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Value at Risk Analysis and Investment Portfolio Optimization of Asian Stocks

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Abstract— This study investigated the Value at Risk (VaR) and the Component Expected Shortfall (CES) to find an optimal portfolio investment for 15 Asian stock markets. The data is collected from 2006 to 2019, and then categorized into three pre-crisis periods, crisis, and post-crisis of the global financial crisis in 2008. Empirical results showed that the VaR had increased from 0.0034 to 0.0062 (82.35%) during the crisis period, but it had decreased from 0.0062 to 0.0035 (43.55%) after the crisis. Obviously, the crisis influenced the risk of Asia stock markets. According to the portfolio analysis, the result revealed that Malaysian stock was suggested as the highest investment proportion for pre-crisis, and crisis period. After the crisis, Indonesian stocks are suggested as the highest investment proportion, whereas the investment in stock markets of Singapore, Turkey, and Russian is not suggested.

***Keywords*—** Financial Economics, Asian Stock Markets, Value at Risk, Components of Risk.

I. INTRODUCTION

Recently, the world is under the globalization era, which promotes and increases interdependence among regions worldwide. Without a doubt, nowadays, international financial markets are extremely interrelated [1]. However, this high degree of connectedness could generate investment and speculative prospects, but it also sometimes brings contagion and spillover effects among the markets, especially during the financial crisis, particularly the global financial crisis of the United States in 2008.

This crisis was mainly caused by deregulation in the financial industry. US Banks utilized various programs for trading with derivatives. Then their demands for mortgages increased in order to support the profitable sale of these derivatives. However, many bad debtors could not pay the higher interest rates of these derivatives and thereby leading a shortage of liquidity among financial institutions [2]. During this crisis, there was substantial evidence of high fluctuation of the financial and capital markets, in particular stock markets around the world [3].

As the interconnection of the financial markets worldwide, the investors could get the profit from worldwide stock markets, and one of the interesting markets is the Asian stock markets. Asian countries are an interesting market as the emerging countries' economic growth is faster than developed

countries [4]. Asian stock markets have connected to each other because they have the same directions. More specifically, the stock markets have been rising before the 2008 global financial crisis until they have decreased in the same directions during the

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crisis. Afterward, they are well increasing in the same directions during the economic recovery stage from the Bloomberg database. However, they are always violent fluctuation during these pre-crisis, crisis, and post-crisis.

Reference [5] categorized the risks into two types which are 1) systematic risk and 2) unsystematic risk. The systematic risk arises from macroeconomic factor, and investors could not eliminate or decrease it from diversification. The systematic risk will influence the whole stock market. For unsystematic risk, it is caused by the risks of money, administration, and industry. This unsystematic risk could be avoided by doing the diversification [6]. Thus, to achieve risk reduction, the investors consider the diversification of risk during pre-crisis, crisis, and post-crisis of the U.S. financial crisis.

Accordingly, this study realizes the importance of the fluctuation and risk as a factor affecting the stock returns. Many studies have suggested that stock market returns' volatility is highly related to uncertainty in the world financial events [7]. They suggested that investors could manage or avoid this risk by understanding the risk behavior and sources of risk. Hence, this study aims to reinvestigate the Value at Risk (VaR) of Asian stock exchanges in three sub-periods of the U.S. financial crisis: pre-crisis, crisis, and post-crisis. This study utilizes the Vine copula-EGARCH model. Driven by the fear generated by the threat of the U.S. financial crisis, this study represents one of the first efforts to analyze the impact of the U.S. financial crisis on the return and volatility of the Asian stock market indices in the top 15 countries based on GDP. This study aims to fill the literature gap by decomposing the sources of Asian financial market risk in three sub-periods of the Crisis using the Component Expected Shortfalls (CES).

