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The dynamic dependence between the Chinese market and the international stock markets: A copula approach

1. Introduction

The dependence between financial markets has always been an important issue for both financial economists and investment practitioners (Bartram and Dufey, 2001). Researches on the market dependence typically gained wide responses in the literature because of its implications for international diversification and market integration. Recent studies have demonstrated evidence of contagion in equity markets (Ane and Labidi, 2006; Jondeau and Rockinger, 2006; Bekaert et al., 2005; Poon et al., 2004; Longin and Solnik, 2001; Forbes and Rigobon, 2002). However, these studies usually emphasized the developed economies such as the United States, the United Kingdom, Germany, France, and Japan. Few studies have investigated the role of China regarding her increasing integration into the international markets (Lane, 2006).

Between the beginning of 1991 and the end of 2006, the total market capitalization in China realized a remarkable increase from US$2,028 million to US$786 billion, making China the largest of all emerging markets and fourth in the world. By the end of September 2007, a total of 1,517 companies had been listed in her stock markets. According to a 2009 IMF report,[1] China has replaced Germany as the world's third largest economy. The dramatic growth in China has attracted many international speculators and investors, despite worries about the market crash due to price bubbles which may affect other markets.

A recent incident shows the possible dependences between markets in China and other major markets in the world. On February 27, 2007, the Shanghai Stock Exchange's Composite Index dropped 8.8% unexpectedly, the largest 1-day decline in 10 years. Later in the same day, the Dow Jones Industrial Average tumbled 3.3% and the NASDAQ declined 3.9%, the sharpest declines since the 911 crisis. Other European and Asian markets experienced similar responses. There is no doubt that an event in China might trigger international reactions around the world due to China's market integration with other markets. Bekaert et al. (2005) and Goetzmann et al. (2005) reported positive causality between market integration and market dependence. Campa

[1] Global Economic Outlook 2009, IMF.

and Fernandes (2006) found country risks smaller for markets integrated more with international markets. In particular, Chan et al. (2007) illustrated how China's financial market has emulated and integrated over time with developed markets. Sun et al. (2008) pointed out that China's increased integration mainly came from the opening up of her markets to foreign investor and the cross-border listings. In this study, we inquire whether China's financial market becomes more interdependent with those of the rest of the world's and, if so, whether her country risk declines as her degree of financial integration increases.

Furthermore, as China's economy has attracted huge foreign speculators, a crash in her stock market may prompt abrupt withdrawals, and financial contagion could erupt consequently. A particular aim of our study is to examine the time-varying dependence structures between the Chinese market and other major markets of the world. The nature of this dependence is of great importance in understanding the market co-movements between China and other countries. The dynamic relationship between these markets certainly provides essential implications for portfolio diversification, risk management and international asset allocation.

To assess these changing dependence structures over time, we estimate the time-varying copula models between indices of these stock markets. The parameters in the copula functions are considered as dynamic processes conditional on available information to account for non-linear and time-dependent relationships.

Compared with existing literature, our study provides two contributions. First, few studies have focused on the co-movement of Chinese market with other international markets despite her noticeable growth and increasing integration with other major markets,. Some were confined to China's regional roles (Cheng and Glascock, 2005, 2006; Baur, 2007; Chang et al., 2000). As China's production and trade also have significant global influence[2], we purport that the regional role should be extended worldwide.

The second contribution is the demonstration of how a conditional copula model can be applied which will benefit portfolio diversification and active asset allocation for investors interested in Chinese markets. A copula-based measure can specify the structures of dependence and take the non-linear property into account without the constraint of normality. In particular, using an extended time-varying copula model with the conditional joint distribution, we can obtain conditional means, variances, and correlations, as well as the time paths of other dependence measurements such as rank

[2] Chan et al. (2008) pointed out that the trade between China and the rest of the world has become more direct in recent years.

correlation or tail dependence (Patton, 2006a). Our copula model investigates both conditional dependence structures and conditional tail dependences between the stock market of China and other major stock markets[3]. This forward-looking assessment can provide useful information to actively diversify the international portfolios and manage the assets worldwide.

Specifically, the daily stock indices for Morgan Stanley Capital International (MSCI) China, MSCI Japan, MSCI United States, MSCI Europe, MSCI emerging markets, MSCI World, and MSCI AcWorld are collected over the period 2002–2007. We consistently find that, with markets in Japan, in the Pacific, and in the emerging countries, the Chinese market experiences not only a higher degree of dependence but also a higher variation of dependence, implying that the probability of joint crashes will be high for markets in these areas once bubbles burst in China. Portfolio managers should become more alert to take into account this co-movement.

The remainder of this paper is structured as follows: Section 2 presents our empirical methodology of a time-varying copula model. Data and summary statistics are reported in Section 3. Empirical results are discussed and analyzed in Section 4, and conclusion is provided in Section 5.

2. Empirical methodology

Multivariate normality is not suitable for measuring the dependence structure of equity returns (Longin and Solnik, 2001; Poon et al., 2004). Researchers are concerned about the methodology used to specify their co-movements or contagion effects, especially for the asymmetric parts, between the stock markets. Longin and Solnik (2001) and Poon et al. (2004) have suggested the extreme value theory (EVT) for the study of the dependence structure between international equity markets. However, choosing an optimal threshold to identify the extreme values may be difficult.[4] The

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[3] Patton (2006a) was the first to apply a time-varying copula to exchange rate dependence. Bartram et al. (2007) and Ane and Labidi (2006) used the same method to examine the Euro and European financial market dependence, but they did not explore any time-varying tail dependence.

[4] Choosing a high threshold value leads to few observations of return exceedances and implies inefficient parameter estimates with large standard errors. On the other hand, choosing a low threshold value can provide many observations of return exceedances, but induce biased parameter estimation. Hence, Longin and Solnik (2001) applied Monte Carlo simulation to determine the optimal threshold values.

dependence function used for estimating the threshold may not be well defined.[5] Furthermore, the main difficulty with EVT is that it is constrained by a static measure. Using EVT in a dynamic setting is only true if the explanatory variables are exogenous. If they are endogenous, the difficulty mentioned by Forbes and Rigobon (2002) emerges.

Kroner and Ng (1998), Engle (2002), and Cappiello et al. (2006) have developed generalized autoregressive conditional heteroskedasticity (GARCH) models with time-varying covariances and correlations. Engle (2002) provided a univariate GARCH model that allows for conditional asymmetries in both volatilities and correlations. Cappiello et al. (2006) extended Engel's (2002) model to two-dimensional environments. Both Engle (2002) and Cappiello et al. (2006) contribute a computational advantage over multivariate GARCH models by providing a two-step estimation procedure, the univariate GARCH estimation followed by the correlation estimation. Intuitively, the aim is to separate the modeling of variances from that of correlations. Hyde et al. (2007) applied an asymmetric generalized dynamic conditional correlation GARCH (AG-DCC-GARCH) model to investigate the correlation dynamics among Asia–Pacific, European Union, and U.S. stock returns.

