Modelling dependency structures of crude oil prices and stock markets of developed and developing countries: A C-vine copula approach

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Abstract. This paper aims to investigate the impact of oil price on the stock price of developed countries (represented by the Group of seven) and the stock price of developing countries (represented by BRICS) by using C-vine copula approach. A C-vine based GJR-GARCH is used to measure the conditional dependence between stock price and oil price and investigate the difference between developed countries and developing countries. The empirical evidence shows that G7 and BRICS countries have a positive and significant dependence between oil returns, and there is an even stronger dependence between oil returns for the G7 countries. Some countries in the developed and the developing countries have the tail relationship in the low market or in bear market, further, both groups do not have a relationship with oil return when the stock is in a boom market.

1. Introduction

If "oil is the blood of industry", best describes the industrial era, then "oil is the driving force of economy and production" best describes the modern world. In fact, there has not previously been a commodity that can shock human society and international politics and the economy as crude oil. Many researchers are curious in the relationship between oil price and stock price, for example, Gilber and Mork [1] deem that there is a relationship between oil price and stock market. Jones and Kaul [2] found that there is a lagged effect of oil prices on stock prices. The stock market is a barometer of the economy, and the state of the economy will respond to the stock market, if we can capture the dependence of oil price and stock price, we can make a better evaluation of stock price and have a deep understanding the relation between oil price and stock price. The developed countries and the developing countries have a difference in economic level, the accumulation in Industry age, model of economic development, population, culture and political system, as the world has moved from the industrial age into the global information age, it is noticeable that we should compare the oil price which may have a different dependence relation in the developed and the developing countries. In order to compare the dependence of crude oil prices and stock market of the developed and the developing countries, we select G7 and BRICS as a sample, the main reasons are as followed; first, Russia and South Africa are not only self-sufficient in oil but also have a surplus for export, the rest of G7 and BRICS countries share in world imports of oil and are in the top 15 in the world, all the
countries in G7 and BRICS are very dependent on oil; secondly, the G7 countries not only occupy 64% of the world's wealth but also take over 46% of the global GDP; thirdly, BRICS have an enormous population and maintain a momentum as the emergent economy and exhibits a huge market. Hence, the G7 and BRICS can be a good sample of the developed and the developing countries.

In earlier studies, some researchers have provided some empirical evidence that the stock price is associated with oil price change by using different approaches; nevertheless, their research is based on different countries, so they may obtain opposite results [3-8]. Ono [9] declared that the stock price in BRIC (Brazil, Russian, India and China) countries positively correspond to the oil price statistical significance except Brazil. Compared with G7, Diaz et al. [10] found that the high volatility of the crude oil price has a negative effect on the G7 countries' stock markets. Since the developed and developing countries have different economic Dynamics, their responses to the oil prices also vary, Syed [11] et al provided an empirical evidence that oil price have a strong impact on finance market in emerging countries, while the increase in oil price contribute to the depresses real stock returns [12]. Limited research has studied the impact of the change of crude oil price on the stock market by comparing the developed and the developing countries.

Moreover, previous studies in this issue were based on the assumption of normality, and the dependence are symmetric. Consequently, the relationship is captured by linear correlation. For example, Bhatiai and Mitra [13] employed GO-GARCH to investigate the dynamic co-movement between crude oil and stock market by G7 and BRICS (Brazil, Russia, India, China and South Africa) based on linear and no-tail dependence assumption. Many researchers have found that the stock price is asymmetric [14] [15] and the relationship between financial variables have a non-linear relationship [16]. Thus, Sriboonchitta et al [17] relaxed this assumption to capture the co-movement and tail dependence of three countries in Asia stock price by employing a vine copula approach and found that there is the greatest dependence among three countries. The copula models joint between distributions which allow the interested variables with arbitrary marginal distributions to be combined while incorporating arbitrary dependencies between them. The copula models have various families; therefore, they can capture the different structures of dependencies. Thus, the copula model provides more details of the dependence structure between the oil price and the stock market than the traditional approaches.