II. Literature Review

Several studies have examined linkages among financial assets and investigated the optimal asset allocation and hedge ratios for the stock portfolio during the U.S. financial crisis. They studied the risk of assets in five channels: industry, commerce, real estate, utility, and conglomerates group to manage portfolio optimization using the Bivariate copula-GARCH. They also quantified the Value at Risk (VaR) and Expected Shortfall (ES) to learn the portfolios' risk [8]. Reference [9] evaluated the allocation of investment portfolios among stocks in the Shanghai stock exchange using Vine Copula-GARCH Model. Nguyen and Nguyen used the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model to investigate the risk in the Vietnamese stock market and reported that stock returns have intense volatility, especially between 2006 and 2010. They revealed that the market's volatility could be acquired from the effects of the 2008 global financial crisis [10]. Sahadudheen employed the generalized autoregressive conditional heteroskedasticity (GARCH) and exponential GARCH (EGARCH) models. He suggested a negative relationship between exchange rate and stock prices in India [11]. Moreover, they confirmed that the global financial crisis in the 2008 period could decrease the financial inflows into Vietnam [12]. According to the result, they analyzed the co-movement and found the optimal portfolio investment for investors and risk managers in financial markets of the G7 countries. From the 2008-2009 crisis, the G7 countries have been impacted by the global financial system, and the catastrophic event could easily trigger and spread to the global financial market [13].

III. Data

In this study, weekly data of 15 Asian stock markets are used. There were 15 major stock markets in Asia which consist of Stock Exchange of Thailand (SET), Straits Times (S.T.) of Singapore, Philippine Stock Exchange Index (PSEI), Ho Chi Minh City Stock Exchange (HCMC) of Vietnam, The FTSE Bursa Malaysia Index Series (FTSE), Jakarta Stock Exchange Composite (JKT), Bombay Stock Exchange (BSE) of India, Karachi Stock Exchange (KSE) of Pakistan, ChinaAMC CSI 300 Index ETF

(CSI), Nikkei Stock Average (NIKKIE) of Japan, Korea Stock Exchange KOSPI Index (KOSPI), Taiwan Stock Exchange (TWSE), Borsa İstanbul Stock Exchange (BIST) of Turkey, Kazakhstan Stock Exchange (KASE), and the Russian Trading System (RTS). The data are collected from January 4, 2006, to December 30, 2019, and it divided into three periods: pre-crisis period covering January 4, 2006, to July 31, 2007, crisis period covering August 1, 2007, to December 31, 2012, and post-crisis crisis during January 4, 2013, to December 30, 2019. If there was no data due to holidays or other reasons, the stock index price is given as the previous day's trading price [14]. All stock index prices are collected from the Bloomberg database; then each price is transformed as the logarithm return

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

where $P_{i,t}$ is stock price *i* at time *t*; and $P_{i,t-1}$ is stock price *i* at time $t-1$

IV. Research Method and Model

A. The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

The exponential GARCH Model [15] is an asymmetric volatility model, and it is used to estimate the conditional variance of the random variable. The model can be estimated by (2)

$$\log(h_t) = \omega + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{i=1}^{q}\beta_i\log(h_{t-i}) + \sum_{i=1}^{k}\gamma_i\left(\frac{|\varepsilon_{t-i}|}{h_{t-i}} - \sqrt{\frac{2}{\pi}}\right) \tag{2}$$

where h_t is conditional variance at time *t*, ω, α, β and γ are the estimated parameters, $\Delta r_t = \varepsilon_t$. This model was used to obtain the standardized residuals of the Asian stock returns (marginals).

B. Vine Copula Model

First introduced the copula approach concept [16], which further used to investigate the dependence between the marginal distributions of the random variables. Later the Vine copula [17] is introduced to deal with the complex dependence measures among the multivariate marginal. The Vine Copula could be written by (3)

$$f_{j|i}\left(x_j \mid x_i\right) = \frac{f\left(x_i, x_j\right)}{f_i\left(x_i\right)} = c_{ij}\left(F_i\left(x_i\right), F_j\left(x_j\right)\right)\cdot f_j\left(x_j\right) \tag{3}$$

where x is standardized residual obtained from EGARCH and $f(\cdot)$ is the density function. $F(\cdot)$ is marginal distribution which is assumed to have skewed student-t distributed.

There are two famous structure of Vine copula, namely C-Vine and D-vine copulas.

