Volatility spillover and co-movement among Chinese shipping sector stock index, oil futures price, ocean freight charge and exchange rate

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Abstract. This study aims to analyze the co-movement and volatility spillover among four stock markets consist of Chinese shipping sector stock index, oil futures, shipping freight and currency market. We estimate dependence among these four markets using the multivariate copula model. Then we use the VAR model and impulse response function to investigate the volatility spillover among them. The empirical results show that the Gaussian copula is the most appropriate dependence mode as the AIC and BIC of this copula are the lowest when compared to other candidate copula models. The dependence correlation coefficients show a weak volatility dependence among these four markets. In addition, the results of the VAR suggest a spillover effect from shipping stock and oil to freight market.

1. Introduction
In the present day, shipping sector, oil, freight and currency act a pivotal part in China’s economy. In the context of economic globalization, interactions among markets are becoming closer. China is a major export country and has the third largest commercial fleet. China’s shipping prosperity index has risen around 119.94 points since 2010, and the overall index broke through 1500 points in the fourth quarter in 2017. This indicates the substantial growth of Chinese shipping sector in this decade which corresponds to the high growth of China’s economy.

As an important factor which affects the cost and profit of shipping, oil has played an important part in most of the economies in the world as well as in China. Its demand and supply will contribute a direct and potential impact on the financial markets [1]. In fact, the oil futures price continues to fluctuate along this decade. Consequently, the link between oil and oil-related industries are strengthened because of this volatility [2]. Freight rate is another factor which affects an import and export volume. Since 2018, the freight price of the Panamax continues to rise, especially in the first half of June, accounting for 21%. As it is most widely used in bulk cargo transportation, the fluctuations of freight price can improve substantial business risks on investors, shipowners, ship operators, and charterers [3]. Since July 2005, the Chinese exchange rate was reformed as a floating exchange rate, the Chinese yuan has appreciated against the US dollar and reached a peak of 6.05 yuan per dollar in January 2014 and then reached 6.50 yuan per USD at the end of 2017, an increase of 23% over the 12 years [4]. The exchange rate fluctuation can be viewed as a factor affecting the freight rate in US dollar in terms of the cost of transportation.
In sum, this study examines the co-movement and volatility spillover among these four markets (shipping sector, oil futures, shipping freight and currency). To capture the correlation and volatility spillover among these four markets, we first use the ARMA-GARCH model to quantify the marginal distributions and conditional volatilities. Next, we use multivariate copula model to link the marginal distributions to analyze the dependence between the four series. Copula model can be easily used to obtain multivariate distributions and is more flexible than traditional methods (see [5] and [6]). Finally, we capture volatility spillover effects using the VAR model and impulse response function.

The paper is arranged as follows. In Section 2, we present the methodology, which includes the GARCH model for marginals, multivariate copulas for dependency, VAR model, impulse response function for volatility spillover effects. Section 3 analyses the empirical results. The conclusion is provided in the last section.

2. Related studies
As we mentioned above, there is an economic relationship among these four markets. In the methodology literature, the relationship among these variables has been already investigated. Extensive research on the linkage of oil and stock provided evidence of a negative link [7], a positive link [8] and no connection [1, 2]. Several existing studies aimed at revealing the linkage between oil market and freight market [9] found that the demand for tankers is a derivative of the oil demand. The freight and oil price are positively correlated. Studies on the high and low frequency components of oil price and freight rates have shown a linkage of these two variables when considering the relevance structures [10]. The correlation between oil market and currency market has been analyzed. In the long run, there are a significant impact of the U.S. dollar exchange rate on oil prices, but short term influences are slight [11]. In the latest research, [4] found there is a negative relationship between China’s stock market and currency market.

