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Research on Spillover Effects in Financial Risk

by

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Abstract:

The research on spillover effect in financial markets is frontier theory and technology. The global financial crisis of 2007-2009 affects the stock markets deeply. But, the economic consequences are different among some cross-markets. As an emerging high-speed growth securities market established in 1990, the Chinese securities market has developed significantly. Again in the current international financial crisis, it is being closely watched that how deeply China's market affected by the financial crisis and the role making a major contribution to stabilizing the global financial situation. Both GARCH and Granger causality test are used to measure the volatility spillover in the existent literatures. However, in case of the correlations of some markets are not linear relationship, Copula functions have recently become popular. In this paper, we have tested for spillover effects in financial risk between the Shanghai market and the other main stock markets. We use the kernel smoothing function to estimate the marginal density distribution, and use the Copula functions to estimate the joint distribution of the marginal distribution. Furthermore, we use the bivariate Archimedean copula to estimate the symmetrical and asymmetrical distribution. The main findings are that Shanghai market is not affected by New York market significantly in the financial crisis, it can not exert on significant influence to New York market as well. The similar degree of market efficiency, the similar attitude about considering on risk and earnings are more important on leading to the spillover effect in stock markets than the real economic link between Shanghai market and New York market.

Keywords: Spillover Effect; Financial Risk; Copula; Kernel Function

1 Introduction

A significant decrease in asset prices and increase in market volatility usually indicates a financial crisis. However, this kind of financial risk can be transmitted from one market to the others due to the markets integrating and the other spillover channels. The volatility spillover effect is the primary process to transmit the financial risk. If there is a significant difference between two stock markets during the periods before and after the shock, namely, if the nature of the relationship between the two markets was altered by a certain financial event, especially a financial crisis, it would be considered as the volatility spillover effect of the two markets.

Therefore, when the investors use the capital assets pricing model to decide the optimized portfolio to seeking the investment opportunities, the systemic risk among different markets is also an important decision making element. Information about correlation between returns and risks of different markets becomes necessary in the course of risk evaluating or portfolios choosing. In case the original condition of constant correlation is violated due to the financial shock, the volatility spillover effect should have direct influence on portfolio performance and risk management.

The global financial crisis of 2007-2009 affects the stock markets deeply. But, the economic consequences are different among some cross-markets. During the Asian financial crisis that broke out a decade ago, China played a decisive role in response to the crisis by keeping the RMB exchange rate stable and was thus praised by the international community and Southeast Asian countries in particular. Again in the current international financial crisis, it is being closely watched that how deeply China's market affected by the financial crisis and the role making a major contribution to stabilizing the global financial situation. So the market information transmission and the cross-market volatility transmission on the internal and external market of China become a key problem.

In the case of China, the government has been engaged in step by step financial liberalization. As an emerging high-speed growth securities market established in 1990, the Chinese securities market has developed significantly over the past two decades. The Chinese securities market plays a vital role in promoting reform in state-owned enterprises and Chinese economic structure adjustment. However, we take notice of these phenomena in Chinese mainland stock markets.

At first, the China stock market is classified into several categories -Red chips, H-shares, B-shares and A-shares. The H-share market is made up of the companies incorporated in mainland China but traded in Hong Kong stock market. The B-shares are quoted in foreign currencies. The B-share market was originally designed for overseas investors but has been opened to domestic investors since March 2001. The A-shares refer to companies incorporated in mainland China and traded in the mainland A-share markets. Furthermore, the A-shares are divided into shanghai A-share and Shenzhen A-share. Secondly, it's remarkable that A-share of Chinese mainland stock markets remained between 1000 and 2000 during the year 2005. In the spring of 2006, China's stock markets became a bull market; A-stock rose 130% in one year. Shanghai market index peaked at 6124.04 on 16th Oct. 2007. After that, the index of Shanghai market continued to decline sharply till it had reverted in October 2008 to around 2000, close to the average level before this bull market. Thirdly, in 2007, the Shanghai and Shenzhen A-share markets value hit a new high, rising by 269% YOY. The aggregate A-share markets value of Shanghai Stock Exchange and Shenzhen Stock Exchange ranked the 4th in the world, following USA, Japan and UK[1]. After the financial crisis, China's markets

[1] The statistic data sources are world federation of exchanges (http://www.world-exchanges.org)

maintained the momentum of rapid development. Till August-25th 2009, the aggregate markets value of Shanghai ranked 4th in the world and the aggregate markets value of whole Chinese mainland markets (added Shenzhen markets) ranked 3rd in the world[2]. The asset securitization level in Chinese markets catches up with the world advanced level within one year. From 2008H2, Chinese stock markets also suffered losses as did other markets. However, in 2009, Chinese markets began to recover strongly.

Based on those phenomena, we want to know how do co-movement changes between Chinese markets and the other markets abroad compare before and after the financial crisis? How do changes among the Chinese mainland internal markets compare before and after the financial crisis? Did Shanghai stock market really receive a volatility spillover from the crisis, especially while its indices were transforming dramatically between bear market and bull market conditions? What influence do the Shanghai markets exert on the other markets?

To better understand how such co-movement changes between Chinese markets with the other markets abroad, as well as among the Chinese mainland internal markets, the focus here is on financial markets volatility spillover. Both GARCH and Granger causality test are used to measure the volatility spillover in the existent literatures. However, in case of the correlations of some markets are not linear relationship, Granger causality test has a certain limitation. Copula functions have recently become popular in the finance literature due to a number of reasons. It can be argued that copulas are more informative measures of dependence between variables than standard linear correlation (Johansson, 2009). This is the case when the joint distribution of the variables is nonelliptical and the typical linear correlation measure is not enough to describe the dependence between the variables (Patton, 2006). Copulas have been used to study the asymmetric nature of dependence between financial variables (e.g. Patton, 2006) as well as contagion effect (Rodriguez, 2007).

In this paper, Copula theory is introduced into financial analysis to avoid defects of linear correlation coefficient and classical analysis methods. Based on fully understanding of copula theory, the paper will investigate measure of non-linear dependence and measure of tail dependence that can be derived from copulas.

