DEPENDENCE AND VOLATILITY OF STOCK SECTORS IN SHANGHAI STOCK EXCHANGE: VINE COPULA GARCH APPROACH

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Abstract - This paper constructs a framework by using the vine copula-GARCH model to capture the inter-dependence structure between the assets in shanghai stock exchange A shares. And the volatility will be a standard of risk measurement. Research studies data period from January 4, 2010, to December 31, 2014. The objective of this study is to show: Firstly, we will focus on the inter-dependent structure among 12 stock sectors, and find the strongest and weakest inter-dependent structure. Secondly, we suppose to find that unexpected shock for volatility in stock sectors have the long duration, while there is tiny influence in short-term. Thirdly, we suppose that the spot prices will have influence the related sectors. In the methods, we choose the ARMAX-GARCH Vine copula model, and we assume that this model can explain volatility and dependence well.

Keywords - Vine copula; inter-dependence; shanghai stock exchange

I. INTRODUCTION

Nowadays, stock market continues to expand, with the more diversified investment options, higher securities prices, and stronger volatility. The numbers of investment participants continue to increase. How to control risk becomes an important topic for professional investors. Portfolio is a collection of stocks, bonds, and derivative financial products held by investors or financial institutions, and the risk can be diversified through the portfolio, which means the concept like “no eggs put in the basket”. Buying is an investment strategy that focuses on buying market stocks at specific prices and holding a relatively long time as their prices are likely to rise (Chen, Kao, Lyuu, & Wong, 1999). Thus, in order to maximize revenue, investors need portfolio optimization tools to support the analysis of large stock data sets. Therefore, for investors, portfolio optimization has important personal and practical significance. With the investors increasing in China, the number of investors in China's stock market extended 100 million on January 21th 2016. At April 17, the number of A-share accounts in Shanghai stock exchange was 198 million. People willing to invest in stock market getting more return. In general, investors by using the method to analyze the volatility of the broader stock market will be able to avoid a certain amount of risk losses and increase their volatility based on fluctuations and declines between the different sectors, also, by reducing the risk of pre-judgment of investors, to gain the ultimate profit. For example, a common strategy for reducing losses by poorly performing market sectors is to buy stocks belonging to various industries (Meric, Ratner, Meric, 2008; Ratner, Leal, 2005). Some research work (Chen, Mabu, Hirasawa, Hu, 2007; Kantardzic, Sadeghian, Shen, 2004; Parque, Mabu, Hirasawa, 2009) has also been working to determine a sector of the stock that maximizes revenue while minimizing risk less diversified. The vine copula approach can also be extended to the case where some margins are continuous and others are discrete (Stöber et al., 2015). The advantage of Vine copula GARCH model as: Vine copulas are multivariate Copulas. Vine copulas can specify the selected random variables. And it can measure the dependence and conditional dependencies of all marginal distribution functions. Copula more relies on the dependence of two (or more) variables on linear information.These measurements derived from copulas have been applied widely (Cheng et al., 2007; Wei & Hu, 2002; Vondenhende & Lambert, 2003). What`s more, it can be applied to describe more complicated multivariate dependence structures, like, nonlinearities and tail dependence (Hürlimann, 2004). The famous GARCH model can explain high volatility accompanied by high (low) volatility in markets, also fits well, which is wildly reported in literature, as shown by Engle (1996) for an outstanding survey. Joe et al. (2010) studied the extremal dependence of vine copulas and show that vine copulas can have a flexible range of bivariate lower and upper tail dependence parameters. Therefore, it is important to study the stock section with Vine copula GARCH model. In conclusion, this study has the basis of research, in terms of basic knowledge, theoretical preparation and related information is sufficient. This study can provide a suitable combination of investment methods indifferent sectors at Shanghai Stock Exchange. Also, this study can give the guide line to investor, and people who are interested in shanghai stock exchange market and want to do investment. In this study, we support to do the interdependence between different industries. How the spot prices of gold, spot prices of oil, the dollar index and the Shanghai Composite

Index impact on the relevant sectors. And what is the volatility between the stock sectors.

II. CONTRIBUTION TO LITERATURE

Athayde and Flores 2002 tacked into account the asset allocation under asymmetric distribution conditions: minimizing variance and kurtosis and minimizing any odd matrix in the case of the first two odd moment moments. Jondeau and Rockinger 2005 considered the joint non-normal distribution and time-varying characteristics of the yield, including the volatility aggregation, asymmetry and fat tail characteristics. Proposed partial normal distribution to measure the impact of high-order moments, and can fully consider the skewness of the higher order moments, and then the first-order condition to optimize the asset allocation. These measurements derived from copulas have been applied widely (Cheng et al., 2007; Wei & Hu, 2002; Vondenhende & Lambert, 2003). What`s more, it can be applied to describe more complicated multivariate dependence structures, like, nonlinearities and tail dependence (Hürlimann, 2004). The famous GARCH (generalized autoregressive conditional heteroskedasticity) model can explain high volatility accompanied by high (low) volatility in markets, also fits well, which is wildly reported in literature, as shown by Engle (1996) for an outstanding survey.

III. MATERIAL AND METHODOLOGY

We use the step parameter estimation program (Joe, 1997) to estimate the Copula and marginal distribution parameters. So we first use the skew Student-t distribution of the GARCH model to estimate each sector. Each marginal normalized residual is assumed to be i.i.d. Then the normalized residual is into an uniform distribution between 0 and 1. Thereafter, we select the preferable sequences of vine copulas in different orderings of the variables according to the sum of empirical Kendall's tau. The ARMAX-GARCH model with skewed Student-t distribution for the marginal is discussed in study.

ARMAX-GARCH has been further modeled by the same variance of the normal regression model. Significance is often more than the value of the analysis and prediction of the value itself for the analysis and prediction of volatility.

$$r_t = c + \sum_{i=1}^{p} \emptyset_i r_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \sum_{i=1}^{n} x_{t-\alpha} + \varepsilon_t,$$

$$\varepsilon_t = h_t * \eta_t, h_t^2 = \omega + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{l} \beta_i h_{t-i}^2 .$$

where ε_t is the random error, h_t is the conditional variance of volatility of ε_t, ϕ_i is the i^{th} lag AR parameter, ψ_i is the i^{th} lag MA parameter, α is the ARCH parameter associated with ε_{t-i}^2 to represent the short-run shock, β is the GARCH parameter associated with the volatility spillover effect from h_{t-i} to represent the persistence of volatility, and η_t is the standardized residual. $X_{i,t-\alpha}$ is an external variable. In addition, we impose the conditions $\sum_{i=1}^{p} \emptyset_i < 1$, $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\sum_{i=1}^{k} \alpha_i + \sum_{i=1}^{l} \beta_i < 1$ to ensure that the conditional variance process is positive and stationary. If the value of α_i is large, the short-term unexpected factors affecting the volatility have great influence. If the value of $\sum_{i=1}^{k} \alpha_i + \sum_{i=1}^{l} \beta_i$ is large, the impact of unexpected shock to volatility has the long duration. Copula function describes the correlation between variables, in fact, which is a class of joint distribution function and their respective edge is connected, so it was called the connection function. Sklar (1959) first gave the definition of a copula as follows: Let $x = (x_1, x_2, \dots, x_n)$ be a random vector with the joint distribution function H and the marginal distribution $F_1, F_2, \dots, F_n$, there exists a function C called copula function such that: $F(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F(x_n))$

