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The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach

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ABSTRACT

The purpose of this paper is to study the dependence structures between the Chinese market and other major world markets, a reflection of China's increasing integration into the global economy. We used time-varying copula models to show that conditional copulas outperform both unconditional copulas and conventional GARCH models. We consistently found the Chinese market to have the highest levels of dependence, as well as the greatest variability in dependence, with markets in Japan and the Pacific. Our results provide investors interested in the Chinese market with more timely suggestions for portfolio diversification, risk management, and international asset allocation than those derived from static models.

1. Introduction

The dependence between financial markets has always been an important issue for both financial economists and investment practitioners (Bartram & Dufey, 2001). The subject has drawn considerable attention in the literature because of its implications for international diversification and market integration. Recent studies have provided evidence of contagion in equity markets (Ane & Labidi, 2006; Jondeau & Rockinger, 2006; Bekaert, Harvey, & Ng, 2005; Poon, Rockinger, & Tawn, 2004; Longin & Solnik, 2001; Forbes & Rigobon, 2002). However, these studies have usually emphasized developed economies such as the United States, the United Kingdom, Germany, France, and Japan. Few studies have investigated the role of China's increasing integration into international markets (Lane, 2006).

According to data released by the China Securities Regulatory Commission (CSRC), 1837 companies in China have gone public as of March 2010. China's equity market capitalization is 23 trillion Yuan, third highest in the world, and it replaced Japan as the world's second largest economy. China's dramatic growth has attracted many international investors and speculators, despite worries about the price bubbles and the market crash that may affect other markets. Meanwhile, research on China's financial markets is increasing (Lien & Chen, 2010; Jalil, Feridun, & Ma, 2010).

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The recent experience of stock markets around the world suggests that a catastrophic event in China could easily trigger international reactions.[1] Xu and Fung (2002) found significant mutual feedback of information about China-backed stocks that were dual-listed in Hong Kong and New York. Li (2007) found a weak integration of the Chinese stock exchanges with the regional developed markets. Chan, Fung, and Thapa (2007) illustrated how China's financial market has emulated and become integrated with developed markets over time. Using an asymmetric dynamic conditional correlation GARCH model (AG-DCC-GARCH), Hyde, Bredin, and Nguyen (2007) found significant time-varying conditional correlations among equity markets in the Asian-Pacific countries, Europe, and the US. Sun, Tong, and Yan (2009) pointed out that China has been able to increase its integration with other countries primarily because it has opened its markets to foreign investments and cross-border listings. In a further exploration of time-varying dependence structures in Chinese and US financial markets, Hu (2010) found their association to be quite volatile over time. On the other hand, Lai and Tseng (2010) observed no significant dependences among China and the G7 countries, regardless of whether market conditions were normal or abnormal. They suggested that the Chinese stock market is a good candidate for hedging when global markets are normal and a safe haven when they are turbulent. On the other hand, Guo and Huang (2010) found that speculative capital inflow (hot money) affected China's real estate and stock markets.

The purpose of the present study was to determine whether China's financial market becomes more related with other world markets by applying dynamic copula models to the time-varying dependence structures. Because China's economy has attracted a huge number of foreign speculators, a crash of its stock market would likely prompt sudden withdrawals, which could become contagious. The dynamic relationships among these markets have important implications for portfolio diversification, risk management, and international asset allocation. For example, the greater the dependence between China and another country, the greater the risk to the financial assets of both countries. Thus, fund managers should pay more attention to diversifying the investment of their assets in both countries. Particular attention should be paid to tail dependences which would indicate the effects of diversification during both downturns and upturns.

To assess these changing dependence structures over time, we estimated time-varying copula models to compare selected stock markets indices. To account for non-linear and time-dependent relationships, the parameters of the copula functions were assumed to follow dynamic processes conditional on the available information. This approach differs markedly from conventional linear-based correlation methods such as the CCC-GARCH or DCC-GARCH models, which are somewhat restrictive due to their requirements of normality for the joint distribution and of linear relationships among variables.

Our study represents two advances over previous literature. First, few studies have focused on the co-movements of the Chinese market with those of other world markets, despite China's considerable growth and increasing integration with these countries. Some of these studies have been confined to China's regional role (Cheng & Glascock, 2005, 2006; Baur, 2007; Chang, Chou, & Wu, 2000). Because China's production and trade have attained significant global influence (Chan, Lien, & Weng, 2008), we hypothesize that the connections between the Chinese market and other world markets will be further increased.

The second contribution of the present study is to demonstrate how a conditional copula model can be applied to increase portfolio diversification and improve active asset allocation for investors interested in Chinese markets. A copula-based measure can specify the dependence structures and account for non-linearity without the constraint of normality. In particular, an extended time-varying copula model with a conditional joint distribution can be used to calculate conditional means, variances, and correlations as well as the temporal paths of other dependence measures, such as tail dependence and rank correlations (Patton, 2006a). Our copula models allow us to investigate both the conditional dependence structures and the conditional tail dependences between the Chinese and other major stock markets. This forward-looking assessment can provide useful information for those who seek to actively diversify their international portfolios and manage their worldwide assets.

Specifically, data were collected from the daily stock indices of Morgan Stanley Capital International (MSCI) China, MSCI Japan, MSCI United States, MSCI Europe, MSCI Pacific, MSCI World, and MSCI AcWorld from 2000 to 2009. We consistently found that the Chinese market experienced greater, and also more variable, dependence with markets in Japan and the Pacific. This result suggests that the probability of a joint crash will be high for markets in these areas once the bubble bursts in China. It also demonstrates the dramatic impact of China's market on its neighbors. Thus, portfolio managers should pay more attention to these co-movements.