Furthermore, there are many methods to study the relationship between variables. [12] Used VAR and Granger causality models to examine the dynamic forms of the causal relation of oil price on stock markets. [13] Used GARCH models with time-varying copula to research the dependence between oil and stock market. They found decreasing benefits from pluralism with oil for stock portfolios in the last decade. The copula models are used to discuss the correlation between oil prices and stock market indices [14]. The paper draws conclusions about the relationship between exchange rates, stocks and oil prices. They found that exchange rates and stock displayed higher oil price dependency in the most oil exporter countries.

Unlike the existing studies, this study contributes to the extant literature in the following ways: First, apart from price and return time series relationship analyses that have a majority in recent studies, the time series relationship among volatility of China’s shipping sector stock, shipping freight, currency and oil markets also deserves an examination because volatility transmission among the four markets seems to be an important and common way that explains the flow of information among these markets. Many studies focus on examining the linkage between financial market and the composite stock market index or some typical stocks. Our second contribution is the use of industry level data (shipping sector) rather than individual listed shipping companies stock price. Since the shipping companies are not in the same level, the sector data can better describe the overall situation. The third contribution is that many researchers have modeled dependence structures using copula models, but our investigation analyzes all these variables simultaneously using multivariate copulas, which differs from the relevant researches that has focused on specific markets.

3. Methodology

3.1. Generalized autoregressive conditional heteroskedasticity
Firstly, we describe the GARCH model proposed by Bollerslev [15]. Then, we combine the autoregressive (AR) and moving average (MA) terms with skewed student-t distribution to find the
marginal distributions. This model can capture important characteristics of financial series volatility. The model is expressed in the following equations as:

\[ r_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t, \]  
(1)

\[ \epsilon_t = h_t^{-\frac{1}{2}} z_t, \]  
(2)

\[ h_t = \omega_0 + \alpha \epsilon_{t-1}^2 + \beta h_{t-1}. \]  
(3)

Equation (1) present the ARMA (p, q) process, where \( r_{t-i} \) is autoregressive term of \( r_t \) and \( \epsilon_t \) is a residual, then this residual is defined as the production between the conditional variance \( h_t \) and random variable \( z_t \) in Equation (2). The GARCH (1,1) process is displayed in Equation (3), where \( \omega_0 > 0 \), \( \alpha, \beta \geq 0 \) and \( \alpha + \beta < 1 \) are sufficient to ensure that the conditional variance \( h_t > 0 \). The ARCH term is represented by the \( \alpha \epsilon_{t-1}^2 \) and \( \alpha \) refers to the short-run persistence of shocks. The GARCH term is represented by the \( \beta h_{t-1} \) and \( \beta \) indicates the contribution of shocks to long-run persistence (\( \alpha + \beta \)).

In Equation (2), we assume that \( z_t \) follows the skewed student-t (SkT) distribution, where \( \lambda \) and \( \nu \) denote the asymmetry parameter and degree of freedom, respectively. The formula is expressed as follows:

\[
g(z_t; \lambda, \nu) = \begin{cases} 
q \left( 1 + \frac{1}{\nu-2} \left( \frac{q z_t + d}{1 - \lambda} \right)^{\nu/2} \right)^{-\nu/2}, & z_t \leq -d/q \\
q \left( 1 + \frac{1}{\nu-2} \left( \frac{q z_t + d}{1 + \lambda} \right)^{\nu/2} \right)^{-\nu/2}, & z_t \geq -d/q 
\end{cases}
\]  
(4)

where the constants \( d, q \) and \( c \) are given as follows:

\[ d = 4 \lambda c \left( \frac{\nu-2}{\nu-1} \right), \quad q^2 = 1 + 3 \lambda^2 - d^2, \quad c = \Gamma \left( \frac{\nu+1}{2} \right) \left( \sqrt{\pi (\nu-2)} \Gamma \left( \frac{\nu}{2} \right) \right)^{-1} \]  
(5)

### 3.2. Copula model

The copula function can tell us more information about the degree of dependence that we want to investigate in this study. The Sklar’s theorem [16] is the fundamental theorem of the copula.