Vine copulas are kind of multivariate, using bivariate copulas to construct multivariate distributions, and specify the dependence and conditional dependence of selected pairs of random variables and all marginal distribution functions. A dimensional vine copula is decomposed into n×(n–1)/2 pair-copulas, and the densities of multivariate vine copulas can be factorized in terms of pair-copulas and margins.

The principle is to model dependence by using simple local building blocks (pair-copulas) based on conditional independence. A joint probability density function of n variables x_1, x_2, …, x_n can be decomposed without loss of generality by conditioning iteratively, as : $f(x_1, x_2, \dots, x_n) = f(x_1) \cdot f(x_2|x_1) \cdot f(x_3|x_1, x_2) \dots f(x_n|x_{n-1}, \dots, x_1)$. Each term in the product can be further decomposed by using the case Copulas. For example, the first conditional density can be decomposed into the copula function c_{12} (the copula linking x_1 and x_2) multiplied by the density of x_2, as shown in Equation where $F_i(.)$ is the cdf of x_i: $f(x_2|x_1) = c_{12}(F_1(x_1), F_2(x_2)) \cdot f(x_2)$.

Thus, the joint densities of the three-dimensional case of C-vine and D-vine copulas can be represented by a function of the bivariate conditional copulas and a function of the marginal densities, respectively, such that:

$$f_{123}(x_1, x_2, x_3) = c_{12}(F_1(x_1), F_2(x_2)) c_{13}(F_1(x_1), F_3(x_3)) \times c_{23|1}(F_{2|1}(x_2|X_1), F_{3|1}(x_3|x_1)) \times f_1(x_1) \times f_2(x_2) \times f_3(x_3).$$

And

$$f_{123}(x_1, x_2, x_3) = c_{12}(F_1(x_1), F_2(x_2)) c_{23}(F_2(x_2), F_3(x_3)) \times c_{13|2}\left(F_{1|2}(x_1|X_2), F_{3|2}(x_3|x_2)\right) \times f_1(x_1) \times f_2(x_2) \times f_3(x_3).$$

This study concentrates on the inter-dependence structures between 12 different sectors, and volatility of 12 stock sectors in shanghai stock exchange and spot price in gold and oil; dollar index and The Shanghai composite index. So, the equation will be showed by three parts:

A: $Y_{nt} = \beta_{0n} + \beta_{1n}X_{1t} + \beta_{2n}X_{2t-1} + \varepsilon_{nt}$,

$\varepsilon_{nt} = \eta_{nt} * \sigma_{nt}$,

$\sigma_{nt}^2 = \omega_n + \alpha\varepsilon_{nt-1}^2 + r\sigma_{nt-1}{}^2$.

B: $Y_{mt} = \beta_{0m} + \beta_{1m}X_{1t} + \beta_{2m}X_{2t-1} + \beta_{3m}X_{3t} + \varepsilon_{mt}$,

$\varepsilon_{mt} = \eta_{mt} * \sigma_{mt}$,

$\sigma_{mt}^2 = \omega_m + \alpha\varepsilon_{mt-1}^2 + r\sigma_{mt-1}{}^2$.

C: $Y_{pt} = \beta_{0p} + \beta_{1p}X_{1t} + \beta_{2p}X_{2t-1} + \beta_{3p}X_{4t} + \varepsilon_{pt}$,

$\varepsilon_{pt} = \eta_{pt} * \sigma_{pt}$, $\sigma_{pt}^2 = \omega_p + \alpha\varepsilon_{pt-1}^2 + r\sigma_{pt-1}{}^2$

where, Y_{nt}: the n stock sectors at time period t (include 10 sectors: coal mining industry (zhongguoshenhua); textile industry(hailanzhijia); home appliance industry (haixindianqi); cement and other building materials (Conch Cement); Iron and steel industry (baogang shares); railway construction (zhongtiegongye); car, road transport(yutongkeche); Communications industry (zhongguoliantong); Commercial bank (ICBC bank); Insurance company (China Life Insurance). The stock names in brackets.

Y_{mt}: the stock related crude oil sectors (sector 11:crude oil industry (zhongguoshihua). Y_{pt}: the stock related gold sectors (sector 12 : gold (shandonghuangjin)) X_{1it}: the US dollar index at time period t. X_{2it-1}: the Shanghai composite index at last time period t-1. ε_{it}: the random error. σ_{it}: the conditional variance of volatility of ε_{it}. η_{it}o: the standardized residual. β_{ii}: the parameter associated with the long-run volatility from σ_{it-1}o to represent the persistence of volatility. ω_i: constant term.

In addition, we impose the conditions$\omega_i > 0$, $\beta_i > 0$ and ensure the conditional variance process is positive and stationary.

IV. DATA

This research studies data period from January 4, 2010, to December 31, 2014. Data used in this research are in 12 different A-shares stock sectors in Shanghai Stock Exchange (the sector name show in above equations). Also we interested that how the spot prices of gold, spot prices of oil, the dollar index and the Shanghai Composite Index impact on the relevant sectors. The data is frequency data, which is 5 days a week. We do the stationary process in all data. Then the source of data is come from Sohu Securities and Sina Finance.