One of multivariate copulas is Vine copulas. It uses the pair copula construction (PPC) to decompose a multivariate probability density into bivariate copula models [18]. The benefit of Vine copula is that the parameter estimated results are not affected by the curse of high-dimensional data. Nagler and Czado [19] had shown supporting evidence that the convergence rate of vine copula is independent with the number of dimensions. Among Vine-copula models, C-vine and D-vine have been popularly applied in various fields. Liu and Sriboonchita [20] showed the evidence that C-vine and D-vine provide the better performance result compared to others. Zhang and Singh [21] proposed that C-vine is better than D-vine in the case that we know the main variable governing interactions among the selected variables.

Therefore, this paper aims to compare the effects of oil prices on the stock markets between the developed countries and the developing countries using C-vine copula which is the first study of this issue using C-vine approach. This paper structure is as follows: The methodology we employ will be shown in section 2. The layout of section 3 is data and some primary findings. In section 4, we will go into detail on the findings, and a further conclusion will be made in section 5.

2. Methodology

2.1. Copula functions

The basic concept of the copula is the joint distribution between variables which is illustrated by Sklar’s theorem. In other words, considering the case of two variables. Suppose that $F(x_1, x_2)$ be any marginal cumulative distribution function (cdf) of two variables. Regarding Sklar’s theorem, if the marginal distribution functions are continuous, there is a unique copula function $C$ so that
The joint density function can be shown as

\[ f(x_1, x_2) = \frac{\partial^2 F(x_1, x_2)}{\partial x_1 \partial x_2} = c(u_1, u_2) f_1(x_1) f_2(x_2) \]

where the function \( C: [0,1]^2 \to [0,1] \). There are three different kinds of copula to link the dependence structure of each other, namely, Elliptical copula, which combines different levels of correlation between marginal, Archimedean copula, which administrates the strength of dependence, and rotated Archimedean copula takes responsibility for the negative Kendall’s tau.

2.2. GJR-GARCH model

In order to apply the copula model, the marginal distribution for each time series must be specified first. Most financial time series exhibit some specific characteristics such as heavy tails, volatility clustering, and conditional heteroskedasticity. The GARCH model proposed by Engle [22] is widely applied to model of financial data. Jondeau and Rockinge [23] showed supporting evidence that the GARCH model can capture the financial behaviour with different features such as skewness, autocorrelation, and kurtosis. However, the GARCH model is not appropriately used for the asymmetric volatility, which is ubiquitous in financial data, and researchers just assume it is symmetry to estimate a first approximation. To handle this issue, GARCH had been extended to be EARCH, GJR-GARCH and so on.

Among these models, the GJR-GARCH model is the most widely used for modeling financial data since it allows the data to have asymmetric volatility and the leverage effect when there is a shock in the market.

The \( GJR-GARCH (1,1) \) can be expressed as

\[ r_t = u_t + \epsilon_t \]

\[ \epsilon_t = \sigma_t z_t - i.i.d \]

\[ \sigma_t^2 = w + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \psi[\epsilon_{t-1} < 0] \epsilon_{t-1}^2, \]

where \( r_t \) denotes the price of the stock, \( \mu, \omega, \alpha, \beta, \gamma \) denote the parameters in which \( \gamma \) refers to the coefficient of the leverage, and \( z_t \) denotes the innovations consisting of independent and identically distributed components. This study uses \( GJR-GARCH (1,1) \) with different distributions, namely Skew Student-t Distribution (sstd), Skew Normal Distribution (snorm), and Skew Generalized Error Distribution (sged). To choose the best-fitted model, we use Akaike Information Criterion (AIC) as a criterion.

2.3. Pair-copula construction (PPC)

The single multivariate copula provides the worse performance when the data have high-dimension to the complex dependence structure. Then, Joe [24] proposed the method to decompose a high-dimensional copula into simple bivariate copula models. There are many ways to decompose a high-dimensional distribution. One of the most popular models is Canonical vines (C-vines) proposed by Bedford and Cooke [25].