Dependence analysis is a core issue in multivariate financial analysis. Characters of several important copulas used in dependence analysis are discussed in this study and multivariate financial time series models based on copula theory, such as Copula-N model and Copula- t model, are established. Estimation and test methods of copula models are also studied.

Kernel smoothing function is the non-parameter method to estimate the probability

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and China securities regulatory commission (http://www.csrc.gov.cn).
[2] The statistic data source is China securities regulatory commission (http://www.csrc.gov.cn).

distribution function, when we can not find any befitting function to estimate the probability distribution.

The empirical results suggest that Shanghai market usually suffers volatility spillover from the Shenzhen market and Hong Kong market, while the London market is affected by volatility spillover from the New York market. The lower tail dependence of (SSE, HSI) and (SP, FTSE) might attribute to the financial crisis, however, the lower tail dependence of (SSE, SZ) must because of the convergence between shanghai market and Shenzhen market. Remarkable, Shanghai market is not affected by New York market significantly in the financial crisis, it can not exert on significant influence to New York market as well.

This paper is organized as follows. After analyzing on the core literature review, Section 3 discusses the data and provides descriptive statistics. Section 4 outlines the methodology used. Section 5 presents the empirical results and discusses the findings. Finally, Section 6 provides a summary of the findings and concludes.

2. Core literature review

King and Wadhwani (1990), Lee and Kim (1993), and Calvo and Reinhart (1996) reach the conclusion that financial contagion was indeed present during every major financial and economic crisis in the last decade or so. Calvo and Reinhart (1996) enriched the set of theoretical sources of contagion. They have examined “spillover” or “contagion” effect in light of the Mexican crisis in December 1994. They pointed out that institutional practice also could be a channel of spillovers. Eichengreen, Rose and Wyplosz (1995) explain the contagion effect by the "bandwagon" effects as herding behavior in which investor’s sentiment does not discriminate among different macroeconomic fundamentals across countries. Calvo and Reinhart (1996) find regional preferences of foreign investors lead to the contagion, implying that investors first select the larger, usually better known, countries as a place to invest.

Ades and Chua (1993), Easterly and Levine (1994), explain the contagion effect by real links. Ades and Chua (1993) think the correlated trade patterns and arrangements are important factors to cause the contagion. Easterly and Levine (1994) explain the contagion effect by technological factors and political instability. Hoffmaister and Végh, Talvi, (1994) provide a financial explanation about the contagion effect because of highly integrated capital markets.

Boyer, Gibson and Loretan (1999), Loretan and English (2000), and Forbes and Rigobon (2001a, 2002) have proposed an adjustment to the correlation coefficient, which under very specific conditions can account for the heteroskedasticity bias and, subsequently, reject the financial contagion hypothesis in favor of an only interdependence hypothesis. Corsetti, Pericoli and Sbracia (2002), Cipollini and Kapetanios (2003), Arestis, Caporale and Cipollini (2003), and Bekaert, Harvey and Ng (2005) have observed that the key to the only interdependence result is the specification of the theoretic measure of interdependence.

Forbes and Rigobon (2002), Corsetti et al. (2002) reject interdependence in favor of financial contagion for at least five countries using one of the leading case studies. Hamao et al. (1990), and Edwards (1998) rely on the ARCH and GARCH econometric framework to show the presence of significant volatility spillovers across countries during financial crises. Kroner and Ng (1998), Engle and Sheppard (2001), Sheppard (2002), and Edwards and Susmel (2003) use some type of multivariate GARCH or bivariate SWARCH parameterization of the variance-covariance matrix. Bessler and Yang (2003) addressed this issue by improving the vector error correction model (VECM) in order to identify the contemporaneous structural dependence in the neighborhood of the financial crisis. Ehrmann, Fratzcher and Rigobon (2005) exploit the heteroskedasticity of asset prices to identify a VAR representation of a given set of European and U.S. financial markets' returns.

Costinot et al. (2000), Bae et al. (2003), Longin and Solnik (2001), Hu (2003), Patton (2002), Martell (2003), and Bartram and Wang (2005) integrate the distributions hypothesis and extreme value theory, including statistical concepts such as copula functions.

3. Data and summary statistics

Daily closing index values for the Chinese Exchanges, including Shanghai market (SSE) and Shenzhen market (SZ), New York Exchange (S&P500), London (FTSE 100), and Hong Kong Exchange (HSI) are collected from Yahoo Finance and CCER database for the period from 07/2005 to 04/2010. The software of Mathworks Matlab 2009a is used to compute the arithmetic and the models.

The long sample period overall from 07/2005 to 04/2010 is chosen in order to examine the effect of the financial crisis on the stock markets, as well as on the dynamic relationship between Chinese markets and the primary stock market during the periods before and after the shock.

The difference of logarithm (%) is used in the calculation of market returns:

$$R_{i,t} = 100 * \log(P_{i,t} / P_{i,t-1})$$

Where R_t denotes the closing value of the index and the return of market i on trading days, respectively. The sign of i represents the different markets. The indices are in terms of local currency.

Table 1: statistics of the returns of the five markets

	SSE	SZ	SP	HSI	FTSE
N	1257	1257	1257	1257	1257
Mean	0.00080	0.00112	-0.00001	0.00032	0.00005
Median	0.00121	0.00123	0.00074	0.00026	0.00011
Std. Deviation	0.01981	0.02175	0.01522	0.01938	0.01421
Skewness	-0.43744	-0.42552	-0.25504	0.09550	-0.12093
Kurtosis	2.72184	2.10186	10.01946	7.72797	8.22029

Table 1 and Figure 1 list the summary statistics of the returns of the five markets. As shown in the table 1, the average daily returns of the markets for the five years are both close to 0. But the mean value of Shanghai market (SSE) and Shenzhen market (SZ) are bigger than the others. The standard variances range from 0.01421 (London) to 0.02175 (Shenzhen market).