Recently, the copula method has been emphasized because of its capacity for modeling the contemporaneous interdependence between either univariate time series or innovations of univariate parametric time series models. The copula method is becoming more and more popular because it allows the analysis of dependence structure beyond linear correlation and a higher degree of flexibility in estimation by separating marginal and joint distributions. Furthermore, the method can be extended to a time-varying specification to capture the dynamics in the dependence structure. Patton (2006a,b) introduced the method of time-varying copula and applied it to measure conditional asymmetries in the exchange rate dependences. Bartram et al. (2007) and Ane and Labidi (2006) employed the copula model to measure dependences between some European stock indices. Following their settings, our empirical time-varying copula is modeled as demonstrated below.

2.1. The models for the marginal distribution

We assume that the marginal distribution for each index return is characterized by a GJR-GARCH(1,1)-AR(1)-*t* model because the impact of asymmetric information is

[5] Typically, logistic function is used to make this estimation, although this solution is not good.

well known for financial assets.[6] Let $R_{i,t}$ and $h_{i,t}$ denote index i's return and its conditional variance for period t, respectively, and Ω_{t-1} denotes the previous information set. The GJR-GARCH(1,1)-AR(1)-t model for the index return is

$$R_{i,t} = u_i + \emptyset_i R_{i,t-1} + \varepsilon_{i,t} \tag{1a}$$

$$h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2} s_{i,t-1}\varepsilon^2_{i,t-1} \tag{1b}$$

$$z_{i,t}|\Omega_{t-1} = \sqrt{\frac{df_i}{h_{i,t}(df_i - 2)}}\varepsilon_{i,t} \qquad z_{i,t} \sim iid\ t_{df_i} \tag{1c}$$

with $s_{i,t-1} = 1$ when $\varepsilon_{i,t-1}$ is negative, and $s_{i,t-1} = 0$ otherwise. df_i is the degree of freedom.

Fisher (1932) and Rosenblatt (1952) demonstrated that random variable $U_{i,t} = F_{i,t}(z_{i,t}|\Omega_{t-1})$ has Uniform(0,1) distribution, regardless of its original distribution. Thus, the value of the random variable from conditional marginal distribution $F_{i,t}(z_{i,t}|\Omega_{t-1})$ should be between zero and 1. Typically, the technique of "probability integral transform"[7] for conditional random variables, $z_{i,t}|\Omega_{t-1}$, can be applied to satisfy this requirement.

2.2. The models for the copula

Equity returns have behaved in the manner of exhibiting more joint negative extremes than joint positive extremes, leading to the observation that stocks tend to crash together but not to boom together (Poon et al., 2004; Longin and Solnik, 2001; Bae et al., 2003). Accordingly, dependence structure should be examined in either tail of the return distribution. We therefore employ the Gaussian, the Gumbel, and the rotated Gumbel copulas for specification and calibration, all with and without time variation. The Gaussian copula is generally viewed as a benchmark for comparison, whereas the Gumbel and the rotated Gumbel copulas are used to capture the upper and lower tail dependences, respectively.

The conditional Gaussian copula function is the density of joint standard uniform variables(u_t, v_t), as the random variables are bivariate normal with a time-varying correlation, ρ_t. Moreover, let $x_t = \Phi^{-1}(u_t)$ and $y_t = \Phi^{-1}(v_t)$, where $\Phi^{-1}(.)$

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[6] The conditional densities of equity index returns are leptokurtic, and its variances are asymmetric functions of previous returns (Nelson, 1991; Engle and Ng, 1993; Glosten et al., 1993).

[7] $\hat{u}_{i,t} = \hat{F}_i(x_{i,t}) = \frac{1}{T+1}\sum_{j=1}^{T} I\{x_{i,j} < x_{i,t}\}$ $\forall$t, i=1,…,n, where I{.} is an indicator function.

denotes the inverse of the cumulative density function of the standard normal distribution. The density of the time-varying Gaussian copula can be illustrated as

$$c_t^{\text{Gau}}(u_t, v_t|\rho_t) = \frac{1}{\sqrt{1-\rho_t}} \exp\left\{\frac{2\rho_t x_t y_t - x_t^2 - y_t^2}{2(1-\rho_t^2)} + \frac{x_t^2+y_t^2}{2}\right\} \tag{2}$$

Tail dependence captures the behavior of random variables during extreme events. In our study, it measures the probability of a simultaneous market crash in various countries, given that the bubbles in Chinese stock markets have been pricked. The Gumbel and the rotated Gumbel copulas can efficiently capture the tail dependence arising from the extreme observations caused by asymmetry. The density of the time-varying Gumbel copula is

$$c_t^{\text{Gum}}(u_t, v_t|\delta_t^U) = \frac{(-\ln u_t)^{\delta_t^U-1}(-\ln v_t)^{\delta_t^U-1}}{u_t v_t} \exp\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln v_t)^{\delta_t^U-1}\right]^{\frac{1}{\delta_t^U}}\right\}$$

$$\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln v_t)^{\delta_t^U-1}\right]^{\left(\frac{1-\delta_t^U}{\delta_t^U}\right)^2} + (\delta_t^U - 1)\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln v_t)^{\delta_t^U-1}\right]^{\left(\frac{1-2\delta_t^U}{\delta_t^U}\right)}\right\} \tag{3}$$

where $\delta_t^U \in [1,\infty)$ measures the degree of dependence between u_t and v_t. $\delta_t^U = 1$ implies an independent relationship and $\delta_t^U \to \infty$ represents perfect dependence. The Gumbel family has upper tail dependence, with $\lambda_t^U = 2 - 2^{1/\delta_t^U}$. The rotated Gumbel copula has a similar density function to that of the Gumbel copula and its time-varying version is

$$c_t^{\text{R.Gum}}(1-u_t, 1-v_t|\delta_t^L) =$$

$$\frac{(-\ln(1-u_t))^{\delta_t^L-1}(-\ln(1-v_t))^{\delta_t^L-1}}{(1-u_t)(1-v_t)} \exp\left\{-\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-v_t))^{\delta_t^L-1}\right]^{\frac{1}{\delta_t^L}}\right\}$$

$$\left\{-\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-v_t))^{\delta_t^L-1}\right]^{\left(\frac{1-\delta_t^L}{\delta_t^L}\right)^2} + (\delta_t^L - 1)\left[(-\ln(1-v_t))^{\delta_t^L-1} + (-\ln(1-\right.\right.$$

$$\left.\left.v_t))^{\delta_t^L-1}\right]^{\left(\frac{1-2\delta_t^L}{\delta_t^L}\right)}\right\} \tag{4}$$

The lower tail dependence measured by the rotated Gumbel copula is $\lambda_t^L = 2 - 2^{1/\delta_t^L}$

2.3. Parameterizing time-varying copula model

Assuming time-invariant dependence between two index returns seems unreasonable in reality. So, a conditional copula with a time-varying dependence parameter is prevalent (Patton, 2006a,b; Bartram et al., 2007; Jondeau and Rochinger, 2006; Rodriguez, 2007; Ane and Labidi, 2006). Following the studies of Patton (2006a) and Bartram et al. (2007), we assume that the dependence parameter is determined by past information, such as its previous dependence and the historical absolute difference between cumulative probabilities of two index returns.

