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AN APPLICATION OF COPULA AND QUANTILE REGRESSION TO ANALYSE THE DEPENDENCE OF SOME RETURNS OF SHARE ON VIETNAM STOCK MARKET

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Abstract

Copula functions represent a methodology that describes the dependence structure of a multi-dimension random variable. Combining copula and the forecast function of the GARCH model, called conditional copula-GARCH. We use this model to analyses static and time varying correlations. Apart from, this paper also estimates time-varying coexcedances and use the quantile regression model to analyses dependence. And this paper applies this models to analyses the dependence of some returns of share on Viet Nam Stock Market.

1. Introduction

Study dependence between financial markets is an important topic of financial analysis, specially in the period of market volatility or large crisis. When large volatility or crisis from a financial market, the evaluation of its contagion to

Key words: Extreme values, Quantile Regression, Contagion in financial markets, Coexceedance, Fat tail distribution, Tail dependence Coefficient.

other markets is necessary but not easy. To analyze the change of the dependence between the markets or the assets, we first have to have a method to measure the dependence of them. Normally, we use the Pearson correlation coefficient to measure the dependence between the assets in normal market condition, as well as in period of big changes. However, the Pearson correlation coefficient can not fully describe the contagion of the financial market, the dependence of the assets, especially their dependence expressed as non-linear or the dependence of extreme values. We can use the extreme values theory (EVT) ([5], [6]) to describe and analyze the extreme events. And tail dependence coefficients are used to measure the dependence of extreme events; copula method ([5], [6]) is used to describe the dependence structure of random variables. In addition, when combined with the GARCH model, we obtain the copula-GARCH models, these models has shown the time variation of assets and had a combined flexible way of structural dependence of the assets.

Moreover, we also apply regression models to analyze the dependence of the variables. In linear regression models mainly study the condition average of the dependent variable, and information about the tail of the distribution is not considered. As we know, the tail of the distribution used to describe rare events, if a return of asset variable has kurtosis coefficient greater than 3 then the market has many big changes, this is a characteristic of the financial data series.

In this paper, we analyze the variation of the co-movement between the assets based on the coexceedance function. Combined with the quantile regression model of Koenker and Bassett units ([4]) to analyze the change of the coexceedance function for the different periods.

In addition to the introduction, the paper is structured as follows: Section 2 outlined the research model consisting of content: Coexceedance function, quantile regression model and the GARCH-copula model; Section 3 presents the empirical analysis results; Section 4 provides some conclusions and issues need further study.

2. Measurement model dependence of the return of stocks

Firstly, we use coexceedance function by approach of Bae K.H., Dirk Baur and Niels Schulze ([2]) to compute coexceedances for the return pairs. The paper use quantile regression model to study change of the coexceedance function on different periods through which we saw the same behavior increase or decrease of the stock change how.

Next, we present dynamic GARCH-copula model to study the dependence of the return pairs. Based on the study of the dynamic of the parameters of the copula function, we know the dependence of the return pairs in normal market condition or in extreme market condition change how.

2.1. Coexceedance values of return pairs

In the study of extreme events, we often choose the value of 5% or 10% of the distribution tails to evaluate for this event. Here, we use the coexceedance function to determine the coexceedances of two return series r_{1t}, r_{2t}:

- **Coexceedance function**

$$\phi_t(r_1, r_2) = \begin{cases} \min(r_{1t}, r_{2t}) & : r_{1t} > 0 \ \text{và} \ r_{2t} > 0 \\ max(r_{1t}, r_{2t}) & : r_{1t} < 0 \ \text{và} \ r_{2t} < 0 \\ 0 & : \ \text{otherwise} \end{cases} \qquad (1)$$

with this approach, the coexceedance values are determined with a varying threshold for every point of time t.

Thus, base on the coexceedance function, we determine the value of simultaneously negative return or positive return of the two return series. To analyze change of the coexceedance function for the other explanatory variables: exchange rate, interest rate, index of international stock markets, the lagged coexceedance ... we can approach by the quantitle regression model ([4]) to study.

- **Quantile regression model**

Suppose Y is a random variable that has the probability distribution function F(y), then γ-percent quantile ($0<\gamma<1$) of Y, denoted $Q(\gamma)$, is defined as follows: $Q(\gamma) = \inf\{y : F(y) \geq \gamma\}$.