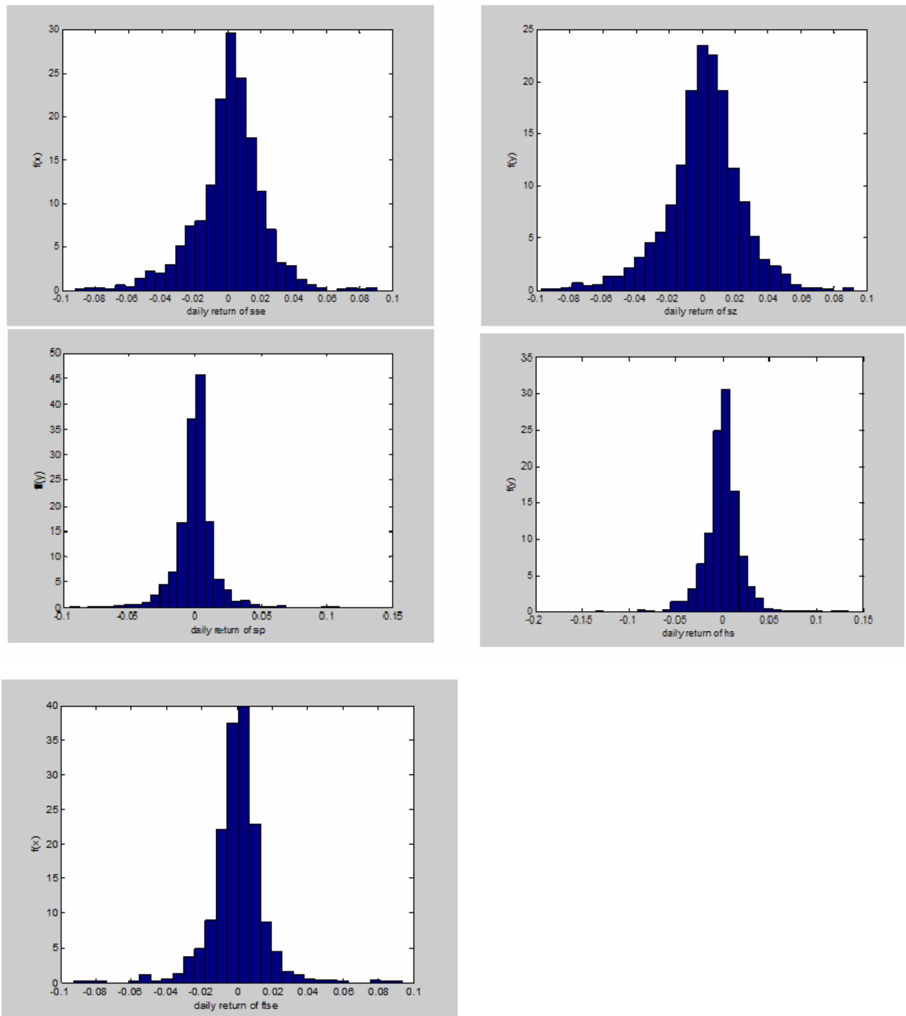


Figure 1: the frequency distribution column diagram of the returns of the five markets.

The measures for Skewness and kurtosis indicate that the distributions of returns for all five markets are negatively skewed and leptokurtic relative to the normal distribution, except for Hong Kong market. The Jarque-Bera statistic rejects normality at any level of statistical significance in all cases. These characteristics of statistics can also be found by figure 1. We can not find any befitting function to estimate the probability distribution perfectly.

4. Methodology

It is difficult to construct a multidimensional probability density function which includes dependence measures between more than two variables. In this section, the concept of copula is introduced and the discussion about copulas is based on Nelson (1999) and Patton (2006). The theory of copulas allows us to decompose a joint distribution of two or more variables into their marginal distributions and the dependence function, i.e. the copula. In this study, bivariate copulas are used and the focus of the following discussion will therefore be on a bivariate setting.

Decomposing the joint distribution into the marginal distributions:

$$F_{XY}(x, y) = C(F_x(x), F_y(y))$$

where $F_{xy}(x, y)$ is the cumulative distribution function and $F_x(x)$ and $F_y(y)$ are the marginal distributions, respectively. If density functions are used instead, the relationship can be written as:

$$f_{xy}(x, y) = f_x(x) \cdot f_y(y) \cdot c(F_x(x)F_y(y))$$

If the distribution function $F_{xy}(x, y)$ is a continuous multivariate distribution function, Sklar's theorem shows that we can separate the marginal distribution for the two variables from that of the dependence structure. There are several reasons for why copulas in many situations are preferable to other measures of dependence (see, Rodriguez, 2007, for an excellent discussion on the statistical properties of copulas).

It is known that non-normality at the univariate level is associated with skewness and leptokurtosis phenomena, and what is known as the fat-tail problem. In a multivariate setting, the fat-tail problem can be referred both to the marginal univariate distributions and to the joint probability of large market movements, which is called tail dependence. The copula functions can be used to model these two features, fat tails and tail dependence, separately. So, the Garch model can be improved to Copula-Garch-N or Copula-Garch-t.

Copula-Garch-N:

$$y_{nt} = \mu_{nt} + \varepsilon_{nt}, \qquad n = 1, \cdots, N; \qquad t = 1, \cdots, T$$

$$\varepsilon_{nt} = h_{nt}^{1/2} \xi_{nt}$$

$$h_{nt} = \varpi_n + \sum_{i=1}^{q} \alpha_{ni} \varepsilon_{nt-i}^2 + \sum_{i=1}^{p} \beta_{ni} h_{nt-i}$$

$$(\xi_{1t}, \cdots, \xi_{Nt}) | I_{t-1} \sim C_t \left(\Phi(\xi_{1t}), \cdots, \Phi(\xi_{Nt}) | I_{t-1} \right)$$

Copula-Garch-t:

$$y_{nt} = \mu_{nt} + \varepsilon_{nt}, \qquad n = 1, \cdots, N; \qquad t = 1, \cdots, T$$

$$\varepsilon_{nt} = h_{nt}^{1/2} \xi_{nt}$$

$$h_{nt} = \varpi_n + \sum_{i=1}^{q} \alpha_{ni} \varepsilon_{nt-i}^2 + \sum_{i=1}^{p} \beta_{ni} h_{nt-i}$$

$$(\xi_{1t}, \cdots, \xi_{Nt}) | I_{t-1} \sim C_t \left(\mathrm{T}_{\nu_1}(\xi_{1t}), \cdots, \mathrm{T}_{\nu_N}(\xi_{Nt}) | I_{t-1} \right)$$

Kernel smoothing function is the non-parameter method to estimate the probability distribution function, when we can not find any befitting function to estimate the probability distribution.