Let \( H \) be an n-dimensional distribution function with marginal distributions \( F_1(x_1), \ldots, F_n(x_n) \). Let \( X = (x_1, \ldots, x_n) \) be a random variables vector with distribution function. If the margins are continuous, then \( C \) is unique:

\[ H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)), \]  
(6)

where \( C \) is a copula and \( F_1(x_1), \ldots, F_n(x_n) \) are distribution functions, then the above function \( H(x_1, \ldots, x_n) \) in Equation (6) is a joint distribution function with marginal distribution \( F_1(x_1), \ldots, F_n(x_n) \). N-dimensional copula \( C \) can be interpreted as the distribution function of an n-dimensional random variable on space \([0,1]^n\) with uniform margins.

\[ C(u_1, \ldots, u_n) = H(F_1^{-1}(u_1), \ldots, F_n^{-1}(u_n)) \]  
(7)

In this study, the six copula families are chosen to measure the dependence. Elliptical copulas are the copulas of elliptical distributions and are also easy to obtain according to Sklar’s Theorem. The densities of Archimedean families of Clayton, Frank, Gumbel and Joe is given by [17]:

- **Multivariate Gaussian copula**

The n-dimensional Gaussian copula has the following expression:

\[ C(u_1, \ldots, u_n) = \Phi_n \left( \Phi_1^{-1}(u_1), \ldots, \Phi_n^{-1}(u_n) \right), \]  
(8)
where \( \Phi^n \) denotes \( n \)-dimension standard normal cumulative distribution function and \( \sum \) the corresponding correlation matrix. The density can be written as:

\[
c(u_1, \ldots, u_n) = \frac{1}{\sqrt{\det \sum_n}} \exp \left( -\frac{1}{2} \left( \begin{array}{c} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_n) \\ \end{array} \right)^T \left( \sum_n^{-1} - 1 \right) \left( \begin{array}{c} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_n) \\ \end{array} \right) \right),
\]

(9)

where \( I \) denotes \( n \times n \) identity matrix. The Gaussian copula has zero tail dependence.

- **Multivariate Student-t copula**
  
  The \( n \)-dimension student-t copula is defined as:
  
  \[
  C(u_1, \ldots, u_n) = \int_{-\infty}^{u_1} \cdots \int_{-\infty}^{u_n} \prod_{j=1}^n f_{t_\nu}(x) \, dx,
  \]
  
  (10)

  where \( f_{t_\nu}(x) \) denotes \( n \)-dimensional student-t density function and \( t_\nu \) denotes the quartile function of a standard univariate student-t distribution with degree of freedom \( \nu \), respectively. The student t-copula has symmetric non-zero tail dependence.

- **Multivariate Clayton copula**

  \[
  c_\theta(u) = \prod_{j=1}^n (\theta^{m+1} \prod_{j=1}^n u_j^{\cdot(1-\theta)} (1 + t_\theta(u_j))^{-(\nu+1)/\theta}),
  \]

  (11)

  where \( \theta > 0 \) satisfies the decreasing means, which can reflect the lower tail dependence. The Clayton copula provides strong lower tail dependence.

- **Multivariate Frank copula**

  \[
  c_\theta(u) = \theta^{m+1} \prod_{j=1}^n (\log u_j) \exp(-\theta \sum_{j=1}^n u_j),
  \]

  (12)

  where \( h_\theta(u) = (1 - e^{-\theta})^{-1} \int_{-\infty}^{u} \cdots \int_{-\infty}^{u} \prod_{j=1}^n \{1 - \exp(-\theta u_j)\} \, dx \). \( L_i \) means logarithmic integral function. Then the marginal distribution becomes radially symmetric; further, \( \theta \in (-\infty, +\infty) \{0\} \) also holds true.