The remainder of this paper is structured as follows: Section 2 explains the time-varying copula models. Data and summary statistics are reported in Section 3. Empirical results are analyzed and discussed in Section 4, and our conclusions are provided in Section 5.

2. Methodology

Multivariate normality assumption is not suitable for measuring the dependence structure of equity returns between two markets, especially with respect to their asymmetric co-movements or contagion effects (Longin & Solnik, 2001; Poon et al., 2004). The copula method was chosen for this study because it can model contemporaneous interdependence between univariate time series or their innovations. It allows analysis of the dependence structure that goes beyond linear correlation. Also, by separating the marginal and joint distributions, the copula method makes the estimation process more flexible. The seminal work of Patton (2006a,b) has extended this methodology by adding a time-varying specification to capture the dynamics of the dependence

[1] For instance, on February 27, 2007, the Shanghai Stock Exchange's Composite Index unexpectedly dropped 8.8%, its largest 1-day decline in 10 years. Later that same day, the Dow Jones Industrial Average tumbled 3.3% and the NASDAQ declined 3.9%, its sharpest drop since the 9/11 crisis. Other European and Asian markets experienced similar declines.

structure. Bartram, Taylor, and Wang (2007) and Ane and Labidi (2006) have used the copula model to measure dependences among some European stock indices. Following their settings, we model our empirical time-varying copula as described below.

2.1. The model 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 that takes account of the effects of asymmetric information (Nelson, 1991; Engle & Ng, 1993; Glosten, Jagannathan, & Runkle, 1993). Let $R_{i,t}$ and $h_{i,t}$ denote index *i*'s return and its conditional variance for period *t*, respectively, and let Ω_{t-1} denote the previous information set. The GJR-GARCH(1,1)-AR(1)-*t* model for the index return is thus

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

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

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

where $s_{i,t-1}=1$ when $\varepsilon_{i,t-1}$ is negative; otherwise, $s_{i,t-1}=0$. $z_{i,t}$ is the standardized residual from the first-stage estimation, and df_i represents the degree of freedom.

2.2. The copula models for the joint distributions

As stocks tend to crash together but not boom together (Poon et al., 2004; Longin & Solnik, 2001; Bae, Karolyi, & Stulz, 2003), the dependence structure should be examined on both tails of the return distribution. We therefore employed the Gumbel, Clayton, symmetrized Joe–Clayton (SJC) copulas for specification and calibration purposes, with the Gaussian copula as the benchmark. The Gumbel and Clayton copulas were used to capture the right and left tail dependences respectively. The SJC copula is more general, because it allows the tail dependences to be either symmetric or asymmetric. These copula models and the statistical inferences derived from them are briefly discussed below. How to choose the best fitting copula model is explained in Section 4.

The conditional Gaussian copula function is the density of the 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 $\Phi^{-1}(.)$ denotes the inverse of the cumulative density function of the standard normal distribution. The density of the time-varying Gaussian copula is then

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

Tail dependence captures the behavior of random variables during extreme events. In our study, it measures the probability of a simultaneous market crash in each country following a prick in the Chinese stock market bubble. The Gumbel, Clayton and SJC copulas efficiently capture the tail dependences arising from the extreme observations caused by the asymmetry. The density of the time-varying Gumbel copula is

$$\begin{aligned} c_t^{\text{Gum}}(u_t, v_t\,|\,\delta_t) = {} & \frac{(-\ln u_t)^{\delta_t-1}(-\ln v_t)^{\delta_t-1}}{u_t v_t}\exp\left\{-\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\frac{1}{\delta_t}}\right\} \\ & \times\left\{-\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\left(\frac{1-\delta_t}{\delta_t}\right)^2} + (\delta_t-1)\left[(-\ln u_t)^{\delta_t-1} + (-\ln v_t)^{\delta_t-1}\right]^{\left(\frac{1-2\delta_t}{}\right)}\right\} \end{aligned} \tag{3}$$

where $\delta_t \in [1,\infty)$ is the degree of dependence between u_t and v_t. $\delta_t = 1$ implies no dependence and $\delta_t \to \infty$ represents a fully dependent relationship. The Gumbel family has an upper-tail dependence, with $\lambda_t^U = 2 - 2^{1/\delta_t}$.

The density of the time-varying Clayton copula is

$$c_t^{clay}(u_t, v_t\,|\,\theta_t) = (\theta_t + 1)\left(u_t^{-\theta_t} + v_t^{-\theta_t} - 1\right)^{-\frac{2\theta_t+1}{\theta_t}} u_t^{-\theta_t-1} v_t^{-\theta_t-1} \tag{4}$$

where $\theta_t \in [0,\infty)$ is the degree of dependence between u_t and v_t. $\theta_t = 0$ implies no dependence, and $\theta_t \to \infty$ represents a fully dependent relationship.

The lower-tail dependence measured by the Clayton copula is $\lambda_t^L = 2^{-\frac{1}{\theta_t}}$.

Table 1
Summary statistics for each index.