The density function of Gumbel Copula function has asymmetrical distribution, and the density distribution looks like a “J” type, namely the upper tail is higher than the lower tail. So the Gumbel Copula is sensitive to the volatility appearing near the upper tail, which is usually used to illustrate the correlations in the Bull market.

Gumbel Copula:

$$C_G(u, v; \alpha) = \exp\left\{ - \left[(-\log u)^{\frac{1}{\alpha}} + (-\log v)^{\frac{1}{\alpha}} \right]^{\alpha} \right\}$$

$$c_G = \frac{C_G(u, v; \alpha)(\log u \cdot \log v)^{\frac{1}{\alpha}-1}}{uv\left[(-\log u)^{\frac{1}{\alpha}} + (-\log v)^{\frac{1}{\alpha}} \right]^{2-\alpha}} \left\{ \left[(-\log u)^{\frac{1}{\alpha}} + (-\log v)^{\frac{1}{\alpha}} \right]^{\alpha} + \frac{1}{\alpha} - 1 \right\}$$

The density function of Clayton Copula function also has asymmetrical distribution, but the density distribution is opposite to the Gumbel Copula, and looks like a “L” type, namely the lower tail is higher than the upper tail. So the Clayton Copula is sensitive to the volatility appearing near the lower tail, which is usually used to illustrate the correlations in the Bear market.

Clayton Copula:

$$C_C(u,v;\theta) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}$$

$$c_C(u,v;\theta) = (1+\theta)(uv)^{-\theta-1}(u^{-\theta} + v^{-\theta} - 1)^{-2-1/\theta}$$

The density function of Frank Copula function has symmetrical distribution. The density distribution looks like a "U" type, namely the lower tail is similar with the upper tail. So the Frank Copula is usually used for the volatility appearing with symmetrical distribution.

Frank Copula:

$$C_F(u,v;\lambda) = -\frac{1}{\lambda}\log\left[1 - \frac{(1-e^{-\lambda u})(1-e^{-\lambda v})}{1-e^{-\lambda}}\right]$$

$$c_F(u,v;\lambda) = \frac{\lambda(1-e^{-\lambda})e^{-\lambda(u+v)}}{\left[(1-e^{-\lambda}) - (1-e^{-\lambda u})(1-e^{-\lambda v})\right]^2}$$

Figure 2 is the frequency distribution plots of empirical and the Copulas when u=v.

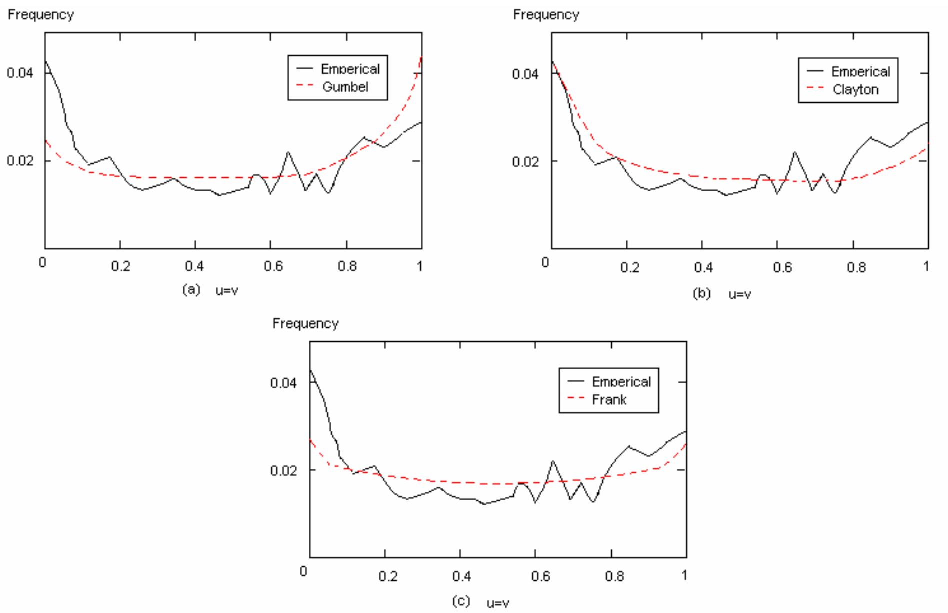


Figure 2 : The frequency distribution plots of empirical and the Copulas when u=v

5. The empirical results

5.1 Kernel smoothing function to estimate the density distribution

This paper utilizes the ksdensity function to estimate the kernel distribution of the sampling markets, including Shanghai market (SSE) and Shenzhen market (SZ), New York Exchange (S&P500), London (FTSE 100), and Hong Kong Exchange (HSI) for the period from 07/2005 to 04/2010, and kernel distribution estimations comparison with the empirical distribution functions are described as figure 3.

It is noticeable that the Kernel smoothing function can be used to estimate the empirical distribution function properly, in some circumstances, it has better ability to estimate the complicated distribution than traditional GARCH model.

