CSCanada
Management Science and Engineering
Vol. 7, No. 3, 2013, pp. 123-134
DOI:10.3968/j.mse.1913035X20130703.2667

ISSN 1913-0341 [Print]
ISSN 1913-035X [Online]
www.cscanada.net
www.cscanada.org

Asymmetric Influence Detection and Forecasting of Global Stock Markets Based on the Copula Theory

ZHANG Chengzhao[a],*; PAN Heping[b, c]; CHEN Wen[a]

[a]School of Management and Economics, University of Electronic Science and Technology of China, Chengdu, China.
[b]Chongqing Institute of Finance, Chongqing Technology and Business University, Chongqing, China.
[c]School of Economics, Sichuan University, Chengdu, China.
*Corresponding author.

Received 12 May 2013; accepted 26 August 2013

ZHANG Chengzhao, PAN Heping, CHEN Wen (2013). Asymmetric Influence Detection and Forecasting of Global Stock Markets Based on the Copula Theory. *Management Science and Engineering*, *7*(3), 123-134. Available from: URL: http://www.cscanada.net/index.php/mse/article/view/j.mse.1913035X20130703.2667
DOI: http://dx.doi.org/10.3968/j.mse.1913035X20130703.2667

Abstract

Correlation analysis of financial markets is an important starting point for modern financial theory of financial market risks. Along with the deepening of financial globalization, global financial markets have become more and more interdependent. Correlation analysis of global financial markets has become a hot issue for many scholars. On the basis of an in-depth study of Copula theory, this paper applies the theory to the asymmetric correlation analysis of the global major stock market indexes. First, asymmetric correlations among the selected stock indexes are modeled and detected using the relevant metrics of the Copula function on the logarithmic yield of stock indexes; The detected asymmetric correlations are put together to form a directed acyclic graph. Then, artificial neural networks (ANN) are used as a nonlinear model to predict the nearest future of the target stock index; the prediction accuracy is measured in terms of hit rate and mean square error. Test is done on historical daily data with the results showing that the Copula correlation coefficients are more informative for finding the influential leading markets for the predefined target market better than the traditional linear correlation coefficients. The hit rate of the ANN prediction using the detected leading markets found by Copula correlation coefficients is about 3% to 10% higher than that by the linear correlation coefficients.

Key words: Copula theory; Correlation; Asymmetric influence; Super Bayesian Influence Networks; Hit rate

INTRODUCTION

The correlation analysis between financial markets is an important basis for capital asset pricing, portfolio theory and market forecasting. It plays an important role especially in multi-asset, multi-market portfolio construction and risk management. It is important to search for the reliable estimate of correlation coefficients of financial markets for portfolio management. In the age of the Internet and information technology so highly developed, many scholars focus on building predictive models of global financial markets. Correlation analysis between major international stock markets is an important research issue. Pan (2004; 2011) first proposed "Super Bayesian Influence Network" (SBIN) of the global financial markets and regarded the inter-influence of global financial markets (Dong, Pan, Yao, & Li, 2012) may be captured by a dynamic Bayesian network but of which the conditional probability distribution is modeled using ensemble of neural networks. This paper uses Copula theory to analyze the correlation of the global major stock markets and derives "Super Bayesian Network" diagrams according to the influence relationship of international stock markets.

1. LITERATURE REVIEW

The global stock market correlation analysis attracts the attention of many finance scholars. From the existing literature, Chong, Wong and Yan (2008) found that the group of seven (G7) stock markets and the Japanese stock market has lead-lag relationship. Markwat, Kole and Dijk (2009) found the risk of stock market which was transmitted by domino effect. A stock market crash in a region will turn to a wider regional stock market crash. Huang, Yang and Hu (2000) found that the U.S. stock market has significantly positive lead to Hong Kong and Taiwan markets and relatively weak influence to the Japanese market. Cheng and Glascock (2005) studied linkage relations among the U.S. stock market, Japan's stock market and the stock markets in the Greater China, including Chinese Mainland, Hong Kong, Taiwan. They found that the U.S. stock market has greater influence on the Greater China stock markets than on the Japanese stock market. Within the Greater China, the influence of the U.S. stock market to Hong Kong market is the largest.

Fan, Zhao and Wang (2010) used the linear and non-linear Granger causality to test the mean and volatility spillover effect between world stock markets at different stages. They carried out the empirical analysis on the variation characteristics and the results showed that the mean of stock returns and the stock market risk overflow have nonlinear characteristics. Huang, Gu, Li and Su (2010) adopted an accurate topology sequence method of the super metric space to analyze 52 most representative international stock indexes. The results showed that after the outbreak of the financial crisis, the geographic aggregation effect of international stock indexes became more obvious, the correlation degree between the indexes significantly increased, the influence of U.S. stock decreased, while the influence of China is increasing. Cheng, Lu and Yang (2012) selected 32 major economies with 21 quarterly data about subprime crisis. The spatial panel regression model is introduced to show the financial markets association degree of Copula contagion index for an empirical analysis of the transmission channel. Their results showed that the transmission between regional economic organizations is stronger than that between geographical relationship.

Most researchers use Pearson correlation coefficient to study the correlation between global stock markets for the above-mentioned scholars. But the Pearson linear correlation coefficient is a coefficient which can not well describe the non-linear relationship between the stock markets. In order to study the nonlinear relationship between stock markets, this paper introduces the Copula theory to characterize the correlation between international stock markets.

