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國家別信用違約相依性探討：以拉丁美洲為例
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行政院國家科學委員會補助專題研究計畫■成果報告
□期中進度報告

國家別信用違約相依性探討：以拉丁美洲為例

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計畫中文摘要

完整且有系統的瞭解信用違約的傳染對於國家風險之評估是非常重要的。透過2001年阿根廷信用危機為研究背景，探討拉丁美洲國家間是否產生高度的信用違約相依性。其中阿根廷、巴西、墨西哥及委內瑞拉的信用違約交換日資料透過CreditTrade 資料庫取得。研究方法乃採copula，以利拉丁美洲國家間信用相依性結構之呈現。研究結果如下：（1）在阿根廷信用危機期間，拉丁美洲國家間的信用違約相依性大為提高；（2）並且這些信用相依性結構可能屬非對稱性；（3）國家的信用評等等級將影響/決定其受信用危機波及之程度。本研究亦討論相關的發現對於政府政策制定、國際貨幣基金及銀行、基金經理人的意涵及應用。

計畫英文摘要

Using the eruption of Argentina debt crisis in 2001 as a natural experiment, we investigated the correlated default at the sovereign level for some Latin American countries. Daily closing market quotes for sovereign credit default swaps (CDS) of Argentina, Brazil, Mexico and Venezuela were obtained from *CreditTrade* database. Using copula approach, we observed increased dependences among sovereign CDS markets during the crisis period. Their dependence structures were found to be asymmetric. Moreover, the degree of credit contagion was related to the creditworthiness of the country. This study also discussed the implications of these findings for policymakers.

Keywords: Credit contagion; Sovereign credit default swaps; Copula

1. Introduction

In a world of increasing economic interdependencies the issue of credit contagion is of critical concern, particularly in the presence of economic distress. (Gelos and Wei , 2005; Bekaert, et al., 2005; Elkinawy, 2005; Caporale, et al, 2005; Forbes, 2004; Han et al., 2003). Credit contagion refers to the credit deterioration of one country that indirectly leads to similar deterioration of other countries (Avellaneda and Wu, 2001). The propagation of this distress is accompanied by a sudden jump in sovereign spreads, reflecting the market re-assessment of all countries affected by the default.

In order to characterize the comovements that may exist among sovereign bonds during a financial crisis, we collected data on sovereign CDS spread for some Latin American markets and used copula method to analyze the nature of credit contagion in that region. Embrechts et al. (1999) first discussed the dangers of using linear correlation in studying dependence. Copula method overcomes the problem that data is non-normal and non-linear, and provides robust measures of dependence structures. It contains all the information that researchers need to know about the dependence structures between variables. Furthermore, it offers the modeling flexibility due to the separation of marginals from dependence in its functional form.

Recent literature has shown evidence of contagion in equity markets (Jondeau and Rockinger, 2006; Bekaert et al., 2005; Longin and Solnik, 2001; Forbes and Rigobon, 2002). Relatively few studies focus on bond and credit derivative markets (Kan, 1998; Beattie, 2000; Copeland and Jones, 2001; Han et al., 2003; Sander and Kleimeier, 2003; Yang, 2005). Ene and Vlad (2002) pointed out that credit derivatives are largely used to protect against sub-grade debts, so they have gained popularity in the emerging market, which tend to be more volatile. Neftci et al. (2005) argues that in emerging markets financial crises are never caused by market risk. Instead, they are precipitated by events such as currency devaluation or sovereign bond default. Compared with the cases in equity, foreign exchange, and domestic money markets, comovement in bond markets, particularly for sovereign bonds, is strongest during times of distress. According to the findings of Kaminsky and Reinhart (2002), there is a great degree of international comovement among sovereign bond markets, which often share common lenders and foreign investors. This phenomenon appears to be increasing. As Mauro et al. (2002) have found, sovereign spreads across emerging markets commove significantly more than they did historically (1870-1913).