Index	Mean	Standard deviation	Skewness	Kurtosis	Jarque–Bera normality test
China	0.0248	1.4816	−0.2076	3.7192	$p<0.00005$
World	−0.0074	0.8333	−0.4172	6.0307	$p<0.00005$
U.S.	−0.0115	0.9308	−0.3351	5.7255	$p<0.00005$
Europe	−0.0024	1.0258	−0.3126	5.7772	$p<0.00005$
Japan	−0.0186	1.0413	−0.0180	2.7676	$p<0.00005$
AcWorld	−0.0050	0.8364	−0.4241	5.9700	$p<0.00005$
Pacific	−0.0085	0.9612	−0.1653	3.6720	$p<0.00005$

Note: This table shows summary statistics for the percentage log returns of the MSCI China, MSCI World, MSCI US, MSCI Europe, MSCI Japan, MSCI AcWorld and MSCI Pacific. The p-values of Jarque–Bera normality test are shown in the last column. The sample period covers from 2000 to 2009. There were 2608 daily observations collected for each index.

The SJC copula is Patton's (2006a) modification of the Joe–Clayton (JC) copula. It is more general because the symmetry property of the JC copula is only a special case. The density of the JC copula is

$$C_{JC}\left(u,v|\tau^U,\tau^L\right) = 1-\left(1-\{[1-(1-u)^{\kappa}]^{-\gamma} + [1-(1-v)^{\kappa}]^{-\gamma}-1\}^{-\frac{1}{\gamma}}\right)^{\frac{1}{\kappa}} \tag{5}$$

where $\kappa=1/\log_2(2-\tau^U)$, $\gamma=-1/\log_2(\tau^L)$. $\tau^U\in(0,1)$ and $\tau^L\in(0,1)$ are the measures of the upper- and lower-tail dependencies respectively. The density of the generalized SJC copula is

$$C_{SJC}\left(u,v|\tau^U,\tau^L\right) = 0.5\left[C_{JC}\left(u,v|\tau^U,\tau^L\right) + C_{JC}\left(1-u,1-v|\tau^U,\tau^L\right) + u + v-1\right]. \tag{6}$$

The SJC copula is symmetric when $\tau^U=\tau^L$ and asymmetric otherwise.

2.3. Dependence parameters of the time-varying copula models

In applying the conditional copula with a time-varying dependence structure, we assume that the dependence parameter is determined by past information and follows an ARMA(1,10)-type process.[2] The dependence process of the Gaussian copula is, therefore,

$$\rho_t = \Lambda\left(\beta_\rho\rho_{t-1} + \omega_\rho + \gamma_\rho\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right). \tag{7}$$

The conditional dependence, ρ_t, determined from its previous level, ρ_{t-1}, captures the persistence effect, and the average of the 10 previous absolute differences, $\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|$, captures the variability of the dependence.[3] $\Lambda(x)$ is defined as $(1-e^{-x})(1+e^{-x}) = tanh\left(\frac{x}{2}\right)$, which is the modified logistic transformation needed to keep ρ_t within $(-1,1)$ interval at all times. The estimation of the copula parameters, $\theta_c=(\beta_\rho,\omega_\rho,\gamma_\rho)'$, will be discussed in Section 2.4.

The dynamics of the conditional Gumbel, conditional Clayton, and conditional SJC dependences are also assumed to follow the ARMA(1,10)-like process. We propose the following time-varying dependence processes for the Gumbel and Clayton copulas:

$$\delta_t = \beta_U\delta_{t-1} + \omega_U + \gamma_U\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}| \tag{8}$$

$$\theta_t = \beta_L\theta_{t-1} + \omega_L + \gamma_L\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|. \tag{9}$$

The conditional SJC copula is constructed in the same way. The Eqs. (10) and (11) indicate the dynamics of the upper- and lower-tail dependences, respectively.

$$\tau^U = \Pi\left(\beta_U^{SJC}\tau_{t-1}^U + \omega_U^{SJC} + \gamma_U^{SJC}\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right) \tag{10}$$

$$\tau^L = \Pi\left(\beta_L^{SJC}\tau_{t-1}^L + \omega_L^{SJC} + \gamma_L^{SJC}\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}-v_{t-i}|\right) \tag{11}$$

where Π is the logistic transformation to keep τ^U and τ^L within the (0,1) interval.

[2] The LM test indicates that the square returns are serially correlated up to lag 10.
[3] Unlike Patton (2006a,b) and Bartram et al. (2007), Ane and Labidi (2006) characterized their conditional dependence coefficients as a pure AR(1), which means that only persistence in the dependence process was emphasized.

Table 2
Association measures between the Chinese and other indices.

China versus	Pearson r	Kendall ô	Spearman ñ
World	0.4945	0.3198	0.4549
U.S.	0.3443	0.2209	0.3192
Europe	0.4728	0.2984	0.4255
Japan	0.4717	0.3039	0.4350
AcWorld	0.5276	0.3429	0.4857
Pacific	0.5762	0.3781	0.5318

Note: This table shows the Pearson, Spearman, and Kendall correlations between China's index return and the other index returns.