Here, we consider linear quantile regression model with explanatory variables $X_2, ..., X_k$:

$$Q(\gamma/X_{2i}, \dots, X_{ki}) = \beta_1(\gamma) + \beta_2(\gamma)X_{2i} + \dots + \beta_k(\gamma)X_{ki} \qquad (2)$$

Based on the sample size n, we find the estimates of the regression coefficients $\hat{\beta}_j(\gamma)$:

$$\hat{\beta}(\gamma) = \arg\min_{\beta(\gamma)} \Big\{ \sum_i \rho_\gamma(Y_i - \beta_1(\gamma) - \beta_2(\gamma)X_{2i} - \dots - \beta_k(\gamma)X_{ki}) \Big\}.$$

with checked function: $\rho_\gamma(u) = u(\gamma - 1(u < 0))$, $1(u)$ is index function.

We use quantile regression model to assess any quantiles of the coexceedance function without assumptions about the distribution of its. Thus, for low quantiles (such that 0.01, 0.05,...) of the coexceedance function will give us information about the same level of discounts with large amplitude of two assets on the market. Similarly, for high quantiles (such that 0.95, 0.99,...) of the coexceedance function will give us information about the same level of price increases with large amplitude of two assets on the market.

We will examine the quantiles of the coexceedance function that is different between the study periods or not? In other words, we study the behavior of the same discounts or increase price of stocks that is different between the study periods or not?

2.2. GARCH-copula model

Copula functions represent a methodology that describes the dependence structure of a multi-dimension random variable. We base on the marginal distributions and a copula function to characterize the dependence structure of the components of a multivariate distribution.

***2.2.1.* Specification for copula**

The following theorem is known as Sklar's Theorem ([5],[6]). It is the most important theorem about copula functions because it is used in many practical applications.

Sklar's theorem: Let F be an n-dimensional c.d.f. with margins $F_1, F_2 \cdots F_n$. Then there exists a function copula $C : [0,1]^n \to [0,1]$ such that:

$$F(x_1, x_2, \cdots, x_n) = C(F_1(x_1), F_2(x_2), ..., F_n(x_n)), \text{for all } x_1, ..., x_n \in [-\infty, \infty].$$

If the margins $F_1, F_2 ... F_n$ are continuous, then C is unique.

Conversely, if C is a copula function and $F_1, ..., F_n$ are the distribution functions, then function $F(x_1, \ldots, = C(F_1(x_1), \ldots, F_n(x_n))$ is an n-dimensional probability distribution function with marginal distribution $F_1, \ldots, F_n$.

Depending on the characteristics of data that we have choice of different copula ([5], [6]): the Gaussian copula, Student-t copula, ... or some of Archimedean copulas (Clayton, Frank, Plackett, Gumbel, ...), ... to analyze.

2.2.2. Dynamic GARCH-copula model

Copula method approach to study the dependence of the return series, we can use unconditional copula model and conditional copula model. With conditional copula model, people often use the model classes: model ARMA (m, n) describes the average return and model GARCH (p, q) describes the variance for each return series:

Suppose we consider N assets, denote by $r_{jt}, j = 1, \ldots, N; t = 1, \ldots, T$, is the return of the asset j at time t.

• Mean equation

$$r_t = \mu_t + u_t, \mu_t = \phi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{i=1}^{n} \theta_i n u_{t-i} \tag{3}$$

•Variance equation

$$u_t = \sigma_t \epsilon_t, \epsilon_t \text{ i.i.d},$$

$$\sigma^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{s=1}^{q} \beta_s \sigma_{t-s}^2 \tag{4}$$

$$\alpha_0 > 0; \alpha_1, \ldots, \alpha_p \geq 0; \quad \sum_{t=1}^{\max(p.q)} (\alpha_i + \beta_i) < 1.$$

if $p > q$ then $\beta_s = 0$ with $s > q$, if $p < q$, then $\alpha_i = 0$ with $i > p$.

After estimating the mean equation and the variance equation of each series, we get the residuals $\hat{u}_t$ from the mean equation and standard deviation estimates $\hat{\sigma}_t$ of the conditional variance equation; and we have the standardized residual values $\hat{\epsilon}_t = \frac{\hat{u}_t}{\hat{\sigma}_t}$. Next, we use the copula function to describe the dependence structure of the standardized residual series.