2. AN ECONOMETRIC MODEL OF COPULA CORRELATION

2.1 Copula Function Definition

Copula function is actually a function cluster that connects the joint distribution function with the marginal distribution functions. It was first proposed by Sklar in 1959. He proposed that an N-dimensional joint distribution function can be decomposed into N marginal distribution functions and a Copula Function which describes the correlation between variables. The term of Copula is French and the original meaning is to connect and exchange. It began to be used in the financial field in the late 1990s with the development of modern information technology. Copula function attracted more and more attention in the financial markets, statistical modeling and other areas in recent years. Nelson first systematically summarized the definition of Copula and construction methods and he offered the strict definition of Copula function in 1999. Copula function is the connecting function that connects the joint distribution function $F(x_1,x_2,...,xn)$ of the random vector $X_1,X_2,...,X_N$ with the respective marginal distribution functions $F_{X1}(x_1),...,F_{X_N}(x_N)$, that is function $C(u_1,u_2,...,u_n)$ defined by

$$F(x_1, x_2, \cdots, x_N) = C[F_{X_1}(x_1), F_{X_2}(x_2), \cdots, F_{X_N}(x_N)] \quad (1)$$

2.2 Copula Function Clusters

There are two major categories in the commonly used Copula models in financial correlation analysis: Elliptic Copula models and Archimedean Copula models. Elliptic Copula models include normal Copula model and t-Coupla model. Several commonly used Archimedean Copula models include Gumbel Copula model, Clayton Copula model and Frank Copula model.

2.3 Copula Function and Correlation Measurement

There are a number of methods to measure the random variable correlation such as Pearson correlation coefficient ρ, Kendall rank correlation coefficient τ, Spearman rank correlation coefficient ρ_s.We will introduce one by one as follows (Xie, 2010, pp.191-192).

2.3.1 Pearson Linear Correlation Coefficient ρ

Suppose the mathematical expectation E (X), E (Y) and the variance var (X), var (Y) of the random variables X and Y exist, the Pearson linear correlation coefficient ρ of X and Y is calculated as follows:

$$\rho = \frac{\operatorname{cov}(X,Y)}{\sqrt{\operatorname{var}(X)}\sqrt{\operatorname{var}(Y)}} = \frac{E(X\ Y) - E(X)E(Y)}{\sqrt{\operatorname{var}(X)}\sqrt{\operatorname{var}(Y)}} \quad (2)$$

2.3.2 Kendall Rank Correlation Coefficient τ

Let (x_1,y_1),(x_2,y_2) be two observations of a two-dimensional random vector (X, Y), if $(x_1-x_2)(y_1-y_2)>0$, (x_1,y_1) and (x_2,y_2) are said to be harmonious, else if $(x_1-x_2)(y_1-y_2)<0$, they are disharmonious.

Assume (x_1,y_1) and (x_2,y_2) be independent of each other and have the same distribution of a two-dimensional random vector (X,Y), let $P[(X_1-X_2)(Y_1-Y_2)>0]$ represent the probability of their harmony and $P[(X_1-X_2)(Y_1-Y_2)<0]$ their disharmony, the difference between these two probabilities is then called the Kendall rank correlation coefficient τ of

X and Y, and it is calculated as follows:

$$\tau = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0] \quad (3)$$

We can see that $\tau \in [-1,1]$ from formula (3). Let C (u, v) be the corresponding Copula function of (X,Y), then τ can be obtained by C(u,v) function as follows:

$$\tau = 4\int_0^1 \int_0^1 C(u,v)\, d\, C(u,v) - 1 \quad (4)$$

2.3.3 Spearman Rank Correlation Coefficient ρ_s

(X1, Y1), (X2, Y2) and (X3, Y3) are mutually independent and have the same distribution of a two-dimensional random vector (X,Y), the Spearman rank correlation coefficient ρ_s between X and Y are calculated as follows:

$$\rho_s = 3\{P[(X_1 - X_2)(Y_1 - Y_3) > 0] - P[(X_1 - X_2)(Y_1 - Y_3) < 0]\} \quad (5)$$

It can be seen from the formula (5) that Spearman rank correlation coefficient is the multiple of the difference between the probability of harmony and disharmony of (X1, Y1) and (X2, Y3). When the Copula function C (u, v) of (X,Y) is given, we can prove that Spearman rank correlation coefficient ρ_s can be given by the corresponding Copula function:

$$\rho_s = 12\int_0^1 \int_0^1 C(u,v)\, dudv - 3 \quad (6)$$

2.3.4 Copula Function is a More Reasonable Correlation Measurement

Beyond the Pearson correlation coefficient from the previous section, the correlation measurements of two time series also include Kendall rank correlation coefficient and Spearman rank correlation coefficient. Both correlation coefficients are closely linked with Copula function. Copula function is a cumulative distribution function that connects the marginal distribution functions of the respective random variables. Correlation structure between random variables separates with the marginal distribution of variables. The choice of the marginal distribution of random variables is not restricted. It is more suitable for the correlation analysis between random variables with different marginal distribution characteristics and the application scope is more extensive. At the same time, the nonlinear correlation among random variables can be derived from Copula correlation measurement. And the correlation measurement does not change for the strictly monotone increasing conversion. Therefore, if the variable was implemented by the monotone increasing transformation, the correlation measurement values derived by the Copula function remain unchanged. In addition, Copula function organically combines the correlation degree and correlation patterns between random variables when the correlation analysis is carried out. We can not only get the specific value of the correlation degree between the random variables, but also estimate the related parameters of Copula function. Therefore, Copula function is a more reasonable correlation measurement.

3. DATA CHARACTERISTICS OF MAJOR INTERNATIONAL STOCK MARKET INDEXES

3.1 Data Description

We focus on the representative 14 stock market indexes in the paper: the U.S. standard & poor’s 500 index (S&P), British FTSE 100 index (FTSE), Japan Nikkei index N225 (N225), French CAC40 index in Paris (CAC40), German Frankfurt DAX30 index (DAX30), Italian FTSE MIB index (MIB), Russian RTS Index (RTS), Brazilian IBOVE SPA index (BVSP), Indian SENSEX30 Index (SENSEX), Australian S&P/ASX 200 index (AXJO), Spainish IBEX35 index (IBEX), Singaporean Straits Times Index (STI), Hong Kong Hang Seng Index (HSI) and Chinese Shanghai Composite Index (SSE), as shown in Table 1. The historical period of these 14 stock market indexes is from January 3, 2006 to October 4, 2012, which is divided into three stages: from January 3, 2006 to September 15, 2008; from September 16, 2008 to October 9, 2010; from October 10, 2010 to October 4, 2012. Historical data come from Yahoo finance website. The Bank of America purchased Merrill Lynch which was one of the largest global securities retailers and investment institutions and Lehman brothers filed for bankruptcy protection in the United States for the U.S. subprime mortgage financial crisis in September 15, 2008. On the same day, the European central bank and the bank of England invested 70 billion Euros and 20 billion pounds in financial markets respectively. October 10, 2010 is the last day of international monetary fund and World Bank annual conference 2010. The New York Fed President William Dudley and People’s Bank of China governor Zhou Xiaochuan delivered an important speech respectively on this day. Bank of England deputy governor, general manager of the BIS, vice chairman of the Federal Reserve Ferguson released an important report on the global banking regulation.