2.4. Estimation and calibration of the copula parameters

The calibration of copula parameters using real market data has recently attracted much interests in literature (Meneguzzo & Vecchiato, 2004; Mashal & Zeevi, 2002; Breymann, Dias, & Embrechts, 2003; Galiani, 2003). Parameters are usually estimated in two steps, the first for the marginals and the second for the copula. This approach is similar to the inference-function-for-margins (IFM) method. The IFM method is superior to the exact maximum likelihood (EML) method, because the latter needs extensive computation, especially for estimations in the higher dimensions. The EML method requires that the parameters of the marginals and the copula functions be estimated simultaneously. With the IFM, on the other hand, the parameters of the marginal distributions can be estimated before those of the copula functions. Efficiency is therefore enhanced by using Eqs. (12) and (13).

$$\hat{\theta}_{it} = \arg\max \sum_{t=1}^{T} \ln f_{it}\left(z_{i,t} \mid \Omega_{t-1}, \theta_{it}\right) \tag{12}$$

$$\hat{\theta}_{ct} = \arg\max \sum_{t=1}^{T} \ln c_t\left(F_{1t}\left(z_{1,t} \mid \Omega_{t-1}\right), F_{2t}\left(z_{2,t} \mid \Omega_{t-1}\right), \ldots F_{nt}\left(z_{n,t} \mid \Omega_{t-1}\right), \theta_{ct}, \hat{\theta}_{it}\right). \tag{13}$$

As suggested by Joe and Xu (1996), we applied the jackknife method to estimate the standard errors of the parameters.

3. Data and summary statistics

The daily stock indices from January 2000 to December 2009, provided by MSCI, were obtained from the Datastream database. Maghyereh (2004) has explained why the MSCI indices are better than other local stock indices. For each index, 2608 daily observations were collected.

To control for non-synchronous trading problems, MSCI index returns were calculated as the rolling averages of 2-day returns, as suggested by Forbes and Rigobon (2002). The Chinese, United States, and Japanese MSCI indices were chosen for the country-level comparisons. To indicate which regional stock market has the highest correlation with China's, possibly because of its geographical proximity to or trade relationship with China, we included the European and Pacific MSCI indices, the latter of which does not include China. To assess international dependence, we included the MSCI World index, which covers 23 developed countries (excluding China), and the MSCI AcWorld index, which combines the market indices of 48 developed and developing countries, with China representing less than 1.1% of the weights on yearly average.

The summary statistics for each index return are reported in Table 1. According to the results of Jarque–Bera test, none of the index returns were normally distributed. Table 2 gives the Pearson, Spearman, and Kendall correlations between each index return

Table 3
Estimated parameters for the GJR-GARCH(1,1)-AR(1)-*t* marginal distributions.

Index	AR(1)	GARCH constant	Lagged residual	Lagged variance	Asymmetric residual	Degree of freedom
China	0.5021	0.0137	0.0459	0.8999	0.0501	9.5391
	(0.0169)	(0.0001)	(0.0003)	(0.0006)	(0.0007)	(0.1797)
World	0.5184	0.0041	0.0216	0.9014	0.1110	21.2449
	(0.0167)	(0.0000)	(0.0018)	(0.0019)	(0.0003)	(1.7436)
U.S.	0.4135	0.0048	−0.0005	0.9104	0.1433	22.0452
	(0.0178)	(0.0000)	(0.0003)	(0.0003)	(0.0003)	(0.1428)
Europe	0.4768	0.0077	0.0276	0.8927	0.1157	25.1718
	(0.0172)	(0.0000)	(0.0002)	(0.0002)	(0.0003)	(0.1445)
Japan	0.4428	0.0283	0.0484	0.8543	0.0941	21.9795
	(0.0176)	(0.0001)	(0.0001)	(0.0003)	(0.0004)	(0.1230)
AcWorld	0.5318	0.0042	0.0243	0.8987	0.1076	19.5259
	(0.0166)	(0.0000)	(0.0003)	(0.0002)	(0.0007)	(0.1358)
Pacific	0.4706	0.0252	0.0455	0.8444	0.1058	20.5313
	(0.0173)	(0.0001)	(0.0002)	(0.0004)	(0.0006)	(0.1625)

Note: This table presents the estimated parameters of the marginal distributions for each index return. They are assumed to be characterized by the GJR-GARCH (1,1)-AR(1)-*t* model represented by Eqs. (1a), (1b), and (1c). The numbers in parentheses are standard deviations.

and China's index return. Because Pearson correlations give linear associations, they are neither robust for distributions with long tails nor appropriate for indicating non-linear relationships. On the other hand, nonparametric rank correlations, such as Kendall's τ and Spearman's ρ, are relatively insensitive to the observations at the tails. As illustrated in Table 2, no matter which correlation measure is used, the Pacific has the highest correlation with China, followed by AcWorld.

The parameter estimates for the marginal distributions of all the index returns are presented in Table 3. The parameters are assumed to be characterized by the GJR-GARCH(1,1)-AR(1)-t model, represented by Eqs. (1a), (1b), and (1c). We used the Kolmogorov–Smirnov test to determine whether the transformed series are $Unif(0,1)$, and the residual series pass the goodness-of-fit test for all index returns.

4. Empirical results

4.1. Unconditional copula models

For comparison with conditional models, the estimated parameters of the unconditional copula models are presented in Table 4, including the unconditional Gaussian, Clayton, Gumbel and SJC copula functions. Note that all the copula functions have positive parameters, indicating that China's index return correlates positively with all the index returns of the other markets in the sample. We consistently find that, irrespective of the assumed copula functions, the dependence between the China and Pacific index returns is the highest, followed by China with Japan. Bekaert et al. (2005) and Goetzmann, Li, and Rouwenhorst (2005) claimed that capital market integration and increased trade are embedded with predictions about the dependences between markets. Therefore, higher dependence of the Chinese market with the Japanese or Pacific market than with other market implies a limited opportunity for portfolio diversification. This limitation is attributable to China's more frequent trading with the Pacific countries, which in turn is caused by their geographical proximity and regional economic developments. If the growth of the Chinese economy unexpectedly slows, these markets may suffer severely. This result is similar to findings reported by Evans and McMillan (2009) and Li (2007). We further propose that these dependences will become increasingly evident, the reason being that China will join the ASEAN Free Trade Area (AFTA) in 2010 to strengthen its cooperation with ASEAN countries by eliminating tariffs and non-tariff barriers.

