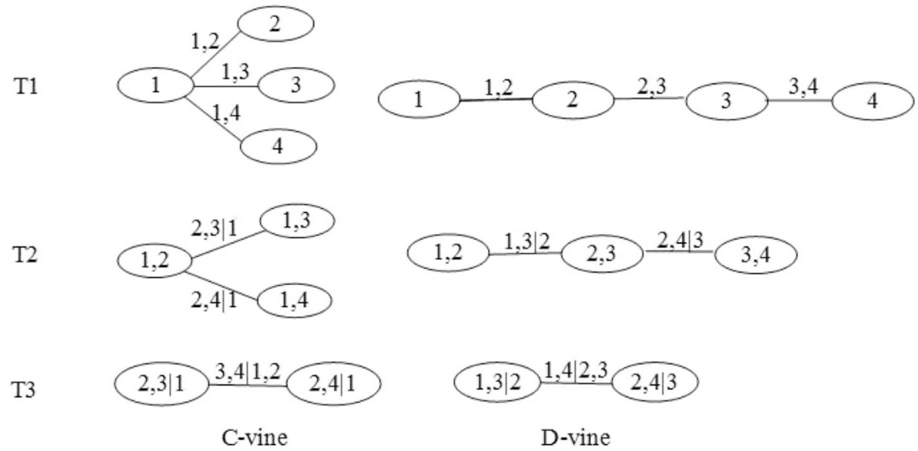

Fig. 1. An illustrative representation of C-vine and D-vine copulas.

$$B_M(j) = \{m_{i,i}, D\} | k = i+1, \cdots, d; D = \{m_{k,i}, \{m_{k+1,i}, \cdots, m_{d,i}\}\} \tag{16}$$

$$B_M(j) = \{m_{i,i}, D\} | k = i+1, \cdots, d; D = \{m_{i,i}\} \cup \{m_{k+1,i}, \cdots, m_{d,i}\}\} \tag{17}$$

According to the definition of the RVM, the d-dimensional density function of the R-Vine copula is decomposed in Eq. (18).

$$f(z_1, \cdots, z_d) = \prod_{j=1}^{d} f_j(z_j) \prod_{k=d-1}^{1} \prod_{i=d}^{k+1} c_{m_{k,k}, m_{i,k} | m_{i+1,k}, \cdots, m_{d,k}} \left(F_{m_{k,k} | m_{i+1,k}, \cdots, m_{d,k}}, F_{m_{i,k} | m_{i+1,k}, \cdots, m_{d,k}}\right) \tag{18}$$

To estimate the R-Vine, we use the previous method based on maximum spanning tree to maximize the sum of absolute dependences (Brechmann & Czado, 2013). It can be defined as:

$$\max \sum_{e=\{i,j\}} |\delta_{ij}|, \quad 1 \le i, j \le N \tag{19}$$

where e denotes an edge. δ_{ij} is used to measure the bivariate dependence of the nodes connected to the edges. More specifically, we in this paper use the Kendall's τ coefficient to measure the dependence among variables. First of all, we use marginal data to estimate the pair-copula of the first tree, and then use this information to obtain the observations of the second tree through Sklar's theorem. Suitable bivariate copulas are selected by minimizing Akaike information criterion (AIC) (pair-copula functions are classified into two categories, namely elliptical and Archimedean bivariate copula according to their statistical features on capturing dependence structure, tail situations and asymmetry). In the following procedures, we just repeat the above steps to estimate the rest of trees. Consequently, we obtain the R-vine structures.

2.5. Quantifying spillover effects

VaR is a common estimate of the maximal loss when the position declines due to market movements in the financial domain. It can be used by financial regulator to assess the faced risks at a given probability level during a horizon. Based on this framework, the daily log return is defined as:

$$r_t = \mu_t + h_t z_t \tag{20}$$

where the filtered innovations z_t. r_t is return series, μ_t is conditional mean and h_t is conditional variance. We adopt a POT model of the EVT to compute upside and downside risk.

$$VaR_{t|t-1}^{1-p} = \mu_t + \left\{\eta + \frac{\widehat{\beta}}{\widehat{\xi}}\left[\left(\frac{1-p}{k/n}\right)^{-\widehat{\xi}} - 1\right]\right\} h_{t|t-1}, \quad \Pr\left(r_{t|t-1} < VaR_{t|t-1}^{1-p}\right) = 1-p \tag{21}$$

where $VaR_{t|t-1}^{1-p}$ represents maximal loss of long position. If we calculate the short position, p substitutes for $1-p$.