For C-vine, the last v_j was selected to be the conditional variable, as the following (4)

$$F\left(x\right)=\prod_{k=1}^{n} f_k\left(x_k\right)\times\prod_{i=1}^{n-1}\prod_{j=1}^{n-i} c_{i,i+j|1:(i-1)}\begin{pmatrix} F\left(x_i\left|x_1,...,x_{i-1}\right.\right), \\ F\left(x_{i+j}\left|x_1,...,x_{i-1}\right.\right)\middle|\theta_{i,i+j|1:(i-1)} \end{pmatrix} \quad (4)$$

For D-vine, the first v_j was selected to be the conditional variable, as the following (5)

$$F\left(x\right)=\prod_{k=1}^{n} f_k\left(x_k\right)\times c_{\mathrm{j,j+}i|(j+1):(j+i-1)}\begin{pmatrix} F\left(x_j\left|x_{j+1},...,x_{j+i-1}\right.\right), \\ F\left(x_{j+i}\left|x_{j+i},...,x_{j+i-1}\right.\right)\middle|\theta_{\mathrm{j,j+i}|(j+1):(j+i-1)} \end{pmatrix} \quad (5)$$

where n is the number of Asian stock returns. This model is used to measure the interdependence among the marginal distribution of Asian stock returns.

C. Value at Risk (VaR)

Value at Risk was the maximum loss of return (R_L) corresponding to probability (α) [18]. Accordingly, the VaR can be measured by (6)

$$VaR_i=\mu_{i,R}-z_{i,\alpha}\sigma_{i,R} \quad (6)$$

where $\mu_{i,R}$ is the mean of stock market return i ; $\sigma_{i,R}$ is the standard deviation of stock market *i*. Z_α is the standard score (Z-score) with the probability corresponding to the probability of loss α .

Note that this study assume $\alpha=0.05$. This means that there is a 0.05 probability that the portfolio will loss more than the value of VaR_i in each sub-period.

D. Component Expected Shortfall (CES)

The expected shortfall was the expected tail loss from the asset investment [19], this loss can be measured as in (7)

$$ES_{\mathrm{i},t+1}=E_{i,t+1}\left[r_{\mathrm{i},t+1}\middle|r_{\mathrm{i},t+1}<-VaR_{i,t+1}\right] \quad (7)$$

where $r_{i,t+1}$ is the return of the investment in the stock market at the period $t+1$

later proposed Component Expected Shortfall (CES*)* to measure risk sources in the portfolio investment [20]. This risk measure can be obtained as in (8)

$$CES_{it} = w_{it}\frac{\partial ES_{i,t+1}}{\partial w_{it}} = W_{i,t+1}E_{t+1}\left[r_{i,t+1}\middle|r_{i,t+1} < -VaR_{i,t+1}\right] \quad (8)$$

E. The portfolio optimization base on the Component Expected Shortfall (CES)

$$\text{Min} \qquad CES_{it} = w_{i,t+1}E_{i,t+1}\left[r_{i,t+1}\middle|r_{i,t+1} < -VaR_{i,t+1}\right] \qquad (9)$$

$$\text{Subject to} \qquad r = \left[\left(w_1 \times r_{1,t+1}\right) + ... + \left(w_{15} \times r_{15,t+1}\right)\right] \qquad (10)$$

$$w_1 + ... + w_{15} = 1 \qquad (11)$$

$$0 \le w_i \le 1 \qquad (12)$$

where $i = 1$ Stock Exchange of Thailand (SET), $i = 2$ Straits Times (S.T.), $i = 3$ Philippine Stock Exchange Index (PSEI), $i = 4$ Ho Chi Minh City Stock Exchange (HCMC), $i = 5$ The FTSE Bursa Malaysia Index Series (FTSE), $i = 6$ Jakarta Stock Exchange Composite (JKT), $i = 7$ Bombay Stock Exchange (BSE), $i = 8$ Karachi Stock Exchange (KSE), $i = 9$ China AMC CSI 300 Index ETF (CSI), $i = 10$ Nikkei Stock Average (NIKKIE), $i = 11$ Korea Stock Exchange KOSPI Index (KOSPI), $i = 12$ Taiwan Stock Exchange (TWSE), $i = 13$ Borsa İstanbul Stock Exchange (BIST), $i = 14$ Kazakhstan Stock Exchange (KASE), and $i = 15$ the Russian Trading System (RTS).