In this context, it is important to understand how dependence between sovereign bond markets can be measured. A thorough understanding of correlated defaults at sovereign level is of critical importance. First, mutual fund managers require higher premiums to compensate their exposures to correlated sovereign risk. If there is a credit contagion, the sovereign bond spread which reflects the country risk premium may be affected. Kraay et al. (2004) take sovereign risk into account when modeling net foreign asset positions, and empirically show that modest amounts of sovereign risk can lead to substantial reductions in both bond price and flow of foreign investments. From the bank's perspective, higher credit premiums are required in order to offset potential losses caused by correlated default.

In addition, the likelihood of a contagious sovereign debt crisis should influence the monetary policies. Because credit default swaps reflect the sovereign risk[1] and because they are used by investors to assess a country's economic and political fundamentals, the increased joint default probabilities in sovereign credit default swaps may imply a forthcoming financial crisis. We think that the comovement in sovereign credit default swaps can serve as an important indicator of financial crises and can be used to supplement other indicators, many based on fundamental variables, which have been criticized for poor predictive power (Berg and Patillo, 1999; Edison, 2003). For example, IMF can use it to predict the possibility of a forthcoming contagious crisis.

The rapid growth in Latin American bond market is frequently affected by financial crises (Bustillo and Velloso, 2000). Compared with Asia, Europe, and G-7countries, Latin America exhibits the most significant comovement in bond markets (Kaminsky and Reinhart, 2002). The 2001 Argentina crisis provided a unique opportunity to design a natural study of the effect of correlated default among Latin American countries, since Argentina debts represented from one-fifth to one-quarter of tradable issues in the emerging bond markets at that time, and, according to IMF, a loss of confidence in Argentina can rapidly become contagious.

In this study, we first test whether dependences in sovereign CDS market increase during the crisis period. We hypothesize that countries whose sovereign CDS spread exhibited a high degree of dependence with that of Argentina would be more vulnerable to contagion during crisis. A copula-based measure is used to specify the structure of dependence as well as the degree of dependence, which would not only take the non-linear property into account but would also allow a more comprehensive understanding of correlated default. Genius and Strazzera (2008), Turgutlu and Ucer (2007) and Hu (2006) all showed that the copula approach is especially beneficial under strong departures from normality assumption, which is the case for our sample data.

Second, we examine whether the dependence structures during the crisis were asymmetric or not. Copula can efficiently capture the tail dependence arising from the extreme observations caused by asymmetry. Longin and Solnik (2001) and Bae, et. al. (2003) have emphasized the relationship between the tails of CDS spread distributions. However, the top- and bottom-tail, which are coexceedances in their models, were arbitrarily identified and separately estimated, thereby not able to provide consistent results.

Finally, we explore whether the degree of credit dependence is related to the credit quality of the sovereign bonds. Higher ratings can attract more confident investors, so the magnitude of credit contagion in such countries may be reduced.

Our results show that dependence in sovereign CDS spread is increased among sample countries during the debt crisis. The sudden default by Argentina accelerated the degree of comovement in Latin America. Before the crisis, there was no tail dependence between Argentine CDS spreads and those of other countries. However, we observed right tail dependences with Brazil and Venezuela during that crisis, indicating that once the contagion happened, impact on Brazil and Venezuela might have been more severe than it was on Mexico. The degree of this

[1] For example, as mentioned in Ene and Vlad (2002), two months before the actual news of the collapse of Enron was out, the default swaps market had already begun pricing it.

dependence is probably related to a sovereign's creditworthiness. As a result, Mexico, whose credit rating was higher at that time, seemed immune to the impact of contagion from the 2001 Argentina crisis.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Empirical results are analyzed in Section 3. Finally Section 4 concludes.

2. Data and methodology

The trading of credit derivatives in Latin America accounts for 50-60% of the overall market shares for emerging countries (Ranciere, 2002). According to a 2005 survey[2] by The Federal Reserve Bank of New York, sovereign single-name credit default swaps are the most liquid credit derivative instruments. A single-name sovereign CDS is a contract that provides protection against the default risk of a sovereign entity. The protection buyer makes periodic payments, i.e., the CDS spread, to the protection seller until the contract matures or a credit event occurs. In return, the protection seller must buy the bonds at its par when a credit event occurs before the CDS contract matures.