V. RESULT OF THE STUDY

A. Application to China's sector indices

	Bank	Textile industry	insurance	Communications industry	Iron and steel industry	Railway construction	Cement and other building materials	Car, road transport
Mean	-0.00009	0.00049	0.00007	-0.00033	-0.00009	0.00014	-0.00064	0.00008
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.0723	1.0937	0.1906	0.0959	0.2513	0.1020	0.0955	0.0796
Minimum	-0.1233	-1.1011	-0.1054	-0.1020	-0.6809	-0.0960	-0.6382	-0.5435
Std. Dev.	0.0132	0.0500	0.0201	0.0172	0.0360	0.0246	0.0320	0.0260
Skewness	-0.6366***	-0.1729***	1.0519***	0.4968***	-5.4234***	0.7177***	-8.0995***	-7.5499***
Kurtosis	17.0779***	385.3726***	12.3715***	8.2078***	113.5785***	5.5433***	152.1332***	160.4429***
Jarque-Bera	10056.99***	7359182.00***	4643.29***	1414.80***	621377.80***	429.2832***	1132657.00***	1259153.00***
	Crude oil industry	Nonferrous metals industry	Coal mining industry	Home appliance industry	US dollar index	Shanghai composite index	spot price in oil	spot price in gold
Mean	-0.00063	-0.00141	-0.00045	-0.00068	0.00012	-0.00002	-0.00030	0.00005
Median	-0.0012	-0.0004	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000
Maximum	0.0956	0.4507	0.0953	0.0957	0.0199	0.0604	0.0736	0.0507
Minimum	-0.3052	-0.5581	-0.0943	-0.4427	-0.0252	-0.0558	-0.0825	-0.0891
Std. Dev.	0.0177	0.0354	0.0175	0.0310	0.0051	0.0120	0.0152	0.0112
Skewness	-4.0113***	-4.7143***	0.1905***	-4.4927***	-0.1374***	-0.2054***	-0.1704***	-0.7975***
Kurtosis	76.9231***	115.1794***	6.5410***	67.7488***	4.8990***	5.4713***	5.6178***	10.0992***
Jarque-Bera	278292.50**	637879.70***	638.41***	215081.50**	185.31***	315.91***	350.78***	2664.80***

Fig.1 Descriptive Statistics for Return of Stock Sectors

Note: "*," "," and "***" denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. For mean, skewness, the null hypotheses are: mean, skewness. For Kurtosis, the null hypothesis is Kurtosis = 3. For Jarque–Bera, null hypothesis: variable follows a normal distribution.**

Before we apply the vine copula GARCH model to study the relationship between different stock sectors in shanghai stock exchange. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. The estimates of kurtosis are the flattening coefficient of the distribution, and it is significantly positive for all sectors, and larger than normal distribution. The results of the (Jarque–Bera) normality test, tests for skewness and kurtosis coefficients tests confirm that the distribution of returns for all sectors is not normal. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the 1% level of significance for the variable.This means that using normal Copula is not advisable.

B. Kendall's tau

	Bank	Textile industry	Insurance	Communications industry	Iron and steel industry	Railway construction	Cement and other building materials	Car, road transport
Bank	1	0.1693***	0.3479***	0.3168***	0.2102***	0.2616***	0.2766***	0.1630***
Textile industry	0.1693***	1	0.2059***	0.2259***	0.2749***	0.2910***	0.2544***	0.2235***
Insurance	0.3479***	0.2059***	1	0.3556***	0.2636***	0.3257***	0.3382***	0.2263***
Communications industry	0.3168***	0.2259***	0.3556***	1	0.2731***	0.3153***	0.3045***	0.2286***
Iron and steel industry	0.2102***	0.2749***	0.2636***	0.2731***	1	0.2965***	0.2749***	0.2044***
Railway construction	0.2616***	0.2910***	0.3257***	0.3153***	0.2965***	1	0.3337***	0.2360***
Cement and other building materials	0.2766***	0.2544***	0.3382***	0.3045***	0.2749***	0.3337***	1	0.2671***
Car, road transport	0.1630***	0.2235***	0.2263***	0.2286***	0.2044***	0.2360***	0.2671***	1
Crude oil industry	0.3604***	0.2266***	0.3016***	0.3724***	0.2898***	0.3117***	0.3208***	0.2174***
Nonferrous metals industry	0.1713***	0.2351***	0.2285***	0.2270***	0.2667***	0.2325***	0.2170***	0.1857***
Coal mining industry	0.3736***	0.2858***	0.1087***	0.3884***	0.3340***	0.3703***	0.4120***	0.2566***
Home appliance industry	0.1664***	0.2775***	0.2747***	0.2576***	0.2720***	0.3154***	0.3328***	0.2510***
US dollar index	0.0903***	0.0761***	0.0843***	0.1220***	0.0783***	0.0664***	0.0567***	0.0525***
Shanghai composite index	-0.0593***	0.0012*	-0.0095*	0.0092*	0.0205*	-0.0026*	0.0161*	0.0065*
Spot price in oil	0.0581***	0.0698***	0.0657***	0.0527***	0.0613***	0.0467**	0.0591***	0.0311*
Spot price in gold	0.0368*	0.0743***	0.0422**	0.0332***	0.0616***	0.0210*	0.0313*	0.0389**

	Crude oil industry	Nonferrous metals industry	Coal mining industry	Home appliance industry	US dollar index	Shanghai composite index	Spot price in oil	Spot price in gold
Bank	0.3604***	0.1713***	0.3736***	0.1867***	0.0903***	0.0592***	0.0581***	0.0368*
Textile industry	0.2068***	0.1351***	0.1858***	0.1577***	-0.0764***	0.0013*	0.0498***	0.0743***
Insurance	0.3010***	0.2285***	0.4087***	0.2747***	0.0843***	0.0095*	0.0657***	0.0432**
Communication s industry	0.3724***	0.2279***	0.3884***	0.2576***	-0.1139***	0.0092*	0.0527***	0.0352***
Iron and steel industry	3899***	2667***	3340***	3703***	-.0783***	0.0285*	0.0613***	0.0616***
Railway construction	0.3117***	0.2225***	0.3703***	0.2367***	0.0664***	0.0026*	0.0467**	0.0216*
Cement and other building materials	0.3208***	0.2470***	0.4126***	0.3328***	-0.0907***	0.0161*	0.0691***	0.0313*
Car, road transport	0.2154***	0.1857***	0.2566***	0.2510***	-0.0525***	0.0065*	0.0611*	0.0589**
Crude oil industry	1	0.2281***	0.4288***	0.2463***	0.1118***	0.0072*	0.0852***	0.0528***
Nonferrous metals industry	0.2281***	1	0.3110***	0.2244***	-0.1324***	0.0015*	0.0979***	0.2870***
Coal mining industry	0.4288***	0.3110***	1	0.3038***	-0.1434***	-0.0245*	0.0824***	0.0367***
Home appliance industry	0.2463***	0.2244***	0.3038***	1	-0.0660***	0.0210*	0.017***	0.0285*
US dollar index	-0.1118***	-0.1324***	-0.1434***	-0.0660***	1	-0.0065*	-0.0417**	-0.1555***
Shanghai composite index	0.0072*	0.0015*	0.0245*	0.0210*	0.0065*	1	0.0035*	0.0458**
Spot price in oil	0.0852***	0.0979***	0.0824***	0.0017***	-0.0417**	0.0035*	1	0.1072***
Spot price in gold	0.0529***	0.2870***	0.0367***	0.0285*	0.1553***	0.0458**	0.1072***	1

Fig.2 Kendall's tau of Stock Sectors

Note: "*," "," and "***" denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. For Kendall's tau, the null hypotheses is Kendall's tau = 0.**

In addition, we use the Kendall's tau–b in this study. Kendall's tau displayed in Fig.2 reveal that the returns for each pair of sectors are closely related to each other, with the biggest dependence being that between the "Coal mining industry" and "Crude oil industry" sectors. And the spot prices in oil and gold have the positive significantly dependence with "Crude oil industry" and "Nonferrous metals industry" sectors.