To sum up, the portfolio optimization of the Asian stock returns is based on the loss probability through the CES, and the optimal portfolio investment is achieved by minimizing the risk of portfolios.

V. RESULT AND DISCUSS

This study employs the EGARCH (1, 1) to model the marginal distributions for pre-crisis, crisis, and post-crisis periods. The results for the margins are summarized in Table I. This study finds that the estimated ARCH coefficient (α) and GARCH coefficient (β) are most significant at the 1% level for all stock returns, shown that the volatility in all stock returns for three periods. Moreover, the conditional variance equations (α + β) are found to be less than one and very close to 1 for all cases. This infers the high volatility persistence of our stock returns. Hence, this study suggesting that the residual distribution cannot be normally distributed and that applying the Skew-t distribution is suitable for our EGARCH (1, 1) model.

Accordingly, the results also show that BSE of India, HCMC of Vietnam, CSI of China, and KASE of Kazakhstan have the highest volatility and provide the returns in the opposite way in the pre-crisis. During crisis, CSI of China and NIKKIE of Japan have the highest volatility and provided the returns in the opposite way. Besides, there is the highest volatility and providing the returns in the opposite way in CSI of China, and BIST of Turkey after the crisis. Consequently, the CSI of China deviates in all three periods. Otherwise, providing the highest volatility from CSI and NIKKIE of Japan during the crisis means that they have a higher risk.

After estimating the EGARCH models, we can obtain the standardized residuals for 15 stock returns from the EGARCH models. These standardized residuals will be used as marginal distributions in the regular vine copula models for 15 stock markets in three periods. However, EGARCH has some drawbacks, such as incorrect conditions and no clear explanation, leading to misleading interpretation. In order to guarantee that the marginal is uniformly distributed, this paper use the Kolmogorov-Smirnov test (KS-test) and this paper also use Ljung-Box test to guarantee that the residuals are independent and identically distributed random variable. Hence, the finding of Standardized Residuals estimation of ARMA-EGARCH (1, 1) is reliable, and it could continuously be estimated in the Vine Copula model.

Accordingly, the Vine Copula model is employed in this study to investigate the Value at Risk (VaR) and the Component Expected Shortfall (CES) to find an optimal investment portfolio as well as a source of risk. Moreover, this paper would like to evaluate the effectiveness of the models to test their reliability. To clarify, two popular models in the past, which are the C-vine Copula and D-vine Copula model, are considered base on the lowest Akaike Information Criterion (AIC) analysis, Bayesian Information Criterion (BIC), and highest Log-Likelihood (L.L.) to obtain the most optimal model, as shown in Table II.

TABLE I

THE RESULT OF THE ARMA-EGARCH MODEL FOR PRE-CRISIS, DURING CRISIS, AND POST-CRISIS OF GLOBAL FINANCIAL CRISIS IN 2008.