We collected the daily closing mid market quotes in the year of 2001 for sovereign CDS with a two-year maturity from *CreditTrade* database. Due to liquidity consideration, we only consider those of Argentina, Brazil, Mexico and Venezuela. Sovereign CDS markets in other Latin American countries are much less liquid to provide reliable results. We chose only CDS with the same maturity to make it easier to compare across countries. Although these sovereign CDS are popular with investors and are relatively liquid, large withdrawals of deposits from Argentine banks in July 2001 caused the sales of CDS stopped temporarily until the government announced a "zero-deficit" plan, a measure that was endorsed by the IMF. We therefore divided our 2001 sample period into: (1) *the pre-crisis period*, which covered the time period from March to June 2001 and (2) *the crisis period*, which covered the period from August to October, 2001. After October no trading was being done of Argentine CDS, since very few protection sellers would sell in a market in which the default risk was so high. By mid-November, due to the severe losses of foreign exchange reserves, the IMF finally refused to lend any more financial support. The Argentine default was officially announced in December, 2001.

Dealing with the possible misspecification of the dependence relationship[3] for non-normal data, we used the copula technique to provide robust measures of dependence structures based on the joint distributions of variables. The structure rather than the degree of dependence gives a more comprehensive understanding for relationship between these variables. Moreover, copula can more readily capture the tail dependence arising from the asymmetric extreme observations.

Recent researchers have been concerned over the methodology used to identify the effects of contagion (Forbes and Rigobon, 2002; Longin and Solnik, 2001). Longin and Solnik (2001) have

[2] See Dages et al. (2005), an overview of the emerging market credit derivatives market, Federal Reserve Bank of New York Working Paper.

[3] Correlations calculated with equal weights assigned to small and large returns are not appropriate for evaluation of return dependence on which extreme values may have different impacts.

suggested that the Extreme Value Theory (EVT) be used to study the dependence structure of international equity markets. In this method, the tails of the distribution need to be identified first before the dependence structure of extreme observations can be estimated. Choosing an optimal threshold to identify the extreme values can be difficult[4]. The dependence function used to estimate the threshold may not be well defined. And another problem is the number of parameters in the dependence structures[5]. Typically, logistic function is used to make the estimations, though this solution is less than ideal. For example, Bae et al. (2003) develop a multinomial logistic regression model for Asian markets to measure the joint occurrences of large returns. The extreme returns in their model are arbitrarily defined as 5^{th} and 95^{th} quantiles of return distribution. However, they found it difficult to apply to other markets like in Latin America.

In the present study, we fit the joint distribution of sovereign CDS spreads with various copulas in order to find the best dependence structure to describe their relationship. Specifically, three different copula types were examined: *Gaussian, Student's t,* and *Gumbel copula.* Of these, the Student's t copula was used to catch the fat-tailed phenomena, and the Gumbel copula, an Archimedean-form copula, to capture the right tail dependence. The Gaussian copula served as the benchmark. The functional forms of these copulas are described as follows:

Bivariate Gaussian Copula

$$C^{Gau}(u,z) = \Phi_{\rho_{Gau}}\left(\Phi^{-1}(u), \Phi^{-1}(z)\right)$$

$$= \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(z)} \frac{1}{2\pi\sqrt{1-\rho_{Gau}}} \exp\{\frac{-(x^2-2\rho_{Gau}\, xy+y^2)}{2(1-\rho_{Gau}^2)}\}\, dxdy \quad (1)$$

where u, z are standard uniform variables, ρ_{Gau} is the correlation coefficient and $\Phi^{-1}(u)$ denotes the inverse of the cumulative normal distribution function.