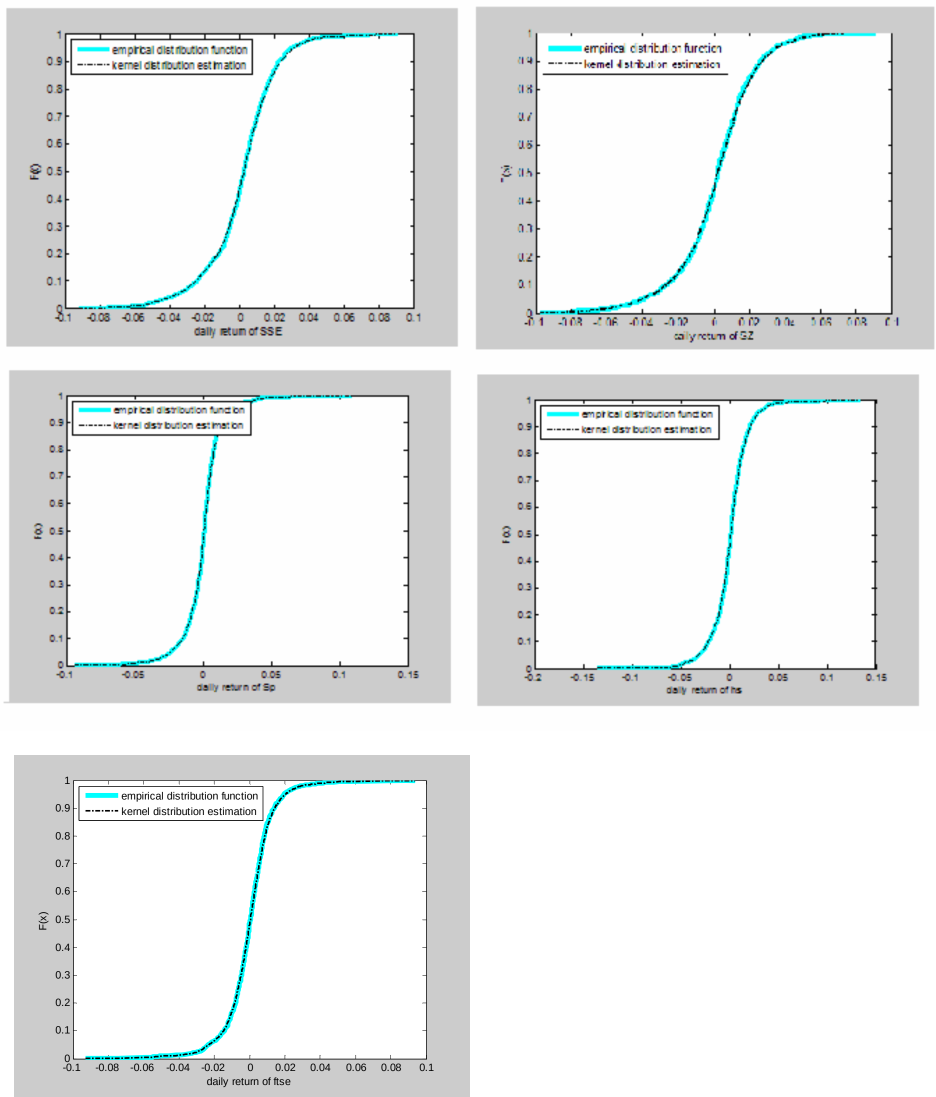


Figure 3: Empirical distribution and Kernel distribution estimation

5.2 The correlations between bivariate settings

5.2.1 The correlations of the marginal distribution

Figure 4 shows the frequency column diagram of marginal distributions between each bivariate setting. It can be seen that the marginal distribution of SSE and SZ appears significant correlations near the areas of (0, 0) and (1, 1). The pairs of (SSE, HSI) and (SP, FTSE) also appears significant correlations near the areas of (0, 0) and (1, 1), but there are much more scatter than (SSE, SZ) in the other areas. Then, on one hand, we can draw a preparatory conclusion that SSE and SZ appear significant co-movement trends during increasing and decreasing in stock price, especially affected by the big shock. On the other hand, we cannot get the evidence that the co-movement changes between Chinese markets and the other markets abroad compare before and after the financial crisis. Based on Figure 4, SSE has not significant correlations with SP or with FTSE. It seems that Shanghai stock market does not receive the volatility spillover from the crisis, especially while its indices were transforming dramatically between bear market and bull market conditions. Furthermore, it has not significant influence which exerted by Shanghai markets on the other main markets aboard.