The VaR concepts are associated with multivariate copula functions to calculate CoVaR. We just give the downside CoVaR equation that extreme returns of one market are conditional on extreme returns of the other market. Upside CoVaR is similar (upon request available). The downside CoVaR is given below:

$$\Pr\left(r_t^4 \leq CoVaR_{\beta,t}^{4|1,2} \middle| r_t^1 \leq VaR_{\alpha,t}^{1|2}, r_t^2\right) = \beta \tag{22}$$

$$\frac{C_{4,1|2}\left(F_{4|2}\left(CoVaR_{\beta,t}^{4|1,2}\right), \alpha\right)}{F_{1|2}\left(VaR_{\alpha,t}^{1|2}\right)} = \beta \tag{23}$$

where α and β represent the corresponding quantile of the estimated GPD. r_t^i denotes return at time t of the stock market i.The value of $F_{1|2}(VaR_{\alpha,t}^{1|2})$ is α probability level under maximal loss. For obtaining CoVaR of the variable 4, corresponding conditional cumulative distribution functions are computed as:

$$F_{4|2}\left(u_t^4 \middle| u_t^2\right) = \frac{\partial C_{4,2}\left(F_4\left(u_t^4\right), F_2\left(u_t^2\right)\right)}{\partial F_2\left(u_t^2\right)} \tag{24}$$

We give relevant steps of calculating CoVaR with copulas through three steps. The specific procedures (Reboredo & Ugolini, 2015a; 2015b) are described as follows:

1. Given quantile α and β for VaR and CoVaR, respectively, they are applied to estimated copula functions to obtain the value of $F_{4|2}(CoVaR_{\beta,t}^{4|1,2})$ according to eq. (23).
2. Applying the above results to obtain $F_4(CoVaR_{\beta,t}^{4|1,2}) = u^1$ through Eq. (24).
3. Using the value u^1 to obtain $F_4^{-1}(u^1) = CoVaR_{\beta,t}^{4|1,2}$ by inversing the estimated GPD function.

Finally, the risk spillover effects of one stock market on the other one are calculated by a relative approach proposed by Adrian and Brunnermeier (2011).

$$P\left(r_t^4 \leq CoVaR_{\beta|0.5,t}^{4|1} | r_t^1 = Q_t^1(0.5)\right) = \beta \tag{25}$$

$$\Delta CoVaR_{\beta|\alpha,t}^{4|1} = \left(CoVaR_{\beta|\alpha,t}^{4|1} - CoVaR_{\beta|0.5,t}^{4|1}\right) \Big/ CoVaR_{\beta|0.5,t}^{4|1} \tag{26}$$

$$\Delta CoVaR_{\beta|\alpha,t}^{4|1,2} = \left(CoVaR_{\beta|\alpha,t}^{4|1,2} - CoVaR_{\beta|0.5,t}^{4|1,2}\right) \Big/ CoVaR_{\beta|0.5,t}^{4|1,2} \tag{27}$$

where the formula measures relative spillover effects. r_t^1 is equal to its quantile 0.5 when the stock market 1 is a normal state. $\Delta CoVaR_{\beta|\alpha,t}^{4|1}$ means the risk spillovers of the stock market 1 to the stock market 4. $\Delta CoVaR_{\beta|\alpha,t}^{4|1,2}$ represents the risk spillovers of the stock market 1 conditional on the stock market 2 to the stock market 4.

For checking the spillover effects, we follow a operation adopted by Bernal et al. (2014) and Reboredo and Ugolini (2015b) Who applied the bootstrap Kolmogorov-Smirnov (KS) test developed by Abadie (2002) to examine whether there are significant spillover effects. This test is defined as follows:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_x |F_m(x) - G_n(x)| \tag{28}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR distribution functions in extreme and normal states, respectively. m and n are the number of the two samples. We just need to test whether the following null hypothesis is rejected:

$$H_0^1: \quad CoVaR_{\beta|\alpha,t}^{4|1} = CoVaR_{\beta|0.5,t}^{4|1} \tag{29}$$

$$H_0^2: \quad CoVaR_{\beta|\alpha,t}^{4|1,2} = CoVaR_{\beta|0.5,t}^{4|1,2} \tag{30}$$

3. Data descriptions

East Asian stock markets include four major stock markets. We use the SSE Composite index (China), the HS (Hong Kong) index, the N225 index (Japan) and the KOSPI Composite index (South Korea) to reflect their market movement. After the launch of the Shanghai-Hong Kong Stock Connect program, the spillovers of the Chinese stock market are more interesting and important, so we choose its launch time as onset time of the observations. These indexes from Yahoo Finance cover 17 November 2014 to 17 August 2018.[4] The

[4] We have justified the sample period by changing the finish time according to the anonymous comments.

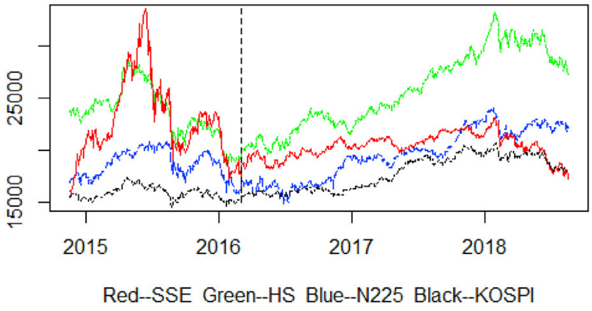

Fig. 2. Relative stock index prices.