- **Multivariate Gumbel copula**

  \[
  c_\theta(u) = \theta^{m+1} C_\theta(u) \prod_{j=1}^n (\log u_j) \exp(-\theta \sum_{j=1}^n u_j),
  \]

  (13)

  where \( P_{n,m}(x) = \sum_{\alpha} \binom{n}{\alpha} a^*_n (\alpha) x^\alpha \cdot \bar{a}^*_n (\alpha) = (-1)^m \sum_{\alpha} a^*_n (\alpha) s(n, m) s(m, j) = \frac{\Gamma(1+m-n)}{\Gamma(1+1-n)} \cdot \frac{\Gamma(m+1)}{\Gamma(1)} \cdot (m+1, m \in \{1, \ldots, n\}) \) and \( s \) denotes the Stirling numbers of the first kind and \( S \) denotes the Stirling numbers of the second kind. The Gumbel copula is non-symmetric and exhibits strong upper tail dependence.

- **Multivariate Joe copula**

  \[
  c_\theta(u) = \theta^{m+1} \prod_{j=1}^n (1-u_j)^{\theta-1} \frac{h_{1-\theta}(u)}{h_\theta(u)} P_{n,m}^{1-\theta}\frac{h_\theta(u)}{1-h_\theta(u)},
  \]

  (14)

  where \( h_\theta(u) = \Gamma(1-(1-u)^{\theta}) \), \( P_{n,m}^{1-\theta}(x) = \sum_{\alpha} \binom{n}{\alpha} a_{1-\theta}^*(\alpha) x^\alpha \cdot \bar{a}_{1-\theta}^*(\alpha) = S(n, m+1) (m-\alpha) \cdot m \in \{0, \ldots, n-1\} \) and \( (m-\alpha)m \) denotes the falling factorial. The Joe copula have only upper tail dependence.

### 3.3. Vector autoregression (VAR) model

VAR model is well known as an efficient tool analyzing a relation between variables under some condition. We set up a covariance stationary \( N \)-variable VAR \( (P) \) [18], and it is given by:

\[
H_i = \psi_0 + \sum_{j=1}^d \psi_j H_{i-j} + \epsilon_i,
\]

(15)
where \( H_t = \{h_t, \ldots, h_N\} \) denote an \((N \times 1)\) vector of conditional volatilities obtained from GARCH process. \( \varphi_c \) is the deterministic components of the VAR system, and the \( \varphi_j \) is \( N \times N \) coefficient matrices. The \( \varepsilon \sim (0, \Sigma) \) is a vector of independently and identically distributed disturbances. In our study, we test the volatility spillovers using a four-variables VAR model across different markets.

Then, we can investigate the impulse response function through the moving average specification \( R_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \), where \( A \) is the \( N \times N \) coefficient matrices following \( A = \Psi_0 A_e + \Psi_1 A_{e-1} + \ldots + \Psi_p A_{e-p} \), with \( A_0 \) the \( N \times N \) identity matrix and \( A_i = 0 \) for \( i < 0 \).

### 4. Data and empirical result

#### 4.1. Data

We use daily closing prices of the shipping sector stock index as measured by 20 shipping companies listed in the Shanghai Stock Exchange. In addition, WTI oil futures has significant linkage with Brent oil and OPEC Basket oil price. They are also major standard in oil pricing. Hence, we choose WTI oil futures to measure the oil price. The freight price as measured by average chartering of 4 routes of Panamax in China. The exchange rate as measured by the RMB/USD nominal closing exchange rate, starting from 1st January 2007 to 30th March 2018. All data are obtained from EcoWin database. We transform each price data into the logarithmic returns, \( \ln \left( \frac{1}{p-1} \right) \).