Table 1
14 Countries and Regions to be Investigated

Country	Continent	Organization	Market	Stock index
U.S.	America	APEC	Developed	S&P
U.K.	Europe	EU	Developed	FTSE
Japan	Asia	APEC	Developed	N225

To be continued

Continued

Country	Continent	Organization	Market	Stock index
France	Europe	EU	Developed	CAC40
Germany	Europe	EU	Developed	DAX30
Italy	Europe	EU	Developed	MIB
Russia	Europe	APEC	Developing	RTS
Brazil	America	--	Developing	BVSP
India	Asia	--	Developing	SENSEX
Australia	Oceania	APEC	Developed	AXJO
Spain	Europe	EU	Developed	IBEX
Hong Kong	Asia	APEC	Developed	HSI
Chinese Mainland	Asia	APEC	Developing	SSE

3.2 Data Statistics and Unit Root Test

The stock market logarithmic yield is calculated using the following formula:

$$R_t = \log P_t - \log P_{t-1} \qquad (7)$$

In formula (7) R_t represents the stock market logarithmic yield of date t, P_t,P_{t-1} represent the stock market index of date t and date t-1. Table 2 shows 14 stock index logarithmic yield major statistics in stage 1.

Table 2
The Stock Index Logarithmic Yield Statistics in Stage 1

Sample interval	Stock index	Mean	Standard deviation	Skewness	Kurtosis
2006-1-3~ 2008-9-15	S&P	-8.81e-5	0.010038	-0.366764	5.464811
	FTSE	-0.000125	0.011258	-0.228941	5.364446
	N225	-0.000394	0.013635	-0.337472	4.316654
	CAC40	-0.000194	0.011937	-0.391796	5.873747
	DAX30	0.000149	0.011331	-0.549545	7.019337
	MIB	-0.000396	0.010447	-0.453974	5.051297
	RTS	0.000180	0.018463	-1.131432	8.502742
	BVSP	0.000481	0.017276	-0.395894	4.497579
	SENSEX	0.000498	0.017995	-0.270926	4.958178
	AXJO	1.24e-5	0.011804	-0.277225	6.228440
	IBEX	1.06e-5	0.012118	-0.492835	7.760096
	STI	6.88e-5	0.012492	-0.721399	8.539767
	HSI	0.000368	0.016126	-0.111002	7.885539
	SSE	0.000830	0.020886	-0.621743	5.538285

Table 3 shows major statistics of the 14 stock index logarithmic yields in stage 2.

Table 3
The Stock Index Logarithmic Yield Statistics in Stage 2

Sample interval	Stock index	Mean	Standard deviation	Skewness	Kurtosis
2008-9-16~ 2010-10-9	S&P	-7.60e-5	0.098592	0.128584	244.1449
	FTSE	0.000221	0.018257	-0.045284	8.850725
	N225	-0.000357	0.022095	-0.353989	9.825682
	CAC40	-0.000154	0.021077	0.280014	7.908949
	DAX30	9.94e-5	0.019905	0.331800	8.294100
	MIB	-0.000463	0.022114	0.204062	6.938940
	RTS	0.000608	0.033926	-0.180401	10.38678
	BVSP	0.000678	0.024501	0.166687	9.153754
	SENSEX	0.000754	0.021024	0.415941	11.78749
	AXJO	-2.75e-5	0.015800	-0.473951	6.406156
	IBEX	-3.29e-5	0.021394	0.367833	8.821735
	STI	0.000462	0.017258	-0.123160	7.076815
	HSI	0.000422	0.023264	0.177811	9.660356
	SSE	0.000599	0.018837	-0.103718	5.562031

Table 4 shows 14 stock index logarithmic yield major statistics in stage 3.

Table 4
The Stock Index Logarithmic Yield Statistics in Stage 3

Sample interval	Stock index	Mean	Standard deviation	Skewness	Kurtosis
2010-10-10~ 2012-10-4	S&P	0.000437	0.011607	-0.556471	7.809119
	FTSE	5.22e-5	0.011343	-0.237608	4.685412
	N225	-0.000160	0.012484	-1.419701	16.24160
	CAC40	-0.000198	0.015682	-0.099789	4.812118
	DAX30	0.000283	0.015408	-0.160317	4.961653
	MIB	-0.000570	0.019163	-0.211486	4.089065
	RTS	-0.000132	0.018588	-0.345741	5.839676
	BVSP	-0.000374	0.014291	-0.324586	5.868930
	SENSEX	-0.000126	0.011553	0.125529	3.331181
	AXJO	-0.000103	0.010113	-0.201800	4.540879
	IBEX	-0.000607	0.017666	0.093915	4.023754
	STI	-4.74e-5	0.009503	-0.370083	4.671825
	HSI	-0.000201	0.013582	-0.236642	5.380952
	SSE	-0.000573	0.011377	-0.201018	4.672598

In order to measure each stock market risk in three stage, unit root test was carried out in each sample interval logarithmic return series. The results are shown in Table 5 ADF statistics. The logarithmic return series are stationary sequence in three stages and can be directly modeled and the results do not appear spurious regression.