In this paper, we use some copula functions to describe the dependence structure of the standardized residual series: Student copula, SJC copula. Moreover, when studying the GARCH-copula models, we can consider two cases: Case of the copula parameters are constant, and case of the copula parameters change, also known as the dynamic copula-GARCH model.

Here, we choose the model to analyze the change of the parameters of the copula function as follows:

•For T- copula, the correlation evolves through time as in the DCC(1,1) (Dynamic Conditional Correlation-DCC) model of Engle (2002) ([3]):

$$R_t = \mathrm{diag}(q_{11}^{1/2}, \ldots, q_{NNt}^{1/2}) Q_t \mathrm{diag}(q_{11}^{1/2}, \ldots, q_{NNt}^{1/2}), \qquad (5)$$

$TQ_t = (q_{ijt})_{N\times N}$ is the $N \times N$ symmetric positive definite matrix defined as:

$$Q_t = (1-\alpha-\beta)Q + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1},$$

where $\epsilon_{it} = \frac{u_{it}}{\sigma_{it}}; \alpha.\beta$ are non-negative scalars that $\alpha + \beta < 1$, Q is the $N \times N$ unconditional variance matrix of ϵ_{t-1}. Then we have the model: DCC-T-copula.

•For SJC-copula, we consider parameters: upper tail dependence coefficient-τ_U, lower tail dependence coefficient-τ_L following this equations: (form of Patton (2006)) ([1]) as follows:

$$\tau_t = \Lambda\Big(\omega + \alpha_1\tau_{t-1} + \alpha_2.\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\Big).$$

with Λ is the logistic transformation, $\Lambda(x) = (1+e^{-x})^{-1}$, to ensure that the parameters of the SJC-copula in $(0,1)$.

Here, we will apply this models to empirical analysis on Vietnam's stock market.

3. Empirical results

3.1. Data

This paper uses the closing price (P_t) of a selected number of shares to calculate the VN30, VN-Index and HNX index. The sample is selected from 2/1/2007 to 12/28/2012 for analysis. We will select the shares: CII, DRC, FPT, GMD, RITA, KDC, PVD, REE, STB, VNM, VSH, there are sufficient number of observations from 2/1/2007 to 28/12 / 2012 of the shares of the VN30. Then, we have: RCII, RDRC, RFPT, RGMD, RITA, RKDC, RPVD, RREE, RSTB, RVNM, RVSH, RHNX, RVNINDEX return series $(Ln(\frac{P_t}{P_{t-1}}))$ of the closing price of shares and the HNX index, VNINDEX respectively, every series has 1491 observations.

3.2. Analysis of character of co-movement of the stock and market indice pairs

This section, the paper study coexceedance function of return pairs that are different between the study period or not? Thereby see the same behavior increased, reduction of price of the stock pair how in research period. Firstly, we denote: COERCII, COERFPT, COERGMD, COERKDC, COERPVD, COERSTB, COERVSH, COERREE, COERDRC, COERVNM, COERITA, COERHNX that are coexceedance functions of pairs RCII-RVNINDEX, RFPT-RVNINDEX, RGMD-RVNINDEX, RKDC-RVNINDEX, RPVD-RVNINDEX, RSTB-RVNINDEX, RVSH-RVNINDEX, RREE - RVNINDEX, RDRC - RVNINDEX, RVNM-RVNINDEX, RITA-RVNINDEX, RHNX-RVNINDEX. We have graph of the coexceedance functions:

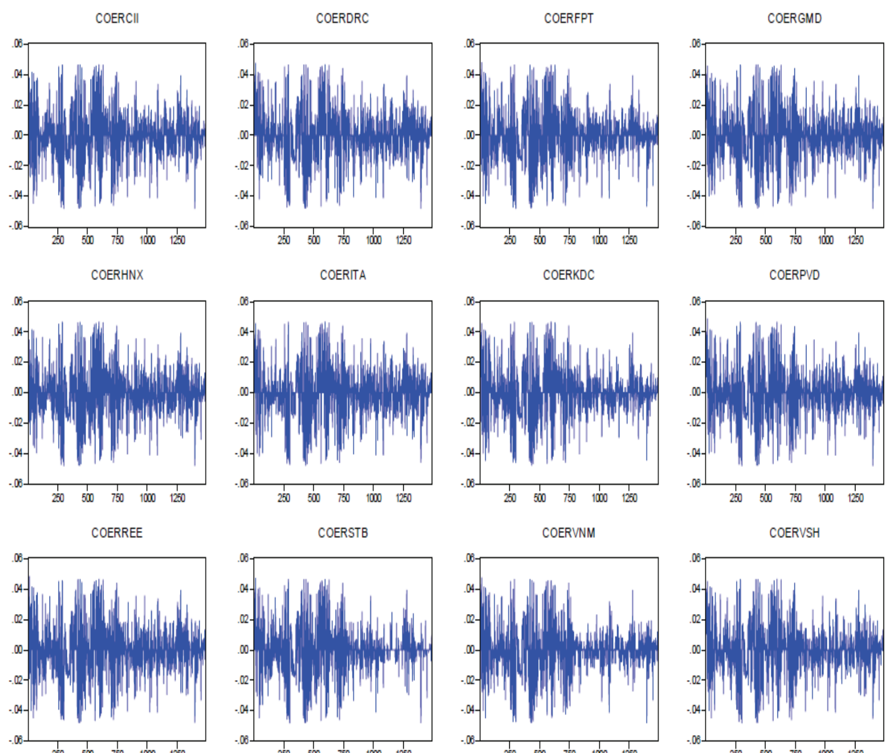

Figure 1. The graph of the coexceedance functions

Looking at the graph of the coexceedance functions we see their volatility in the period be different substantially, thereby showing the same behavior increase or reduction price of the securities be different at different stages of the study sample.

To select the analysis periods of sample, we have somes comment as follows: The time period from 1/2007 to 1/2008, this is the period of Vietnam's stock market that is quite good. Moreover, looking at the monetary policy of the goverment, we see that less volatile interest rates, low inflation, VN-index of Ho Chi Minh City'stock exchanges has the highest level (VNINDEX reached 1170.7 points on 12/3/2007).

The period from 2/2008 to 8/2008, state bank increase base interest rates (from 8.25% / year to 14.0% / year), whereas the VNINDEX reduces from 1041 points to 548 points. After that period from 9/2008 to 2/2009, with loose monetary policies of state bank, on the stock market, VN- index fell to its lowest level and at 234.6 points. From 3/2009 so far, this index has stages of growth to over 400 points but still difficult, and can not recover. We will divide our sample into some periods: period from 1/2007 to 1/2008, period from 1/2/2008 to 27/2/2009, and period from 3/2009 to 12 / 2012.

To assess the trend of coexceedance of return pairs in the period from 1/2/2008 to 27/2/2009 difference how the remaining period of the study sample, we continue to perform quantile regression analysis of the coexceedance functions with dummy variable BG (BG receives value 1 if the observation belongs range from 1/2/2008 to 27/2/2009 and BG receives value 0 if the observation of the remaining period).

Thus, we have model:

$$Q(\gamma/BG_i) = \beta_1(\gamma) + \beta_2(\gamma)BG_i \tag{8}$$

From the estimated results (Appendix 1), we will have the same information on coexceedance of the stocks of how changes in the various periods, following we will explain the estimated result of the number of quantiles of COERITA coexceedance function:

In quantile $\gamma = 0.01$, we have : $Q(\gamma/BG_i) = -0.04032 - 0.00655 * BG_i$

$$\scriptstyle P-value \quad (0.0000)\ (0.0001)$$

so, with a significance level 0.05, coefficient of BG is statistically significant, the estimated value of the coefficient of BG is -0.0065<0, that there are larger negative coexceedances of RVNINDEX and RITA during the period from 1/2/2008 to 27/2/2009 than rest periods. In other words, the same behavior reduction of price with large amplitude of the ITA and VNINDEX in the period from 1/2/2008 to 27/2/2009 happen more remaining periods.