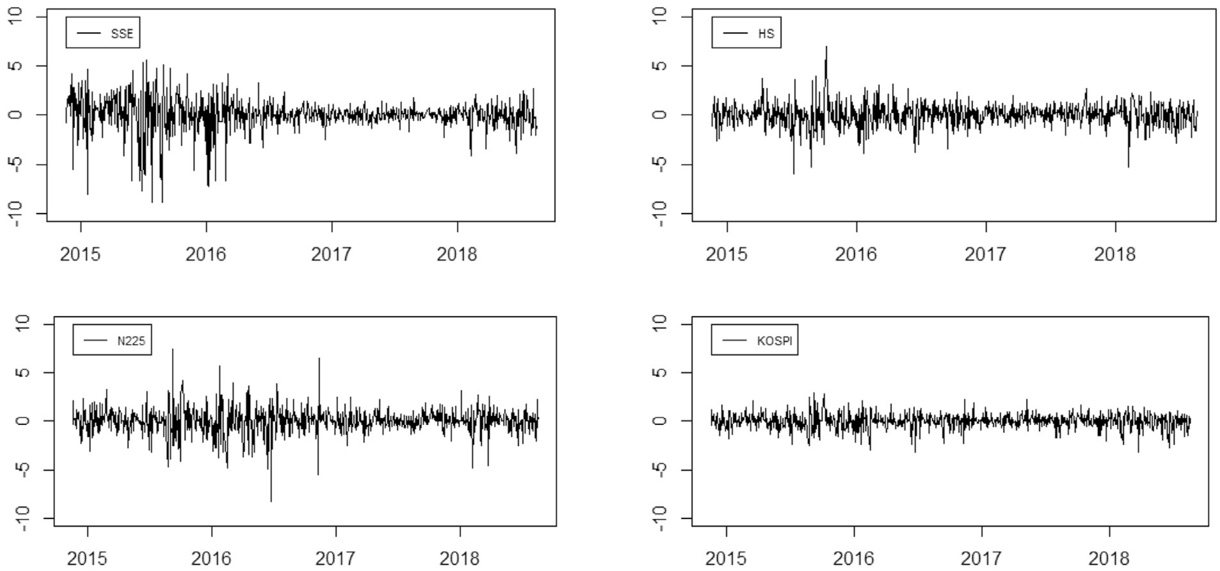

Fig. 3. Stock indexes return series.

Table 1
Descriptive statistics for index returns.

	SSE	HS	N225	KS
Min	−8.873172	−6.018288	−8.252933	−3.226967
Max	5.603560	6.986948	7.426169	2.912435
Mean	0.008214	0.014613	0.029585	0.015802
Std.dev	1.627715	1.125628	1.262113	0.750929
Skewness	−1.239772***	−0.201632***	−0.325141***	−0.440743***
Kurtosis	6.318008***	3.801459***	5.904265***	2.114478***
Jarque-Bera	1772.6142***	563.3197***	1358.4271***	202.6448***
ADF	−9.2761***	−9.4299***	−10.167***	−10.63***
Q^2 (20)	646.25***	79.787***	122.06***	82.906***
ARCH(20)	11.55***	2.77***	3.795***	3.113***

Notes: The standard errors reject 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. KS is the KOSPI Composite index.

missing data are complemented by last-observed-carried-forward (LOCF). The stock index returns are calculated by $100(\ln x_t - \ln x_{t-1})$ where x_t is the close price at day t. Considering the effect of the Chinese stock crisis, the index data are divided into two periods.[5] Due to special merits of the turbulent and calm periods, we also model the whole sample period to study whether the dependence structure and the

[2] We also consider another asymmetric model, MS-GJR-GARCH, which has less goodness-of-fit compared with MSEGARCH model according to the AIC, BIC and LL, but we obtain same conclusion through it (available upon request).

[5] This division is determined by the filtered probability which checks whether there is a significant change in return series.

Table 2
The correlation coefficients.

Correlation	SSE	HS	N225	KS
Turbulent period				
SSE	1.0000000	–	–	–
HS	0.5576116	1.0000000	–	–
N225	0.2775409	0.5589114	1.0000000	–
KS	0.2332332	0.5631333	0.6149111	1.0000000
Calm period				
SSE	1.0000000	–	–	–
HS	0.5517013	1.0000000	–	–
N225	0.2856334	0.5097924	1.0000000	–
KS	0.3516507	0.6123960	0.5326077	1.0000000
Fperiod				
SSE	1.0000000	–	–	–
HS	0.5271412	1.0000000	–	–
N225	0.2601950	0.5331460	1.0000000	
KS	0.2524820	0.5862832	0.5694722	1.0000000

Notes: correlation stands for the Pearson's correlation coefficient among the Asian stock markets. The correlation coefficients reflect linear relationships among the markets. Fperiod stands for the full sample period.

Table 3
Estimations of MSEGARCH models.