For a time-varying Gaussian copula, its conditional dependence parameter can be modeled as an AR(1)-like process because autoregressive parameters over lag 1 are rarely different from zero (Bartram et al., 2007;[8] Samitas et al., 2007). The dependence process of the Gaussian copula is, therefore,

$$\rho_t = \Lambda(\beta_\rho \rho_{t-1} + \omega_\rho + \gamma_\rho |u_{t-1} - v_{t-1}|) \tag{5}$$

The conditional dependence, ρ_t, depends on its previous dependence, ρ_{t-1}, and historical absolute difference, $|u_{t-1} - v_{t-1}|$. Thus, the persistence and the variation in the dependence process can both be captured[9]. $\Lambda(x)$ is defined as $(1 - e^{-x})(1 + e^{-x}) = \tanh\left(\frac{x}{2}\right)$, which is the modified logistic transformation to keep ρ_t in (-1,1) at all times (Patton, 2006a). The coefficient, β_ρ, captures the degree of persistence, and γ_ρ captures the adjustment in the dependence process. The estimation of copula parameters, $\theta_c = \left(\beta_\rho, \omega_\rho, \gamma_\rho\right)'$, will be discussed in Section 2.4.

Both conditional Gumbel dependence and rotated Gumbel dependence are assumed to follow an AR(1)-like process as well. We propose the time-varying dependence process for the Gumbel copula and the rotated Gumbel copula as follows:

$$\delta_t^U = \beta_U \delta_{t-1}^U + \omega_U + \gamma_U |u_{t-1} - v_{t-1}| \tag{6}$$

$$\delta_t^L = \beta_L \delta_{t-1}^L + \omega_L + \gamma_L |u_{t-1} - v_{t-1}| \tag{7}$$

where $\delta_t^U \in [1, \infty)$ measures the degree of dependence in the Gumbel copula and has a lower bound equal to 1, indicating an independent relationship, whereas $\delta_t^L \in [1, \infty)$ measures the degree of dependence in the rotated Gumbel copula. After estimation of the Gumbel copula parameters $\theta_c = (\beta_U, \omega_U, \gamma_U)'$, the conditional upper tail dependence coefficients, $\{\lambda_t^U | \delta_t^U\}$, are obtained by

$$\lambda_t^U = \Psi(2 - 2^{\frac{1}{\delta_t^U}}), \tag{8}$$

[8]Bartram et al. (2007) assumed that the time-varying dependence process follows an AR(2) model.

[9] Unlike Patton (2006a,2006b) and Bartram et al. (2007), Ane and Labidi (2006) characterized their conditional dependence coefficients as a pure AR(1), which means that only the persistence in the dependence process is emphasized.

where $\Psi \stackrel{\text{def}}{=} (1+e^{-x})^{-1}$ is the logistic transformation to keep λ_t^U in (0,1) at all times. Similarly, the conditional lower tail dependence coefficients, $\{\lambda_t^L | \delta_t^L\}$, are obtained by the same method.

2.4. Estimating and calibrating copula models

The calibration of copula parameters using real market data has attracted much interest in recent statistical literature (Meneguzzo and Vecchiato, 2004; Mashal and Zeevi, 2002; Breymann et al., 2003; Galiani, 2003). The exact maximum likelihood method (EML) is a well-known parametric method for estimation. However, the EML must estimate the parameters of the marginals and the copula functions simultaneously. As the power of a copula model is to express a joint distribution by separating the marginal distributions from their dependence, the estimations for copula models are naturally decomposed into two steps: the first for the marginals and the second for the copula, which is the concept of the inference function for margins method (IFM). The IFM improves EML because the latter is computationally intensive, especially for estimations of higher dimensions. IFM can be performed by estimating parameters of marginal distributions, $\hat{\theta}_{it}$, prior to those of copula functions, $\hat{\theta}_{ct}$. Efficiency is therefore enhanced through Eqs. (9) and (10).

$$\hat{\theta}_{it} = \arg\max \sum_{t=1}^{T} \ln f_{it}(z_{i,t} | \Omega_{t-1}, \theta_{it}) \tag{9}$$

$$\hat{\theta}_{ct} = \arg\max \sum_{t=1}^{T} \ln c_t\left(F_{1t}\left(z_{1,t} | \Omega_{t-1}\right), F_{2t}\left(z_{2,t} | \Omega_{t-1}\right), \ldots F_{nt}\left(z_{n,t} | \Omega_{t-1}\right), \theta_{ct}, \hat{\theta}_{it}\right) \tag{10}$$

3. Data and summary statistics

The daily stock indices provided by MSCI were obtained from the Datastream database over the period from January 1, 2002, to June 30, 2007. A total of 1,434 daily observations for each index were collected. To control the non-synchronous trading problems, MSCI index returns were calculated as rolling averages of 2-day returns suggested by Forbes and Rigobon (2002). Maghyereh (2004) noted the reasons why the MSCI indices are better than other local stock indices. For each country's level, the MSCI China, MSCI United States, and MSCI Japan indices are selected. To specify which regional stock market is better correlated with China's, possibly as a result of their geographic ties or trade relationships, we use the MSCI Europe and MSCI Pacific. To detect whether emerging markets have experienced higher dependences than developed markets, both the MSCI world index and the MSCI emerging markets index were collected. The MSCI world index contains the market indices of 23 developed countries, whereas the MSCI emerging markets index includes the market indices of 25 emerging countries. Moreover, the MSCI AcWorld index, which combines the market indices of 48 developed and developing countries, was collected to measure the worldwide-level dependence.

The summary statistics of each index return are reported in Table 1. Table 2 illustrates Pearson's, Spearman's, and Kendall's correlations for each index return paired with China's index return. Pearson's correlation is a measurement of linear association, which implies that it is neither robust for heavily tailed distributions nor adequate for a non-linear relationship. However, the nonparametric rank correlations, such as Kendall's τ and Spearman's ρ, are less sensitive to the observations in the tails. As illustrated in Table 2, no matter which measurement is used, the China–emerging pair has the greatest correlation, followed by the China–Pacific pair and the China–Japan pair.