In quantile $\gamma = 0.99$, we have: $Q(\gamma/BG_i) = 0.041632 + 0.004568 * BG_i$

$P-value$ (0.0000) (0.046)

so, with a significance level 0.05, coefficient of BG is statistically significant, the estimated value of the coefficient of BG is 0.004568>0, that there are larger positive coexceedances of RVNINDEX and RITA during the period from 1/2/2008 to 27/2/2009 than rest periods. In other words, the same behavior increase of price with large amplitude of the ITA and VNINDEX in the period from 1/2/2008 to 27/2/2009 happen more remaining periods. At the different quantiles of the coexceedance function, it shows the different amplitude levels of the same increase of price, reduction of price of stock pairs.

From the estimated results (Appendix 1), we have some conclusions:

•In quantiles 0.01, 0.05, 0.1: By LR (quasi-likelihood ratio) test criterion, the models are fit at significance level 0.05. Moreover, the coefficients of the dummy variable (BG) are statistically significant and the value is negative, that there are larger negative coexceedances of every return pair during the period from 1/2/2008 to 27/2/2009 than rest periods.

•In quantiles: 0.9, 0.95, 0.99:

In quantile 0.9: By LR (quasi-likelihood ratio) test criterion, the models are fit at significance level 0.05 (specific cases RGMD-RVNINDEX is fit at significance level 0.1). Moreover, the coefficients of the dummy variable (BG) are statistically significant and the value is positive, that there are larger positive coexceedances of every return pair during the period from 1/2/2008 to 27/2/2009 than rest periods.

In quantile 0.95: With significance level 0.1, there are larger positive coexceedances of some return pairs (RVNM- RVNINDEX, RSTB- RVNINDEX, RPVD-RVNINDEX, RFPT-RVNINDEX, RCII- RVNINDEX) during the period from 1/2/2008 to 27/2/2009 than rest periods.

In quantile 0.99: The models are fit at significance level 0.05 (specific two cases RGMD-RVNINDEX, RHNX- RVNINDEX are fit at significance level 0.1). Moreover, the coefficients of the dummy variable (BG) are statistically significant and the value is positive, that there are larger positive coexceedances of every return pair during the period from 1/2/2008 to 27/2/2009 than rest periods.

Thus, using coexceedance function to describe coexceedance values of return pairs and combined with the quantile regression model, we can show the same trend increased, the reduction of the price of the stock pair how at different stages of the research sample. The above analysis helps us to know how to change the trend of negative coexceedances and positive coexceedances of every stock pair. However, we did not assess the degree of dependence of the return pairs when the extreme market. Here, we'll approach copula method to research this content.

3.3. The estimation results of GARCH-copula model

This section analyzes the empirical with copula-GARCH models, we will choose return series that has ARCH effect . Firstly, we consider stationary property of the return series:

a. Testing stationarity

From unit root test result, we have:

Table 1. Testing stationarity

	RCII	RITA	RDRC	RFPT	RGMD	RHNX
Satistic	-32.9845	-34.5157	-32.5458	-33.4246	-30.5743	-32.3421
Prob.	.0000	.0000	.0000	.0000	.0000	.0000

	RKDC	RPVD	RREE	RSTB	RVNINDEX	RVNM	RVSH
Statistic	-32.424	-34.53	-34.5677	-32.2689	-16.0808	-36.8412	-33.3567
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

With significance level 0.05, by Dickey-Fuller test, all return series are stationary.

b. Selection models for each return series

Based on correlogram of the return series, we select mean equation for the return series. After fitting mean equation, we have residuals and square of residuals of the model. Based on correlogram of the square of residuals series, we see that RHNX, RVNINDEX, RCII, RFPT, RGMD, RKDC, RITA have ARCH effect.

According to the estimation results for the parameters of the copula-GARCH models in equation (**??**), (**??**) and (**??**) of the return pairs RHNX-RVNINDEX, RCII-RVNINDEX, RFPT-RVNINDEX, RGMD - RVNINDEX, RKDC - RVNINDEX, RITA - RVNINDEX, we give some analysis on the change of the degree of dependency of that return pairs in normal market condition, as well as extreme market condition:

c. Analysis of estimation results

According to the estimation results shows the conditional correlation coefficients in the copula-GARCH-DCC-T model of the return pairs that have large variation and linear dependence between RCII, RFPT, RGMD, RKDC, RITA with RVNINDEX around 60% and lower than the linear dependence between RHNX with RVNINDEX.