	SSE	HS	N225	KS
ω^{s_1}	−0.0066***	0.0013***	−0.0212***	−0.0556***
	(0.0003)	(0.0000)	(0.0002)	(0.0017)
ω^{s_2}	0.3798***	0.0530***	0.0141***	−0.0219***
	(0.0532)	(0.0000)	(0.0001)	(0.0003)
α^{s_1}	0.0636***	0.0822***	0.0727***	0.0127***
	(0.0018)	(0.0000)	(0.0002)	(0.0003)
α^{s_2}	0.1359***	−0.2797***	−0.1523***	0.0496***
	(0.0506)	(0.0000)	(0.0003)	(0.0012)
β^{s_1}	0.9876***	0.9340***	0.8149***	0.9926***
	(0.0001)	(0.0000)	(0.0000)	(0.0003)
β^{s_2}	0.8216***	0.8945***	0.9503***	0.9514***
	(0.0311)	(0.0000)	(0.0000)	(0.0006)
γ^{s_1}	−0.0905***	−0.1399***	−0.3038***	0.0448***
	(0.0015)	(0.0000)	(0.0002)	(0.0009)
γ^{s_2}	−0.1735***	−0.1761***	−0.2734***	−0.1131***
	(0.0028)	(0.0000)	(0.0006)	(0.0010)
p_{11}	0.9971***	0.9955***	0.9919***	0.0268***
	(0.0018)	(0.0000)	(0.0000)	(0.0079)
p_{12}	0.0094***	0.1584***	0.0092***	0.1199***
	(0.0009)	(0.0000)	(0.0000)	(0.0003)
Q^2 (20)	16.079	8.381	14.284	19.892
	[0.7117]	[0.989]	[0.8158]	[0.4647]
ARCH(20)	0.7604	0.404	0.7294	0.9963
	[0.763]	[0.991]	[0.7979]	[0.4639]
AIC	2793.6781	2653.0028	2657.644	1904.9182
BIC	2861.1888	2720.5136	2725.1547	1972.429
LL	−1382.839	−1312.5014	−1314.822	−938.4591
BDS	−0.4466	−0.3345	0.5415	−0.1717
	[0.6552]	[0.7380]	[0.5882]	[0.8637]

Notes: Table 3 represents estimated parameters for the above models. Q^2 (20) is the Ljung-Box Q-statistics for lags 20 and ARCH (20) is the Lagrange Multiplier test for lags 20 on heteroskedasticity. Akaike information criterion (AIC), Bayesian information criterion (BIC) and Log likelihood (LL) are used to evaluate the fitting of models. p_{12} represents the probability of the state 2 transforming to the state 1, p_{11} alike. The Null hypothesis of the BDS test for whether series are i.d.d., and the statistic is calculated at the dimension 2. ***, ** and * is statistically significant at 1%, 5% and 10%, respectively. The standard errors are reported in round brackets and p values are reported in square brackets.

spillovers may be affected if the sample is divided into the two periods. The turbulent period is on the left side of the dashed line and the calm period is on the other side. In Fig. 2 and Fig. 3, the four index prices have same upward and downward trends for the turbulent period. The index returns also detect this co-movement in their tail. From a visional perspective, the Hong Kong index price exhibits strong correlation with the other indexes. This situation means the Chinese stock market conditional on the Hong Kong market spills over to the other stock markets. The return plots show volatility clustering and dynamics. Thus, using the regime-switching model is proper.

Table 1 provides descriptive statistics for the index return series. The mean is close to zero and large standard deviation indicates significant dispersion in statistics. All index returns are significantly left-skewed, which implies possible abrupt drops and underlying leverage effects. The Chinese stock market and the Japanese display larger Kurtosis than the other stock indexes. Meanwhile, the maximum and minimum values reflect the presence of larger extreme returns. All index returns present significant leptokurtic. The Jarque-Bera tests indicate return series reject normality. On the other hand, the Augmented Dickey-Fuller (ADF) tests reject the null hypothesis of a unit root for all index returns at significance 1%. Q^2 (20) and ARCH (20) at the significance 1% level ensure the presence of ARCH effects in index return series.

Table 2 reports the correlation among the stock markets. For the correlation coefficients for the different periods, the correlation with the Chinese stock market indicates strong relationships with the Asian stock markets, especially in the correlation with the Hong Kong. On the other hand, the correlation coefficients with the Hong Kong stock market indicate close links in magnitude with the Japan and South Korea stock markets. In this respect, these cases indicate there are possible direct and indirect spillovers of the Chinese stock market. According to correlation coefficients, the Japan stock market and the South Korea always keep strong relationships for different periods, so there are complicated situations on tail dependence among the Asian stock markets. Therefore, we need to use vine copulas to capture multivariate dependence among them. However, it should be noted that correlation coefficients have some differences from tail dependence because extreme events are nonlinear. In summary, the extreme price changes of the Chinese stock market, to the great extent, impact the other stock markets in direct and indirect ways, and furthermore these effects may have some differences for different periods.

4. Empirical results

4.1. MSEGARCH results

The empirical results reported in Table 3 display estimations of the MSEGARCH model for the East Asian stock markets. The parameter β reflects high volatility persistence of stock markets. For all series, the parameter γ is significant at the 1% level, which implies significant leverage effects on volatility. This is, shocks of bad news to volatility are higher in magnitude than good news. It also reflects the price drops have stronger impetus to the East Asian stock markets. With respect to fits, AIC, BIC and LL values evaluate the goodness-of-fit for model estimations. Meanwhile, Q^2 (20) and ARCH (20) tests confirm no ARCH effects in standardized residuals. The BDS test shows the filtered residuals are i.d.d.. It is strong evidence that the model specification is appropriate. Therefore, the standardized residuals are applied to model extreme returns by the EVT.