C. Estimation for GARCH model

Parameters	Bank	Textile industry	insurance	Communications industry	Iron and steel industry	Railway construction
ω	0	0.0002	0	0	0	0
	[0]	[0]	[0]	[0]	[0]	[0]
α	0.1109***	0.2085***	0.0533***	0.0437*	0.2306***	0.0571***
	[0.009]	[0.0544]	[0.0139]	[0.0352]	[0.0316]	[0.0058]
β	0.8179***	0.5328***	0.9402***	0.8928***	0.7678***	0.9285***
	[0.0239]	[0.0986]	[0.0176]	[0.0283]	[0.0269]	[0.0112]
γ	1.0722***	0.9656***	1.0666***	1.0762***	1.0648***	1.0727***
	[0.0416]	[0.0348]	[0.0413]	[0.0445]	[0.0305]	[0.0433]
v	3.4385***	3.9456***	4.6968***	4.6311***	3.7314***	4.9649***
	[0.3144]	[0.4758]	[0.6814]	[0.7157]	[0.2069]	[0.6627]
log-likelihood	3822.393	2949.724	3171.338	3322.14	2781.735	2877.523
Parameters	Cement and other building materials	Car, road transport	Crude oil industry	Nonferrous metals industry	Coal mining industry	Home appliance
ω	0	0	0	0	0	0
	[0]	[0]	[0]	[0]	[0]	[0]
α	0.001*	0.0008***	0.0739***	0.0005***	0.0581***	0.0946***
	[0.0004]	[0.0001]	[0.0230]	[0.0001]	[0.0051]	[0.0297]
β	0.9979***	0.9972***	0.8357***	0.9955***	0.9155***	0.7562***
	[0.0002]	[0.0002]	[0.0415]	[0.0003]	[0.0118]	[0.0611]
γ	0.9549***	1.0620***	1.0918***	1.0268***	0.9781***	1.0106***
	[0.0383]	[0.0411]	[0.0398]	[0.0406]	[0.0386]	[0.0168]
v	3.6162***	5.4770***	3.8032***	2.7006***	4.1888***	0.9863***
	[0.8388]	[0.7492]	[0.4431]	[0.1040]	[0.4683]	[0.0434]
log-likelihood	2853.237	2994.217	3459.167	3086.3	3308.727	2757.347

Fig3 Results of GARCH Model for Returns of Sectors

Note: "*," "," and "***" are the 10%, 5%, and 1% significance levels, respectively. The numbers in the parentheses are the standard deviations.**

We use the ARMAX-GARCH model, and the behavior is long-return. We select the best ARMAX-GARCH model with the skewed Student-t distribution. The fig3, we notice the estimate in asymmetry parameter,γ is significantly smaller than the one for each return, implying that all the returns are skewed to the left. β is relatively large, indicating that time-dependent correlations show a high degree of persistence, α is the ARCH parameter, β and α are both positive significantly. In addition, there is a high persistence of shocks in the volatility, the sum of the estimates α and β are close to one, and the impact of unexpected shock volatility has the long duration. The parameter ν is significantly positive, and this is reflected in the long-term trend of rising stock prices. In addition, we find that the estimates of the degree of freedom ν are significant for all sectors with the degrees of freedom for "Nonferrous metals industry" and "Home appliance industry" being smaller than other sectors.

D. Test for marginal distribution for sectors

Before we proceed with Copula analysis, we must test the marginal distribution of each series satisfies and independence assumption, that it is uniform distributed (0, 1). Thus, we use the KS test and Box-Ljung test to test whether it is distributed as uniform (0, 1). Fig.4 shows that the probability values for both Box-Ljung and KS tests are greater than 5% in first moment, implying that the margins satisfy, and accept the null hypothesis and unif uniform distributed assumptions. And the model is appropriate with skewed Student-t distribution. Thus, the test shows that marginal distribution is uniform distributed (0, 1) and the data are independently distributed. In turn, the ARMAX-GARCH with SST distribution is fit to the margins.

Parameters	Bank	Textile industry	insurance	Communications industry	Iron and steel industry	Railway construction
KS test statistics p value	0.9933	0.4684	0.9499	0.9948	0.0508	0.8100
Box-Ljung test (first moment)	0.8806	0.3832	0.8275	0.4372	0.8172	0.6841
Parameters	Cement and other building materials	Car, road transport	Crude oil industry	Nonferrous metals industry	Coal mining industry	Home appliance industry
KS test statistics p value	0.8114	0.6190	0.7721	0.9364	0.8604	0.2833
Box-Ljung test (first moment)	0.9705	0.2934	0.2202	0.1287	0.7818	0.8812

Fig.4 KS Test and Box-Ljung Test

E. Results for copulas

copula	family	lower and upper tails	parameter1	parameter2	Kendall's tau	AIC	BIC
C12	student T copula	0.639	0.2292*** [0.7085]	8.6770*** [1.487]	0.1669	-90.0366	-80.6432
C13	student T copula	0.3588	0.2266*** [0.5037]	4.1857*** [0.6133]	0.3531	-426.3397	-415.9462
C14	survival Bell copula	lower 0.6142 upper 0.6509	0.1502*** [0.3027]	1.5172*** [0.0401]	0.2992	-309.4248	-299.2314
C15	survival BB8 copula	0	1.6852*** [0.4371]	0.8077*** [0.1284]	0.1971	-129.8946	-119.6014
C16	student T copula	0.103	0.3652*** [0.3859]	5.8501*** [4.3648]	0.2685	-308.8585	-298.6650
C17	student T copula	0.0033	0.4207*** [0.3947]	7.7646*** [1.7034]	0.2765	-331.6607	-321.4673
C18	Frank copula	0	1.4407*** [0.1754]	C [C]	0.1569	85.7346	80.6379
C19	student T copula	0.1776	0.3130*** [0.3020]	5.0349*** [1.1193]	0.2911	-386.7357	-376.5423
C110	student T copula	0.04	0.2005*** [0.2081]	5.7000*** [2.3600]	0.1718	-86.2278	-76.0343
C111	student T copula	0.2136	0.2412*** [0.2021]	5.4105*** [0.9571]	0.3643	-432.8943	-422.7009
C112	survival BB8 copula	0	0.3405*** [0.3834]	0.6510*** [0.2033]	0.1885	-99.8285	-89.6354