The density of the C-vine in the case of m-dimensions can be expressed as

\[ f(x_1, \ldots, x_m) = \prod_{j=1}^{m} f_j(x_j) \prod_{j=1}^{m} \prod_{\alpha_j \neq \emptyset} c_{\omega_{j}} \left( F_{\omega_{j}}, F_{\emptyset}, F_{\omega_{j}} \right), \]

where \( \omega_{j} = \{1, \ldots, j-1\} \). Let \( h(.) \) is the conditional distribution function which can be expressed as
where $\Theta$ denotes the parameters’ set for the bivariate copula, which is function to two uniform distributions $U_i$ and $U_j$.

For simplicity, we consider the C-vine structure in the case of three variables which can be expressed as

$$f(x_1, x_2, x_3) = f(x_1) \cdot f(x_2) \cdot f(x_3) \cdot c_{12}(F(x_1), F(x_2)) \cdot c_{13}(F(x_1), F(x_3)) \cdot c_{23}(F(x_2), F(x_3))$$

To illustrate, the C-vine for three variables can be shown as a sequence of dependency trees $T = [T_1, ..., T_{m-1}]$. Therefore, in this case will have two trees which are $T_1$ and $T_2$.

To give you an idea, we provide you an example of C-vine structure for $m=3$ as shown in Figure 1.

![C-vine structure for m=3.](image)

The data description and statistics for the price are described in detail in Table 1. In the BRICS group, all of the means of stock price and kurtosis are positive, while all of the skewness are negative, a negative skewness and a positive kurtosis hint a long tail in the negative direction and has a heavier tail than a normal distribution. On the contrary, the results in the G7 are entirely the opposite, the means of stock price are positive (beside France and Italy), further, they always have a negative kurtosis and the distribution is highly skewed, a negative kurtosis means that the distribution is flatter than a normal curve with the same mean and standard deviation.

The kurtosis and skewness values suggest that the skew-normal distribution, skew-student-t and skew-generalized error distribution might be more appropriate for modeling conditional marginal distributions. In this study, we use the Akaike information criterion (AIC) to choose the best-fitted distribution of the price. The results of the best-fitted to the distribution of each variable are shown in Table 3.
4. Empirical results

4.1. Marginal distribution

The marginal distribution’s parameters are estimated by using GJR-GARCH. It is clear that the price in the majority of countries (Canada, France, Japan, UK and India) and crude oil are more suitable for skew-normal distribution, the second-most distribution is the skew-generalized error distribution (China, South Africa, Italy and USA); moreover, the rest of the country correspond to the skew-student-t. Secondly, in the first step, the marginal distribution parameters are estimated by using GJR-GARCH, we apply standardized residuals into uniform distribution. These marginal distributions are substituted into the C-vine copula, since we aim to investigate how the stock prices associate with the oil price. Thirdly, the highly significant coefficient beta of GARCH (-1) implies persistent volatility clustering.

Table 1. Stationarity test by using Augmented Dickey-Fuller Test (ADF).

| Variables  | ADF  | Bayes factors |
|------------|------|---------------|
| Crude Oil  | -6.568 | 0.054         |
| Canada     | -6.254 | 0.054         |
| France     | -5.182 | 0.054         |
| German     | -5.281 | 0.054         |
| Italy      | -5.461 | 0.054         |
| Japan      | -5.366 | 0.054         |
| UK         | -4.728 | 0.054         |
| USA        | -5.374 | 0.054         |
| Brazil     | -5.263 | 0.054         |
| Russia     | -5.917 | 0.054         |
| India      | -5.729 | 0.054         |
| China      | -4.307 | 0.054         |
| South Africa | -5.030 | 0.054      |

Table 1 shows the stationarity test of the oil price return and stock market return. The bayes factor for all variables is 0.054 which refers that the all variables of oil price are stationary time series. Held and Ott [26] stated that if the bayes factor is in the range of 0.033 to 0.01, there is strong evidence against the null hypothesis that the time series data contains a unit root. Thus, we can conclude with strong evidence that all the variables are stationary time series. The estimated results of GJR-GARCH model, and its AIC are shown in Table 2. Most of variables are skewed. Thus, they are likely to have tail dependence.