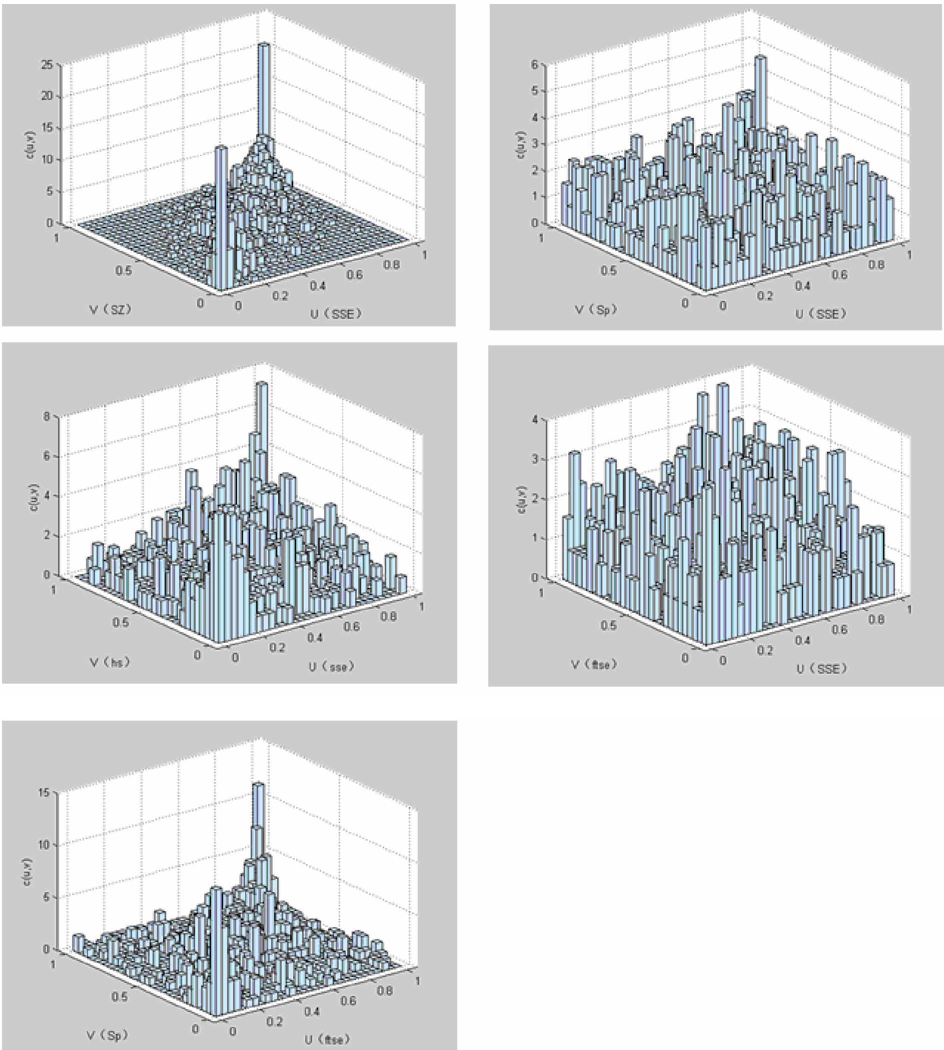


Figure 4: frequency column diagram of marginal distribution

5.2.2 The Coefficient of correlation of bivariate market pairs

To better understand how such co-movement changes between Chinese markets with the other markets abroad, as well as among the Chinese mainland internal markets, the focus here is on the coefficient of correlation of bivariate market pairs as shown in Table 2. (SSE, SZ), (SSE, HIS), and (SP, FTSE) have significant linear and no-linear correlations. And their correlations usually obey t distribution, or t distribution can depict their joint distribution more fitful than normal distribution.

Table 2: The Coefficient of correlation of bivariate market pairs

rho_norm	**SSE**	**SZ**	**SP**	**HSI**	**FTSE**
SSE	1	0.9226*	0.0551	0.4378*	0.1273
SZ	0.9226*	1			
SP	0.0551		1		0.538*
HSI	0.4378*			1	
FTSE	0.1273		0.538*		1
rho_t	**SSE**	**SZ**	**SP**	**HSI**	**FTSE**
SSE	1	0.9267*	0.0538	0.4411*	0.1269
SZ	0.9267*	1			
SP	0.0538		1		0.5569*
HSI	0.4411*			1	
FTSE	0.1269		0.5569*		1
Kendall_norm	**SSE**	**SZ**	**SP**	**HSI**	**FTSE**
SSE	1	0.7479*	0.0351	0.2885	0.0812
SZ	0.7479*	1			
SP	0.0351		1		0.3616*
HSI	0.2885			1	
FTSE	0.0812		0.3616*		1
Kendall_t	**SSE**	**SZ**	**SP**	**HSI**	**FTSE**
SSE	1	0.7547*	0.0342	0.4215*	0.081
SZ	0.7547*	1			
SP	0.0342		1		0.376*
HSI	0.4215*			1	
FTSE	0.081		0.376*		1

Note * means the correlation is significant at 5%.

Figure 5 shows the density function distribution of bivariate Normal-Copula and t-Copula. It is direct viewing the co-movements between different stock markets on the background of global financial crisis in 2007-2009.