C23 | 1	survival BB8 copula	0	1.5282*** [0.2249]	0.8788*** [0.0943]	0.1417	-63.1802	-52.9868
C24 | 1	survival BB8 copula	0	1.7744*** [0.2990]	0.8238*** [0.1022]	0.1691	-81.1271	-70.9337
C25 | 1	survival BB8 copula	0	1.6805*** [0.1387]	0.9312*** [0.0348***]	0.2103	-174.3504	-164.1569
C26 | 1	survival BB8 copula	0	1.8677*** [0.1814]	0.9238*** [0.0409]	0.2502	-203.1666	-192.9731
C27 | 1	survival BB8 copula	0	1.7808*** [0.2404***]	0.8751*** [0.0733]	0.1978	-116.7122	-106.5188
C28 | 1	survival BB8 copula	0	2.2037*** [0.5637]	0.7222*** [0.1474]	0.1901	-103.1429	-92.9495
C29 | 1	survival BB8 copula	0	2.4951*** [1.1976]	0.5918*** [0.2604]	0.1641	-71.1720	-60.9785
C210 | 1	survival BB8 copula	0	1.9332*** [0.3390]	0.8035*** [0.1015]	0.1884	-102.1784	-91.9850
C211 | 1	survival BB8 copula	0	3.6908** [1.9119]	0.5185*** [0.2286]	0.2292	-140.2951	-130.1016
C212 | 1	survival BB8 copula	0	1.9477*** [0.2323]	0.8932*** [0.0571]	0.2451	-183.9914	-173.7979
C34 | 12	rotated Gumbel	lower 0.2733 upper 0	1.2690*** [0.0270]	0 [0]	0.2120	-160.2256	-155.1289
C35 | 12	survival BB8 copula	0	2.3353*** [0.8170]	0.6215*** [0.1963]	0.1602	-79.1049	-68.9114
C36 | 12	survival BB8 copula	0	2.8491*** [1.1148]	0.6127*** [0.1976]	0.2101	-120.2168	-110.0233
C37 | 12	student T copula	0.0241	0.3382*** [0.0262]	12.1384*** [4.3594]	0.2196	-141.1359	-130.9425
C38 | 12	survival BB8 copula	0	1.5306*** [0.1959]	0.8711*** [0.0833]	0.1388	-61.6168	-51.4234
C39 | 12	Frank copula	0	2.4490*** [0.1837]	0 [0]	0.2573	-178.5987	-173.5020
C310 | 12	rotated Gumbel	lower 0.1713 upper 0	1.1483*** [0.0228]	0 [0]	0.1292	-64.6446	-59.5479
C311 | 12	student T copula	0.1176	0.4257*** [0.0245]	6.7038*** [1.3864]	0.2799	-248.1796	-237.9861
C312 | 12	Frank copula	0	1.5945*** [0.1771]	0 [0]	0.1728	-79.2600	-74.1633
C45 | 123	Frank copula	0	0.9618*** [0.1678]	0 [0]	0.1059	-30.9889	-25.8922
C46 | 123	survival BB8 copula	0	1.9885*** [0.6655]	0.6817*** [0.2135]	0.1427	-53.1933	-42.9999
C47 | 123	Frank copula	0	1.0917*** [0.1755]	0 [0]	0.1199	-36.7616	-31.6648
C48 | 123	Frank copula	0	0.9551*** [0.1741]	0 [0]	0.1052	-28.1058	-23.0091
C49 | 123	Frank copula	0	1.6832*** [0.1798]	0 [0]	0.1820	-86.1188	-81.0221
C410 | 123	survival BB8 copula	0	1.3658*** [0.1623]	0.8965*** [0.0894]	0.1075	-33.6387	-23.4453
C411 | 123	survival BB8 copula	0	2.0801*** [0.6785]	0.7260*** [0.1982]	0.1743	-81.6506	-71.4571
C412 | 123	Frank copula	0	1.0590*** [0.1759]	0 [0]	0.1164	-34.3355	-29.2388

Fig.5 Estimated Result of C-vine Copula

copula	family	lower and upper tails	parameter1	parameter2	Kendall's tau	AIC	BIC
C56 | 1234	survival BB8 copula	0	1.3051*** [0.1450]	0.91025 [0.0666]	0.1256	-106.1938	-89.6079
C57 | 1234	survival BB8 copula	0	1.4340*** [0.1858]	0.8518*** [0.1005]	0.1684	-37.3083	-27.0739
C58 | 1234	survival BB8 copula	0	1.1400*** [0.0612]	0.9770*** [0.03***]	0.0704	-18.2410	-8.0516
C59 | 1234	Frank copula	0	1.0634 [0.1650]	0 [0]	0.1160	-26.3670	-34.2711
C510 | 1234	survival BB8 copula	0	2.2742*** [0.9643]	0.5727*** [0.2413]	0.1342	-51.1350	-40.9423
C511 | 1234	Frank copula	0	1.3488*** [0.1693]	0 [0]	0.1472	-62.3869	-57.2900
C512 | 1234	survival BB8 copula	0	3.0533*** [0.6036]	0.6765*** [0.1114]	0.1801	-78.5993	-68.3988
C67 | 12345	Frank copula	0	1.7500*** [0.1780]	0 [0]	0.1896	-85.9581	-80.8549
C68 | 12345	survival BB8 copula	0	1.3407*** [0.1336]	0.8709*** [0.1776]	0.0781	-14.7119	-4.5183
C69 | 12345	survival BB8 copula	0	1.3118*** [0.1642]	0.8713*** [0.1176]	0.0858	-15.0915	-4.8978
C610 | 12345	Frank copula	0	0.7880*** [0.1776]	0 [0]	0.0852	-8.8578	-3.7649
C611 | 12345	rotated Gumbel	lower 0.1569 upper 0	1.1330*** [0.0237]	0 [0]	0.1179	-46.4439	-41.3472
C612 | 12345	survival BB8 copula	0	1.5246*** [0.4978]	0.7099*** [0.1695]	0.1449	-53.4379	-43.2445
C78 | 123456	survival BB8 copula	0	1.2696*** [0.1293]	0.9437*** [0.0722]	0.0943	-26.4883	-15.2648
C79 | 123456	survival BB8 copula	0	1.1744*** [0.1353]	0.9531*** [0.1416]	0.0525	-4.7817	5.4417
C710 | 123456	Gaussian copula	0	0.1500*** [0.0178]	0 [0]	0.0958	-25.3693	-20.2756
C711 | 123456	survival BB8 copula	0	1.4572*** [0.1515]	0.9200*** [0.0553]	0.1505	-79.2710	-69.0785
C712 | 123456	Frank copula	0	1.3402*** [0.1807]	0 [0]	0.1473	-73.7845	-68.6877
C89 | 1234567	rotated Clayton	0	0.0728* [0.0311]	0 [0]	0.0036	0.0138	5.1076
C810 | 1234567	Frank copula	0	0.5526*** [0.1745]	0 [0]	0.0337	-6.1674	-1.2006
C811 | 1234567	Frank copula	0	0.7635*** [0.1720]	0 [0]	0.0715	-5.7496	-0.1959
C812 | 1234567	BB8 copula	0	1.2018*** [0.1898]	0.9324*** [0.1575]	0.0745	-14.8317	-4.6984
C910 | 1234567	survival BB8 copula	0	1.1915*** [0.1210]	0.9385*** [0.1052]	0.0494	-2.6446	8.1481
C911 | 1234567	BB8 copula	0	1.3892*** [0.3399]	0.9125*** [0.1586]	0.1236	-44.4257	-34.2323
C912 | 1234567	Clayton copula	lower 0.2002 upper 0	0.2784*** [0.0182]	0 [0]	0.1202	-8.9411	-3.8444
C1011 | 12345678	survival BB8 copula	0	1.5203*** [0.3493]	0.7698*** [0.1364]	0.1022	-25.4578	-15.2644
C1012 | 12345678	Gumbel copula	lower 0 upper 0.0589	1.0409*** [0.0171]	0 [0]	0.0389	-5.6218	-0.5282
C1112 | 123456789	survival BB8 copula	0	1.0307*** [0.0434]	0.9781*** [0.0465]	0.0315	-0.4712	9.7222
Sum						10.1681	6011.7279	5917.0870