To see the dependence of the return pairs in extreme market condition change how, we study the change of the lower tail dependence coefficient and the upper tail dependence coefficient of the return pairs. Here, we have some graphs to describe the variation of the degree of dependence in normal market condition (using correlation coefficient) and in extreme market condition (using tail dependence coefficient) for every return pair:

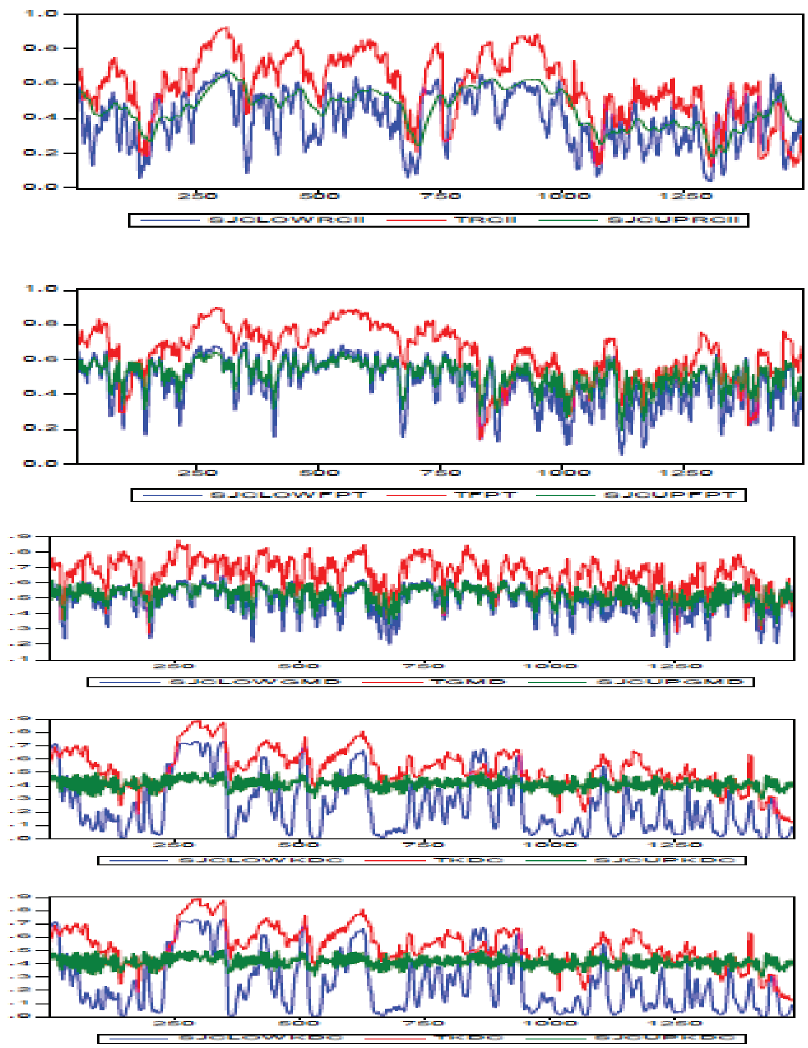

Figure 2. Garph of change in the degree of dependence of the pairs by the correlation coefficient and the tail dependence coefficient

Looking at the graph of the variation of the lower tail dependence coefficient and the upper tail dependence coefficient of the return pairs, I find most of the value of the lower tail dependence coefficient of some pairs: RCII-RVNINDEX, RFPT-RVNINDEX, RGMD-RVNINDEX, RITA - RVNINDEX, RKDC - RVNINDEX and RHNX - RVNINDEX that are smaller than values of the upper tail dependence coefficient the corresponding, in which the most obvious difference shown in RITA-RVNINDEX pair.

Moreover, looking at the graph, we see that in general the degree of dependence of the pairs in normal market condition is higher than in extreme market condition.

4. Conclusion

Based on the empirical analysis results on the dependence of some return pairs, we have the following conclusions:

•Behavior the same reduction of price or the same increase of price with large amplitude of each pair of securities: CII-VNINDEX, DRC-VNINDEX, FPT-VNINDEX, GMD-VNINDEX, ITA-VNINDEX, KDC-VNINDEX, PVD-VNINDEX, REE-VNINDEX, STB-VNINDEX, VNM - VNINDEX, VSH - VNINDEX, HNX - VNINDEX in during the period from 1/2/2008 to 27/2/2009 happens more than the rest periods.