Table 4
Estimations of EVT parameters.

	SSE	HS	N225	KS
Turbulent period				
Lower tail				
η^l	−1.1433	−1.2686	−1.3129	−1.2887
ξ^l	0.0076	−0.3358	−0.5628	−0.2248
β^l	1.0844	0.9706	1.0836	0.8160
Upper tail				
η^u	1.2183	1.3164	1.2203	1.2363
ξ^u	−0.1076	0.2263	0.3537	−0.1552
β^u	0.3504	0.4577	0.2744	0.6900
KS	0.0127	0.0178	0.0146	0.0125
	[1]	[0.9999]	[1]	[1]
Calm period				
Lower tail				
η^l	−1.0310	−1.1646	−1.0797	−1.0887
ξ^l	0.1536	0.1622	0.2837	−0.1059
β^l	0.6472	0.5442	0.5320	0.9446
Upper tail				
η^u	1.0438	1.1380	1.0973	1.1035
ξ^u	−0.0630	0.1438	0.2837	0.0801
β^u	0.4864	0.3777	0.5332	0.4335
KS	0.0069	0.0098	0.0081	0.0096
	[1]	[1]	[1]	[1]
Fperiod				
Lower tail				
η^l	−1.0672	−1.2284	−1.1498	−1.1703
ξ^l	0.1610	0.1234	0.0983	−0.1263
β^l	0.7346	0.5697	0.6587	0.8866
Upper tail				
η^u	1.1130	1.1480	1.1650	1.1565
ξ^u	−0.0574	0.1228	0.0977	0.0713
β^u	0.4268	0.4729	0.4016	0.4679
KS	0.0063	0.0071	0.0069	0.0078
	[1]	[1]	[1]	[1]

Notes: the observations of the turbulent and the calm periods are 315 and 603, respectively. η is the threshold, ξ is the shape and β is the local parameter, respectively. The null hypothesis of the Kolmogorov Smirnov (KS) tests for whether an empirical distribution is equal to a uniform distribution. p values are reported in the square brackets. Fperiod represents the full sample period.

Table 5
Estimation results of the copulas[61].

Period	Direct			Indirect	
	(SSE,HS)	(SSE,N225)	(SSE,KS)	(SSE,N225|HS)	(SSE,KS|HS)
Turbulent period					
Copula	RGumbel	Norm	Norm	RTawn90	Frank
$Para_1$	1.52 (0.08)	0.27 (0.03)	0.20 (0.03)	−20.00 (11.89)	−0.75 (0.30)
$Para_2$	–	–	–	0.01 (0.00)	–
Tau	0.34	0.17	0.13	−0.01	−0.08
AIC	−107.17	−21.33	−11.2	−198.81	−206.64
Calm period					
Copula	RBB1	RBB7	RGumbel	Independence	RClayton90
$Para_1$	0.21 (0.08)	1.16 (0.05)	1.21 (0.04)	–	−0.06 (0.04)
$Para_2$	1.37 (0.06)	0.12 (0.05)	–	–	–
Tau	0.34	0.13	0.17	0.00	−0.03
AIC	−196.56	−35.86	−60.12	−322.64	−452.06
Fperiod					
Copula	RBB1	RBB7	RGumbel	Independence	Frank
$Para_1$	0.17 (0.06)	1.15 (0.04)	1.17 (0.03)	–	−0.50 (0.17)
$Para_2$	1.39 (0.05)	0.14 (0.05)	–	–	–
Tau	0.34	0.14	0.15	0.00	−0.06
AIC	−299.63	−54.08	−65.83	−516.72	−649.66

Notes: KS is the KOSPI Composite index. RGumbel, RBB1 and RBB7 are that Gumbel, BB1 and BB7 copulas are rotated by 180°, respectively. RTawn90 and RClayton90 are that Tawn and Clayton copulas rotated by 90°, respectively. Normal and Frank copulas describe symmetric dependence, the other copulas otherwise. I represents an independence copula. Para represents parameters of the estimated copula. Tau is the Kendal's coefficient. Fperiod represents the full sample period.

The filtered residuals are used to model extreme returns by the POT (Peak-over-threshold) method. Choosing a proper threshold is significant for an excess distribution, if the threshold is higher, the estimation bias can be reduced. On the other hand, over this threshold of the observations is too small to reduce the estimation variance when the observations are used to estimate corresponding parameters. However, there is still no a consensus about choosing this threshold (Marimoutou et al., 2009; Nieto & Ruiz, 2016; Youssef et al., 2015). Considering the above situation, we choose 10% exceedances suggested by researchers in extant literatures (Koliai, 2016; Liu, Wei, Chen, Yu, & Hu, 2018; Sahamkhadam et al., 2018; Tsay, 2010). For the estimated parameters in Table 4, we find almost all of the thresholds in the turbulent period are greater in magnitude than in the calm period. The results indicate there are more extreme returns for the turbulent period. If the sample were not divided into turbulent and calm periods, the extreme situation would have been measured mistakenly. From the threshold of the different periods, we find thresholds of the full period are higher than the calm period and lower than the turbulent period. It means the extreme events may be underestimated in the turbulent period and overestimated in the calm period. Thus, the period division is necessary.

