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Dependence structure analysis between stock index futures and spot markets in the case of the "Golden week" effect

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ABSTRACT

The dependence structure analysis of a financial time series of returns is significant when applied to contemporary financial risk management. Copula function is a flexible and effective tool to be used on modeling the financial model and risk management. This paper aims to set up the dependence structure between CSI300 index and futures by Copula-ARMA-GARCH models and find out which copula can provide a better fit to the empirical data in case of the "Golden Week" effect. Moreover, we analyze the degree of linear dependence, rank correlation and tail dependence between CSI300 index and futures. The empirical results indicate that there is high degree of dependence between CSI300 index and futures. The asymmetric tail dependence description is better, and tail dependence is significantly high. It also demonstrates that the "Golden week" effect could decline the rank correlation and slightly weaken the dependence between CSI300 index and futures.

Keywords: Dependence, Stock index futures, Spot markets, "Golden week" effect, Copula-ARMA-GARCH models

JEL Classification: C22, C58, G11

1. Introduction and rationale

The global economy had entered a post-crisis era in 2010. After such a crisis since 2008, we should pay attention to the cognition and research of correlation models between the different financial markets, and then we could take effective measures to prevent risks shock from other markets. In the April 16, 2010, CSI300 index futures officially listed for trading in China Financial Futures Exchange, which marked the end of China's capital unilateral market. The launch of CSI300 index futures will make the research on dependence of financial risk more complicated and the challenge stronger.

In 1999, Chinese Legal Holidays were adjusted to the three "Golden week" holidays, the formation of the Spring Festival, Labor Day and National Day. These gave birth to the holiday economy's "Golden week", which aroused the summit of travel, leisure, shopping and entertainment consumption. From 2008 onwards, Labor Day was excluded from the "Golden week" so that the three "Golden week" holidays were reduced to two. The "Golden week" effect is one type of calendar effect. Both the pre-holiday and post-holiday lead to abnormal returns and fluctuation. These phenomena found that the Efficient Market Hypothesis (EMH) was not perfect, and the market wasn't effective all the way.

2. Literature Reviews

Compared with the traditional GARCH class model, copula function provides a new, more robust and flexible analysis method for the study of multivariate correlation. It does not limit the specific choice of marginal distributions. Furthermore, the consistency and tail dependence measure based on copula function can accurately and effectively describe the nonlinear, asymmetric relationship between random variables. Wei and Zhang (2004) based on the comparison of different marginal distribution models of each sector index return series in the Shanghai stock market established the Copula-GARCH-t model, and then researched on the conditional dependence for each sector. The empirical results show that different index returns series have different marginal distribution. When you combine copula function, there are strong positive correlations between these series. Zhao and Ai (2010) use a Copula-GARCH-t model for describing the marginal distribution and correlation of the sequence. Compared with traditional methods VECH, CCC model, BEKK model, it was found that Copula-GARCH model could fit the characteristics of financial time series better and make data analysis easier. Ni and Jiang (2011), using Copula-GARCH models, found that there are a high positive dependence and tail dependence between Shanghai Composite stock index return and CSI300 index futures return. In addition, it showed these two return sequences have the joint thick tail, with a higher upper tail and lower tail dependence.

The holiday effect or special event effect is not quite common around the world. It has very strong regional characteristics and is often related to the local cultures. Yi and Liu (2005) found that the Legal holidays all presented the abnormal return and the Chinese New Year was the most obvious. Lu and Liu (2008) found evidence of a pre-holiday effect and a post-holiday effect in the stock market in China. In addition, the study showed that anomaly returns in pre-holiday and post-holiday are not for other calendar effects (Monday Effect, Friday Effect and January Effect). Wu (2009) found empirical evidence of existence and continuance of holiday effects in the Chinese stock market by using the ARMA-GARCH model. It also indicated that the closer in proximity to the holiday, the more obvious the holiday effects are. Sudtasan (2012) found that the “Window dressing” at the end of the year affected to shift of stock prices from lower to higher regimes. Moreover, Sudtasan and Suriya (2014) also revealed that the event of XD dates both in April and August raised the stock prices and increased the opportunity of investors to make profit from the speculation in these periods.