The parameters of the marginal distribution for each index return are estimated and presented in Table 3. The parameters are assumed to be characterized by a GJR-GARCH(1,1)-AR(1)-*t* model given by Eq. (1). As illustrated in Table 3, most parameters are significant at the 5% level at least. Furthermore, we test whether the transformed series are *Unif*(0,1) using the Kolmogorov–Smirnov test, and the residual series pass the goodness-of-fit test for all index returns.

[Insert Table 1 here]

[Insert Table 2 here]

[Insert Table 3 here]

4. Empirical results

4.1. Unconditional copula models

For comparison, the results of unconditional copula models are presented in Table 4. The estimated parameters and results of goodness-of-fit test for static Gaussian, rotated Gumbel, and Gumbel copula functions are reported. As shown in Table 4A, all copula functions have positive parameters, indicating that the index return of China positively correlates with all index returns considered in the current study. We consistently find that, irrespective of the assumed copula functions, the dependence between the index return of the emerging markets and that of China is the highest, followed by the China–Pacific pair and the China–Japan pair. Bekaert et al. (2005) and Goetzmann et al. (2005) claimed that capital market integration and increased trade are embedded with a prediction about the dependence between markets. Therefore, the dependence of the Chinese market with emerging markets is relatively higher than her dependence with developed markets, implying limited portfolio diversification opportunities. This may be attributed to high trade frequencies between these emerging countries and China because they are usually China's key suppliers for energy, minerals, crops, and various commodities. When the growth of the Chinese economy unexpectedly slows, emerging markets may suffer severely. The high degree of dependence between China and the Pacific or between China and Japan may be a result of their geographic ties. This is similar to the results of Evans and McMillan (2006), who reported that there is more evidence of upward correlations within regional groups. We further infer that these dependences will be more evident as China proposes to join the ASEAN Free Trade Area (AFTA) in 2010 to strengthen their cooperative and competitive abilities through eliminating tariffs and non-tariff barriers.

The value of the Akaike information criterion (AIC)[10] is applied for the goodness-of-fit test from the maximized log-likelihood values (lnL) in Table 4A. We compute the AIC for each copula and then rank the copula models accordingly. Table 4B contains the AIC values for three chosen copulas. Except for China–World, China–AcWorld, and China–U.S. pairs, the lowest AIC value from the rotated Gumbel copula indicates that it is the best fitting model and the lower tail dependence exists for Europe, Japan, Pacific, and emerging pairs. This finding is consistent with the literature that equity returns have exhibited more joint negative extremes than joint positive extremes, leading to the observation that stocks tend to crash, but not to boom, together. However, the use of AIC may not be sufficient. We will apply the likelihood ratio test conducted in Section 4.4 for further comparison of the models and discuss their significance levels.

[Insert Table 4 here]

4.2. Conditional copula models

The estimated parameters of time-varying dependences in the Gaussian copula are reported in Table 5A. The time-varying dependence model in Eq. (5) is estimated and

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[10] $\mathrm{AIC} = -2L(\hat{\theta}; x) + 2q$, where q is the number of parameters needed to be estimated in each specific model.

calibrated for each pair of index returns. The parameter β_ρ, represents the degree of persistence, and γ_ρ captures the adjustment in the dependence process. Table 5A demonstrates that the emerging markets, the Pacific, and the Japanese markets all experience higher degrees of dependences with the Chinese market. Meanwhile, the log-likelihood functions for these areas are higher than for other areas. Additional statistics such as conditional mean and conditional standard deviation of estimated time-varying dependence in each copula model are summarized in Table 5. Significant variations in dependences between markets over time are evident, especially for the China-Europe, China–Pacific, the China–Japan, and the China–emerging-markets pairs. They not only demonstrate greater conditional dependences, but also have higher variations in dependences, which provide useful insights into active risk management for portfolios. Fig. 1 illustrates the implied time path of conditional dependence for each pair of index returns across the sample period.

[Insert Table 5 here]

4.3. Conditional tail dependence

Table 5B and C report the estimated parameters of time-varying tail dependence specified by the rotated Gumbel and the Gumbel copulas, respectively. Time-varying upper tail dependences can be calculated through the use of Eq. (8), where estimated conditional dependences, δ_t^U, is from Eq. (6). Time-varying lower tail dependences can be similarly obtained. We can demonstrate that the emerging markets, the Pacific, and the Japanese markets show higher degrees of dependences in both tails with the Chinese market. Furthermore, the tail dependences in both tails are more volatile for the China–Europe, China–Pacific, China–Japan, and China–emerging markets pairs, whereas the China–U.S. pair is the most stable. In addition, the conditional means of the estimated time-varying tail dependences from rotated Gumbel copula are generally higher than those from the Gumbel copula, indicating that all pairs seem to have a tendency toward left tail dependence. The emerging, the Pacific, and the Japanese markets especially experience higher degrees of lower tail dependences with the Chinese market, which may induce a higher probability of a joint market crash in these regions if the bubbles in Chinese stock markets burst. Figs. 2 and 3 present the plots of conditional dependences for lower and upper tails specified by the time-varying rotated Gumbel and Gumbel copula models, respectively.

[Insert Fig. 1 here]

[Insert Fig. 2 here]

[Insert Fig. 3 here]

4.4. *Goodness-of-fit test and comparisons*

The evaluation of multivariate density models becomes prominent as the development of the multivariate conditional distributions grows dramatically (Christoffersen, 1998; Rivers and Vuong, 2002; Granger et al., 2006; Chen and Fan, 2006; Patton, 2006a). Chen and Fan (2006) proposed a pseudo-likelihood ratio test for model selection between two semiparametric copula-based multivariate dynamic models. Patton (2006a) conducted a likelihood ratio test for his purely parametric copula-based dynamic model. The difference between the two approaches is whether the marginal distributions of the standardized innovations are specified.[11] For the purpose of empirical applications of copulas in forecasting, it is more common to employ purely parametric models to fit the data and compare the results from different models. Therefore, we apply the bivariate "hit" tests[12] proposed by Patton (2006a) to evaluate our models.

Patton (2006a) decomposed the density model into a set of "region" models.[13] Each region model should be correctly specified under the null hypothesis that the density for the entire region is correctly specified. The intuition is to compare the number of observations in each region with what would be expected under the null hypothesis.