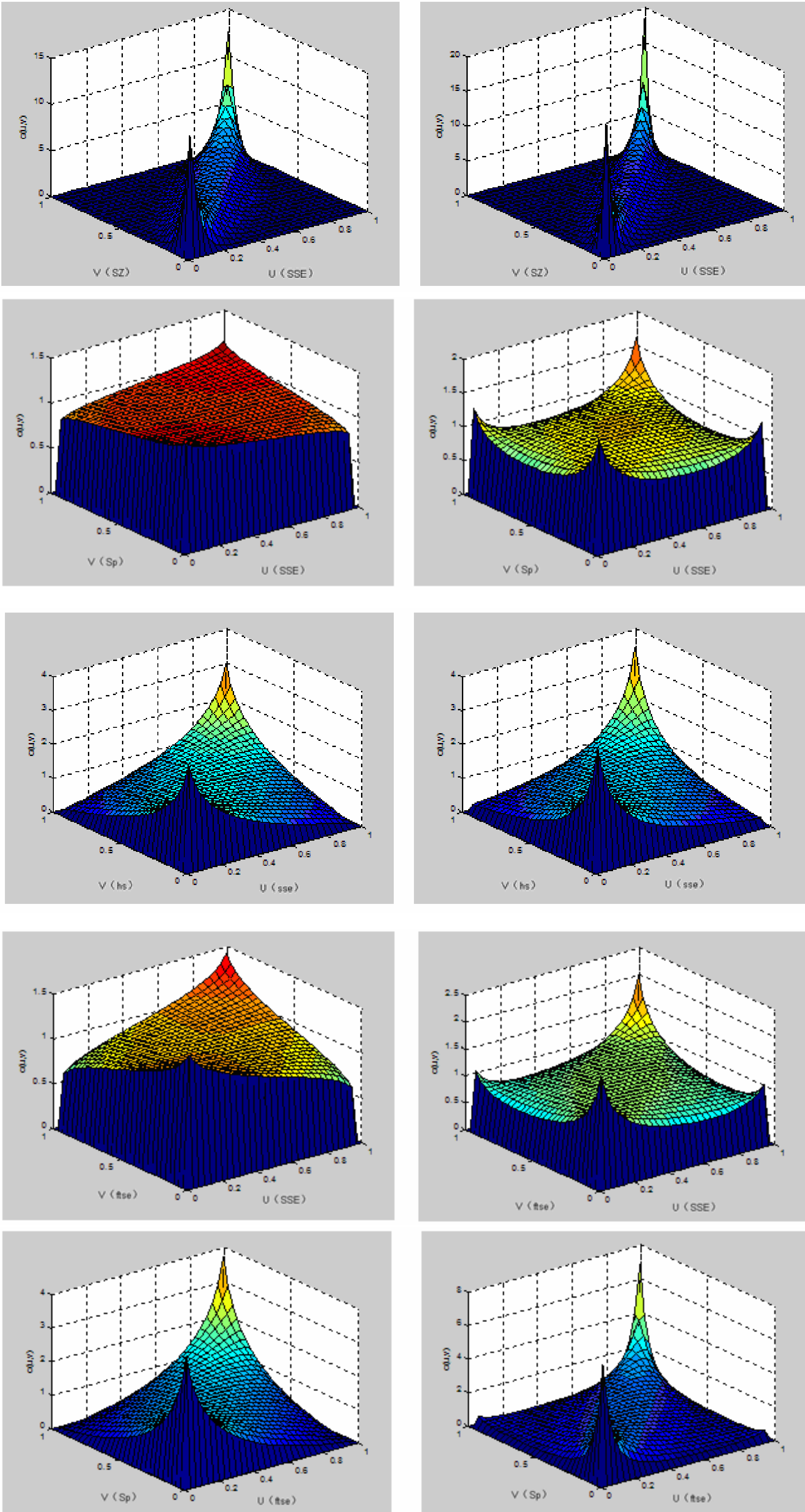


Figure 5: Density function distribution of bivariate Normal-Copula and t-Copula

The pairs of (SSE, SZ), (SSE, HSI) and (SP, FTSE) appears significant correlations near the areas of (0, 0) and (1, 1), but the wave crests on the (0, 0) and (1, 1) are sharper than the others, due to the (SSE, HSI) and (SP, FTSE) have much more scatter than (SSE, SZ) in the other areas. Namely, (SSE, SZ), (SSE, HSI) and (SP, FTSE) have significant spillover effects in financial risk.

Moreover, we can see that the wave crests on the (0, 0) and (1, 1) are sharper than the others when we use the t-Copula, which is also the evidence that the density function distribution of bivariate t-copula is more fitful than Normal-Copula.

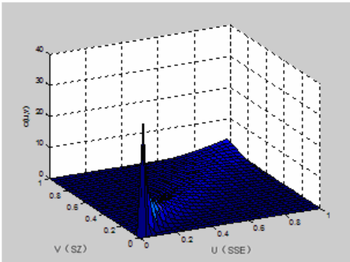
5.2.3 The tail dependence of correlation of bivariate market pairs

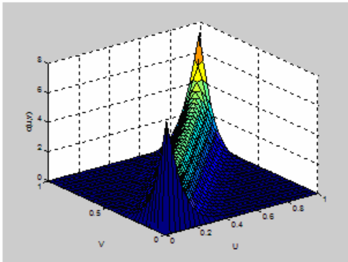
We test the density function distribution of bivariate Archimedean copula; the results are shown at Figure 6.

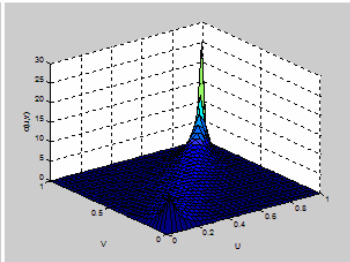
The density function of Clayton Copula function has asymmetrical distribution, and the density distribution looks like a “L” type, namely the lower tail is higher than the upper tail. So the Clayton Copula is sensitive to the volatility appearing near the lower tail, which is usually used to illustrate the correlations in the Bear market. From the Figure 6, it can be seen that the pairs such as (SSE, SZ), (SSE, HSI) and (SP, FTSE) have significant tail dependence near the lower tail. Namely, those pairs of markets appear significant spillover effects in financial risk. The lower tail dependence of (SSE, HSI) and (SP, FTSE) might attribute to the financial crisis, however, the lower tail dependence of (SSE, SZ) must because of the convergence between shanghai market and Shenzhen market. The correlation between shanghai market and New York market is not significant in the financial crisis, even it is not significant than it’s between shanghai market and London market.

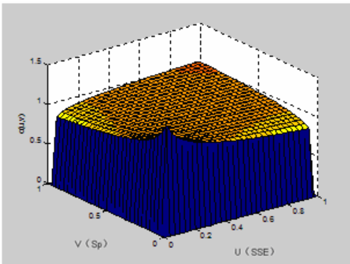
The density function of Gumbel Copula function also has asymmetrical distribution, but the density distribution looks like a “J” type, namely the upper tail is higher than the lower tail. So the Gumbel Copula is sensitive to the volatility appearing near the upper tail, which is usually used to illustrate the correlations in the Bull market. From the Figure 6, it can be seen that the pairs of (SSE, SZ), (SSE, HSI) and (SP, FTSE) have significant tail dependence near the upper tail. Namely, those pairs of markets appear significant co-movement in Bull market. The correlation between London market and New York market is more significant in the good news, even it is significant than it’s between shanghai market and Shenzhen market.

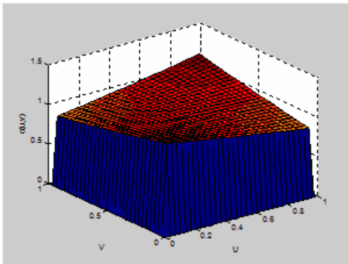
The density function of Frank Copula function has symmetrical distribution. The density distribution looks like a “U” type, namely the lower tail is similar with the upper tail. So the Frank Copula is usually used for the volatility appearing with symmetrical distribution. From the Figure 6, it can be seen that the pairs of (SSE, SZ) and (SP, FTSE) have significant symmetrical distribution. Namely, those pairs of markets appear significant co-movement in good news and bad news. The Frank Copula function is more fitted for depicting the correlation between London market and New York market as well as between shanghai market and Shenzhen market.

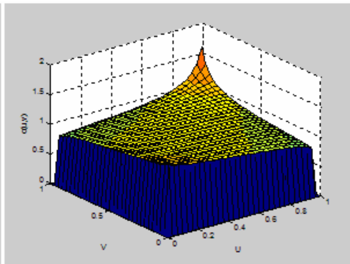

Clayton (SSE, SZ)

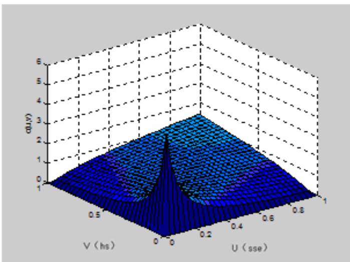

Frank (SSE, SZ)

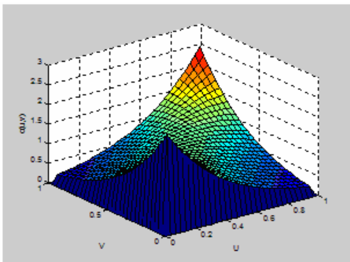

Gumbel (SSE, SZ)