There are a few researches on the sequence of daily return dependency between stock index and index futures. The stock index futures which was specifically less was CSI300, which has been short-time term since its introduction in China from 2010. Therefore, this paper portrays studies of their dependence based upon Copula-GARCH models. More importantly, the goal of this paper is to fill the gap by combining the holiday effect and CSI300 index and futures. In other words, it examines how the dependence structure is when taking into account the “Golden week” effects.

3. Econometrics Models

3.1 The model for the marginal distributions

For the financial return data, a ARMA(p,q)-GARCH(m,n)[1] model is chosen to model the marginal distributions. The ARMA(p,q) (1) and GARCH(m,n) (3) model represent the mean and variance of the financial time series, respectively. It can be described by the following equations:

$$R_t = \mu_t + a_t = \mathrm{c} + \sum_{i=1}^{p} \phi_i (R_{t-i} - c) + \sum_{j=1}^{q} \varphi_j a_{t-j} + a_t \tag{1}$$

$$a_t = h_t^{1/2} \varepsilon_t \tag{2}$$

$$h_t = \omega + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{n} \beta_j h_{t-j} \tag{3}$$

Where, $\sum_{i=1}^{p} \phi_i < 1, \omega > 0, \alpha_i \geq 0, \beta_j \geq 0, \sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{n} \beta_j < 1$. μ_t and h_t are the mean and variance given past information, respectively. ε_t is the innovation process, the standardized residual, which can be assumed for any distribution, GED, student t, Gaussian, skewed t distribution, etc. Student-t and GED distribution are suitable to depict the asymmetric and thick-tailed distribution of financial return series. $\varepsilon_t \sim t(\lambda)$, that is the t distribution with 0 mean and λ degrees of freedom. The probability density function (PDF) of GED distribution is $f(x) = \frac{\nu}{\lambda \cdot 2^{(\frac{\nu+1}{\nu})} \Gamma(1/\nu)} \exp(-\frac{1}{2}\left| x/\lambda \right|^{\nu})$, where

[1] Extensions of the GARCH model, such as EGARCH, TARCH, among others, are also fitted to data in order to find out the best model for the marginals.

$\lambda=\left[\frac{2^{(-2/\nu)}\cdot\Gamma(1/\nu)}{\Gamma(3/\nu)}\right]^{1/2}$, $\Gamma(\bullet)$ is the gamma function. ν is shape parameter (or called DOF) which controls the degree of thickness of tail distribution. ν is equal to 2 with the normal distribution, and with the decrease of ν value, "fat tail" phenomenon is more obvious. That is to say, the probability of extreme events occurrence increases with the decrease of ν. Many researches showed that volatility clustering, fat tail, leptokurtic and skewness of financial time series could be well described by GARCH(1,1)-t/GED and EGARCH(1,1)-t/GED. Moreover, ARMA (1, 1) is sufficient for solving the autocorrelation of series. Specifically, EGARCH could both to ensure the non-negative of h, and then cancel the non-negative limiting of coefficient in GARCH process, and to reflect the asymmetric fluctuation (Leverage effect). The EGARCH model is,

$$\ln(h_t^2)=\omega+\sum_{i=1}^{n}\alpha_i\varepsilon_{t-i}+\sum_{i=1}^{n}\gamma_i\left|\varepsilon_{t-i}\right|+\sum_{j=1}^{m}\beta_j\ln(h_{t-j}^2) \tag{4}$$

$$a_t=h_t\varepsilon_t,\varepsilon_t \sim i.i.d(0,1)$$

Thus, this paper utilizes ARMA(1,1)-GARCH(1,1)/ EGARCH(1,1)-t/GED filter which is applied to the return data to obtain the parameter estimates and the transformed data(i.e., the uniforms).

3.2 The Copula model for the joint distribution

Suppose the marginal distribution function of a multi-dimensional distribution function F(x) is that $F_1(x_1)$, …, $F_n(x_n)$, then there is a copula function satisfies:

$$F(x_1, \dots, x_n) = C(F_1(x_1),F_2(x_2), \dots ,F_n(x_n)) \tag{5}$$

If $F_1(x_1)$, $F_2(x_2)$, … , $F_n(x_n)$ is continuous, the copula function is uniquely determined, and vice versa.