Table 6 contains the results from the joint hit test for the competing copula models. For the China–emerging pair, the conditional Gaussian and all constant copula models are rejected at the 5% significance level. Additionally, the constant Gaussian and Gumbel copula models fail the joint test for the China–Japan pair. However, the goodness-of-fit tests seem to have difficulty in rejecting the other pairs. Thus, we infer that model specification, except conditional Gumbel and conditional rotated Gumbel copulas, tends to reject the pair with not only a higher degree of dependence but also a higher variation of dependence. It is found that conditional Gumbel and conditional

[11]Parametric marginal distributions should be specified in Patton's model, whereas non-parametric marginal distributions are assumed in Chen and Fan's model.

[12]Patton (1996a) extends Christoffersen's evaluation model (1998) for interval forecasting to a bivariate model.

[13]Regions 1 and 2 correspond to the lower and upper joint 10% tail for each variable. Regions 3 and 4 indicate that bivariate variables belong to the 10th and 25th or 75th and 90th quantiles, respectively. Region 5 is the median region. Regions 6 and 7 are extremely asymmetric if one variable is in the 75th quantile, whereas the other is in the 25th quantile.

rotated Gumbel copulas outperform the other competing copula models, especially for describing a higher degree as well as a higher variation in dependence structure.

5. Conclusions

Knowledge of the multivariate conditional distribution, especially for fat tails and asymmetric dependence, is essential in many important financial applications such as portfolio selection, asset pricing models, risk management, and forecasting (Chen and Fan, 2006). In addition, studies on international dependence mainly focused on developed markets. Relatively few studies investigated the role of China, despite the noticeable growth in her capital markets and her increasing integration into the global economy. In this paper, we emphasize the dynamic dependence between the Chinese stock market and other related markets of the world. Using the time-varying copula models to study the relationship between these stock markets, we provide a comprehensive analysis of their dynamic dependences. As China's economic prominence has increased, estimation and measurement of this time-varying nature in dependences enable us to capture the changes in market risk and identify the co-movement between markets.

We demonstrate significant variations in dependences between markets over time. Regardless of the assumed copula functions, we consistently find that the Chinese market experiences not only a higher degree of dependence but also a higher variation of dependence with markets in Japan, in the Pacific, and in emerging countries. This high dependence may be attributed to geographic ties and a close trading relationship. The implication of this finding is that the probability of joint crashes will be high for markets in these areas once bubbles burst in China, and portfolio managers should become more alert to take into account this co-movement. Furthermore, a higher dynamic dependence during bear markets implies that opportunities for portfolio diversification are reduced. Finally, the goodness-of-fit test indicates that the conditional Gumbel and conditional rotated Gumbel copulas outperform the competing copula models. Taking into account this understanding, decisions related to international diversification, portfolio allocation, and risk management based on static models should be carefully reconsidered.

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Table 1

Summary statistics

	Mean	Standard Deviation	Skewness	Kurtosis
China	0.09216	1.01541	-0.21493	1.23572
World	0.02256	0.60362	0.20303	3.51581
U.S.	0.01845	0.67593	-0.06452	3.86734
Europe	0.02040	0.75475	-0.26697	4.78451
Japan	0.03761	0.81159	-0.23544	0.78285
AcWorld	0.02528	0.59691	-0.23345	3.29451
Pacific	0.03852	0.68303	-0.28850	0.81628
Emerging	0.07067	0.64482	-0.56044	1.41661

This table shows summary statistics of the percentage log returns of the MSCI China, MSCI World, MSCI U.S., MSCI Europe, MSCI Japan, MSCI AcWorld, MSCI Pacific and MSCI Emerging Markets. The sample period covers 1 January 2002 to 30 June 2007. 1434 daily observations for each index are collected.

Table 2

Association measurement

China versus	Pearson Correlation	Spearman Correlation	Kendall Correlation
World	0.38112	0.39577	0.27122
U.S.	0.26940	0.28123	0.19036
Europe	0.34003	0.35419	0.24172
Japan	0.46423	0.43358	0.30066
AcWorld	0.40684	0.42094	0.28950
Pacific	0.52958	0.49915	0.34944
Emerging	0.70161	0.67168	0.48863

This table shows the Pearson’s, Spearman’s, and Kendall’s correlations for each index return paired with China’s index return.

Table 3

Estimated parameters for GJR-GARCH(1,1)-AR(1)-*t* marginal distributions

	AR(1)	GARCH constant	Lagged variance	Lagged residual	Asymmetric residual	Degree of freedom
China	0.5280	0.03847	0.81488	0.07434	0.05149	11.17649
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0013)	
World	0.5554	0.00299	0.91221	0.00802	0.10636	18.23378
	(0.0000)	(0.0000)	(0.0000)	(0.0457)	(0.0000)	
U.S.	0.4696	0.00400	0.91955	-0.00010	0.12090	40.22710
	(0.0000)	(0.0000)	(0.0000)	(0.9615)	(0.0000)	
Europe	0.5051	0.00472	0.91581	-0.01622	0.14610	19.23516
	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0002)	
Japan	0.5087	0.01123	0.86290	0.06881	0.06032	15.55969
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	
AcWorld	0.5619	0.00322	0.90604	0.01215	0.10567	18.03765
	(0.0000)	(0.0000)	(0.0000)	(0.0056)	(0.0000)	
Pacific	0.5100	0.01026	0.85278	0.05984	0.08125	15.90558
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Emerging	0.5912	0.01181	0.84651	0.04107	0.09134	17.64657
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

This table reports the estimated parameters of the marginal distributions for each index return. They are assumed to be characterized by a GJR-GARCH(1,1)-AR(1)-*t* model given by Eq. (1). The numbers in brackets are *p*-values, and 0.0000 means that the value is less than 0.00005.

Table 4

Parameter estimations and goodness-of-fit test for unconditional copula models

Unconditional Copula Model							
Paired				*China v.s.*			
Indices	*World*	*U.S.*	*Europe*	*Japan*	*AcWorld*	*Pacific*	*Emerging*
Panel A: Copula estimation							
Gaussian							
ρ	0.2990	0.1293	0.2644	0.4413	0.3289	0.4811	0.6449
	(0.0406)	(0.1156)	(0.0473)	(0.0248)	(0.0361)	(0.0222)	(0.0147)
$ln\, L$	66.0864	11.8772	51.1207	153.1985	80.8102	186.3193	381.6740
rotated Gumbel							
δ^L	1.2167	1.0778	1.1978	1.4001	1.2474	1.4421	1.7964
	(0.0416)	(0.1180)	(0.0467)	(0.0241)	(0.0368)	(0.0220)	(0.0144)
λ^L	0.2322	0.0976	0.2163	0.3594	0.2569	0.3828	0.5291
$ln\, L$	63.4087	11.5079	52.1291	161.6842	78.0483	188.4437	394.6650
Gumbel							
δ^U	1.1903	1.0599	1.1740	1.3827	1.2192	1.3927	1.7550
	(0.05112)	(0.1555)	(0.0561)	(0.0254)	(0.0445)	(0.0259)	(0.0152)
λ^U	0.2098	0.0768	0.1953	0.3491	0.2343	0.3550	0.5157
$ln\, L$	44.8848	7.5171	38.3428	147.7156	56.6800	142.7179	361.4705
Panel B: Goodness-of-fit test (AIC)							
Gaussian	-130.1728	-21.7544	-100.2414	-304.3970	-159.6204	-370.6386	-761.3480
R.Gumbel	-124.8174	-21.0158	-106.2582	-325.3684	-158.0967	-378.8873	-791.3300
Gumbel	-87.7696	-13.0342	-74.6856	-293.4312	-111.3600	-283.4358	-720.9410