Table 1. Summary statistics.

|                   | Shipping Stock | Freight Price | USD_CNY | Oil Futures |
|-------------------|---------------|--------------|---------|------------|
| Mean              | 0.0000        | -0.0004      | -0.0001 | 0.00003    |
| Std.Dev.          | 0.0241        | 0.0392       | 0.0014  | 0.0238     |
| Skewness          | -0.3331       | -0.9458      | 0.5628  | 0.1428     |
| Kurtosis          | 6.2207        | 78.1666      | 20.4130 | 7.9139     |
| Jarque-Bera       | 1320.11***    | 689972.30*** | 37158.94*** | 2956.77*** |
| ADF               | -50.34***     | -20.74***    | -30.38*** | -56.90***  |

Notes: Std.Dev. is the standard deviations. ADF means Augmented Dickey-Fuller test. Significant codes: 0*** 0.01 ** 0.05 * 0.1.

The empirical results of four variables are shown in Table 1. The skewness statistics of the shipping sector stock price and freight price are negative, thereby indicating that the shipping sector stock price and freight price returns are skewed to the left. With respect to the kurtosis statistics, the value of both price returns are greater than 3, which indicates a fat-tailed distribution. Similarly, the Jarque-Bera statistics are large and significant, which means that our data may not follow the normal distribution, thereby implying that the assumption of skewed-t is more appropriate in our study. Furthermore, the results of ADF unit root test shows that four price returns are stationary at level 1%.

#### 4.2. Results of ARMA-GARCH model

In this paper, ARMA (p,q) - GARCH (1,1) model is applied to estimate the marginals for each series, and suppose that all marginals follow skewed student-t distributions. Table 2 gives the parameter estimates. The optimal lag for ARMA(p,q) is selected by using AIC and find that the returns on Shipping Stock, Freight Price, USD_CNY and Oil Futures satisfy ARMA (1,1), ARMA (1,5), ARMA (5,4) and ARMA (3,2) with GARCH(1,1) , respectively. The parameter ARCH and GARCH are significant, and the summation between them are close to one, demonstrating that the conditional volatility is very persistent over time. We also observe that values of asymmetry are both significant, indicating the skewness behavior of our marginals.

To avoid copula model missimplification, the adequacy of the estimated ARMA-GARCH (1,1) models is also tested through auto-correlation Ljung-Box test. We provide several order auto-correlation tests for possible misspecification consisting of Ljung-Box Q(1), Q(5), and Q(9). Table 3
reports the results which show that all standardized residual series are not rejected auto-correlation, verifying the independently distributed. After filtering the data using ARMA-GARCH models, the obtained standardized residuals are transformed to uniforms using the cumulative skewed student-t distributions. The uniform series will be used as input for the multivariate copula. Prior to estimating the copula model, the transformed standardized residuals must be uniformly distributed. The results of KS test are also showed in Table 3 and we observe that four marginal distributions are uniform [0,1].

### Table 2. Estimates of marginal distribution models.

|                  | Shipping Stock | Freight Price | USD_CNY | Oil Futures |
|------------------|----------------|---------------|---------|-------------|
| **Mean equation**|                |               |         |             |
| $\phi_0$         | 0.0004         | 0.0006        | 0.0001  | 0.0003      |
| $\phi_1$         | 0.9943***      | 0.5803***     | 0.2146* | -1.9854***  |
| $\phi_2$         | -0.1044        | 0.0869        | -1.0286*** | 0.0011     |
| $\phi_3$         | 0.2741***      | 0.0709        | -0.0210*** | 0.0006     |
| $\phi_4$         | 0.5126***      | 0.0197        |         |             |
| $\phi_5$         | 0.3850***      | 0.0168        |         |             |

| **Variance equation**|          |               |         |             |
| $\omega$          | 0.0000***   | 0.0011***     | 0.0000  | 0.0001**    |
| ARCH              | 0.1104***   | 0.8388***     | 0.0901*** | 0.0586***   |
| GARCH             | 0.8886***   | 0.1602***     | 0.8964*** | 0.9384***   |
| Asymmetry         | 0.9398***   | 1.0652***     | 0.9693*** | 0.9445***   |
| Tail              | 4.1284***   | 2.7840***     | 4.2871*** | 7.9701***   |

| Log-Likelihood    | 7365.3020  | 8443.6420     | 16223.1700 | 7380.5880   |
| AIC               | -5.0238    | -5.7574       | -11.0670   | -5.0322     |

Notes: The standard error is in parenthesis. Significant codes: 0*** 0.01 ** 0.05 * 0.1.