•Degree of dependence of every return pairs: RCII-RVNINDEX, RFPT-RVNINDEX, RGMD-RVNINDEX, RKDC-RVNINDEX, RPVD-RVNINDEX, RVSH-RVNINDEX, RDRC-RVNINDEX, RITA - RVNINDEX, RHNX - RVNINDEX in normal market condition is higher than in extreme market condition.

•In addition to research applications to dependence, we can use copula method and quantile regression model to study the many contents, such that: asset pricing, risk management.

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Appendix 1. The estimation results of quantile regression models

COERCII							
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.04032	-0.0251	-0.0154	0.000197	0.016484	0.025077	0.041413
	0.0000	0.0000	0.0000	0.6500	0.0000	0.0000	0.0000
BG	-0.00736	-0.01752	-0.01809	-0.00312	0.007844	0.010957	0.004851
	0.0001	0.0000	0.0000	0.0028	0.0006	0.0046	0.0121
Quasi-LR Statistic	13.43595	33.98414	42.92317	Prob(F-statistic)	8.847671	3.021139	6.868123
	0.000247	0.0000	0.0000	0.002778	0.002935	**0.082186**	0.008775
COERFPT							
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03994	-0.02234	-0.01504	0.000124	0.015261	0.025077	0.041631
	0.0000	0.0000	0.0000	0.7759	0.0000	0.0000	0.0000
BG	-0.00753	-0.02084	-0.02042	-0.00478	0.009384	0.010957	0.004178
	0.0003	0.0000	0.0000	0.0000	0.0000	0.0055	0.0493
Quasi-LR Statistic	13.48895	56.82625	63.33151	Prob(F-statistic)	16.63403	3.590175	4.323402
	0.00024	0.0000	0.0000	0.000005	0.000045	**0.058122**	0.037592
COERGMD							
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**

C	-0.04014	-0.02561	-0.016	0.000216	0.017654	0.026378	0.041632
	0.0000	0.0000	0.0000	0.6287	0.0000	0.0000	0.0000
BG	-0.00682	-0.01756	-0.01861	-0.00531	0.004645	0.007458	0.004631
	0.0001	0.0000	0.0000	0.0000	0.0934	0.0989	0.0582
Quasi-LR Statistic	15.61067	42.71419	54.89256	Prob(F-statistic)	3.193012	1.526689	3.55462
	0.000078	0	0	0.000001	**0.073954**	**0.21661**	**0.05938**
			COERKDC				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03914	-0.02047	-0.01352	0.000534	0.015385	0.025185	0.040078
	0.0000	0.0000	0.0000	0.1946	0.0000	0.0000	0.0000
BG	-0.00699	-0.02271	-0.01927	-0.00532	0.006914	0.003803	0.006013
	0.0013	0.0000	0.0000	0.0000	0.0043	0.3766	0.0037
Quasi-LR Statistic	13.11407	69.73297	62.34158	Prob(F-statistic)	4.940767	0.961525	6.582753
	0.000293	0.0000	0.0000	0.0000	0.02623	**0.326803**	0.010297
			COERPVD				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03994	-0.02337	-0.0146	0.000197	0.016129	0.025001	0.040822
	0.0000	0.0000	0.0000	0.6489	0.0000	0.0000	0.0000
BG	-0.00774	-0.01924	-0.01889	-0.00365	0.008198	0.01009	0.004029
	0.0004	0.0000	0.0000	0.0005	0.0001	0.0085	0.0516
Quasi-LR Statistic	14.45119	39.06745	51.6221	Prob(F-statistic)	9.548605	3.388812	4.374546
	0.000144	0.0000	0.0000	0.00045	0.002001	**0.06564**	0.03648
			COERSTB				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03839	-0.02103	-0.01389	0.000241	0.015188	0.02342	0.041632
	0.0000	0.0000	0.0000	0.5688	0.0000	0.0000	0.0000