Table 5
ADF Unit Root Test

Stock index	2006-1-3~2008-9-15		2008-9-16~2010-10-9		2010-10-10~2012-10-4	
	ADF	P	ADF	P	ADF	P
S&P	-30.03922	0.0000	-14.87554	0.0000	-14.59417	0.0000
FTSE	-30.81401	0.0000	-18.59788	0.0000	-21.46698	0.0000
N225	-28.15376	0.0000	-18.17761	0.0000	-23.18211	0.0000
CAC40	-29.87737	0.0000	-18.61256	0.0000	-21.66668	0.0000
DAX30	-28.56728	0.0000	-18.19586	0.0000	-20.59661	0.0000
MIB	-29.40146	0.0000	-22.88904	0.0000	-21.86544	0.0000
RTS	-25.93802	0.0000	-20.32968	0.0000	-20.29685	0.0000
BVSP	-27.57252	0.0000	-23.44117	0.0000	-23.10270	0.0000
SENSEX	-25.26534	0.0000	-21.97550	0.0000	-21.54896	0.0000
AXJO	-28.97026	0.0000	-23.55688	0.0000	-22.15941	0.0000
IBEX	-29.82663	0.0000	-22.89998	0.0000	-20.37977	0.0000
STI	-28.19641	0.0000	-22.50763	0.0000	-21.97022	0.0000
HSI	-28.54433	0.0000	-24.26563	0.0000	-22.48722	0.0000
SSE	-27.06552	0.0000	-22.97007	0.0000	-23.92391	0.0000

4. MODEL ESTIMATION AND RESULT INTERPRETATION

4.1 The Judgment of Asymmetry Influence

Given any two financial markets A and B, we need to find out the asymmetric influence relationship between A and B market, i.e. whether A impacts B or B impacts A. For the given sample series $\{A_t\}$ and $\{B_t\}$, if $\rho(A_{t+1},B_t)>\rho(A_t,B_{t+1})$, we say that market B impacts market A, else if $\rho(A_t,B_{t+1})>\rho(A_{t+1},B_t)$, we say that market A impacts market B (Pan, 2004). ρ is a predefined correlation coefficient, it can be linear correlation coefficient, or Kendall rank correlation coefficient τ or Spearman rank correlation coefficient ρ_s.

4.2 Asymmetry Influence Relationship of Linear Correlation Coefficient

First, the Pearson correlation coefficient of any two stock markets can be calculated. Then, $\rho(A_{t+1},B_t)$ and $\rho(A_t,B_{t+1})$ can be calculated. We can judge the relationship between the two markets by the calculation results according to the methodology of Section 5.1. Finally, all the asymmetric correlations are shown in a graph which represents the structure of a Super Bayesian Influence Network (Pan, 2004). Investigation was carried out on the mutual influence relationship of the 14 selected stock market indexes. Figure 1 shows the asymmetric influence relationship of linear correlation coefficient in stage 1. Figure 2 shows the result in stage 2. Figure 3 shows the result in stage 3.

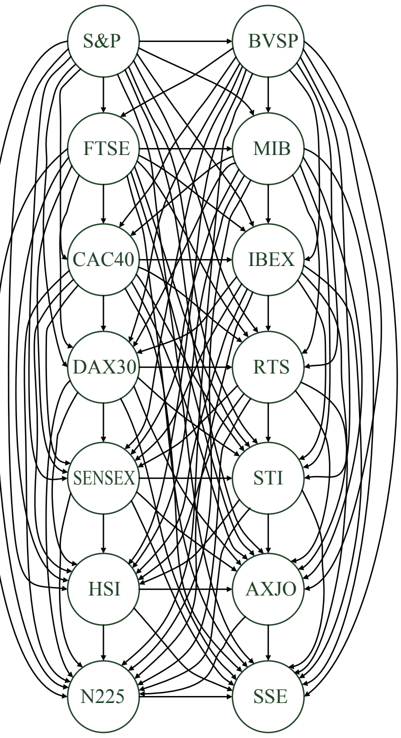

Figure 1
The Asymmetric Influence Diagram of Linear Correlation Coefficients in Stage 1

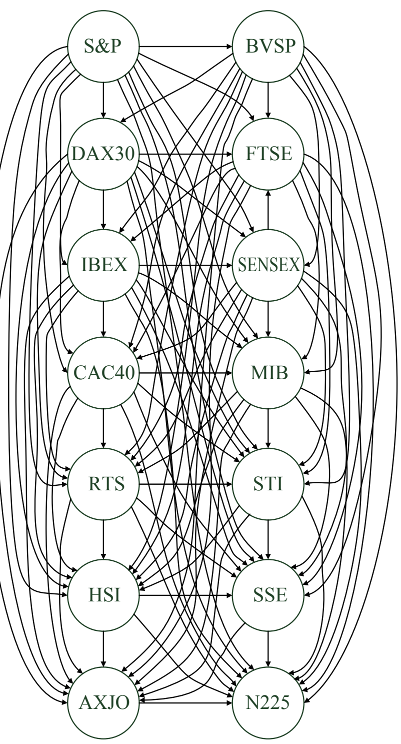

Figure 2
The Asymmetric Influence Diagram of Linear Correlation Coefficients in Stage 2

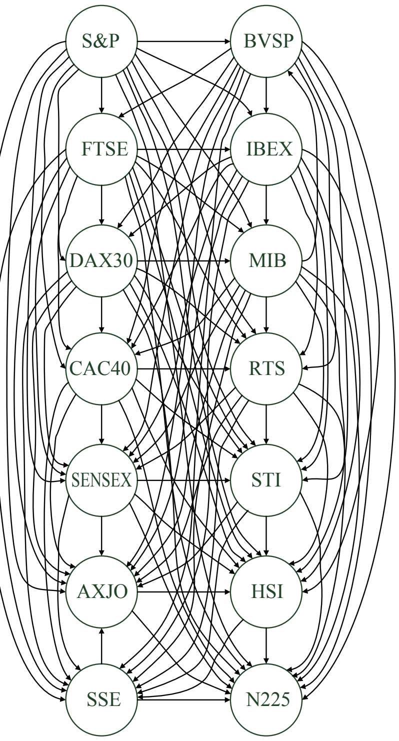

Figure 3
The Asymmetric influence Diagram of Linear Correlation Coefficients in Stage 3

Now we can summarize on asymmetry influence relationships of linear correlation coefficients. The asymmetric influences between the 14 stock markets in stage 1 rank from high to low as follows: U.S., Brazil, U.K., Italy, France, Spain, Germany, Russia, India, Singapore, Hong Kong, Australia, Japan, Chinese Mainland. The interaction influence between the 14 stock markets in stage 2 ranks from high to low as follows: U.S., Brazil, Germany, U.K., Spain, India, France, Italy, Russia, Singapore, Hong Kong, Chinese Mainland, Australia, Japan. But there is an exception, India ranks sixth influence, and Britain ranks fourth. The asymmetric influence between the 14 stock markets in stage 3 ranks from high to low as follows: U.S., Brazil, U.K., Spain, Germany, Italy, France, Russia, India, Singapore, Australia, Hong Kong, Chinese Mainland, Japan. But there are several exceptions, Italy ranks sixth influence, and Brazil ranks second. Chinese Mainland ranks thirteenth influence, and Australia ranks eleventh.