### Table 3. Estimated results for the KS test and Box-Ljung test (Q-test).

|                  | Shipping Stock | Freight Price | USD_CNY | Oil Futures |
|------------------|----------------|---------------|---------|-------------|
| Q(1)             | 0.3680         | 0.9712        | 0.9869  | 0.0232      |
| Q(5)             | 0.2859         | 0.9998        | 1.0000  | 0.1086      |
| Q(9)             | 0.1361         | 0.9990        | 1.0000  | 0.2596      |
| KS               | 0.0535         | 0.2776        | 0.0573  | 0.4089      |

Notes: Q(q) is Ljung-Box p-value for serial correlation order q. The KS means Kolmogorov-Smirnov test for uniformity.

### 4.3. Results of copula model

Prior to analyzing our results, we compare six copula models as mentioned in Section 2. Table 4 shows the test values. of the log-likelihood, the AIC, and the BIC. From the AIC and BIC perspective, and the Gaussian copula displays better explanatory ability than the other copulas as the AIC and BIC values of this copula are 41.0369 and 19.6581, respectively, which is the minimum of all copulas.

Table 5 displays the dependence analysis of Gaussian copula. The dependence correlation coefficients from Table 5 shows that four market volatilities display a weak degree of dependence. We find that the dependence between the shipping sector stock price and currency market is the strongest while the dependence between freight market and oil futures market is the weakest. The copula correlation coefficient between the shipping sector stock price and currency market is -0.1034. This implies that these two markets are related in the opposite direction and the shipping sector movements are affected by the currency market. The relationship between the shipping sector and freight market; and shipping sector and oil futures market are found to have dependence equal 0.0649 and 0.0736, respectively. It means that these two market pairs are slightly related in the same direction. Considering the relationship between freight and currency market; and oil futures and currency market,
they have a low negative coefficient -0.0391 and -0.0756, respectively. These imply that the freight and oil futures market have a negative influence on dependence of currency market. The low correlations among these markets can be illustrated by the price control policy: oil futures prices are related to international crude oil prices which are less affected by the Chinese economy. Another variable exchange rate is also regulated by the government, thus having less links with the international market.

Table 4. Model selection.

| Copulas    | Log-Likelihood | AIC    | BIC     |
|------------|----------------|--------|---------|
| Student-t  | -29.6832       | 42.6198| 26.7015 |
| Gaussian   | -28.9610       | 41.0369| 19.6581 |
| Clayton    | -61.3862       | 93.6157| 93.9871 |
| Frank      | -36.8096       | 42.6318| 40.9869 |
| Gumbel     | -109.6321      | 189.9104| 207.6413|
| Joe        | -74.3618       | 126.7018| 138.1900|

Table 5. Theoretical Kendall tau based Gaussian copula.

|                  | Shipping Stock | Freight Price | USD_CNY | Oil Futures |
|------------------|----------------|---------------|---------|-------------|
| Shipping Stock   | 1.0000         | 0.0649        | -0.1034 | 0.0736      |
| Freight Price    | 0.0649         | 1.0000        | -0.0391 | 0.0112      |
| USD_CNY          | -0.1034        | -0.0391       | 1.0000  | -0.0756     |
| Oil Futures      | 0.0736         | 0.0112        | -0.0756 | 1.0000      |

4.4. Results of VAR model

We then examine the daily volatilities across the shipping sector stock price, shipping freight market, currency market and oil futures market. We use a VAR (1) model, where the lag length of one is chosen by the AIC. Thus, we regress the daily volatility in each market on one lag of itself, as well as one lag of volatility in each of the three other markets.