4.2. Conditional copula models

The parameters of the time-varying dependences in the chosen copula, as shown in Eqs. (7)–(11), were estimated and calibrated for each pair of index returns. The results are reported in Table 5. The parameter β represents the degree of persistence, and γ captures the adjustment in the dependence process. Table 5 shows that the Pacific and the Japanese markets have the greatest dependences with the Chinese market, as indicated by their dependence levels described by ω. Meanwhile, the absolute log-likelihood functions are higher for the Pacific region and Japan than for other areas. Significant variations over time in the dependences between the Chinese and pacific markets and between the Chinese and Japanese markets were also found, as indicated by the relatively negative values of γs, which measure their variations in the dependences. Thus, the results demonstrate

Table 4
Parameter estimates for the unconditional copula models.

Unconditional copula model						
Paired indices	China versus					
	World	U.S.	Europe	Japan	AcWorld	Pacific
Gaussian						
ρ	0.3550	0.1568	0.3408	0.4409	0.3953	0.5300
	(0.0406)	(0.1156)	(0.0473)	(0.0248)	(0.0361)	(0.0222)
ln L	−175.6046	−32.4680	−160.9294	−281.8294	−221.4943	−429.7417
Clayton						
θ	0.4569	0.1807	0.4217	0.6006	0.5250	0.7892
	(0.0416)	(0.1180)	(0.0467)	(0.0241)	(0.0368)	(0.0220)
ln L	−152.8613	−30.9983	−132.5332	−235.8354	−191.1934	−355.6459
Gumbel						
δ	1.2535	1.1000	1.2369	1.3595	1.2967	1.4868
	(0.0511)	(0.1555)	(0.0561)	(0.0254)	(0.0445)	(0.0259)
ln L	−139.3958	−23.4426	−126.3681	−241.0112	−179.2794	−378.3044
SJC						
τ_U	0.1050	0.0074	0.1039	0.1964	0.1352	0.2819
τ_L	0.2136	0.0488	0.1861	0.2777	0.2506	0.3589
ln L	−169.8117	−33.9192	−151.0236	−272.6291	−213.8783	−418.6703

Note: This table presents the estimated results of unconditional copula models. ρ is the correlation parameter of the Gaussian copula, and δ and θ are dependence parameters of the Gumbel and Clayton copulas, respectively. τ^U and τ^L are measures of the upper and lower tail dependences of the SJC copula. The numbers in brackets are standard deviations.

Table 5
Estimated parameters of the time-varying dependences in the chosen copulas.

	World	U.S.	Europe	Japan	AcWorld	Pacific
Time-varying Clayton copula						
β_L	−0.0022	0.1575	−0.0426	0.0016	−0.0141	−0.0194
	(0.0069)	(0.0205)	(0.0147)	(0.0140)	(0.0071)	(0.0087)
ω_L	0.7140	0.2293	0.7538	1.1653	0.8646	1.5354
	(0.0058)	(0.0070)	(0.0133)	(0.0190)	(0.0079)	(0.0122)
γ_L	−0.9646	−0.2457	−1.1643	−2.2514	−1.2967	−3.1585
	(0.0110)	(0.0110)	(0.0262)	(0.0432)	(0.0174)	(0.0244)
LLF(c)	−150.8545	−26.6987	−135.5042	−249.3752	−193.0141	−374.8588
Time-varying SJC copula						
β_L^{SJC}	−0.2190	−1.0473	−0.9207	1.5108	0.3947	1.7202
	(0.0073)	(0.0562)	(0.0005)	(1.6234)	(0.0976)	(0.0442)
ω_L^{SJC}	−0.8140	−1.7612	−0.0296	−0.2108	−1.3536	−0.1483
	(0.0053)	(0.0220)	(0.0005)	(0.0046)	(0.0757)	(0.0848)
γ_L^{SJC}	−1.9105	2.6515	−4.9469	−5.8941	−0.7612	−5.2796
	(0.0022)	(0.0227)	(0.0025)	(0.0230)	(0.0850)	(0.5592)
β_U^{SJC}	4.6874	−22.5591	1.9997	0.7018	5.7229	0.2278
	(0.0153)	(2.4439)	(0.0457)	(0.0745)	(0.6999)	(0.0757)
ω_U^{SJC}	−1.7687	−3.4789	−1.0760	−0.3658	−1.6893	0.0884
	(0.0022)	(0.0503)	(0.0058)	(0.0075)	(0.0163)	(0.0072)
γ_U^{SJC}	−3.3392	2.6286	−5.3024	−5.4121	−5.1149	−5.0182
	(0.0245)	(0.0245)	(0.0178)	(0.0118)	(1.1982)	(1.0721)
LLF(c)	−178.5518	−34.7455	−155.8906	−290.1308	−226.9035	−446.1421
Time-varying Gumbel copula						
β_U	0.1425	0.1533	0.1368	0.0822	0.0028	0.0163
	(0.0065)	(0.0064)	(0.0082)	(0.0060)	(0.3630)	(0.0062)
ω_U	1.2772	1.0279	1.2523	1.5742	1.7634	1.9120
	(0.0119)	(0.0075)	(0.0121)	(0.0112)	(0.4480)	(0.0125)
γ_U	−0.7603	−0.3574	−0.6911	−1.3117	−2.2976	−1.9610
	(0.0155)	(0.0030)	(0.0082)	(0.0151)	(0.0868)	(0.0158)
LLF(c)	−145.757	−26.7382	−131.2221	−253.5185	−135.266	−398.2927
Time-varying Gaussian copula						
β_ρ	0.0569	0.1290	0.0492	0.0179	0.0679	−0.0394
	(0.0086)	(0.0115)	(0.0113)	(0.0116)	(0.0056)	(0.0046)
ω_ρ	0.5662	0.2332	0.5722	0.8411	0.6520	1.0711
	(0.0052)	(0.0037)	(0.0069)	(0.0097)	(0.0042)	(0.0042)
γ_ρ	−0.8038	−0.3069	−0.8720	−1.5101	−1.0089	−2.0205
	(0.0085)	(0.0054)	(0.0121)	(0.0192)	(0.0075)	(0.0104)
LLF(c)	−180.9179	−33.2084	−167.2765	−299.7111	−230.4972	−459.9689