Table 2. The result of marginal distribution and the performance of GJR-GARCH model.

|          | $\omega$ | $\alpha$ | $\beta$ | $\gamma$ | Skew | Distribution | AIC  |
|----------|----------|----------|---------|----------|------|--------------|------|
| Crude Oil| 0.001    | 0.041    | 0.706***| 0.189    | 0.718*** | snorm        | -1.992 |
| Canada   | 0.000    | 0.141    | 0.824***| -0.017   | 0.657*** | snorm        | -3.883 |
| France   | 0.0003* | 0.000    | 0.686***| 0.378*   | 0.619*** | snorm        | -3.338 |
| Germany  | 0.0005* | 0.000    | 0.695***| 0.303*   | 0.648*** | sstd         | -3.056 |
| Italy    | 0.000    | 0.000    | 0.809***| 0.224    | 0.722*** | sged         | -2.853 |
| Japan    | 0.002**  | 0.000    | 0.000   | 0.462    | 0.832*** | snorm        | -3.029 |
| UK       | 0.0002* | 0.000    | 0.738***| 0.269*   | 0.664*** | snorm        | -3.721 |
| USA      | 0.0002** | 0.000   | 0.694***| 0.377*   | 0.679*** | sged         | -3.695 |
| Briza    | 0.000    | 0.000    | 1.000***| -0.008   | 0.758*** | sstd         | -2.288 |
| Russia   | 0.000    | 0.220    | 0.749***| 0.029*** | 9.891    | sstd         | -2.379 |
| India    | 0.000    | 0.072    | 0.902***| 0.035    | 0.763*** | snorm        | -2.713 |
| China    | 0.000    | 0.260    | 0.788***| -0.185   | 0.868    | sged         | -2.442 |
| South Africa | 0.000  | 0.051    | 0.606***| 0.686*   | 0.974*** | sged         | -3.361 |
Table 3. The estimated result from the GJR-GARCH model.

| Variables    | CODE | Mean  | Median | Minimum  | Max       | Std.Dev  | kurtosis | skewness |
|--------------|------|-------|--------|----------|-----------|----------|----------|----------|
| Crude Oil    | CO   | 0.004 | 0.018  | -0.395   | 0.260     | 0.092    | 4.194    | -0.589   |
| Canada       | CA   | 0.003 | 0.009  | -0.186   | 0.106     | 0.040    | -1.146   | 6.300    |
| France       | FR   | 0.000 | 0.004  | -0.170   | 0.118     | 0.050    | -0.660   | 3.808    |
| German       | DE   | 0.003 | 0.010  | -0.233   | 0.143     | 0.059    | -1.035   | 5.478    |
| Italy        | IT   | -0.003| 0.004  | -0.232   | 0.148     | 0.062    | -0.597   | 4.109    |
| Japan        | JP   | 0.000 | 0.005  | -0.306   | 0.126     | 0.055    | -0.802   | 6.399    |
| UK           | GB   | 0.001 | 0.006  | -0.157   | 0.093     | 0.041    | -0.778   | 4.158    |
| USA          | US   | 0.003 | 0.009  | -0.174   | 0.104     | 0.043    | -0.828   | 4.771    |
| Brazil       | BR   | 0.006 | 0.013  | -0.459   | 0.193     | 0.080    | 7.667    | -1.152   |
| Russia       | RU   | 0.011 | 0.017  | -0.339   | 0.285     | 0.082    | 5.040    | -0.568   |
| India        | IN   | 0.009 | 0.010  | -0.273   | 0.249     | 0.066    | 4.920    | -0.506   |
| China        | CN   | 0.003 | 0.006  | -0.283   | 0.243     | 0.078    | 4.799    | -0.537   |
| South Africa | ZA   | 0.009 | 0.010  | -0.150   | 0.131     | 0.047    | 3.598    | -0.259   |

4.2. C-vine copula estimation results

In this part, a detailed analysis of the results of C-vine copula model can exhibit the dependence structure between the oil price and stock prices and focuses on comparing the oil prices associated with the stock prices in the G7 and BRICS, respectively.