Table 6 shows the volatility spillover among four markets. From these results, we can see that only freight price depends on its own lag volatility. In other words, the volatility of shipping sector is strongly influenced by volatility in the previous day. We also observe the significance of Shipping Stock and Oil Futures coefficients, suggesting a spillover effect from shipping stock and oil to freight market. There is no evidence supporting the existence of spillover effect volatility transmission among these three markets. As the shipping companies are oil consumption enterprises, and the change in oil price will lead to the change in the cost of the shipping companies including freight rate. The cash flows, as well as the production and management behaviour will be influenced by the cost, and last affect the enterprise value and stock market price. However, according to the small regression coefficient of Table 6, the correlation between these three markets is weak. This result corresponds to the copula dependence results which suggest a weak dependence among shipping sector, oil futures, freight and currency markets. We thus conclude that low dependence among the markets may bring low volatility transmission among these four markets.

Table 6. Estimated results of VAR model.

|                  | Shipping Stock | Freight Price | USD_CNY | Oil Futures |
|------------------|----------------|---------------|---------|-------------|
| Constant         | -0.0036 [-0.2030] | 0.0231 [0.7210] | 0.0069 [0.1430] | -0.0158 [-0.8510] |
| Shipping Stock t-1 | 0.0324 [1.7520]  | 0.0844* [2.5600]  | 0.0111 [0.2240]  | 0.0199 [1.0430]  |
| Freight t-1      | 0.0070 [0.6780]  | -0.0506** [-2.7410] | 0.0259 [0.9270] | 0.0011 [0.0107]  |
| USD_CNY t-1      | 0.0057 [0.8290]  | -0.0010 [-0.0800]  | 0.0145 [0.7830]  | 0.0002 [0.0290]  |
| Oil Futures t-1  | 0.0614*** [3.4040] | 1.1069*** [3.3320] | -0.0706 [-1.456]  | 0.0096 [0.5180]  |
| Log-Likelihood   | -20957.4200     | 2.9797        |         |             |

Notes: Loglik denotes log-likelihood. T-statistics is in [ ] . Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1.
Finally, we undertake a more in-depth analysis of volatility transmission among the four markets. We concentrate more precisely on the dynamic volatility transmission and magnitude of a shock from one market to the other markets. This can be examined by the volatility impulse response function. Figure 1 depicts the impulse response among four markets. According to the results, four volatilities are positively large in response to their own shocks in the short term. In addition, the impact of the shock on the volatilities of shipping stock, oil futures, freight and currency are lower when compared to their own shocks. Indeed, the volatility in the four markets exhibit a smaller in magnitude. This finding may reflect that these four markets may not play an import role in each other.

5. Conclusions
This paper employs the multivariate copula model and VAR model to estimate the dependence and volatility spillover among shipping sector stock index which is measured by SSE (Shanghai stock exchange) sector indices, Panamax freight price as measured by average chartering of 4 routes, the RMB/USD nominal closing exchange rate and WTI oil futures price. Our analysis consists of two parts. First, we investigate the dependence structures among these four markets using copulas-based GARCH models with skewed student-t distribution. The main result of this part shows that the Gaussian copula is the most appropriate specification, since the AIC and BIC of this specification are the lowest when compared with other candidate copulas. The dependence result shows that these four markets have a weak dependence. In the second part, we use the VAR model and impulse response function to analyze volatility spillover among these four markets. The empirical results show that shipping sector stock index and shipping freight market both have a positive relationship with oil futures market. This paper is divided as two parts to analysis the relationship among these four finical markets. We find that the VAR results corresponds to the copula dependence results which suggest a weak dependence among four variables.

Although this paper analyzes the spillover effect among stock, freight, oil and foreign exchange market, it is still not perfect. The selection of variables should be more diversified, for example,
multiple ship types can be selected for comparison. In terms of method, we may try to use these two multivariate models of vine Copula or spillover index to study the relationship between multiple variables. Inevitably, our future work will center on these issues.

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