Fig.6 Estimated Result of C-vine Copula (Continued)

Note: The significant codes: 0 "*" 0.001 "**" 0.01 "*" 0.05 "." 0.1.The numbers in the parentheses are the standard deviations.**

copula	family	lower and upper tails	parameter1	parameter2	Kendall's tau	AIC	BIC
C12	student T copula	0.0396	0.2682*** [0.0187]	8.6720*** [2.4460]	0.1669	-90.8300	-80.6431
C23	rotated Gumbel copula (survival)	lower 0.2648 upper 0	1.2678*** [0.0267]	0.0000 [0]	0.2049	-149.2357	-144.1390
C34	survival BB1 copula	lower 0.3752 upper 0.0094	0.1501*** [0.0517]	1.4260*** [0.0443]	0.2486	-408.4038	-398.2154
C45	rotated Gumbel copula (survival)	lower 0.2892 upper 0	1.2783*** [0.0256]	0.0000 [0]	0.2177	-200.5428	-195.4459
C56	rotated Gumbel copula (survival)	lower 0.3336 upper 0	1.2573*** [0.0281]	0.0000 [0]	0.2631	-298.3776	-293.2808
C67	rotated Gumbel copula (survival)	lower 0.4016 upper 0	1.4766*** [0.0317]	0.0000 [0]	0.3228	-340.5286	-335.4329
C78	student T copula	0.0828	0.2628*** [0.0254]	7.1734*** [1.9447]	0.2567	193.0713	183.7778
C89	Frank copula	0	1.8202*** [0.1780]	0.0000 [0]	0.2039	-113.2976	-110.1709
C910	student T copula	0.0956	0.2522*** [0.0269]	6.5537*** [1.7010]	0.2292	157.5717	147.3833

C1011	student T copula	0.1763	0.4626*** [0.0241]	5.3085*** [0.9507]	0.3062	-297.7520	-287.5585
C1112	student T copula	0.0716	0.4531*** [0.0232]	9.6387*** [2.7270]	0.2995	-259.6089	-249.4155
C13 | 2	student T copula	0.1954	0.4772*** [0.0237]	4.9970*** [0.8133]	0.3167	-328.7536	-318.5602
C24 | 3	survival BB8 copula	0	1.4099*** [0.1411]	0.9195*** [0.0607]	0.1297	-54.6066	-44.4131
C35 | 4	survival BB8 copula	0	1.8516*** [0.4466]	0.7787*** [0.1480]	0.1622	-86.0075	-75.8140
C46 | 5	survival BB8 copula	0	2.0447*** [0.3155]	0.8670*** [0.0756]	0.2466	-173.8884	-163.6949
C57 | 6	survival BB8 copula	0	1.7151*** [0.2137]	0.8429*** [0.0719]	0.1665	-93.0964	-82.9030
C68 | 7	survival BB8 copula	0	1.5311*** [0.2731]	0.8505*** [0.1259]	0.1302	-50.7785	-40.5851
C79 | 8	student T copula	0.0545	0.3881*** [0.0252]	9.5950*** [2.7024]	0.2537	-185.8806	-175.6871
C810 | 9	survival BB8 copula	0	1.6762*** [0.4071]	0.7778*** [0.1734]	0.1310	-48.0126	-37.8192
C911 | 10	survival BB1 copula	lower 0.3483 upper 0.0838	0.2024*** [0.0552]	1.3813*** [0.0430]	0.3426	-401.5872	-391.3938
C1012 | 11	survival BB8 copula	0	1.4359*** [0.1982]	0.8966*** [0.0976]	0.1264	-42.9063	-32.7128