Table 4. Estimated results from C-vine copula in BRICS.

| Copula        | Family | Tau   | par     | S.E. | par2 | se | utd | ltd | AIC  |
|---------------|--------|-------|---------|------|------|----|-----|-----|------|
| c(CO,BR)      | C      | 0.051 | 0.107** | 0.048| -    | -  | -   | 0.002| 1.402|
| c(CO,RU)      | C      | 0.022 | 0.045   | 0.061| -    | -  | -   | -   | -25.752|
| c(CO,IN)      | F      | 0.240 | 2.267***| 0.438| -    | -  | -   | -   | -20.073|
| c(CO,CN)      | SJ     | 0.142 | 1.290***| 0.392| -    | -  | 0.289| -   | -26.383|
| c(CO,ZA)      | t      | 0.212 | 0.327***| 0.053| 6.950***| 0.397| 0.080| 0.080| 1.724|
| c(BR,RU|CO)    | C270   | -0.012 | -0.023 | 0.061| -    | -  | -   | -7.048|
| c(BR,IN|CO)    | F      | 0.180 | 1.662***| 0.081| -    | -  | -   | -0.725|
| c(BR,CN|CO)    | SBB8   | 0.207 | 1.637***| 0.401| 0.942***| 0.059| -    | -9.779|
| c(BR,ZA|CO)    | F      | 0.160 | 1.474***| 0.034| -    | -  | -   | -24.101|
| c(RU,IN|BR,CO) | N      | 0.066 | 0.103   | 0.409| -    | -  | -   | -11.565|
| c(RU,CN|BR,CO) | SC     | 0.018 | 0.036   | 0.454| -    | -  | -   | -49.035|
| c(RU,ZA|BR,CO) | F      | -0.015| -0.136  | 0.048| -    | -  | -   | 1.884|
| c(IN,CN|RU,BR,CO) | N      | 0.267 | 0.406***| 0.091| -    | -  | -   | 1.615|
| c(IN,ZA|RU,BR,CO) | N      | 0.213 | 0.328   | 5.523| -    | -  | -   | -28.983|
| c(CN,ZA|IN,RU,BR,CO) | F      | 0.139 | 1.270***| 0.102| -    | -  | -   | -8.915|

Table 4 and Table 5 present the results of C-vine copulas and Kendall’s tau of BRICS and G7 countries respectively. The first and second column provide information about the copula dependence structure, the most appropriate joint copula density and dependence structure for each pair-copula based on AIC criteria. Take c(CO, BR) as an example, it represent the copula dependence between oil return and Brazil, the further line give the more information about copula tree dependence structure, for example, c(BR,RU|CO) is represent given oil return as a condition, the copula dependence between Brazil and Russian, we provide the country code in the Table 3. We design the order of the C-vine
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copula according to the size of the stock market. There are 15 pairs of copulas in BRICS, the Archimedean copula (Clayton and Frank) is dominating the joint copula density, followed by Elliptical copula (Gaussian and student t), the rest is rotated Clayton copula (90 degree) and survival BB8, survival Clayton and survival Joe copula, respectively. Meanwhile, in G7, the Frank copula and survival copula are crushingly dominant in the G7 countries copula family and followed by Gaussian Copula. In the third column, Kendall’s tau is transformed from copula parameters so that we can interpret the dependence between variables.