Period	Pre-crisis			During-Crisis			Post-crisis		
Parameter	α	β	γ	α	β	γ	α	β	γ
SET	-0.0788 (0.0540)	0.9881 (0.0045)	0.1618 (0.1618)	-0.0931 (0.0898)	0.9324 (0.0537)	0.3618 (0.1043)	-0.0890 (0.0500)	0.9991 (0.0050)	0.1720 (0.0700)
ST	0.0489 (0.0000)	0.8806 (0.0001)	-0.5655 (0.0001)	-0.2848 (0.0691)	0.9894 (0.0076)	0.2804 (0.0423)	-0.1140 (0.0412)	0.9927 (0.0007)	0.1646 (0.0176)
PSEI	0.0432 (0.5676)	0.7688 (0.9104)	0.1512 (0.5698)	-0.1226 (0.0460)	1.0000 (0.0007)	0.2163 (0.0303)	-0.1341 (0.0308)	0.9933 (0.0007)	0.1308 (0.0269)
HCMC	0.3574 (0.0001)	0.8902 (0.0001)	-0.5857 (0.0001)	-0.1351 (0.1060)	0.8125 (0.1114)	0.5621 (0.2029)	-0.1850 (0.0771)	0.8920 (0.0506)	0.3793 (0.0991)
FTSE	-0.1698 (0.1692)	0.8300 (0.0755)	0.5843 (0.2112)	-0.2486 (0.0424)	0.9931 (0.0000)	0.1873 (0.0340)	-0.1631 (0.0329)	1.0000 (0.0000)	0.0053 (0.0195)
JKT	0.1338 (0.2804)	0.4252 (0.5026)	0.4395 (0.3322)	-0.3173 (0.0880)	0.9375 (0.0437)	0.4881 (0.1408)	-0.0921 (0.0654)	0.9261 (0.0327)	0.3086 (0.0910)
BSE	0.7162 (0.0018)	0.9152 (0.0002)	-0.9316 (0.0004)	-0.1307 (0.0557)	0.9707 (0.025)	0.3402 (0.0977)	-0.1140 (0.0387)	0.9851 (0.000)	0.0791 (0.0115)
KSE	-1.3781 (0.4025)	0.9002 (0.0092)	1.0601 (0.3254)	-0.0566 (0.1120)	0.8247 (0.0651)	0.7019 (0.1640)	-0.1606 (0.0789)	0.7070 (0.1307)	0.2824 (0.1006)
CSI	0.2591 (0.0000)	0.8867 (0.0001)	-0.6340 (0.0002)	-0.0933 (0.0386)	0.9999 (0.0001)	0.0736 (0.0188)	0.0713 (0.0402)	0.9776 (0.0051)	0.2001 (0.0573)
NIKKIE	0.0412 (01412)	0.9278 (0.0753)	0.5407 (0.2432)	-0.0869 (0.0227)	0.9989 (0.0016)	0.0896 (0.0463)	-0.2209 (0.0696)	0.9276 (0.0743)	0.2714 (0.0743)
KOSPI	-0.0948 (0.1712)	0.6312 (0.3296)	0.3574 (0.4105)	-0.3255 (0.0379)	0.9899 (0.0048)	0.20026 (0.0618)	-0.1851 (0.0651)	0.6978 (0.1449)	0.1600 (0.1002)
TWSE	-0.1005 (0.2477)	0.8242 (0.2718)	0.3757 (0.3134)	-0.1108 (0.2007)	1.0000 (0.0000)	0.0462 (0.0190)	-0.1653 (0.0452)	0.9999 (0.0002)	0.1470 (0.0297)
BIST	-0.1893 (0.1625)	0.9172 (0.0719)	0.2893 (0.1871)	-0.1038 (0.0497)	0.9736 (0.0143)	0.2523 (0.0783)	-0.0734 (0.0204)	0.9999 (0.0000)	0.0428 (0.0111)
KASE	0.2741 (0.0000)	0.9355 (0.0001)	-0.3748 (0.0000)	-0.3739 (0.0000)	0.9823 (0.0003)	-0.1414 (0.0000)	-0.0132 (0.0878)	0.7877 (0.1111)	0.6594 (0.1842)
	0.7348	0.9746	1.3406	-0.1568	0.9695	0.3322	-0.1738	0.9907	0.2371

Note: (1). the number in round brackets is Standard Error

TABLE II

THE RESULT OF AN OPTIMAL MODEL SELECTION

Period	Vine copula model	**Statistic for optimal model** Akaikes Information Criterion (AIC)	Bayesian Information Criterion (BIC)	Log likelihood (L.L.)
Pre-crisis	C-vine	**-2473.37**	**-2374.69**	**1277.68**
	D-vine	-2353.7	-2274.28	1209.85
During crisis	C-vine	**-1085.15**	**-968.49**	**574.57**
	D-vine	-1047.95	-909.42	561.97
Post-crisis	C-vine	**-1034.22**	**-874.32**	**558.11**
	D-vine	-967.35	-826.95	519.67