Note: This table shows the estimated results of the time-varying dependences in the chosen copulas. Parameters in Eqs. (7)–(11) are estimated and calibrated for each pair of index returns. β_ρ, β_L, β_U, β_L^{SJC}, β_U^{SJC} capture the degrees of persistence in their dependence processes, and γ_ρ, γ_L, γ_U, γ_L^{SJC}, γ_U^{SJC} capture their variations. *LLF*(c) is the maximum of the copula component of the log-likelihood function. The standard errors in parentheses are estimated by the jackknife method.

not only higher levels of conditional dependence, but also greater variability in these levels. This outcome provides useful insights on how to practice active risk management for portfolios.

Fig. 1, which is based on Eqs. (7)–(11) and the parameter estimates shown in Table 5, illustrates the implied time paths of the conditional dependences between the Chinese and Pacific markets and between the Chinese and Japanese markets during the sample period.[4] The time paths of the conditional correlations implied by the dynamic Clayton, Gumbel and SJC copulas were obtained from simulations based on two marginal models and the estimated time-varying copula models. Specifically, at each time *t*, we generated 1000 pairs of bivariate uniform variables (F_X, F_Y) from each conditional Clayton, Gumbel and SJC copula model. These simulated pairs of uniformly distributed (F_X, F_Y) were transformed into random variables (X, Y) according to the conditional marginal distribution implied by the GJR-GARCH(1,1)-AR(1)-*t* model represented by Eqs. (1a), (1b), and (1c). As can be seen in Fig. 1, we found that the conditional correlations in those chosen copulas seem to show the greatest volatility during the time periods surrounding the 9/11 terrorist attack in 2001 and the U.S. subprime market crash in 2008 and 2009.

4.3. Conditional tail dependences

Tail dependences are very useful for examining the joint extreme events affecting financial returns during periods of high volatility or a market crash (Hu, 2010). Fig. 2 demonstrates the time paths of the conditional lower- and upper-tail dependences

[4] Due to space limitations, we show only the time paths of the China–Pacific and the China–Japan dependencies. Time paths of the Chinese dependencies with other markets are available from the author.