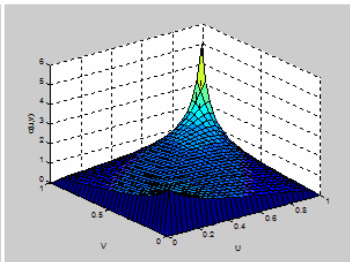

Clayton (SSE, SP)

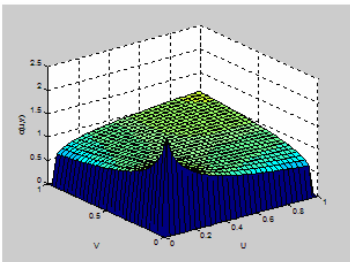

Frank (SSE, SP)

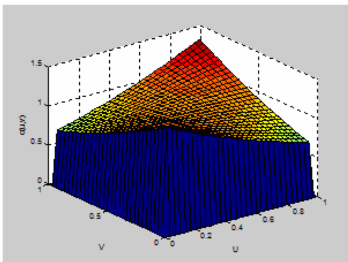

Gumbel (SSE, SP)

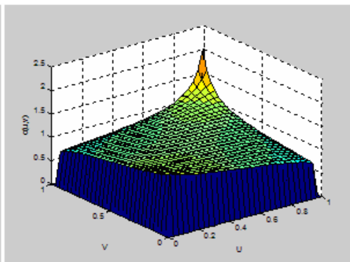

Clayton (HSI, SSE)


Frank (HSI, SSE)


Gumbel (HSI, SSE)


Clayton (FTSE, SSE)


Frank (FTSE, SSE)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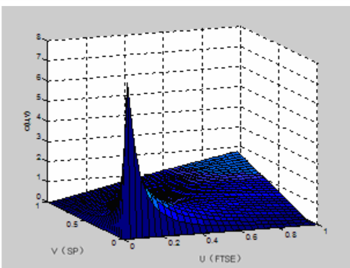
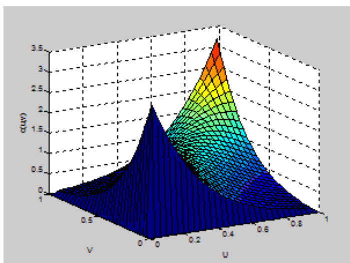

Clayton (SP, FTSE)


Frank (SP, FTSE)

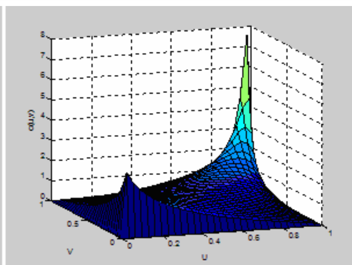

Gumbel (SP, FTSE)

Figure 6: Density function distribution of bivariate Archimedean copula

6. Summary of the findings and concludes

In this paper, we have tested for spillover effects in financial risk between the Shanghai market and the other main stock markets, namely New York, London, Hong Kong, as well as between the Shanghai market and the Shenzhen market.

To account for the complicated distribution and the nonlinear correlation, we use the kernel smoothing function to estimate the marginal density distribution, and use the Copula functions to estimate the joint distribution of the marginal distribution. Furthermore, we use the bivariate Archimedean copula to estimate the symmetrical and asymmetrical distribution.

The tests cover the period of July, 2005 to April, 2010. The main findings are mainly summarized in Figure 5 and Figure 6, which are summarized as follows.

(a) The measures for Skewness and kurtosis indicate that the distributions of returns for all five markets are negatively skewed and leptokurtic relative to the normal distribution, except for Hong Kong market. The Jarque-Bera statistic rejects normality at any level of statistical significance in all cases.

(b) The Kernel smoothing function can be used to estimate the empirical distribution function properly, in some circumstances, it has better ability to estimate the complicated distribution than traditional GARCH model.

(c) The pairs of (SSE, SZ), (SSE, HSI) and (SP, FTSE) appears significant correlations near the areas of (0, 0) and (1, 1). Namely, (SSE, SZ), (SSE, HSI) and (SP, FTSE) have significant spillover effects in financial risk. And their correlations usually obey t distribution, or t distribution can depict their joint distribution more fitful than normal distribution.

(d) In the Bear market, it can be seen that the pairs such as (SSE, SZ), (SSE, HSI) and (SP, FTSE) appear significant spillover effects in financial risk. The lower tail dependence of (SSE, HSI) and (SP, FTSE) might attribute to the financial crisis, however, the lower tail dependence of (SSE, SZ) must because of the convergence between shanghai market and Shenzhen market. Shanghai market is not affected by New York market significantly in the financial crisis, it can not exert on significant influence to New York market as well.

(e) It also can be seen that the pairs of (SSE, SZ), (SSE, HSI) and (SP, FTSE) have significant tail dependence near the upper tail. That is to say, the correlation between London market and New York market is more significant in the good news, even it is significant than it’s between shanghai market and Shenzhen market.

(f) The pairs of (SSE, SZ) and (SP, FTSE) have significant symmetrical distribution. Namely, those pairs of markets appear significant co-movement in good news and bad news. The Frank Copula function is more fitted for depicting the correlation between London market and New York market as well as between shanghai market and Shenzhen market.

In summary, Though, Chinese market has more inseparably close relationships in these years, Shanghai market is not affected by New York market significantly in the financial crisis, it can not exert on significant influence to New York market as well. It can be seen that real economic link is not the inevitable reason to lead to the spillover effect in financial risk. From the correlations between Shanghai market and Shenzhen market, as well as between New York market and London market, we might think that the similar degree of market efficiency, the similar attitude about considering on risk and earnings are more important on leading to the spillover effect in stock markets. In the spring of 2006, China's stock markets became a bull market; A-stock rose 130% in one year. Shanghai market index peaked at 6124.04 on 16th Oct. 2007. After that, the index of Shanghai market continued to decline sharply till it had reverted in October 2008 to around 2000, which is an inimitable phenomenon for the other markets.

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