Fig.7 Estimated Result of D-vine Copula

copula	family	lower and upper tails	parameter1	parameter2	Kendall's tau	AIC	BIC
C14 | 23	rotated Gumbel copula (survival)	lower 0.1834 upper 0	1.1611*** [0.0235]	0.0000 [0]	0.1388	-78.3686	-73.2719
C25 | 34	survival BB8 copula	0	1.5891*** [0.2043]	0.8931*** [0.0707]	0.1637	-98.3722	-88.1788
C36 | 45	survival BB8 copula	0	2.8576** [1.4672]	0.5512*** [0.2557]	0.1794	-81.3027	-71.1092
C47 | 56	frank copula	0	1.5074*** [0.1818]	0.0000 [0]	0.1638	-66.6631	-61.5664
C58 | 67	survival BB8 copula	0	1.1597*** [0.0960]	0.9550*** [0.0701]	0.0627	-15.5364	-5.3429
C69 | 78	survival BB8 copula	0	1.6984*** [0.1723]	0.9059*** [0.0450]	0.1977	-132.3766	-122.1831
C710 | 89	survival BB8 copula	0	1.7309*** [0.4271]	0.8068*** [0.1649]	0.1542	-65.0272	-54.8338
C811 | 910	survival BB8 copula	0	1.5410*** [0.2371]	0.8412*** [0.1106]	0.1287	-49.9078	-39.7144
C912 | 1011	survival BB8 copula	0	1.2109*** [0.0759]	0.9735*** [0.0353]	0.0895	-25.8633	-15.6699
C15 | 234	frank copula	0	0.5378*** [0.1675]	0.0000 [0]	0.0596	-8.3261	-3.2294
C26 | 345	Clayton copula	lower 0.1144 upper 0	0.3197*** [0.0424]	0.0000 [0]	0.1378	-73.3944	-68.2977
C37 | 456	frank copula	0	1.4269*** [0.1790]	0.0000 [0]	0.1554	-61.5782	-56.4814
C48 | 567	survival BB8 copula	0	1.2820*** [0.1226]	0.9004*** [0.0796]	0.0884	-23.4411	-13.2476
C59 | 678	frank copula	0	1.4107*** [0.1698]	0.0000 [0]	0.1537	-67.5739	-62.4772
C610 | 789	survival BB8 copula	0	1.2450*** [0.1200]	0.9305*** [0.0763]	0.0842	-22.8418	-12.6484
C711 | 8910	survival BB8 copula	0	3.0425*** [1.0668]	0.6070*** [0.1741]	0.2261	-141.9094	-131.7160
C812 | 91011	BB8 copula	0	1.6663*** [0.4334]	0.7812*** [0.1838]	0.1305	-49.7414	-39.5480
C16 | 2345	Clayton copula	lower 0.0011 upper 0	0.1013*** [0.0319]	0.0000 [0]	0.0482	-11.0244	-5.9276
C27 | 3456	survival BB8 copula	0	1.3477*** [0.2318]	0.8198*** [0.1677]	0.0795	-14.7529	-4.5594
C38 | 4567	survival BB8 copula	0	1.1808*** [0.1698]	0.8499*** [0.1079]	0.0467	-3.0419	7.1516
C49 | 5678	student T copula	0.0171	0.3061*** [0.0269]	12.8096*** [5.0172]	0.1981	-117.6760	-107.4825
C510 | 6789	frank copula	0	1.1457*** [0.1723]	0.0000 [0]	0.1257	-42.3826	-37.2859
C611 | 78910	survival BB8 copula	0	1.4582*** [0.2344]	0.8928*** [0.1075]	0.1305	-54.3171	-44.1237
C712 | 891011	survival BB8 copula	0	1.6479*** [0.2607]	0.8558*** [0.1053]	0.1584	-66.7951	-56.6017
C17 | 23456	student T copula	0.0003	0.0868*** [0.0300]	21.2685* [12.6019]	0.0553	-7.8991	2.2943
C28 | 34567	survival BB8 copula	0	1.2278*** [0.1024]	0.9456*** [0.0615]	0.0839	-23.3158	-13.1223
C39 | 45678	student T copula	0.0483	0.2481*** [0.0281]	7.7313*** [1.8418]	0.1596	-79.9123	-69.7188
C410 | 56789	survival BB8 copula	0	1.1272*** [0.0717]	0.9597*** [0.0598]	0.0517	-7.1137	3.0797
C511 | 678910	frank copula	0	0.7418*** [0.1698]	0.0000 [0]	0.0820	-17.1016	-12.0049
C612 | 7891011	survival BB8 copula	0	1.3325*** [0.0992]	0.9578*** [0.0392]	0.1254	-54.0535	-43.8601
C18 | 234567	rotated Clayton copula (90	0	(-0.0329* [0.0300]	0.0000 [0]	-0.0162	0.6951	5.7918
C29 | 345678	rotated Gumbel copula (survival)	lower 0.0259 upper 0	1.0192*** [0.0144]	0.0000 [0]	0.0188	-0.6796	4.4171
C310 | 456789	rotated Gumbel copula (survival)	lower 0.0340 upper 0	1.0300*** [0.0159]	0.0000 [0]	0.0291	-9.1753	-4.0786
C411 | 56789	frank copula	0	1.0991*** [0.1797]	0.0000 [0]	0.1207	-35.4656	-30.3689
C512 | 67891011	frank copula	0	0.6014*** [0.1703]	0.0000 [0]	0.0666	-10.4969	-5.4002
C19 | 2345678	frank copula	0	1.2812*** [0.1784]	0.0000 [0]	0.1401	-49.5703	-44.4736
C210 | 3456789	student T copula	0.0015	0.0813*** [0.0305]	15.7740*** [5.9511]	0.0518	-10.3464	-0.1530
C311 | 45678910	frank copula	0	1.4418 [0.1794]	0.0000 [0]	0.1570	-62.7440	-57.6473
C412 | 567891011	BB8 copula	0	1.0726*** [0.0753]	0.9579*** [0.1113]	0.0297	0.6905	10.8839
C110 | 23456789	rotated Clayton copula (90	0	(-0.03761* [0.0293]	0.0000 [0]	-0.0185	0.1755	5.2722
C211 | 345678910	frank copula	0	0.3705*** [0.1770]	0.0000 [0]	0.0411	-2.3819	2.7148
C312 | 4567891011	rotated Clayton copula	0	0.0824* [0.0300]	0.0000 [0]	0.0160	0.7438	5.8405
C111 | 2345678910	frank copula	0	0.9417*** [0.1758]	0.0000 [0]	0.1037	-26.7229	-21.6262
C212 | 34567891011	frank copula	0	0.8436*** [0.1812]	0.0000 [0]	0.0931	-19.6732	-14.5765
C112 | 34567891011	Gaussian copula	0	(-0.0422* [0.0280]	0.0000 [0]	-0.0268	-0.2502	4.8465
Sum						9.2926	-5766.4140	-5231.2590

Fig.8 Estimated Result of D-vine Copula(Continued)

Note: The significant codes: 0 "*" 0.001 "**" 0.01 "*" 0.05 "." 0.1.The numbers in the parentheses are the standard deviations.**

Now we apply C-vine and D-vine copula to analyze the stock sectors in shanghai stock exchange. We report the results of C-vine and D-vine copulas in Fig5, Fig6, Fig7 and Fig8, respectively. In this paper, the copula families that have been used include the

Gaussian, Student T, Clayton, Frank, Gumbel, Joe, BB8, 90 degree and survival copulas. Fig5 and Fig6 represents the estimated results for the C-vine copula with Kendall's tau, AIC, BIC, lower and upper tail dependence, etc., whereas Fig7 and Fig8 represent the estimated results for the D-vine copula. For all Vine copula estimate, we suppose that '1,' '2,' '3,' '4,' '5,' '6,' '7,' '8,' '9,' '10,' '11,' '12,'represent 12 stock sectors ("Bank", "Textile industry", "Insurance", "Communications industry", "Iron and steel industry", "Railway construction", "Cement and other building materials", "Car, road transport", "Crude oil industry", "Nonferrous metals industry", "Coal mining industry", "Home appliance industry"), respectively.