Table 5 Estimated results from C-vine copula in G7

| Copula | Family | Tau par | se | par2 | se | utd | ltd | AIC |
|--------|--------|---------|----|------|----|-----|-----|-----|
| ε(CO,CA) | F | 0.156 | 1.431*** | 0.042 | - | - | - | -7.899 |
| ε(CO,FR) | F | 0.155 | 1.422*** | 0.429 | - | - | - | -9.483 |
| ε(CO,DE) | SJ | 0.142 | 1.292** | - | - | 0.290 | - | -20.295 |
| ε(CO,IT) | C | 0.121 | 0.275 | 0.412 | - | - | 0.081 | -8.387 |
| ε(CO,GB) | C | 0.100 | 0.223 | 0.642 | - | - | 0.045 | -5.922 |
| ε(CO,JP) | N | 0.271 | 0.413 | 0.413 | - | - | - | -40.098 |
| ε(CO,ES) | N | 0.148 | 0.230*** | 0.040 | - | - | - | -15.319 |
| ε(CA,FR) | SBB8 | 0.560 | 5.423*** | 0.043 | 0.793*** | 1.005 | - | -179.547 |
| ε(CA,DE) | SBB8 | 0.390 | 4.015*** | 0.115 | 0.712* | 0.405 | - | -77.509 |
| ε(CA,IT) | SBB8 | 0.535 | 6*** | 0.143 | 0.713*** | 0.046 | - | -159.576 |
| ε(CA,GB) | SBB8 | 0.522 | 4.305*** | 0.562 | 0.849** | 0.410 | - | -165.878 |
| ε(CA,JP) | F | 0.509 | 5.906*** | 0.399 | - | - | - | -133.606 |
| ε(CA,ES) | F | 0.471 | 5.140*** | 0.047 | 0.700*** | 0.061 | - | -109.922 |
| ε(FR,DE) | SC | 0.099 | 0.220 | 1.375 | - | - | 0.043 | -5.127 |
| ε(FR,IT) | t | 0.394 | 0.579*** | 0.057 | 4.035 | 1.039 | 0.299 | -97.206 |
| ε(FR,GB) | BB1 | 0.280 | 0.371*** | 0.091 | 1.171 | 0.048 | 0.192 | 0.203 | -50.020 |
| ε(FR,JP) | F | 0.156 | 1.433 | 1.065 | - | - | - | -10.948 |
| ε(FR,ES) | BB8 | 0.288 | 2.091*** | 0.045 | 0.910 | 0.060 | - | -41.335 |
| ε(IE,FR,CA) | N | 0.176 | 0.273** | 0.129 | - | - | - | -16.171 |
| ε(IE,GB,FR,CA) | F | 0.161 | 1.475*** | 0.045 | - | - | - | -11.334 |
| ε(IE,JP,FR,CA) | F | 0.021 | 0.189 | NAN | - | - | - | 1.762 |
| ε(IE,ES,FR,CA) | F | 0.103 | 0.931*** | 0.273 | - | - | - | -3.334 |
| ε(IT,GB,DE,FR,CA) | SBB1 | 0.404 | 0.285*** | 0.265 | 1.467 | 6.713 | 0.191 | 0.396 | -104.707 |
| ε(IT,JP,DE,FR,CA) | G | 0.083 | 1.090*** | 0.079 | - | 0.112 | - | -6.491 |
| ε(IT,ES,DE,FR,CA) | F | 0.370 | 3.763*** | 0.064 | - | - | - | -69.676 |
| ε(JP,IT,DE,FR,CA) | J | 0.044 | 1.079*** | 0.133 | - | 0.100 | - | -0.801 |
| ε(JP,ES,IT,DE,FR,CA) | F | -0.012 | -0.110 | - | 0.080 | - | - | 1.917 |
| ε(JP,GB,IT,DE,FR,CA) | C90 | -0.035 | -0.073 | 0.090 | - | - | - | -2.928 |

In this study, we focuses on the dependence structure of oil price return and the stock returns, so we mainly interpret the relationship between oil return and stock returns. In the BRICS group, all the countries stock returns have a positive dependence relationship between oil returns; India has the highest dependence with oil returns followed by South Africa which are 0.240 and 0.212 respectively. Meanwhile, Russian oil return poses the lowest relationship between them which is 0.022. The stock returns of Brazil, China, and South Africa have the lower tail dependence with oil return which are
0.02, 0.289 and 0.080, respectively. Thus, the stock market of China, Brazil and South Africa have been affected by oil return when the stocks are in a bear market. Among of these stocks, China stock market has the highest tail dependence with oil return. Given the oil return, most of the BRICS stock markets return have a positive correlation with the stock return of Russia, except stock return of Brazil. Meanwhile, the co-movement between Brazil and India, Brazil and China, Brazil and South Africa are positive. If the Brazilian stock market and oil returns are given as the condition, the Kendall’s tau of the relationship between the Russia and South Africa falls by 1.5%. The Kendall’s tau of the relationship between Russia and India increases by 6.6%.