Note: Bold number indicates the best Vine structure

Table II shown, the AIC of C-vine and D-vine is -2473.37 and -2353.7, whereas BICs are -2374.69 and -2274.28, respectively, in the pre-crisis. During the crisis, AICs are -1085.15 and -1047.95, and BICs are -968.49 and -909.42, respectively. Additionally, the AICs are -1034.22 and -967.35, whereas BICs are -874.32 and -826.95, respectively. In this comparison, the C-vine copula model has a lower AIC and BIC and a higher Log-Likelihood than the D-vine copula in all periods. Accordingly, the C-vine copula model is the best fit copula structure for constructing the joint of 15 Asian stock markets.

TABLE III

THE RESULT OF VALUE AT RISK ANALYSIS AND THE RETURN OF INVESTMENT PORTFOLIO

Period	Portfolio Method	VaR	Return
Pre-crisis	Equally weight	0.0049	-0.0029
	Optimal weight	0.0034	-0.0023
During crisis	Equally weight	0.0072	0.0001
	Optimal weight	0.0062	0.0002
Post-crisis	Equally weight	0.0043	-0.0005
	Optimal weight	0.0035	-0.0005

From the Value at Risk analysis in Table III, the portfolio investment obtained from the equal weight method provides the lower return and the highest risk than the optimal weight method in all periods as the Table III. Nevertheless, the Value at Risks during a crisis increases from 0.0034 to 0.0062 (82.35%). In post-crisis, the Value at Risks increases from 0.0062 to 0.0035 (43.55%). Apparently, the 2008 global financial crisis affects the returns of the Asian stock market and lead to a relatively high risk in portfolio investment. This study then uses the CES to investigate the sources of risk in the Asian stock market.

TABLE IV

THE RESULT OF PORTFOLIO OPTIMIZATION BASE ON
COMPONENT EXPECTED SHORTFALL (CES)

Period	Pre-crisis		During crisis		Post-crisis	
	Weight : W	Source of risk : CES	Weight : W	Source of risk : CES	Weight : W	Source of risk : CES
SET	0.0416	0.0413	0.0135	0.0001	0.0119	0.0115
ST	0.0000	0.0000	0.0374	0.0262	0.0000	0.0000
PSEI	0.1461	0.1816	0.0495	0.0581	0.0574	0.0530
HCMC	0.0329	0.0660	0.0841	0.1892	0.0785	0.0864
FTSE	0.2531	0.1915	0.1793	0.0330	0.1098	0.0984
JKT	0.0600	0.0669	0.1153	0.2102	0.1613	0.2014
BSE	0.0000	0.0000	0.0000	0.0000	0.0961	0.0918
KSE	0.0000	0.0000	0.1070	0.1397	0.0725	0.0754
CSI	0.0609	0.0970	0.0787	0.0689	0.0591	0.0542
NIKKIE	0.0709	0.0555	0.1446	0.0822	0.0190	0.0187
KOSPI	0.0424	0.0450	0.0528	0.0365	0.1487	0.1265
TWSE	0.2348	0.1966	0.1208	0.1492	0.1439	0.1197
BIST	0.0000	0.0000	0.0005	0.0004	0.0000	0.0000
KASE	0.0146	0.0185	0.0000	0.0000	0.0418	0.0624
RTS	0.0426	0.0405	0.0163	0.0068	0.0000	0.0000

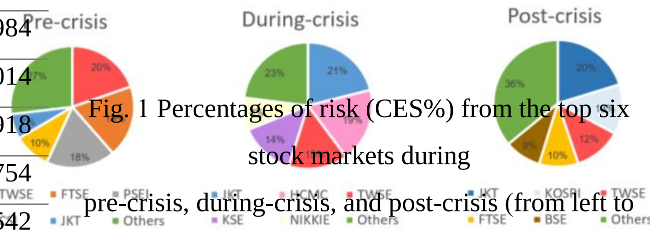

Fig. 1 Percentages of risk (CES%) from the top six stock markets during pre-crisis, during-crisis, and post-crisis (from left to right)