4.3 Asymmetry Influence Relationship of Copula Correlation Coefficient

The Copula correlation coefficient of any two stock markets can be calculated. Then, $\tau(A_{t+1},B_t)$ and $\tau(A_t,B_{t+1})$ can be calculated. We can judge the relationship between the two markets by the calculation results according to the conclusion of section 5.1. Finally, all the correlations are shown in a graph which represents the structure of a Super Bayesian Influence Network. Investigation was carried out on the mutual influence relationship of the 14 selected stock indexes. Figure 4 shows the asymmetric influence relationship of Copula correlation coefficient in stage 1. Figure 5 shows the result in stage 2. Figure 6 shows the result in stage 3.

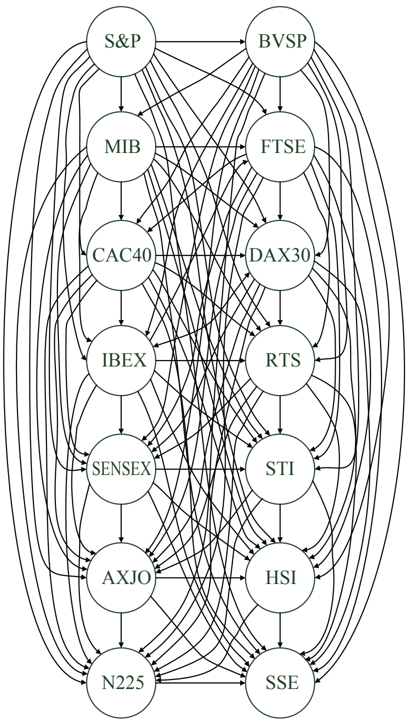

Figure 4
The Asymmetric Influence Diagram of Copula Correlation Coefficients in Stage 1

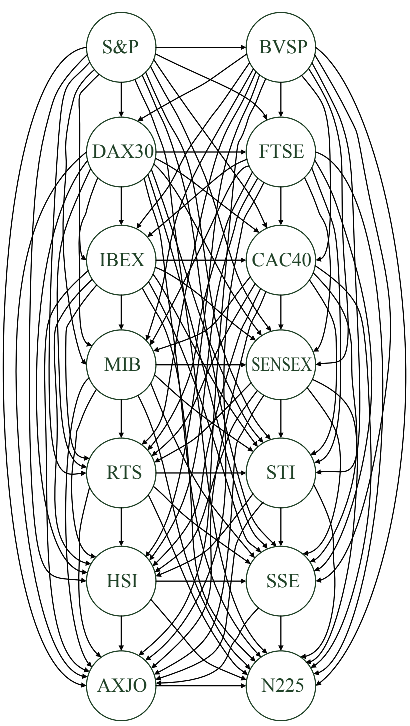

Figure 5
The Asymmetric Influence Diagram of Copula Correlation Coefficients in Stage 2

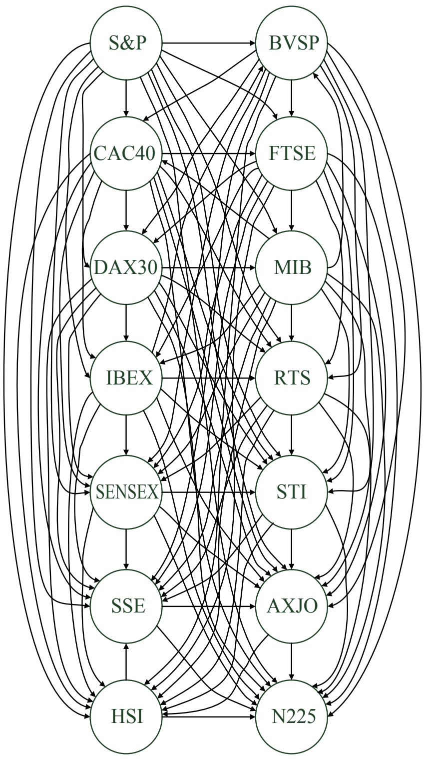

Figure 6
The Asymmetric Influence Diagram of Copula Correlation Coefficients in Stage 3

Comparing the asymmetric influence diagrams of Copula function in different stage, it is not difficult to find that the influence of European and American market and emerging markets of Brazil are in the first group, and the influence of Russia and India market are in the second group, and the influence of the Asia-Pacific stock markets such as Hong Kong and Singapore are in the third group.

Now we can summarize on asymmetry influence relationship of Copula correlation coefficient function. The interaction influences between the 14 stock markets in stage 1 rank from high to low as follows: U.S., Brazil, Italy, U.K., France, Germany, Spain, Russia, India, Singapore, Australia, Hong Kong, Japan, Chinese Mainland. But there is an exception, Spain ranks seventh influence and Britain ranks fourth. The interaction influences between the 14 stock markets in stage 2 rank from high to low as follows: U.S., Brazil, Germany, U.K., Spain, France, Italy, India, Russia, Singapore, Hong Kong, Chinese Mainland, Australia, Japan. The interaction influences between the 14 stock markets in stage 1 rank from high to low as follows: U.S., Brazil, France, U.K., Germany, Italy, Spain, Russia, India, Singapore, Chinese Mainland, Australia, Hong Kong, Japan. But there are several exceptions, Italy ranks sixth influence, Brazil ranks second and France ranks third. Spain ranks seventh influence, and Brazil ranks second. Hong Kong ranks thirteenth influence, and Chinese Mainland ranks eleventh.