This paper utilizes four copula functions from two copula families, Gaussian and Student-t copulas (Elliptical Copula), Gumbel and Clayton copulas (Archimedean Copula functions).

The density function of Gaussian copula is:

$$\begin{aligned}C_{Ga}(u,v,\rho)&=\int_{-\infty}^{\phi^{-1}(u)}\int_{-\infty}^{\phi^{-1}(v)}\frac{1}{2\pi\sqrt{1-\rho^2}}\exp\left(-\frac{x_1^2-2\rho x_1x_2+x_2^2}{2(1-\rho^2)}\right)dx_1dx_2\\&=\phi_\rho\left(\phi^{-1}(u),\phi^{-1}(v);\rho\right)\end{aligned} \tag{6}$$

The Gaussian copula cannot capture tail dependence, which is its critical flaw. Kendall.tau equals to $2/\pi\arcsin(\rho)$.

The density function of Student t copula is:

$$C_t(u,v)=\int_{-\infty}^{T_\nu^{-1}(u)}dx\int_{-\infty}^{T_\nu^{-1}(v)}dy\frac{1}{2\pi\sqrt{1-\rho^2}}\left(1+\frac{x^2-2\rho xy+y^2}{\nu(1-\rho^2)}\right)^{-(\nu+2)/2} \tag{7}$$

$$T_{\nu}(x)=\int_{-\infty}^{x}\frac{\Gamma\left((\nu+1)/2\right)}{\sqrt{\pi\nu}\Gamma(\nu/2)}(1+\frac{z^{2}}{\nu})^{-(\nu+1)/2}dz$$

Student t copulas assign a higher probability to joint extreme co-movements as compared to Gaussian copulas, the lower the parameter ν. It also can capture the tail dependence, $\lambda_{\text{up}}=\lambda_{\text{low}}=2\left\{1-t_{\nu+1}(\sqrt{\nu+1}\sqrt{1-\rho}\big/\sqrt{1+\rho})\right\}$. The tail dependence coefficient means that when one variable is extremum, the probability that the other variable is led to be extremum. The upper tail dependence coefficient describes the probability of two variables simultaneously are the maximum. On the contrary, the lower tail dependence describes the probability of two variables simultaneously are the minimum. The Kendall.tau equals to $2\big/\pi\arcsin(\rho)$.

The density function of Clayton copula is:

$$C_{Cl}\left(u,v;\theta\right)=\left(u^{\theta}+v^{\theta}-1\right)^{-1/\theta} \tag{8}$$

On the contrary, Clayton copula can catch lower tail dependence $\lambda_{low}=2^{-(1/\theta)}$. The parameter $\theta\to 0$ implies the two random variables are independent and $\theta=+\infty$ is perfectly correlated. Kendall.tau equals to $\theta/(\theta+2)$.

The density function of Gumbel copula is:

$$C\left(u,v;\theta\right)=\exp\left(-\left((-\ln u)^{1/\theta}+(-\ln v)^{1/\theta}\right)^{\theta}\right) \tag{9}$$

Where $1\le\theta<+\infty$, greater θ means more dependent. The upper limit of θ is $+\infty$. From Gumbel copula, the Kendall.tau equals to $1-(1/\theta)$. This copula can capture upper tail dependency, $\lambda_{up}=2-2^{1/\theta}$ while the lower tail dependence $\lambda_{low}=0$.

3.3 Estimation method

The maximum-likelihood estimation (MLE) is used to estimate the parameters of copula models. The equation is: $\hat{\theta}=\arg\max\sum_{t=1}^{T}\ln C(u_t,v_t;\theta)$.

4. Empirical analysis

4.1 Data and descriptive statistics

This paper chooses the daily closing price of CSI300 index and futures, covered for three and a half years since the introduction of CSI300 index futures, from 16th April, 2010 to 18th October, 2013, with a total of 847 trading days. Two groups are divided to represent the sample1 (whole data sample) and sample2 (without 3days data of pre- and post-holiday respectively). The “Golden week” effect is considered by sample2. SR1 represents the series of CSI300 index return of sample1 and FR1 is the series of CSI300 index futures return of sample1. Similarly, SR2 represents the series of CSI300 index return of sample2 and FR2 is the series of CSI300 index futures return of sample2. To analyze the Index Returns, we use the 100 times log-differences of each daily closing price ($R_t=100\times(\ln(P_t)-\ln(P_{t-1}))$).