Patton (2006) asserted that data transformed by the probability integral should be subject to a uniform distribution for avoiding copula model misspecification. In considering the suitability of estimation results, we apply the estimated distribution to the tail and the empirical distribution to the middle part to make the probability integral transformation (PIT) of the filtered residuals. The inversed data are examined by the KS test, and the results do not reject the uniform hypothesis. We proceed to use the PIT data to capture dependence structures among the Asian stock markets.

4.2. The R-Vine copula results

The estimated results on corresponding bivariate copulas are reported in Table 5, and the copulas are selected according to the AIC. Direct structures reflect the direct dependence with the Chinese stock market and indirect structures show the dependence conditional on the Hong Kong stock market. More specifically, the indirect structures are consistent with the fact that the Chinese stock market can connect the East Asian stock markets via the Hong Kong stock market.

In the turbulent period, the direct structures describe the dependence structure of the China-Hong Kong, the China-Japan and the China-South Korea. For the Kendal value, it indicates underlying co-moved returns, especially in the China-Hong Kong (0.34). However, the China-Japan and the China-South Korea are described by the normal copula which can depict symmetric dependence, and their Kendal values are weaker in magnitude than the China-Hong Kong. In considering indirect structures, it is of note that the Hong Kong stock market plays a key role like a bridge in connecting the Chinese stock market with the other markets. This structure accounts for the relationships that the China-Japan and the China-South Korea dependence are conditional on the Hong Kong stock market. Their Kendal's values illustrate some negative conditional correlation.

In the calm period, the dependence structures on the estimated copula are different from the turbulent period. The China-Hong Kong still keeps strong dependence according to their Kendal value. The dependence of the China-Japan and the China-South Korea are captured through the rotated BB7 and Gumbel copulas respectively. This period also implies different dependence structures from the turbulent period. Regarding the indirect structures, even though the China-Japan relationships conditional on the Hong Kong stock market become independent, the China-South Korea dependence conditional on the Hong Kong market still show existing negative relationships.

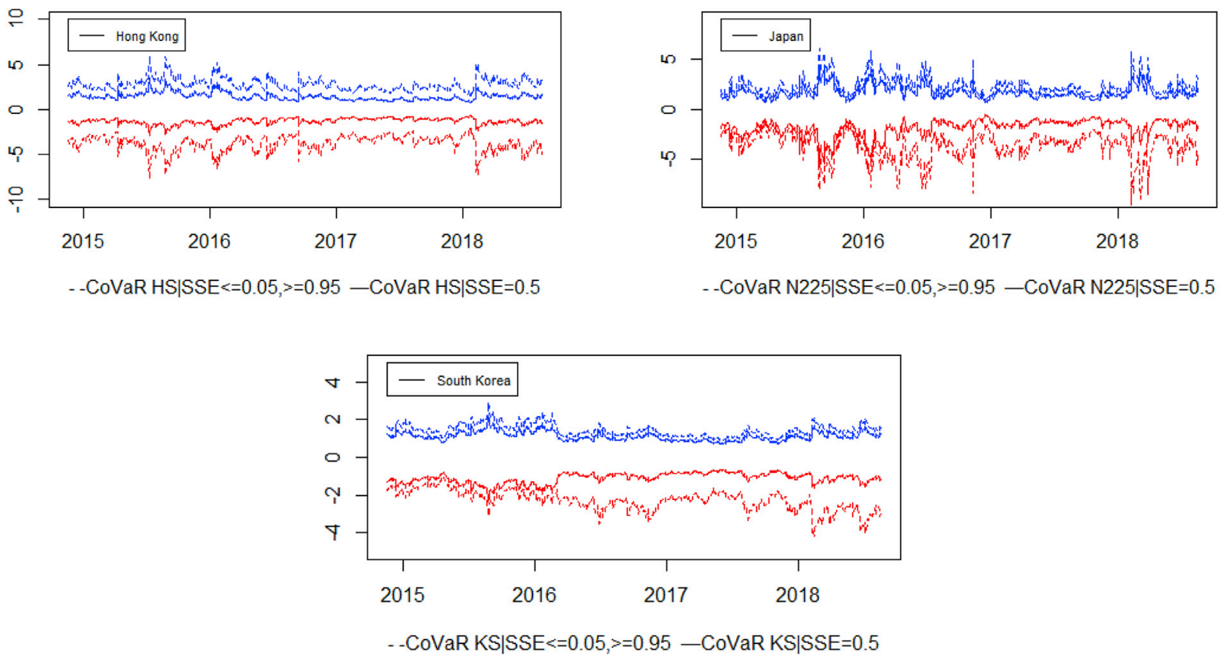

Fig. 4. Direct CoVaR for the turbulent and calm periods.