4.4 Asymmetry Influence Relationship of Linear Correlation Coefficient Considering Partial Correlation Coefficient

In the multivariate correlation analysis, the simple correlation coefficient may not be able to reflect the real relationship between the variables X and Y. Because the relationships between the variables are very complex, they may be affected by more than one variable. At this time the partial correlation coefficient is a better choice. Partial correlation coefficient calculates the correlation coefficient between variables ruling out the influence of the other variables. In multiple regression analysis, the partial correlation coefficient calculates the correlation coefficient between the two variables under the condition of eliminating the influence of other variables. In the previous two sections, we can see the influence of the U.S. market is the highest at all stages in all markets. We can consider the calculation of the partial correlation coefficient of any other two markets given the U.S. market and we can basically eliminate the influence of other markets. When the partial correlation coefficient is less than a critical value, these two markets can be considered not related taking into account the influence of the U.S. market. Figure 7 shows the asymmetric influence relationship of linear correlation coefficient in stage 1 considering the partial correlation coefficient. Figure 8 shows the result in stage 2. Figure 9 shows the result in stage 3.

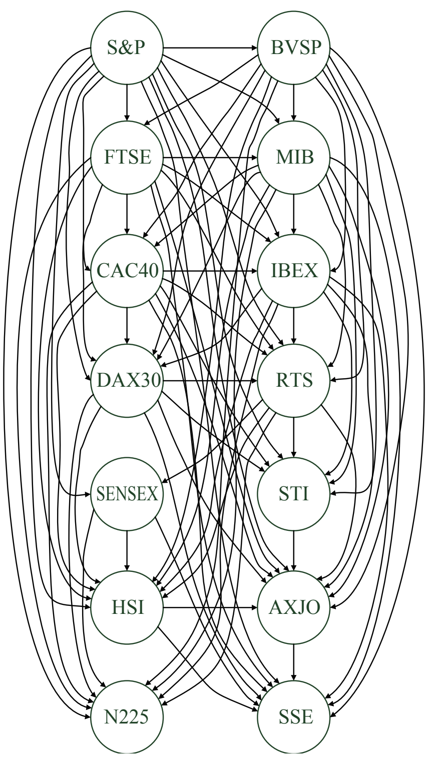

Figure 7
The Asymmetric Influences of Linear Partial Correlation Coefficients in Stage 1

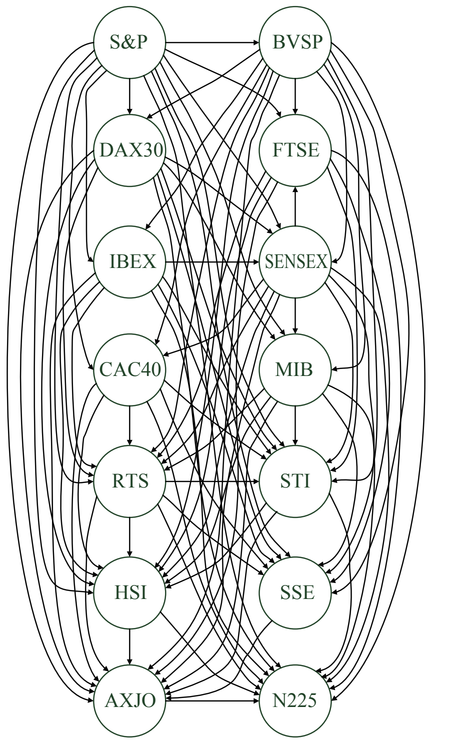

Figure 8
The Asymmetric Influences of Linear Partial Correlation Coefficients in Stage 2

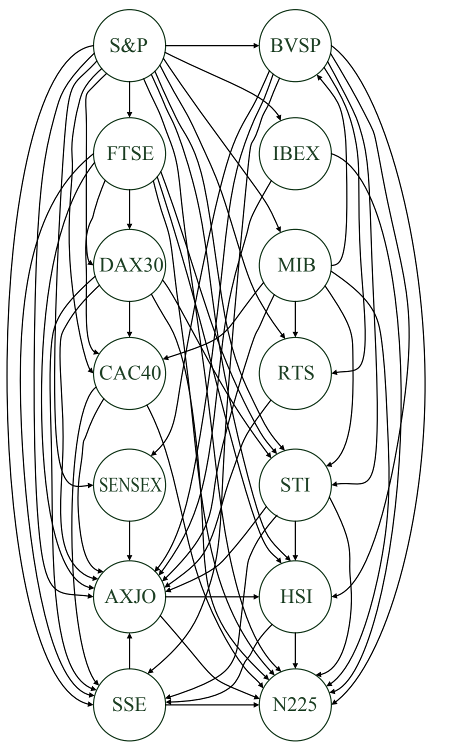

Figure 9
The Asymmetric Influences of Linear Partial Correlation Coefficients in Stage 3

4.5 Asymmetry Influence Relationship of Copula Correlation Coefficient Considering Partial Correlation Coefficient

Figure 10 shows the asymmetric influence relationship of Copula correlation coefficient in stage 1 considering the partial correlation coefficient. Figure 11 shows the result in stage 2. Figure 12 shows the result in stage 3.

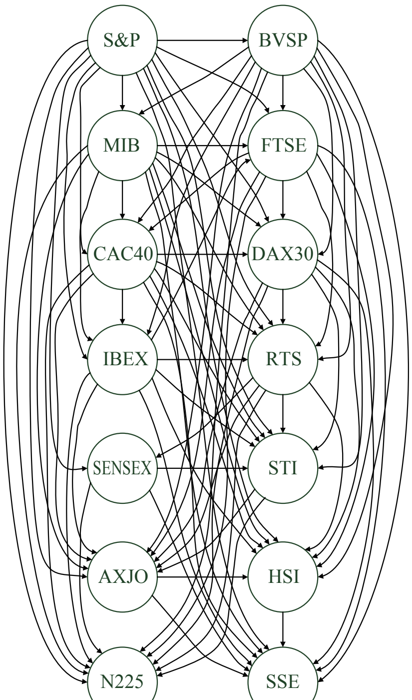

Figure 10
The Asymmetric Influences of Copula Partial Correlation Coefficient in Stage 1