The Fig5, Fig6, Fig7and Fig8 show the C-vine and D-vine copula result. According to the AIC and BIC and Kendall's tua in sum of C-vine and D-vine, AIC and BIC of C-vine are less than D-vine, and Kendall's tua of C-vine is bigger than D-vine. So, the C-vine is better than D-vine. This indicates that the pure oval method of the interdependency of the measurement system does not adequately capture all the relevant dependency characteristics, especially the asymmetric tail behavior. First, the results with highest interdependence between 1(bank) and 3(insurance), and the lowest interdependence between 8(Car, road transport) and 9(Crude oil industry), conditional on 1234567(the first sector to 7th sector) in C- vine, equals to 0.0206 with tiny tail dependence structure.

We are now trying to explain the estimates in Fig7 and Fig8. We need to announce that the second column "copulas" in each table shows the best copula family in terms of AIC and BIC. We can observe that showing copulas are more suitable than other families in C-vine copula and D-vine copula.

CONCLUSION

This paper intend to do the dependent and volatility in stock sectors of shanghai stock exchange. How the spot prices of gold, spot prices of oil, the dollar index and the Shanghai Composite Index impact on the relevant sectors. The result of study is that: First, we analyzed the daily data. The marginal was modeled using the skewed Student-t distribution, and the C-vine copula was observed to have better performance in terms of AIC and BIC. The Gaussian, T, Clayton, Frank, Gumbel, Joe, BB8, 90 degree and survival copulas, it was the best copulas of many candidates, also showed the hierarchical dependency of Kendall's tau and tail dependency. The highest interdependence is between 1(bank) and 3(insurance), which have a similar rank and biggest correlation coefficient. And the lowest interdependence is between 8(Car, road transport) and 9(Crude oil industry), which have a dissimilar rank between the two variables. Second, the each pair of sectors is closely related to each other, with the biggest dependence being that between the "Coal mining industry" and "Crude oil industry" sectors, which equal to 0.4298. Third, the spot prices in oil and gold have the positive significantly dependence with "Crude oil industry" and "Nonferrous metals industry" sectors. For spot prices in gold, it has the biggest dependence (0.2976) on "Nonferrous metals industry". But for spot prices in oil, it has big inter-dependence on "Crude oil industry" (0.0852), "Nonferrous metals industry" (0.0976) and "Coal mining industry" (0.0884). So, the inter-dependence not only related in similar sector, but also others. Fourth, from ARMAX-GARCH model, the sum of the estimates α and β are close to 1, and significant positive in α and β, implying that the impact of unexpected shock to volatilities has the long duration. Last, when we know some of stock sectors changing, we can find the relationship in other sectors. So, we can consider the correlation of each stock. When we know one trend, we could follow this study to find another volatility trend.

REFERENCE

[1] Aas, K., Czado, C., Frigessi, A. and Bakken, H., 2009. 'Pair-copula construction of multiple dependence', Insurance: Mathematics and Economics, Vol.44, 182–198.

[2] Boubaker, H. and Sghaier, N., 2013. 'Portfolio optimization in the presence of dependent financial returns with long memory: A copula based approach', Journal of Banking & Finance, Vol.37, 361–377.

[3] Geidosch, M. and Fischer, M., 2016. 'Application of Vine Copulas to Credit Portfolio Risk Modeling', Journal of Risk and Financial Management, Vol. 9(2), 4; doi:10.3390/jrfm9020004.

[4] Markowitz, H.M., 1952. 'Portfolio selection', Journal of Finance, Vol.7, 77–91.

[5] Wu, Z., Chen, M. and Ye, W., 2006. 'Risk Analysis of Portfolio by Copula-GARCH', Systems Engineering Theory and Practice, Vol.26, 45–52.

[6] Wang, J., & Yang, M., (2009). Asymmetric volatility in foreign exchange markets. Journal of International Financial Markets Institutions and Money 19, 597-615.

[7] Jondeau, E., Rockinger, M., 2006. The copula-GARCH model of conditional dependencies: An international stock market application. Journal of International Money and Finance 25, 827-853.

[8] Smith, M., Min, A., Czado, C. and Almeida, C., 2010. 'Modeling longitudinal data using a pair-copula decomposition of serial dependence', Journal of the American Statistical Association, Vol.105, 1467–1479.

[9] Nelsen, R., 2006. An introduction to copulas, Springer, New York.

[10] Min, A. and Czado, C., 2010. 'Bayesian inference for multivariate copulas using pair-copula constructions', Journal of Financial Econometrics, Vol.8, 511–546.

[11] Nikoloulopoulos, A.K., Joe, H. and Li, H., 2012. 'Vine copulas with asymmetric tail dependence and applications to financial return data', Computational Statistics and Data Analysis, Vol.56, 3659–3673.

[12] Patton, A.J., 2006. 'Modelling asymmetric exchange rate dependence', International Economics Review, Vol.47, 527-556.

[13] McAleer,M.L, Chan,F.D.,& Marinova. (2007). An econometric analysis of asymmetric volatility: theory and application to patents, Journal of Econometrics. 130,259-284.

[14] Patton, J. A. (2007). Copula –based model for financial time series, Working paper, OMI 11/07.

[15] Patton,J.A.(2012). A review of copula model for economic time series, Journal multivariate Analysis 110 (2012)4-18.
[16] Patton,A.J.(2006a).Modelling Asymmetric Exchange rate dependence international Economic Review 47,527-556.
[17] Wu, S., (2014), Construction of asymmetric copulas and its application in two- dimensional reliability modelling. European Journal of Operational Research.
[18] Wang, J., & Yang, M., (2009). Asymmetric volatility in foreign exchange markets. Journal of International Financial Markets Institutions and Money 19, 597-615.
[19] Saghaian, S. H. (2010). "The impact of the oil sector on commodity prices: Correlation or causation?" Journal of Agricultural and Applied Economics 42(03): 477-485.
[20] Demiralay, S., & Ulusoy, V., (2014). Non-linear volatility dynamics and risk management of precious metals. North American Journal of Economics and Finance 30, 183-202.

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