This table reports the estimated results of unconditional copula models in Panel A. ρ is the correlation parameter of the Gaussian copula, and δ^U and δ^L are dependence parameters of the Gumbel and the rotated Gumbel copula, respectively. λ^U is the coefficient of upper tail dependence, while λ^L is the coefficient of lower tail dependence. Relevant results of goodness-of-fit test for static Gaussian, rotated Gumbel and Gumbel copula functions are shown in Panel B. $AIC = -2L(\hat{\theta}\,; x) + 2q$, where q is the number of parameters to be estimated in each specific model. The numbers in brackets are *p*-values.

Table 5

Estimated parameters of time-varying dependences in the chosen copulas

Panel A: Gaussian copula

Parameters	β_ρ	ω_ρ	γ_ρ	*LLF(c)*	*Mean*	*Std*
World	0.87748	0.08955	-0.14708	69.21843	0.30945	0.05199
	(0.0000)	(0.0000)	(0.0000)			
U.S.	0.80710	0.05510	-0.08661	13.10273	0.14192	0.03547
	(0.0000)	(0.0000)	(0.0000)			
Europe	0.99990	0.04363	-0.11279	59.92437	0.30850	0.08259
	(0.0000)	(0.0000)	(0.0000)			
Japan	0.95110	0.14060	-0.31562	171.46440	0.45911	0.09974
	(0.0000)	(0.0000)	(0.0000)			
AcWorld	0.93441	0.07665	-0.14619	84.83814	0.34028	0.05626
	(0.0000)	(0.0000)	(0.0000)			
Pacific	0.99990	0.12485	-0.31447	200.66860	0.49227	0.08746
	(0.0000)	(0.0000)	(0.0000)			
Emerging	0.99990	0.20857	-0.45495	393.58340	0.64097	0.06905
	(0.0000)	(0.0000)	(0.0000)			

Panel B: rotated Gumbel copula

Parameters	β_L	ω_L	γ_L	*LLF(c)*	*Mean*	*Std*
World	0.66313	0.44087	-0.10643	64.13394	0.23612	0.02621
	(0.0000)	(0.0000)	(0.0000)			
U.S.	0.01405	1.00000	0.17598	13.83956	0.08579	0.04480
	(0.40461)	(0.0000)	(0.0000)			
Europe	0.95406	0.09944	-0.15074	66.88846	0.26423	0.12725
	(0.0000)	(0.0000)	(0.0000)			
Japan	0.85215	0.30147	-0.37054	180.25030	0.37059	0.10986
	(0.0000)	(0.0000)	(0.0000)			
AcWorld	0.87166	0.18787	-0.09819	80.49725	0.26486	0.03796
	(0.0000)	(0.0000)	(0.0000)			
Pacific	0.86878	0.26978	-0.33145	199.66960	0.38982	0.08834
	(0.0000)	(0.0000)	(0.0000)			
Emerging	0.95187	0.15197	-0.34045	422.21120	0.53811	0.09827
	(0.0000)	(0.0000)	(0.0000)			

Panel C: Gumbel copula

Parameters	β_U	ω_U	γ_U	*LLF(c)*	*Mean*	*Std*
World	0.86920	0.18787	-0.11095	48.38166	0.09827	0.04789
	(0.0000)	(0.0000)	(0.0000)			
U.S.	0.03353	1.00000	0.07426	7.99380	0.07468	0.01969
	(0.02286)	(0.00006)	(0.08507)			
Europe	0.96746	0.08413	-0.16819	52.45853	0.23435	0.14705
	(0.0000)	(0.0000)	(0.0000)			
Japan	0.96244	0.09404	-0.16640	169.06830	0.36948	0.11664
	(0.0000)	(0.0000)	(0.0000)			
AcWorld	0.91072	0.13891	-0.10694	61.43713	0.24539	0.05377
	(0.0000)	(0.0000)	(0.0000)			
Pacific	0.96037	0.09163	-0.15040	157.58980	0.36936	0.08872
	(0.0000)	(0.0000)	(0.0000)			
Emerging	0.96157	0.11886	-0.26828	387.11070	0.52388	0.09621
	(0.0000)	(0.0000)	(0.0000)			

This table shows the estimated parameters of time-varying dependences in the chosen copulas. The time-varying dependence models in Eqs. (5), (6), (7) are estimated and calibrated for each pair of index returns. The parameters $\beta_\rho, \beta_L, \beta_U$, capture the degrees of persistence in their dependence processes and γ_ρ , γ_L, γ_U, capture their adjustments. *LLF*(c) is the maximum of the copula component of the log-likelihood function. Conditional means and conditional standard deviations of estimated time-varying dependences in each copula models are also reported in the last two columns. The numbers in brackets are *p*-values, and 0.0000 means that the value is less than 0.00005.