BG	-0.00929	-0.02158	-0.02075	-0.00472	0.009457	0.012614	0.004631
	0.0002	0.0000	0.0000	0.0000	0.0000	0.0011	0.0171
Quasi-LR Statistic	11.62296	60.00516	70.83597	Prob(F-statistic)	14.62446	4.769207	5.882437
	0.000651	0.0000	0.0000	0.000004	0.000131	0.028973	0.015293
			COERVSH				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.04017	-0.02337	-0.01464	2.50E-05	0.01511	0.02526	0.039343
	0.0000	0.0000	0.0000	0.9531	0.0000	0.0000	0.0000
BG	-0.00751	-0.01843	-0.01711	-0.00305	0.007189	0.007806	0.00692
	0.0003	0.0000	0.0000	0.0028	0.0237	0.5696	0.0008
Quasi-LR Statistic	13.01921	23.68657	46.96701	Prob(F-statistic)	4.51763	1.000684	8.017845
	0.000308	0.000001	0.0000	0.00283	0.033547	**0.317145**	0.004632
			COERHNX				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03969	-0.0243	-0.0154	0.00011	0.01786	0.025779	0.041413
	0.0000	0.0000	0.0000	0.8029	0.0000	0.0000	0.0000
BG	-0.00799	-0.01799	-0.01841	-0.00425	0.005546	0.007287	0.004788
	0.0003	0.0000	0.0000	0.0001	0.021	0.0659	0.0842
Quasi-LR Statistic	13.58751	37.51228	56.94424	Prob(F-statistic)	5.303649	2.503409	3.634883
	0.000228	0.0000	0.0000	0.000061	0.021281	**0.1136**	**0.056581**
			COERREE				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.04032	-0.02561	-0.01636	0.000377	0.018168	0.028227	0.041413
	0.0000	0.0000	0.0000	0.4089	0.0000	0.0000	0.0000
BG	-0.00655	-0.017	-0.01825	-0.00503	0.00616	0.005609	0.004728
	0.0003	0.0000	0.0000	0.0000	0.0015	0.1926	0.0573

Quasi-LR Statistic	11.90664	34.10942	59.2015	Prob(F-statistic)	8.915863	0.868427	4.100488
	0.000559	0.0000	0.0000	0.000005	0.002827	**0.351391**	0.042871
			COERDRC				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.04014	-0.02293	-0.01457	0.000494	0.017312	0.02526	0.041413
	0.0000	0.0000	0.0000	0.2533	0.0000	0.0000	0.0000
BG	-0.00714	-0.02025	-0.01892	-0.00477	0.006046	0.008576	0.004851
	0.0002	0.0000	0.0000	0.0000	0.0038	**0.0738**	0.0384
Quasi-LR Statistic	14.68547	35.98121	55.49856	Prob(F-statistic)	4.640022	1.997172	5.104374
	0.000127	0.0000	0.0000	0.000004	0.031235	**0.157593**	0.023866
			COERVNM				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.03839	-0.02174	-0.01288	0.000299	0.012896	0.023392	0.040225
	0.0000	0.0000	0.0000	0.4634	0.0000	0.0000	0.0000
BG	-0.00902	-0.02055	-0.01928	-0.00367	0.010462	0.011094	0.005915
	0.0001	0.0000	0.0000	0.0002	0.0003	0.0018	0.003
Quasi-LR Statistic	14.36786	46.13757	41.61033	Prob(F-statistic)	13.17864	4.601506	6.772955
	0.00015	0.0000	0.0000	0.000176	0.000283	0.031944	0.009255
			COERITA				
	0.01	**0.05**	**0.1**	**OLS**	**0.9**	**0.95**	**0.99**
C	-0.04032	-0.0251	-0.01529	0.000298	0.017457	0.026267	0.041632
	0.0000	0.0000	0.0000	0.5018	0.0000	0.0000	0.0000
BG	-0.00655	-0.01808	-0.01932	-0.00456	0.00687	0.0068	0.004568
	0.0001	0.0000	0.0000	0.0000	0.0009	0.2225	0.046
Quasi-LR Statistic	14.3476	41.33978	71.27421	Prob(F-statistic)	8.495089	1.57913	4.202785
	0.000152	0.0000	0.0000	0.000019	0.003561	**0.208886**	0.040358