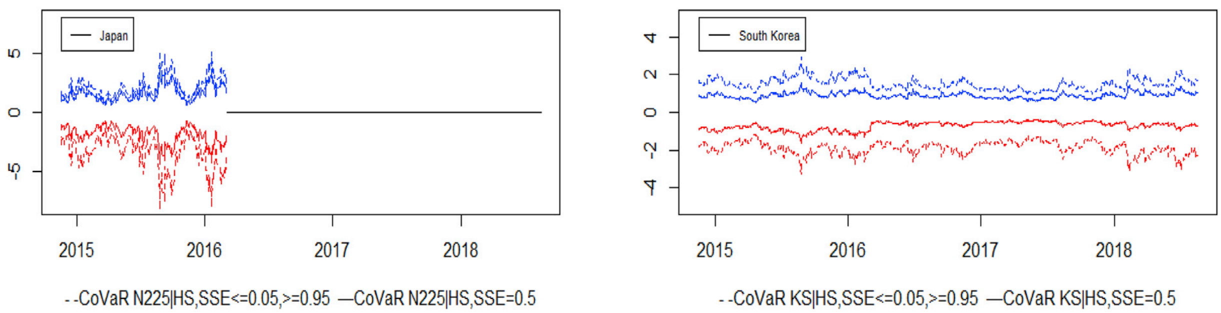

Fig. 5. Indirect CoVaR for the turbulent and calm periods.

In the full sample period, the dependence structures show interesting findings when we use all data to estimate the copulas. These findings show that the estimated copulas are same with the calm period, except for the Frank copula. If we didn't separate the turbulent and calm periods from the full period, we would have ignored unique dependence structures during the different periods. Furthermore, it is also hard to accurately measure the risk spillovers of the Chinese stock market to the East Asian stock markets.

The vital evidence on the above-mentioned results implies that the Chinese stock market conditional on the Hong Kong market exerts strong influences on the other stock markets. The extreme prices of the Chinese stock market spill over to the East stock markets in direct and indirect ways. In what following, we proceed to measure the spillover effects based on the dependence structures.

4.3. Spillover effect results

Using the estimated bivariate copulas, we calculate the downside and upside CoVaR for the turbulent, calm and full sample periods. Fig. 4 and Fig. 5 illustrate CoVaR dynamics for the turbulent and calm periods. In a graphical aspect, they reflect existing spillovers of the Chinese stock market to the other stock markets for the different periods. The corresponding figures for the full sample period are alike (available upon request).

Specific CoVaR results on the descriptive statistics are reported in Table 6. Regarding the direct effects, the downside CoVaR during

[6] For measuring direct spillover effects, we estimate copulas between the Chinese stock market and the other markets. For indirect spillover effects, we take into account the Hong Kong stock market as the condition. We do not give complete vine structures (available upon request) here but just corresponding copulas for the different periods.

Table 6
CoVaR summary statistics.

Period	Direct			Indirect	
	(HS|SSE)	(N225|SSE)	(KS|SSE)	(N225|SSE,HS)	(KS|SSE,HS)
Turbulent period					
CoVaR(down)	−4.0114	−3.3344	−1.8550	−3.4384	−1.9408
	(0.9123)	(1.3669)	(0.3282)	(1.4095)	(0.3434)
ΔCoVaR(down)	1.6092	0.3859	0.3390	0.8643	1.0195
	(0.0127)	(0.0000)	(0.0001)	(0.0001)	(0.0005)
KS_1	0.9841	0.3175	0.5937	0.5841	0.9524
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
CoVaR(up)	3.1296	2.5283	1.7286	2.1802	1.7413
	(0.7348)	(1.0366)	(0.3050)	(0.8939)	(0.3073)
ΔCoVaR(up)	0.7632	0.3889	0.3304	0.3790	0.8622
	(0.0052)	(0.0000)	(0.0001)	(0.0000)	(0.0004)
KS_2	0.8159	0.3206	0.5841	0.3143	0.9302
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Calm period					
CoVaR(down)	−3.6087	−3.7869	−2.5264	–	−1.8755
	(0.7896)	(1.3006)	(0.4526)		(0.3370)
ΔCoVaR(down)	2.0981	1.6040	1.6088	–	2.1879
	(0.0195)	(0.0169)	(0.0065)		(0.0146)
KS_1	0.9934	0.8889	1.0000	–	1.0000
	[0.0000]	[0.0000]	[0.0000]		[0.0000]
CoVaR(up)	2.6458	2.3158	1.2942	–	1.4046
	(0.5596)	(0.7707)	(0.2257)		(0.2453)
ΔCoVaR(up)	1.0669	0.4071	0.2664	–	0.6060
	(0.0090)	(0.0037)	(0.0010)		(0.0027)
KS_2	0.9503	0.4544	0.5191	–	0.8624
	[0.0000]	[0.0000]	[0.0000]		[0.0000]
Fperiod					
CoVaR(down)	−3.9114	−3.8292	−2.4447	–	−1.9524
	(0.9412)	(1.4525)	(0.4488)		(0.3590)
ΔCoVaR(down)	1.9154	1.2487	1.2482	–	1.6935
	(0.0048)	(0.0082)	(0.0033)		(0.0068)
KS_1	0.9848	0.7800	0.9815	–	0.9978
	[0.0000]	[0.0000]	[0.0000]		[0.0000]
CoVaR(up)	3.0278	2.4486	1.3592	–	1.4867
	(0.7224)	(0.9105)	(0.2450)		(0.2683)
ΔCoVaR(up)	1.1948	0.4413	0.2260	–	0.6331
	(0.0029)	(0.0027)	(0.0006)		(0.0020)
KS_2	0.9259	0.4248	0.4150	–	0.8399
	[0.0000]	[0.0000]	[0.0000]		[0.0000]