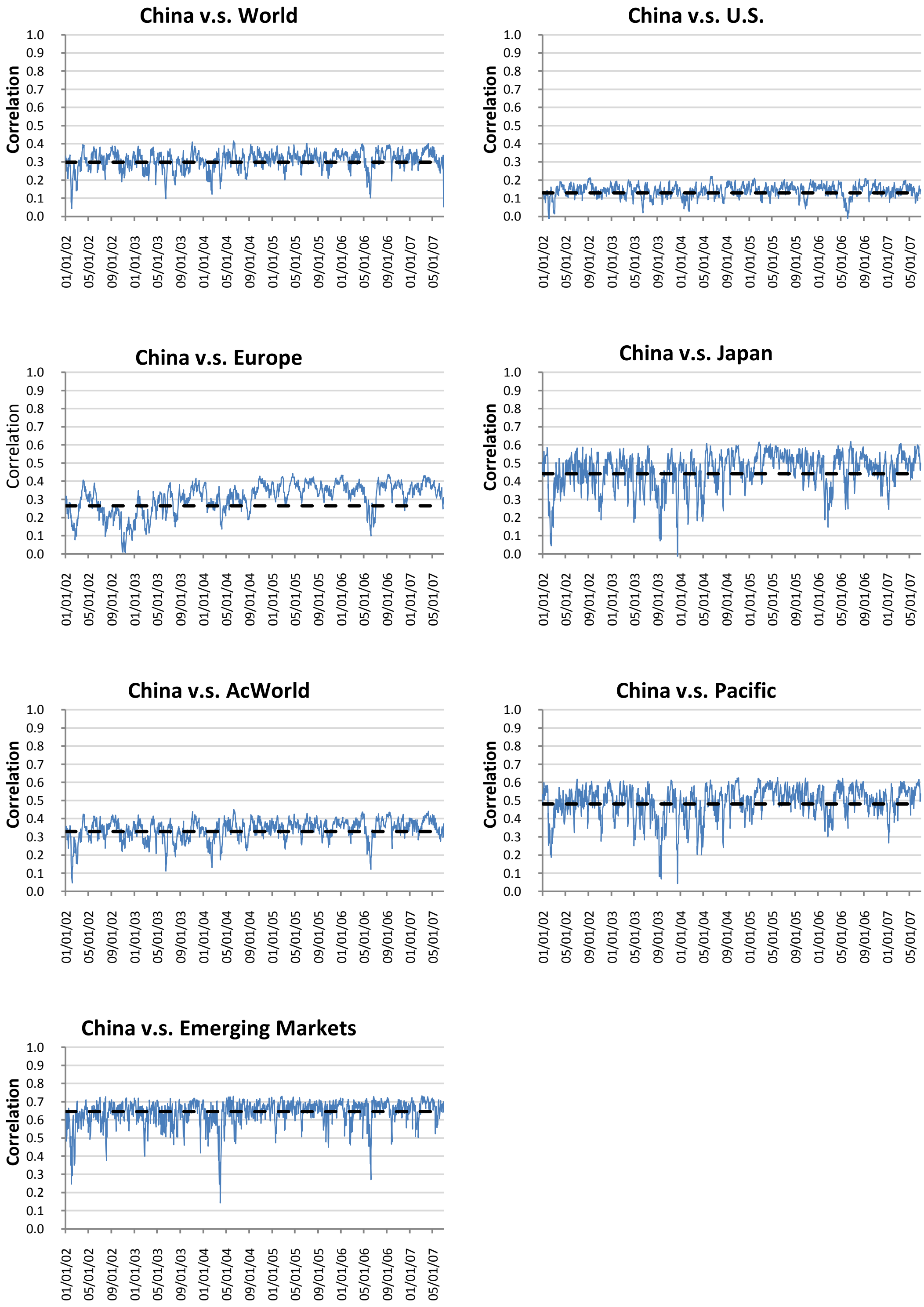
Table 6

Joint hit test for the copula models

	Conditional Gaussian	Conditional Gumbel	Conditional R. Gumbel	Constant Gaussian	Constant Gumbel	Constant R.Gumbel
World	0.98472	0.98917	0.98337	0.95026	0.94930	0.97891
U.S.	0.83290	0.73519	0.74702	0.91240	0.81528	0.87273
Europe	0.12784	0.18948	0.17074	0.07009	0.10765	0.11981
Japan	0.09176	0.15191	0.11742	0.05018*	0.05032*	0.11133
AcWorld	0.93580	0.96153	0.94551	0.78478	0.91568	0.90593
Pacific	0.73842	0.86484	0.83016	0.51797	0.88744	0.86330
Emerging	0.00001*	0.09739	0.09970	0.04440*	0.04203*	0.00143*

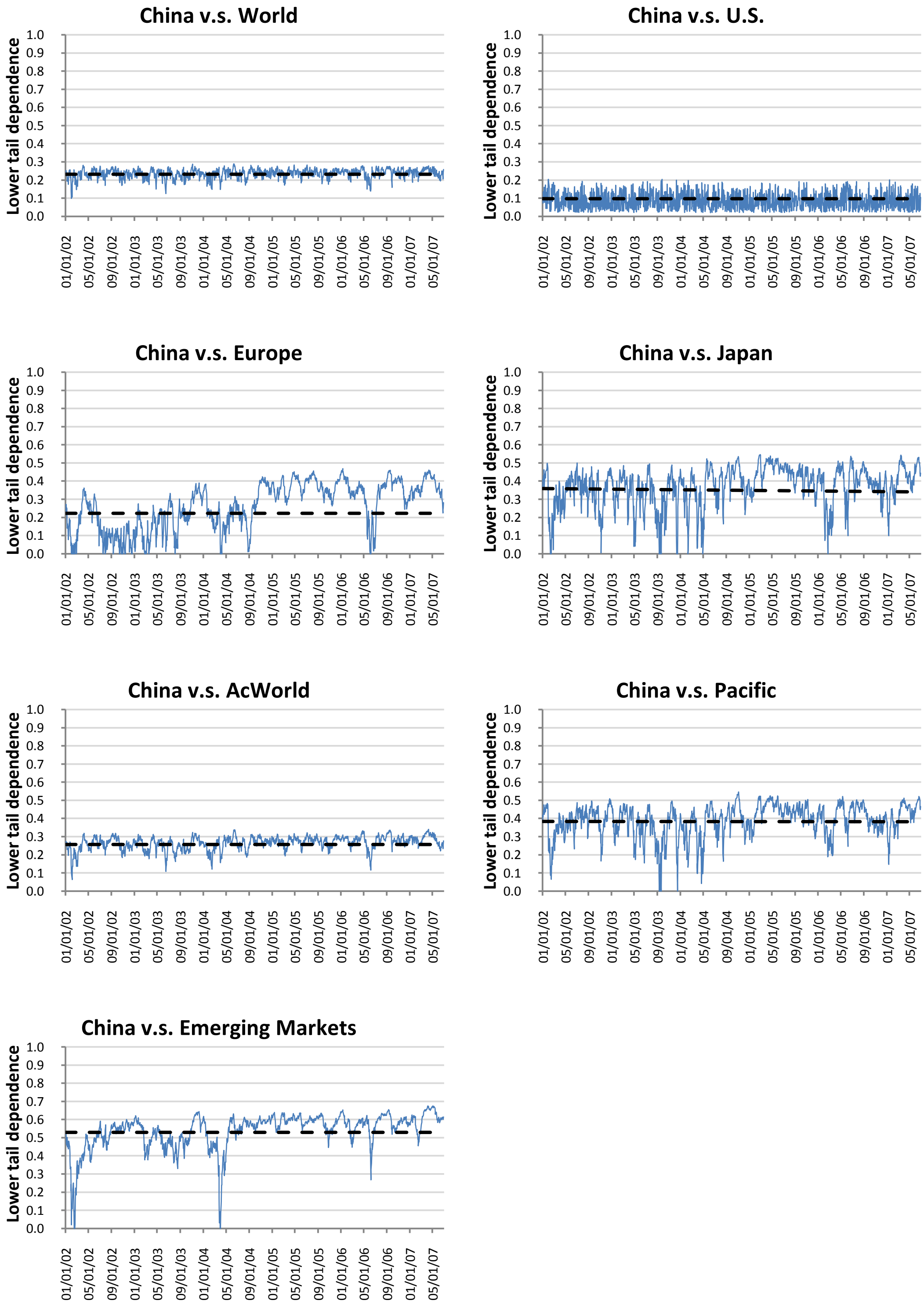
The *p*-values of joint hit tests are reported if the models are correctly specified in all ‘regions’. A *p*-value less than 0.05 indicates a rejection of the null hypothesis that the model is well specified.