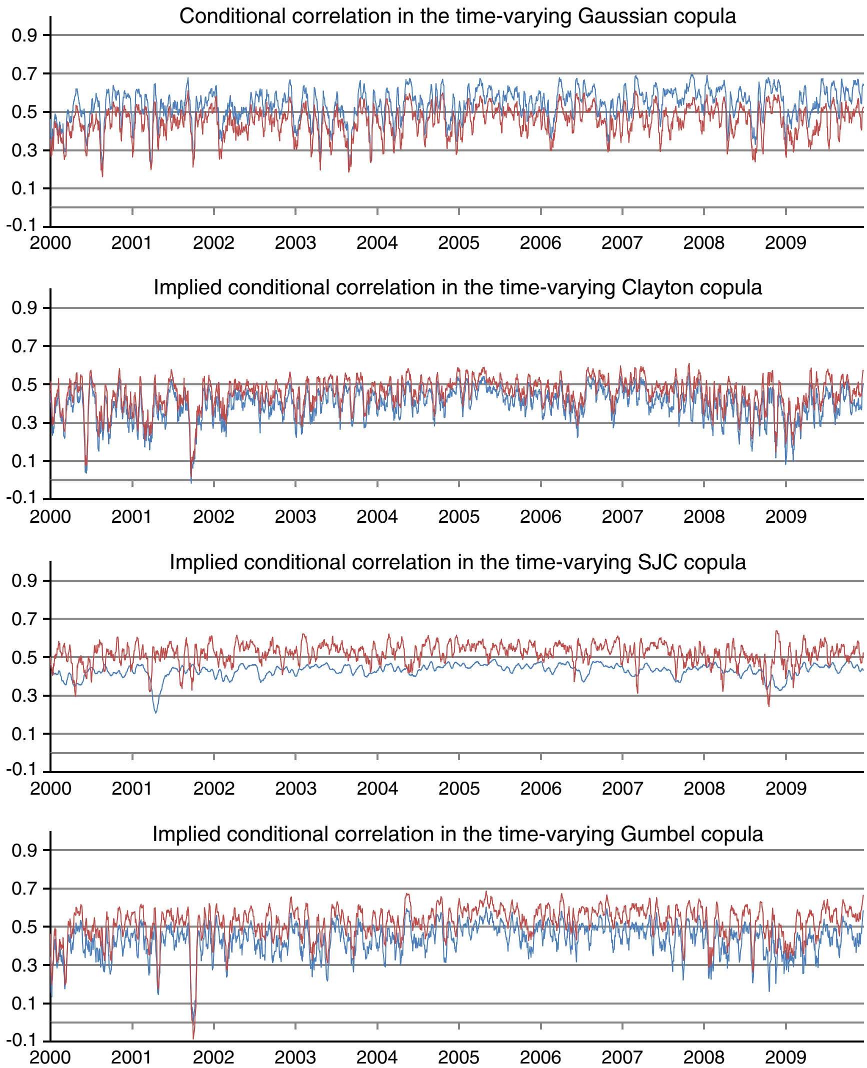

Fig. 1. Conditional correlation estimates from the copula models. Note: Fig. 1 displays the implied time paths of the conditional dependences between the Chinese and Pacific markets (red) and the Chinese and Japanese markets (blue) across the sample period. The time paths of the conditional correlations implied by the time-varying Clayton, Gumbel and SJC copulas are obtained from simulations based on two marginal models and the estimated time-varying copula models.

from the Clayton, Gumbel, and SJC copulas. The fact that equity returns reflect more joint negative extremes than joint positive extremes led us to hypothesize that the conditional left-tail dependences are stronger than the conditional right-tail dependences. From the estimates of parameters in the SJC copula, presented in Table 5, we find that ω_L^{SJC} is generally higher than ω_U^{SJC}, implying that lower-tail dependence is indeed relatively higher. The plot in Fig. 3 of the differences in the time paths between the lower- and the upper-tail dependences leads to a similar conclusion. When the market is down, risk diversification is less effective because of this greater dependence. Thus, financial risk management that uses VaR or other downside risk measures should emphasize the left side of the portfolio return distribution. When this left tail is prominent, the time-varying Clayton and SJC copulas enable risk managers to measure the risk effectively and avoid underestimating the likelihood of a joint crash.

Even after 2007, the differences between the Chinese–Japanese dependences and the Chinese–Pacific dependences seem not to have been affected by the financial tsunami. This fact is reflected by the systematically higher dependences represented by the left tails. Managers of portfolios that include assets from these pairs of countries should be particularly concerned about downside risk exposure and VaR.

4.4. Goodness-of-fit test and comparisons

Evaluations of multivariate density models have become increasingly popular as the use of multivariate conditional distributions has dramatically accelerated (Christoffersen, 1998; Rivers & Vuong, 2002; Granger, Terasvirta, & Patton, 2006; Chen