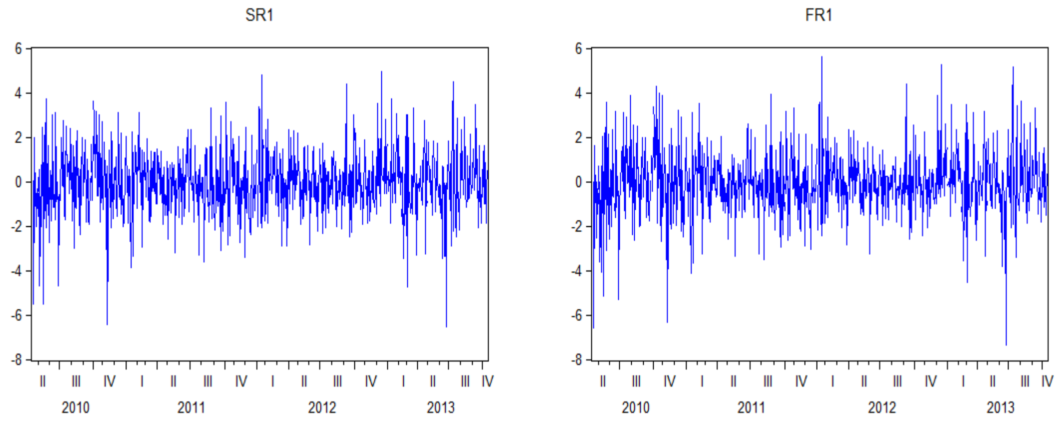

Figure 1. Log daily CSI300 index and futures returns of Sample 1

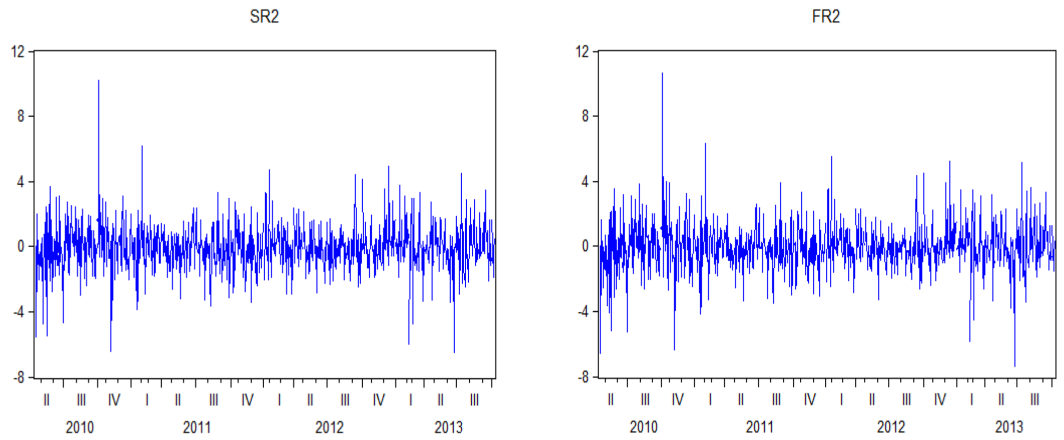

Figure2: Log daily CSI300 index and futures returns of Sample 2

From the two figures, we can see that the daily returns series of CSI300 index and futures have a strong volatility and lots of dates with maximum or minimum values. We can also see, in Sample1 or Sample2, large fluctuations are followed by large fluctuations and small fluctuations are followed by small fluctuations. Furthermore, when the stock market is in a larger volatility, the futures market volatility is relatively larger.

Table1 presents the summary statistics of the data. As can be seen from table 1, the distribution of daily returns is clearly non-normal (the Jarque–Bera test is rejected at a 1% significance level). The negative skewness/asymmetry in sample1 (positive skewness in sample2) and means there is a long tail in the negative direction in sample1 (positive direction in sample2), and excess kurtosis is significantly high (greater than 3) with positive value which is called leptokurtic. The results of Ljung-Box test and ARCH-LM test indicates that all the sequences do not have autocorrelation and ARCH effect (all the p-values are greater than 0.05). To check stationarity, we applied the Augmented

Dickey–Fuller (ADF) test and Phillips–Perron (PP) test in Table2. The null hypotheses (the series has a unit root) of these tests are all rejected whether at 1%, 5% or 10% significance level. That signifies that both of four return series are stationary.