If Brazil and oil return are given as the condition, the Kendall’s tau of the relationship between Russia and South Africa falls by 1.5%. The Kendall’s tau of the relationship between Russia and India increases by 6.6%. If Russia, Brazil, and oil return are given as the condition, the Kendall’s tau of India and China increases by 26.7% followed by the tau of India and South Africa which increases by 21.3%. If the India, Brazil, Russia, and oil return are given as the condition, the relationship between China and South Africa is 13.9% are positive.

For the G7 group, all countries have the positive relationship with the oil return within a small relationship. Japan stock returns have the highest relationship with the oil return which is 0.271 followed by Canada and France 0.156 and 0.155, respectively. Germany’s stock return and oil return possess a high relationship since the lower tail dependence is 0.290. Meanwhile, the smallest relation with the oil return is the UK stock market with only 0.100. However, there was not a great deal of difference among the correlation of oil return and stock markets since the values of tau are slightly different. The UK, Italy, and Germany stock returns have the tail relationship with oil return; all of this tail dependence has the lower relationship with the oil return. These results indicate that the stock market of UK, Italy, and Germany have been influenced by oil return when the stocks are in a bear market.

Given the oil return as the condition, all of the relationships between stocks has the same direction. The stock of Canada and France possess the highest dependence with tau 56.30% followed by the relationship between Canada and the UK (52.2%).

If Canada and oil return are given as the condition, the stock of France and Italy possess the highest dependence with tau 39.4 which includes their upper tail (0.299) and lower tail (0.299). The lowest dependence belongs to the relationship between stock of France and Germany with tau 9.9%.

Overall, all the countries stock markets have been influenced by the oil return in a small relationship which all the Kendall's tau are below 0.3. By giving oil return as a condition, all of the countries stock market dependencies become much stronger, it indicates that G7 countries stock markets have a relatively strong dependence on oil return. According to the first tree of the vine copula construction, the intimate connection between oil return and G7 countries stock markets are stronger than BRICS countries stock markets. Further, from the second tree of the vine copula construction, it shows that the impact of crude oil return on G7 countries stock markets is greater than that on Brics countries stock markets. Some countries in the developed and the developing countries have the tail relationship in the low market or in the bear market. The bear market refers to decrease in a stock market return which a drop of 20 percent or more. Therefore, it means when the stock price return declines 20 percent or more and oil price return is low, there are the relationship between stock market and oil price in some countries for both developed and developing countries.

Furthermore, both groups do not have a relationship with oil price return when the stock is in boom market referring to the case of increasing a large portion of stock returns. That means when the stock a large portion of price returns increase and oil price return are high, there are no the relationship between stock market and oil price for both groups.

5. Conclusions
The object of this paper is to investigate the dependence structure between the stock market and oil return in the developed countries and the developing countries. A C-vine copula based on GJR-GARCH Model, an empirical analysis, shows that the oil return has a positive and a significant
dependency effect on most of the stock returns, in both groups of stock return, namely, G7 and BRICS. Moreover, skew-normal distribution, skew-student-t and skew-generalized error distribution might be more appropriate for modelling conditional marginal distribution; we get the optimal C-vine copula joint distribution. All of the countries stock markets have been influenced by oil return with a small relation in which all the Kendall's tau below 0.3. If both the developed and the developing countries, some stock markets have the tail relationship only in the low market or in a bear market. Therefore, both groups do not have a relationship with oil return when stock is in a boom market. In the developing countries, India has the highest dependence on oil returns. Meanwhile, in developed countries, Japan stock returns have the highest relationship with the oil return. Moreover, the oil return has greater impact on G7 countries stock markets than that on BRICS countries stock markets. The paper contributes to the empirical evidence that the change in oil return may increase the risk in the stock market in both developed and developing countries. For the government, they should speed up the oil strategic reserve system, which will be contribution to the steady supply of oil, the steady supply of oil can reduce the risk of financial market. For the financial institution and investors, when they made investment decisions, they should take the impact of crude oil as a factor, which will have an effect on stock returns.

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