According estimate to the CES, the C-vine copula based on ARMA-EGARCH models is used to simulate the return of the Asian stock market at time $t+1$. Therefore, 10,000 simulated returns are generated. From Table IV, the CES presents the sources of Asian stock markets' risk in three sub-periods. Figure 1 explains the top six stock markets which are contributing the risk to the Asian stock markets. Note that the higher percentage indicates a higher potential systemic risk. As we can see in figure 1, the TWSE of Taiwan and JKT of Indonesia are ranked in the top six stocks contributing a high risk to Asian stock markets in all three periods, indicating that these stock markets have a strong influence on the Asian markets. It is also observed that the TWSE contributes the highest CES% in pre-crisis, while JKT contributes the highest CES% during crisis and post-crisis periods. These findings suggest that investors should be cautious in investing in TWSE and JKT markets.

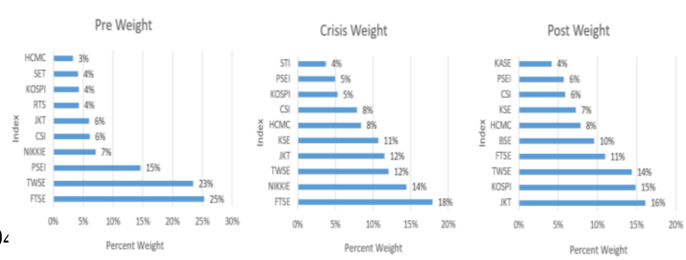

Fig. 2 the first ten average weight percentages for investment portfolio in pre-crisis, crisis, and post-crisis (from left to right)

After quantifying a systemic risk by the CES method, this study then makes a portfolio investment analysis in each period. The trading decision can be made by finding optimal weights for each stock in the Asian market in all crisis periods. The results are reported in figure 2. Each panel describes the top ten weights for portfolio investment in all periods. This study finds that the portfolio investment during the crisis period is more scattered as there is a bit gap between each stock market. This study can observe that Malaysia's FTSE index is suggested as the most suitable stock for pre-and during the crisis, whereas the JKT of Indonesia is an appropriate stock in the post-crisis.

VI. Conclusion

This study investigates the Value at Risk (VaR) and the Component Expected Shortfall (CES) using the C-Vine copula-based EGARCH models to obtain an optimal investment portfolio of 15 Asian stocks as well as sources of risk. The results show that ARMA-EGARCH (1, 1) model with skewed student-t provides reliable ARCH and GARCH effects in all three periods: pre-crisis, crisis, and post-crisis. This study can observe that Asian stock markets exhibit high fluctuation in all sub-periods, particularly during the financial crisis. In the next step, this study investigate the linkage among the Asian financial markets using C and D-Vine couples, and the result shows that the C-vine Copula has the lowest AIC, BIC, and the highest log-likelihood, so the C-vine Copula model is the most suitable model to construct the linkage among the Asian stocks. Then, this study further use the C-Vine copula-based EGARCH to measure the VaR, and CES. Our results show that the VaR has increased from 0.0034 to 0.0062 (82.35%) during the crisis period, but it had decreased from 0.0062 to 0.0035 (43.55%) after the crisis. Obviously, the crisis influenced the risk of Asia stock markets. Therefore, the pre-crisis optimal investment is FTSE of Malaysia, whereas S.T. of Singapore, BSE of India, KSE of Pakistan, and BIST of Turkey are not suggested to invest. During the crisis, Malaysia's FTSE is suggested to invest with the highest proportion, whereas there is zero proportion in BSE of India and KASE of Kazakhstan. In the post-crisis, the JKT of Indonesia is found to have the highest proportion, whereas S.T. of Singapore, BIST of Turkey, and Russia's RTS are not suggested.

The investor could utilize these results to decide on the investment in the Asian stock markets. Although this study help to make the investors' decision, investors ought to consider the situations and current news that affect the stock markets to reduce the risk.

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References

[1] M. Kahler, "Economic security in an era of globalization: definition and provision," *The Pacific Review*, vol. 17, no. 4, pp. 485-502, 2004.

[2] R. Dodd and P. Mills, "Outbreak: U.S. Subprime Contagion," *Finance & Development*, vol. 45, no. 2, Jun. 2008.