Table1. Summary statistics of the CSI300 and index futures daily log-returns

	SR1	FR1	SR2	FR2
Mean	-0.038322	-0.040927	-0.040320956	-0.043062595
Median	-0.036258	-0.075188	-0.043917537	-0.084313806
Std. Dev.	1.424226	1.462056	1.490160538	1.532701952
Skewness	-0.1921	-0.078861	0.204749463	0.352710589
Kurtosis	4.876069	5.533045	7.60768038	8.284664691
Jarque-Bera	129.4231	227.3204	717.7382633	953.4319354
Probability	0	0	0	0
Q(5)	5.2326(0.388)	4.2816(0.51)	3.2224(0.666)	3.4487(0.631)
Q(10)	16.046(0.098)	11.771(0.301)	15.057(0.13)	12.711(0.24)
ARCH LM(2)	5.111(0.07764)	0.4014(0.8181)	1.431(0.4888)	0.5824(0.7474)
ARCH LM(5)	9.358(0.09559)	3.5012(0.6232)	3.371(0.6429)	2.0709(0.8393)
Observations	847	847	805	805

Note: Q(5)&Q(10) and ARCH LM(2)&ARCH LM(5) with the lag order in parentheses correspond to Ljung-Box test and ARCH-LM test statistics with p-value in parentheses, respectively. In addition, the latter is the ARCH LM test for residual sequence after doing GARCH model.

Source: computation.

Table2. Summary of Stationary test

	ADF Test		P-P Test	
	t-Statistic	Prob.	Adj. t-Stat	Prob.
SR1	-29.22101	0.0000	-29.22133	0.0000
FR1	-29.80990	0.0000	-29.80916	0.0000
SR2	-28.16010	0.0000	-28.16029	0.0000
FR2	-28.76049	0.0000	-28.76097	0.0000

Source: computation.

4.2 Estimation results

In this paper, ARMA(1,1)-(E)GARCH(1,1) model is applied to fit the marginal distribution of returns. Since we do not know the specific form of residuals, we suppose that residuals follow the t-distribution and GED distribution for fitting every single series. The model estimation results are showed in Table3 and Table4. By comparing the AIC and BIC values of models, the most appropriate estimation method of each marginal distribution could be selected. The results indicate that all residuals satisfying the GED distribution assumption is superior to t distribution. Meanwhile, we choose ARMA(1,1)-EGARCH(1,1) model to fitting SR1 series and ARMA(1,1)-GARCH(1,1) to the remaining three series, FR1, SR2 and FR2.

Table3: ARMA-GARCH model estimation results on CSI300 stock index return series

	GARCH-t	GARCH-GED	EGARCH-t	EGARCH-GED
Sample 1(Whole data sample)				
AIC	3.4831	3.4693	3.482	3.4578
BIC	3.5223	3.5085	3.5268	3.5026
LogLikelihood	-1468.093	-1462.264	-1466.624	-1456.368
Sample 2(without 3days data of pre- and post-holiday respectively)				
AIC	3.4953	3.4839	3.493	3.4851
BIC	3.5361	3.5247	3.5396	3.5317
LogLikelihood	-1399.849	-1395.269	-1397.924	-1394.765

Source: computation.

Table4: ARMA-GARCH model estimation results on CSI300 index futures return series

	GARCH-t	GARCH-GED	EGARCH-t	EGARCH-GED
Sample 1(Whole data sample)				
AIC	3.472	3.4554	3.4758	3.4581
BIC	3.5112	3.4946	3.5206	3.5029
LogLikelihood	-1463.387	-1456.359	-1464.008	-1456.498
Sample 2(without 3days data of pre- and post-holiday respectively)				
AIC	3.482	3.4727	3.486	3.4768
BIC	3.5228	3.5135	3.5327	3.5235
LogLikelihood	-1394.495	-1390.751	-1395.129	-1391.426

Source: computation.