Notes: CoVaR(down/up) stands for downside or upside CoVaR at the 0.05 and 0.95 quantile level. Indirect spillovers are conditional on the Hong Kong stock market to the other stock markets. Fperiod represents the full sample period. CoVaR and ΔCoVaR are mean value, and their standard deviation is reported in round bracket. KS_1 is the statistic of null hypothesis: CoVaR in the extreme state is equal to it in the normal state, and alternative hypothesis is that: CoVaR in the extreme state is greater than it in the normal state. KS_2 has the alternative hypothesis: CoVaR in the extreme state is less than it in the normal state. p value is reported in square brackets.

the three periods is greater in magnitude than the upside. It indicates more downside co-movements and stronger dependence in the lower tail. The delta downside CoVaR during the three periods is also considerably greater than the upside, except the China-Japan and the China-South Korea during the turbulent period because their copulas are symmetric in this period. The downside spillovers for the turbulent period, in contrast to the calm period, are symmetric in this special period. This evidence on direct spillovers shows bearish and bullish impetus in similar magnitude from the Chinese stock market. KS tests indicate significant direct spillovers. If the sample period were not split into the turbulent and calm periods, the full sample periods would ignore the effect of bearish and bullish impetus.

On the other hand, indirect structures show the China-Japan and the China-South Korea relationships conditional on the Hong Kong market. Only in the turbulent period, the CoVaR of the China-South Korea is measured as they are independent for the other periods. In fact, the indirect downside CoVaR and delta CoVaR also are than the upside during the three periods. Furthermore, KS tests on the downside and upside spillovers provide strong evidence that the indirect risk spillovers are significant. If we used the whole sample to measure the spillovers, the indirect effects would not be captured.

To sum up, the evidence on the direct and indirect spillovers provide a new sight that the risk spillovers differ for the three periods. It is consistent with the dependence structures in Table 5, which display different dependence. The results on the direct spillover effects indicate that Chinese stock market is more integrated with the Hong Kong, and this relationship also is accordance with the fact that the Chinese stock market has closer links with the Hong Kong. Meanwhile, whether the direct delta CoVaR results or the indirect prove that the downside spillovers to the other stock markets are greater than the upside. It reflects more co-movement in the lower tail and less dependence in the upper tail, except for the direct spillovers to the Japan and South Korea stock markets for the turbulent period. More interesting, the exception also confirms the dependence structures are special in this period. Modeling the full sample period ignores the special nature of the different periods and is hard to measure accurately the dependence structure and the spillovers. Therefore, the Chinese stock market has special spillover effects on the East Asian stock markets during the turbulent and calm periods.

5. Conclusions

In this paper, we combine the MSEGARCH, the EVT and the vine copula to model multivariate dependence structures of the East Asian stock markets for the three periods (turbulent, calm and full sample), and use CoVaR approach to calculating the direct and indirect spillovers of the Chinese stock market to the other stock markets. The results show the interesting findings that the spillovers during the three periods indicate stronger dependence in the lower tail, except for the China-Japan and the China-South Korea for the turbulent period. The exception that reflects the special co-movement in this period is line with the estimated dependence structures in Table 5. Furthermore, we find the Chinese stock market does indirectly spill over to the Japan and South Korea stock markets. More importantly, the division of the sample period is necessary in that modeling the whole sample period is hard to measure accurately the extreme risk situation of the stock markets, the dependence structure among the markets and the spillover effects of the Chinese on the other markets.

With foreign and mainland investors more participation in Asian stock markets after the launch of the Shanghai-Hong Kong stock connect, they pay more attention to the Chinese stock market movement due to its unique features in this region. However, capital and information flows may cause more complex situations in this region as the openness of the Chinese stock market increases the degree of market efficiency (Huo & Ahmed, 2017). Our results also confirm the spillovers of the Chinese stock market may result in extreme price co-movement among the Asian stock markets. Bai and Chow (2017) studied the Chinese stock market liberalization based on the stock connect, they found increasing market liquidity and size resulting in risk persistence and exposure to systemic risk. Burdekin and Siklos (2018) quantified the impact of Northbound and Southbound capital flows after starting of the stock connect. They found A-H Share premium is significantly influenced by these cash flows while controlling for sentiment and liquidity effects. Thus, investors must take caution about risk contagion among the Asian stock markets when adjusting hedging strategies, especially in extreme events.

These important findings can give useful references to the investors whose stock portfolios include the Asian stocks for hedging or safeguarding the extreme co-movements. Meanwhile, they should consider the relationships among the East Asian stock markets, especially after the launch of the Shanghai-Hong Kong Stock Connect. Confronted with co-moved extreme risks, risk managers and investors should make prudent decisions and choose suitable portfolios during the different periods according to their dependence structures.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2019.10.009.

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