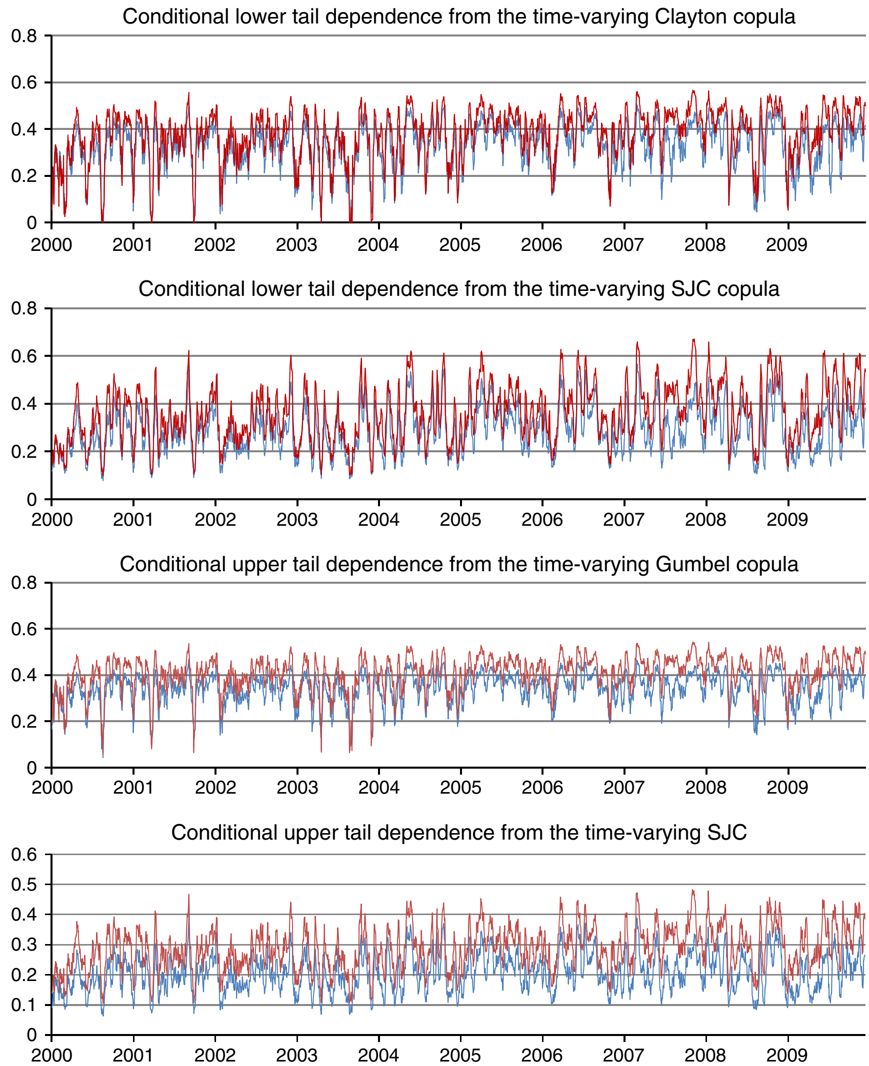

Fig. 2. Conditional tail dependence estimates from the Gumbel, Clayton and SJC copulas. Note: Fig. 2 displays the time paths of the conditional lower and upper tail dependences between the Chinese and Pacific markets (red) and the Chinese and Japanese markets (blue) from the Clayton, Gumbel and SJC copulas.

& 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 two approaches differ in whether the marginal distributions of the standardized

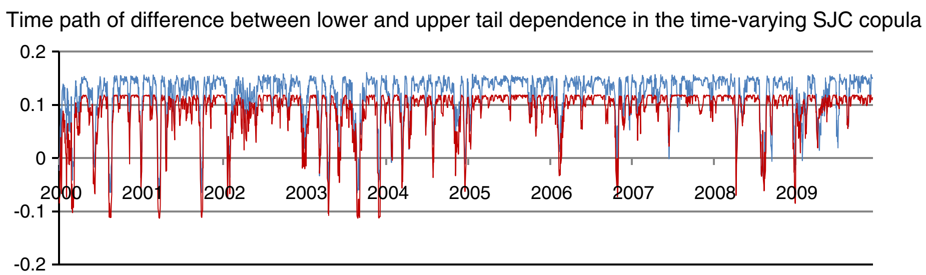

Fig. 3. Difference between the lower and upper tail dependences from the conditional SJC copula. Note: Fig. 3 shows the time paths of the differences of the lower and upper tail dependences between the Chinese and Pacific markets (red) and the Chinese and Japanese markets (blue) from the conditional SJC copula model. Positive difference means that the lower tail dependence is larger than the upper tail dependence.

Table 6
Model comparisons.

	World	U.S.	Europe	Japan	AcWorld	Pacific
Panel A: conditional copula models						
Clayton		✓				
SJC	✓					
Gumbel						
Gaussian			✓	✓		✓
DCC-GARCH						
Panel B: unconditional copula models						
Clayton						
SJC						
Gumbel						
Gaussian					✓	
CCC-GARCH						

Note: The joint hit test is conducted to identify the best model with the highest p-value. It strongly supports the null hypothesis that the density for the entire region is correctly specified. The best model is checked by ✓.

innovations are specified.[5] When applying the copulas to make forecasts, it is most common to employ purely parametric models to fit the data and to compare the results from different models. Therefore, we applied the bivariate "hit" tests[6] proposed by Patton (2006a) to evaluate our models. Patton (2006a) decomposed the density model into a set of "region" models.[7] Each region model must be correctly specified under the null hypothesis that the density for the *entire* region is correctly specified. The intuition of this approach is to compare the number of observations in each region with what would be expected under the null hypothesis.

Table 6 illustrates the results of the joint hit test comparing the copula models to the benchmark DCC-GARCH and CCC-GARCH models. Panel A contains the results for the conditional models and Panel B for the unconditional models. With the exception of the China-World dependence, the conditional models outperform the unconditional models, implying that conditional copula models are capable of improving VaR calculation and asset allocation. Moreover, all the copula models are superior to the conventional GARCH models. Managers of portfolios including the Chinese-World or Chinese–US dependences should pay careful attention to the downside risk, because the conditional Clayton and SJC copulas are superior to the other models.[8] There is a high probability that these markets go down together.

5. Conclusions

Knowledge of the multivariate conditional distribution, especially if it has fat tails and asymmetric dependence, is essential to many important financial applications such as portfolio selection, asset pricing, risk management, and forecasting (Chen & Fan, 2006). However, studies of international dependences have focused mainly on developed markets. Relatively few have investigated the role of China, despite the noticeable growth in its capital markets and its increasing integration into the global economy. China's economic prominence has led us to emphasize the dynamic dependence between the Chinese stock market and other markets of the world using time-varying copula models. Our approach can help quantify downside risk, improve VaR calculation, and allocate assets dynamically.

We found significant variability in the dependences among markets over time. Regardless of which copula function was used, we consistently found that the Chinese market had not only the highest levels of dependence, but also the greatest variability of dependence, with the Japanese and Pacific markets. This high dependence can be attributed to the close geographical proximities and trading relationships between China and the Pacific nations. This finding implies that the probability of joint market crashes in these areas is high if the bubble bursts in China, and portfolio managers should become more alert to and take account of this co-movement. Furthermore, the greater dynamic dependences during bear markets imply that opportunities for portfolio diversification are reduced at such times. Finally, the results from the goodness-of-fit test indicate that the conditional copulas outperform the unconditional models as well as the conventional GARCH models.

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

[6] Patton (2006a) extended Christoffersen's (1998) evaluation model for interval forecasting to a bivariate model.

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

[8] The conditional Clayton and SJC copulas have desirable properties for describing the left-tail dependence, and the left-tail of a distribution is especially important during a market downturn.

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