The estimates of parameters of GARCH models are reported in Table5, using a maximum likelihood estimation method. Then we do the probability integral transformation on the original sequences in order to derive the new marginal distribution (u,v) which have a uniform distribution (0,1) for copula model, as tested by the KS test in Table6. Moreover, the Ljung-Box test for autocorrelation of all series shows that all series have no autocorrelation from the first to the fourth moments. Hence, the copula model could correctly capture the dependency between u and v.

Table5: Estimates of parameters of return series marginal distribution in ARMA(1,1)-(E)GARCH(1,1)-GED

	SR1		FR1		SR2		FR2	
	Estimate (Std. Error)	t value (P(>|t|))	Estimate (Std. Error)	t value (P(>|t|))	Estimate (Std. Error)	t value (P(>|t|))	Estimate (Std. Error)	t value (P(>|t|))
c	-0.046872 (0.036246)	-1.29319 (0.19595)	-0.072834 (0.001608)	-45.2963 (0.000000)	-0.059666 (0.013261)	-4.49935 (0.000007)	-0.074687 (0.002884)	-25.9008 (0.000000)
ar1	-0.830127 (0.039617)	-20.95405 (0.00000)	0.080933 (0.020415)	3.9644 (0.000074)	-0.854539 (0.017418)	-49.06123 (0.000000)	0.282663 (0.081123)	3.4843 (0.000493)
ma1	0.880986 (0.044617)	19.74543 (0.00000)	-0.108537 (0.020737)	-5.2340 (0.000000)	0.899750 (0.023730)	37.91536 (0.000000)	-0.312585 (0.090357)	-3.4594 (0.000541)
ω	0.026550 (0.065991)	0.40233 (0.68744)	0.032369 (0.025860)	1.2517 (0.210684)	0.025259 (0.027373)	0.92275 (0.356136)	0.034096 (0.025131)	1.3568 (0.174857)
α	-0.042433 (0.058642)	-0.72360 (0.46931)	0.026946 (0.012024)	2.2410 (0.025028)	0.008801 (0.007091)	1.24112 (0.214561)	0.021231 (0.009678)	2.1936 (0.028261)
β	0.960543 (0.095434)	10.06499 (0.00000)	0.957354 (0.020060)	47.7242 (0.000000)	0.978641 (0.017569)	55.70207 (0.000000)	0.962715 (0.017020)	56.5641 (0.000000)
γ	0.033566 (0.026434)	1.26981 (0.20415)						
ν	1.140339 (0.075540)	15.09581 (0.00000)	1.035224 (0.066630)	15.5369 (0.000000)	1.027940 (0.065893)	15.60002 (0.000000)	0.937671 (0.058360)	16.0669 (0.000000)

Source: computation.

Table6: Ljung-Box test for autocorrelation and KS test for uniform distribution

	SR1		FR1		SR2		FR2	
	X-squared [KS-Statistic]	P-value	X-squared [KS-Statistic]	P-value	X-squared [KS-Statistic]	P-value	X-squared [KS-Statistic]	P-value
First moment	8.8519	0.5462	7.5061	0.677	8.8624	0.5452	10.7109	0.3805
Second moment	16.7437	0.0802	10.9352	0.3626	18.1259	0.0529	16.095	0.0969
Third moment	7.7891	0.6494	7.3386	0.6931	7.9921	0.6296	9.8764	0.4514
Fourth moment	12.8914	0.2298	8.8227	0.549	13.9809	0.1739	12.2467	0.2689
KS test	[0.034]	1	[0.034]	1	[0.035]	1	[0.035]	1

Source: computation.

Table 7 reports the parameter estimates for four copula functions based on ARMA-GARCH model. As can be seen from the correlation parameter ρ, there is a highly positive correlation (close to 1) between CSI300 index and futures returns in both two cases. From the AIC and BIC perspective, the Gumbel and Gaussian dependence structure exhibit better explanatory ability than other dependence structure for Sample 1. The Gumbel and Clayton dependence structure exhibit better explanatory ability than others for Sample 2. The Student t dependence structure does performs the worst on both of the two samples. Generally speaking, Archimedean copula can provide a better fit for the empirical data, especially the Gumbel copula model. These results imply that introducing the tail dependence adds much to the explanatory ability of the model. Moreover, since the t copula can capture the symmetrical tail dependence and the lower left tail is best described with Clayton copula, while the upper right tail is best described with Gumbel copula. We can therefore deduce that the asymmetric tail dependence description is better than symmetrical of t copula between CSI300 index and futures returns.