[3] Z. Yakubu and A. O. Akerele, "An analysis of the impact of global financial crisis on the Nigeria stock exchange," *Current Research Journal of Social Sciences Journal of Social Sciences*, vol. 4, no. 6, pp. 369-399, 2012.

[4] F. I. Team, "*The reason why "Asia" is such an interesting region*," Finnomena Investment Team Web site. 2019. Available at: https://www.finnomena.com/finnomena-ic/interesting-asia/. Accessed January 20, 2020.

[5] H. Markowitz, "Portfolio Selection," *The Journal of Finance*, vol. 7, no. 1, pp. 77-91, 1952.

[6] D. M. Reeb, C. C. Y. Kwok, and H. Y. Baek, "Systematic Risk of the Multinational Corporation," *Journal of International Business Studies*, vol. 29, no. 2, pp. 263-279, 1998.

[7] K. Zhu, W. Yamaka, and S. Sriboonchitta, "Multi-asset portfolio returns: a Markov switching copula-based approach," *Thai Journal of Mathematics*, pp. 183-200, 2016.

[8] G. Fan, Y. Zeng, and W. K. Wong, "Decomposition of portfolio VaR and expected shortfall based on multivariate Copula simulation," *International Journal of Management Science and Engineering Management*, vol. 7, no. 2, pp. 153-160, 2012.

[9] S. Wang, "Portfolio optimization of stock sectors in Shanghai stock exchange: Vine Copula GARCH approach," M.S. thesis, Chiangmai University, Chiangmai, 2018.

[10] C. T. Nguyen and M. H. Nguyen, "Modeling Stock Price Volatility: Empirical Evidence from the Ho Chi Minh City Stock Exchange in Vietnam," *Journal of Asian Finance, Economics and Business*, vol. 6, no. 3, pp. 19-26, 2019.

[11] I. Sahadudheen, "An Exponential GARCH Approach to the Effect of Impulsiveness of Euro on Indian Stock Market," *Journal of Asian Finance, Economics and Business*, vol. 2, no. 3, pp. 17-22, 2015.

[12] T. T. X. Huong, M. L. T. Nguyen and N. T. K. Lien, "Exchange Rate Volatility and FDI Response during the Financial Crisis: Empirical Evidence from Vietnam," *Journal of Asian Finance, Economics and Business*, vol. 8, no. 3, pp. 119-126, 2019.

[13] P. Phochanachan, J. Liu, and S. Sriboonchitta, "On Mathematical Modeling and Analysis of Co-Movement and Optimal Portfolios of Stock Markets," *Thai Journal of Mathematics*, vol.14, no.2, pp. 283-303, 2016.

[14] P. Maneejuk, and W. Yamaka, "Predicting Contagion from the U.S. Financial Crisis to International Stock Markets Using Dynamic Copula with Google Trends," *Mathematics*, vol.7, no.11, pp. 1032, 2019.

[15] D. B. Nelson, "Conditional heteroskedasticity in asset returns: A new approach," *Econometrica*, vol. 59, no. 2, pp. 347-370, 1991.

[16] A. Sklar, "Fonctions de Répartition à n Dimensions et Leurs Marges," *Publications de l'Institut Statistique de l'Université de Paris*, vol.8, pp. 229-231, 1959.

[17] K. Aas, C. Czado, A. Frigessi, and H. Bakken, "Pair-copula constructions of multiple dependence," Insurance: Mathematics and Economics, vol. 44, no. 2, pp. 182-198, 2009.

[18] A. J. McNeil, R. Frey, and P. Embrechts, "Quantitative Risk Management," *USA: Princeton University Press*, 2015.

[19] P. Artzner, F. Delbaen, J.-M. Eber, and D. Heath, "Thinking Coherently. Risk", vol. 10, no. c, pp 68-71, 1997.

[20] G.-D Banulescu and E.-I Dumitrescu, "Which are the SIFIs? A Component Expected Shortfall approach to systemic risk," *The journal of banking and finance*, vol. 50, no. C, pp. 575-588, 2015.

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