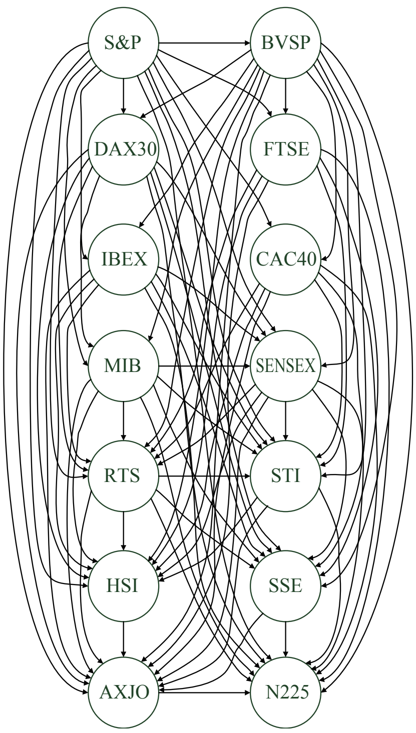

Figure 11
The Asymmetric Influences of Copula Partial Correlation Coefficient in Stage 2

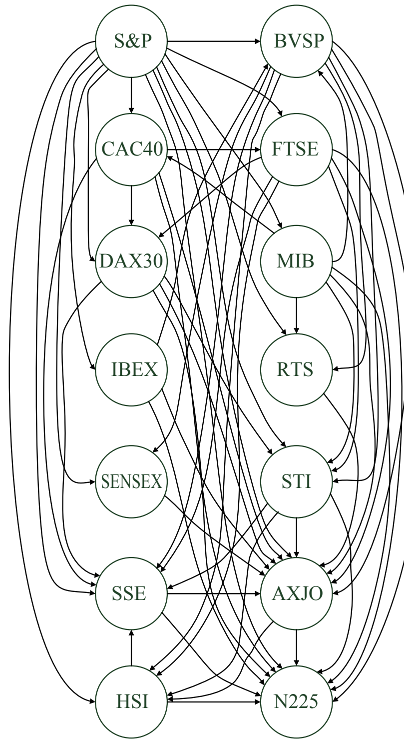

Figure 12
The Asymmetric Influence of Copula Partial Correlation Coefficient in Stage 3

4.6 A Summary on Lead Markets

Comparing the lead market of each market between the linear correlation coefficient and the Copula correlation coefficient in three stages, we find that the lead markets of U.K. are different in all stage, so we predict the U.K. market. The lead market of U.K. is shown in Table 6 in different stage and under different correlation coefficient.

Table 6
The Lead Market of U.K. in Different Stages and Under Different Correlation Coefficients

	Linear correlation coefficient	Copula correlation coefficient
First stage	1 S&P 2 BVSP	1 S&P 2 BVSP 3 MIB 4 IBEX
Second stage	1 S&P 2 BVSP 3 SENSEX	1 S&P 2 BVSP
Third stage	1 S&P	1 S&P 2 CAC40

5. PREDICT THE MARKET USING ARTIFICIAL NEURAL NETWORKS

5.1 Overview of Artificial Neural Network

The prediction research has never stopped since the financial markets come into being. There have been many debates on the predictability of financial market prices. But so far researchers have found quite many theoretical models with certain predictive capabilities. In general, most of the popular prediction models are made on the basis of historical data. In fact, technical analysis has been in existence for a long time, which has discovered many aspects of historical price trend characteristics. These historical price trend characteristics can be captured by the prediction models. Early financial market price prediction models include a variety of regression models, such as ARIMA, GARCH and so on. With the development of computational intelligence, new prediction models appeared based on advanced mathematical tools, such as artificial neural networks, wavelet analysis, neural networks, genetic algorithm and so on. From the current literature, neural networks with strong approximation mapping capabilities are very suitable for modeling nonlinear dynamics of financial markets.

5.2 The Parameters to Test the Model Prediction Effect

Here we use two measurements for the prediction accuracy of the model. They are the Hit Rate and Mean Squared Error. Suppose at time t, the output of the prediction model is $y(t)$, the actual value of market is $x(t)$, so we calculate these measurements as follows:

1. Hit Rate (HR) measures the right number to hit the target of short-term trend direction over the total number of trials. On the financial market price prediction research, the ultimate goal is to find a robust predictive model and apply it into the actual market investment. If the objective is simply to predict the price value of financial market, the utility to the investment decision-making would be limited. So in order to be more effectively linked with the actual trading, the price trend of the market price is the most concerned to the investors. So HR will be the most important criterion to measure the effectiveness of predictive models. HR is calculated as follows:

$$HR = \frac{1}{n}\sum_{k=1}^{n}\left[x(t_k)\,y(t_k) > 0\right] \qquad (8)$$

Where [f] represents the number satisfying the condition f.

2. Mean Squared Error (MSE) is used to measure the predictive accuracy of the model output value. MSE is defined as follows:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}\left(x(t_k) - y(t_k)\right)^2 \qquad (9)$$

5.3 Empirical Research Based on Different Stages and Under Different Lead Markets

We predict the U.K. market on different stages and under different lead markets with artificial neural networks. The results are shown as follows.

Table 7
Prediction Results of U.K. FTSE Index Under Each Lead Market in Stage 1

Lead market	Hit rate			MSE		
	Training	Validation	Testing	Training	Validation	Testing
None	55.35%	54.00%	51.49%	1.38223	0.896196	1.02731
+S&P	56.81%	65.00%	63.37%	1.02656	0.835028	1.21352
+BVSP	57.02%	69.00%	61.39%	1.01039	1.32928	1.11951
+MIB	59.33%	74%	60.40%	0.881561	1.19365	1.32091
+IBEX	59.12%	76%	67.33%	0.861338	1.15647	1.63584

Table 7 shows the prediction result of HR and MSE for the U.K. market with artificial neural networks in stage 1. The first line of data show the prediction result without the lead market, hereafter each line shows the prediction result with a superposition lead market. The lead market of line 2 and line 4 of table 7 is respectively the lead market of the linear correlation coefficient and the lead market of Copula correlation coefficient in stage 1. The lead markets under the Copula correlation coefficient have two more markets of MIB and IBEX than those under the linear correlation coefficient. The hit rate of the lead market under Copula correlation coefficients is respectively 7% and 5.43% higher than that under linear correlation coefficient in the validation and testing sets with artificial neural network.