Table7: The results of estimates of parameters for copula models

		ρ	ν	θ	Std. Error	AIC	BIC
Sample1	Gaussian	0.9454754*			0.002647257	-15.12485886	-10.38315816
	Student t	0.94461*	5.422258*		0.003535/1.319244	-13.40997582	-3.92657443
	Clayton			4.553167*	0.1706592	-14.49244278	-9.750742082
	Gumbel			4.49954*	0.1293565	-15.70280775	-10.96110705
Sample2	Gaussian	0.9480591*			0.002586724	-15.24884232	-10.55800005
	Student t	0.9456166*	3.561411*		0.004111/0.721869	-13.83088062	-4.44919607
	Clayton			4.941486*	0.1861584	-15.42703221	-10.73618993
	Gumbel			4.629059*	0.1366268	-15.68172246	-10.99088019

Note: * indicates under 0.05 significant level, which means the best fit copula fits the data with $p < 0.05$.

Source: computation.

Table8: The results of Kendall's tau and tail dependence coefficients

		Gaussian	Student t	Clayton	Gumbel
Sample1	Kendall's τ	0.7888045	0.7871194	0.6948041	0.7777551
	λ_{up}		0.6828392		0.8334526
	λ_{low}		0.6828392	0.8587872	
Sample2	Kendall's τ	0.7939143	0.7890807	0.7118773	0.7839734
	λ_{up}		0.7369568		0.8384698
	λ_{low}		0.7369568	0.8691227	

Source: computation.

The Kendall's tau and tail dependence coefficients are showed in Table8. It can be determined that each two returns series has the trend consistency by Kendall's tau. In addition, Elliptical copula can describe the rank correlation between each of the two returns series better, and the rank correlation of Sample2 is higher than Sample1. It can be concluded that the “Golden week” effect could decline the rank correlation. As deduced, the tail dependence coefficients of Archimedean copula is higher than t copula’s, and in each of two samples, the lower tail coefficients are slightly greater than upper tail coefficients. That means when stock is down, the probability that futures market follows down is high. That probability is slightly greater than the probability of futures market going up while stock simultaneously up. Moreover, every degree of tail dependence in each sample is high. That is to say, when the stock market has a strong fluctuation, the degree of dependence between CSI300 index and futures will be significantly improved. Specifically, for both the upper tail and lower tail, the coefficient of Sample2 is slightly greater than Sample1. Therefore, it is indicated that the “Golden week” effect could slightly weaken the tail dependence between CSI300 index and futures.

5. Conclusions

In this paper, the Copula-ARMA-GARCH model with GED distribution is established to research the dependence structure between CSI300 index and futures in case of the “Golden week” effect, including these three dependence relationships - correlation parameter ρ, rank correlation Kendall's tau and tail dependence coefficients λ. The correlation parameter ρ are all close to 1 in both of the two circumstances, which illustrates a highly positive dependence between the return series of CSI300 index and futures markets.

By comparing the AIC and BIC between each copula function and empirical copula, we concluded that the dependence structure can be well fitted by the Gumbel copula function in both of two circumstances. Overall, Archimedean copula performs better than Elliptical copula.

However, from the rank correlation perspective, Elliptical copula is superior to Archimedean copula. Taking the “Golden week” effect into account, the “Golden week” effect could decline the rank correlation and slightly weaken the tail dependence between CSI300 index and futures. Referring to weakening the tail dependence, in other words, the “Golden week” effect cannot improve the dependence relationship when there is an extreme event that occurs in one of the two markets.

In brief, it is difficult to reduce the risk by hedging during the “Golden week” holidays. These tail-dependence-results also imply that when the stock market has a strong fluctuation, the degree of dependence between CSI300 index and futures will be significantly improved. Specifically, when the stock price goes down, the probability that the futures market will follow the downward direction is high. This probability is slightly greater than the probability of the simultaneous rises of the indices in both futures and stock markets.

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