* denotes the significance at 5% level.



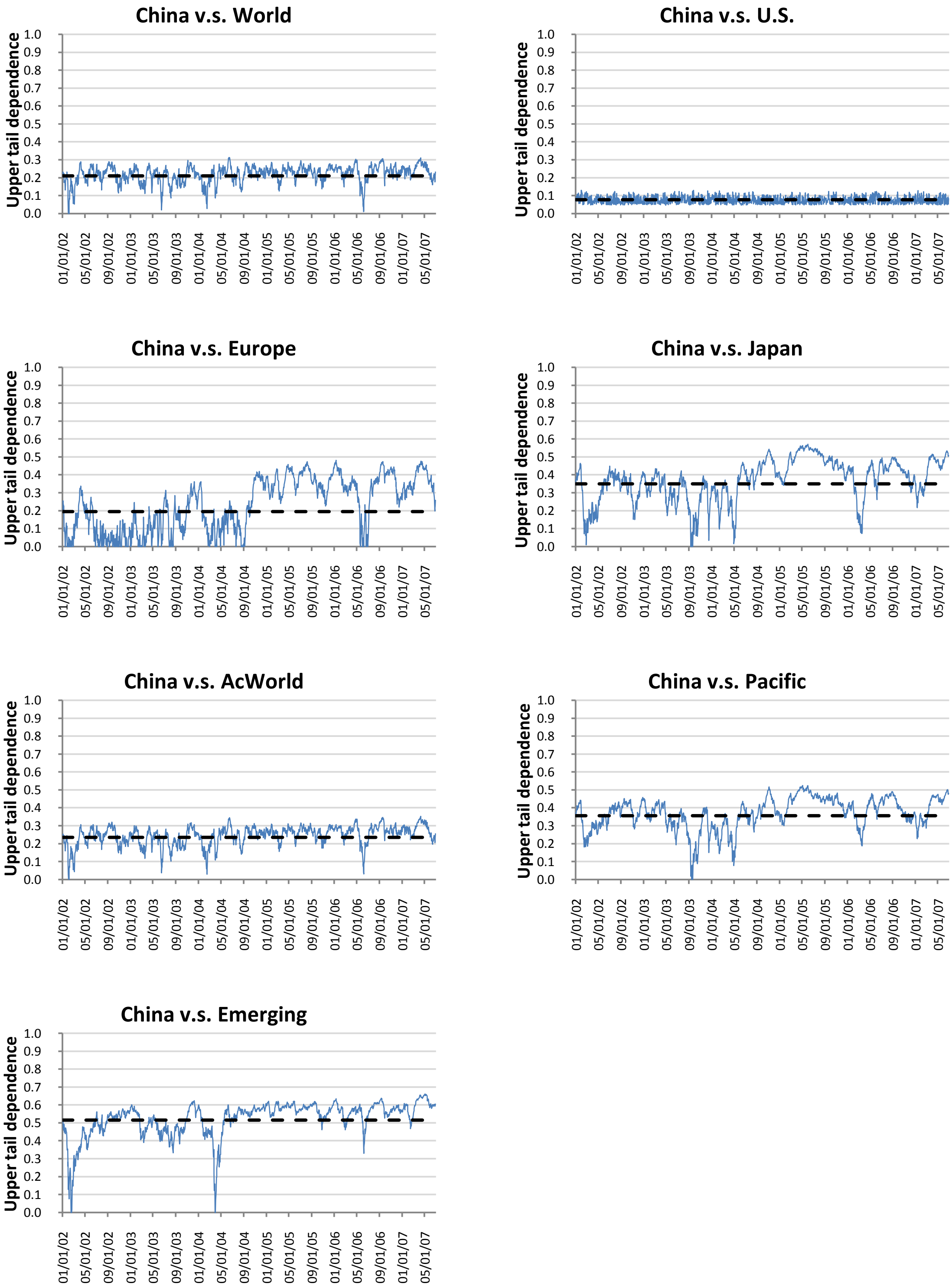
The solid lines in this figure show the time-varying conditional correlations for all index return pairs across the sample period. The dotted lines show their unconditional correlations as estimated in Table 4.

Fig. 1. Conditional correlation estimation from the Gaussian copula.



The solid lines in this figure show the time-varying conditional lower tail dependences for all index return pairs across the sample period. The dotted lines show their unconditional lower tail dependences as estimated in Table 4.

Fig. 2. Conditional lower tail dependence estimation from the rotated Gumbel copula



The solid lines in this figure show the time-varying conditional upper tail dependences for all index return pairs across the sample period. The dotted lines show their unconditional upper tail dependences as estimated in Table 4.

Fig. 3. Conditional upper tail dependence estimation from the Gumbel copula

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

98　年 7 月 10 日

附件三

報告人姓名	陳怡璇	服務機構及職稱	中華大學財務管理學系 助理教授
會議時間 地點	98 年 6 月 3 日至 98 年 6 月 5 日 杜林，義大利	本會核定 補助文號	NSC 97-2410-H-216-003
會議名稱	(中文)2009 財務管理年會歐洲研討會 (英文) 2009 FMA European Conference		
發表論文題目	(中文)應用動態 copula 模型於投資組合風險值研究：模型風險的解釋 (英文) Portfolio Value-at-Risk Estimation with a Time-varying Copula Approach: An Illustration of Model Risk		

報告內容應包括下列各項：

一、參加會議經過

此篇論文報告於 Session 71 "**Risk Management and Measurement**"，報告順序為第三，並且本人亦評論 Session 62 " **Volatility Measurement"**的論文

二、與會心得

與國際知名學者交流，獲得頗多正面的意見

三、考察參觀活動(無是項活動者省略)

四、建議

國際學術研討會對於研究績效有非常實質的助益，希望有更多的經費可補助及鼓勵國內學者多參加，將有助於國際學術交流

五、攜回資料名稱及內容

註冊費收據及會議議程紙本資料

六、其他