Table 8
Prediction Results of U.K. FTSE Index Under Each Lead Market in Stage 2

Lead market	Hit rate			MSE		
	Training	Validation	Testing	Training	Validation	Testing
None	52.88%	52.63%	50.63%	2.86436	2.47914	4.90641
+S&P	61.64%	65.79%	58.23%	2.37343	2.58235	2.30127
+BVSP	64.11%	68.42%	57.16%	1.77549	6.24948	5.94596
+SENSEX	61.92%	69.47%	59.49%	2.70861	5.00260	1.61937

Table 8 shows the prediction result of HR and MSE for the U.K. market with artificial neural networks in stage 2. The lead market of line 3 and line 2 of table 8 is respectively the lead market under the linear correlation coefficient and under Copula correlation coefficient in stage 2. The lead markets under the linear correlation coefficient have one more market of SENSEX than those under the Copula correlation coefficient. The HR of the lead market under linear correlation coefficients is respectively 1.05% and 2.33% higher than that under Copula correlation coefficient in the validation and testing sets with artificial neural network. The difference of HR is small in stage 2 between the lead market under the linear correlation coefficient and the lead market under Copula correlation coefficient.

Table 9
Prediction Results of U.K. FTSE Index Under Each Lead Market in Stage 3

Lead market	Hit rate			MSE		
	Training	Validation	Testing	Training	Validation	Testing
None	51.15%	53.42%	50.00%	1.14290	1.31403	1.65849
+S&P	57.18	58.90%	61.84%	1.00612	1.53545	1.05765
+CAC40	58.46%	68.49%	64.47%	0.954124	1.37523	1.36159

Table 9 shows the prediction result of HR and MSE for the U.K. market with artificial neural networks in stage 3. The lead market of line 2 and line 3 of table 9 is respectively the lead market under the linear correlation coefficient and the lead market under Copula correlation coefficient in stage 3. The lead markets under the Copula correlation coefficient have one more market CAC40 than those under the linear correlation coefficient. The HR of the lead market under Copula correlation coefficients is respectively 9.59% and 2.63% higher than that under linear correlation coefficient in the validation and testing sets with artificial neural network. At the same time we also find that the HR under the lead market is higher than that without lead market in three stages.

CONCLUSIONS

In this paper, the asymmetric influence relationship of the 14 major international stock markets was measured by using the Copula correlation coefficient and the linear correlation coefficient. The Super Bayesian Influence Networks of three stages were built according to the asymmetric influence relationship detected from the data. We have found that:

(a) The asymmetric influence relationship of the international stock markets shows not only linear characteristic but also nonlinear characteristic. Therefore, using a nonlinear model - Copula function to measure the correlation between international stock markets has proved more effective.

(b) The hit rate with lead markets is higher than that without lead market. In most cases, the lead markets found by using the Copula correlation coefficients are better than those found by the linear correlation coefficients. The hit rate of the lead market under Copula correlation coefficients is about 3% to 10% higher than that of the lead market under linear correlation coefficient with artificial neural networks.

(c) The mutual influence and the interactivity between global stock markets continuously strengthen and the route of risk transmission is more complicated. But overall, the correlation between global stock markets is still asymmetric. The influence of U.S. and European stock markets are relatively dominant to that of the Asia-Pacific stock markets.

REFERENCES

Cheng, H., & Glascock, J. L. (2005). Dynamic linkages between the greater China economic area stock markets—Mainland China, Hong Kong and Taiwan. *Review of Quantitative Finance and Accounting*, *24*(4), 343-357.

Cheng, K., Lu, F. B., & Yang, X. G. (2012). Spatial analysis of US subprime mortgage crisis contagion. *Systems Engineering—Theory & Practice*, *32*(3), 483-494.

Chong, T. T.-L., Wong, Y.-C., & Yan, I. K.-M. (2008). International linkages of the Japanese stock market. *Japan and the World Economy*, *20*(4), 601-621.

Dong, J., Pan, H. P., Yao, Y. Y., & Li, C. G. (2012). Empirical study on the correlation of oil, stock and gold markets based on DCC-MVGARCH model. *Forecasting*, *31*(4), 53-57. (In Chinese).

Fan, K., Zhao, X. J., & Wang, S. Y. (2010). Empirical study on time-varying information and risk spillover effects among global main equity markets. *Journal of Management Science in China*, *13*(9), 87-97.

Huang, B. N., Yang, C. W., & Hu, J. W. (2000). Causality and cointegration of stock market among the United States, Japan, and the South China growth triangle. *International Review of Financial Analysis*, *9*(3), 281-297.

Huang, F. X., Gu, J., Li, Y. X., & Su, J. Q. (2010). Linkages and dynamic stability of the national of global primary stock index before and after the financial crisis. *Systems Engineering—Theory & Practice*, *30*(10), 1729-1740.

Markwat, T., Kole, E., & Dijk, D. V. (2009). Contagion as domino effect in global stock markets. *Journal of Banking and Finance*, *33*(11), 1996-2012.

Nelsen, R. B. (1999). *An introduction to copulas*. New York: Springer.

Pan, H. P. (2004). A Swingtum theory of intelligent finance for swing trading and momentum trading. In H. P. Pan, D. Sornette, & K. Kortanek (Eds.), *Intelligent Finance—A Convergence of Financial Mathematics with Technical and Fundamental Analysis* (pp.475-451). Melbourne: University of Ballarat.

Pan, H. P. (2011). A basic theory of intelligent finance. *New Mathematics and Natural Computation*, *7*(2), 197-227.

Sklar, A. (1959). Fonctions de répartition àn dimensions et leurs marges. *Publications de l'Institut de l' Université de Paris*, *8*, 229-231.

Xie, Z. H. (2010). *MATLAB statistical analysis and application: 40 case analysis*. Beijing: Beijing University of Aeronautics and Astronautics Press. (In Chinese).