Bivariate Student's *t* Copula

$$C^{t}(u,z) = T_{\rho_t,v}\left(t^{-1}(u), t^{-1}(z)\right)$$

$$= \int_{-\infty}^{t^{-1}(u)} \int_{-\infty}^{t^{-1}(z)} \frac{1}{2\pi\sqrt{1-\rho_t^2}} \left(1 + \frac{x^2+y^2-2\rho_t xy}{v(1-\rho_t^2)}\right)^{-\frac{v+2}{2}} \quad (2)$$

where ρ_t is the correlation coefficient, $v$is the degrees of freedom and $t^{-1}(u)$ denotes the inverse of the cumulative student's *t* distribution function.

Gumbel Copula

$$C_\theta^{Gum}(u,z) = \varphi^{-1}[\varphi(u) + \varphi(z)] = \exp\left\{-\left[(-\ln u)^\theta + (-\ln z)^\theta\right]^{1/\theta}\right\} \quad (3)$$

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

[5] For bivariate model in the EVT, there are typically seven parameters to be estimated: two tail probabilities, two dispersion parameters, two tail indexes, and the dependence parameter.

where $\theta \in [1, \infty)$ measures the degree of dependence between u and z. $\theta = 1$ implies an independent relationship while $\theta \to \infty$ represents perfect dependence.

Tail dependence refers to the relationship between random variables resulting from extreme observations from the upper and lower quadrants of the joint distribution function. Much evidence indicates that high level of dependence tends to happen during the period of feverish financial market. We expect similar phenomenon for correlated defaults in the sovereign CDS markets.

To measure this dependence, suppose (X, Y) is a bivariate vector of continuous random variables with marginals F_X and F_Y. The coefficient of upper tail dependence, λ_U, is defined as:

$$\lambda_U = \lim_{u \to 1} \Pr[Y > F_Y^{-1}(u) | X > F_X^{-1}(u)], \qquad (4)$$

provided that the limit $\lambda_U \in [0,1]$ exists, and the coefficient of lower tail dependence, λ_L, is:

$$\lambda_L = \lim_{u \to 0} \Pr[Y \leq F_Y^{-1}(u) | X \leq F_X^{-1}(u)], \qquad (5)$$

provided that the limit $\lambda_L \in [0,1]$ exists. The coefficient of tail dependence can be calculated for each tail of the distribution specified by a certain copula function. We summarize below the relevant propositions that can be used to evaluate how the correlated defaults among Latin American countries are related to the Argentina crisis.

Proposition 1: For bivariate Gaussian copula with linear correlation, ρ_{Gau}, as described in equation (1), the coefficient of tail dependence is null.

Proposition 2: For continuously distributed random variables with t copula $T_{\rho_t, v}$ as described in equation (2), the coefficient of tail dependence is given by

$$\lambda_U = \lambda_L = \lambda_t = 2 - 2t_{v+1}(\sqrt{v+1}\sqrt{\frac{1-\rho_t}{1+\rho_t}}) \qquad (6)$$

Proposition 3: For continuously distributed random variables with Gumbel copula C_θ^{Gum} as described in equation (3), the coefficient of upper tail dependence is given by[6]

$$\lambda_U = 2 - 2^{\frac{1}{\theta}} \qquad (7)$$

To estimate and calibrate the parameters in the copula models, we apply *Canonical Maximum Likelihood* (CML) estimation taking into account the computational efficiency and the non-normality in our data set. Using empirical transformation, these parameters can be estimated without specifying the marginals. The sample data can be transformed into uniform variables that can then be used to estimate copula parameters.

The CML method is implemented in two stages. First, we transform the sample data into uniform variables using empirical marginal transformation:

$$\hat{u}_{it} = \hat{F}_i(x_{it}) = \frac{1}{T+1}\sum_{j=1}^{T} I\{x_{ij} < x_{it}\} \qquad \forall t,\ i=1,\dots\dots\dots,n \qquad (8)$$

where $I\{.\}$ is an indicator function and x_{ij} is the CDS spread for the sovereign bond i at time j. The CDS spreads can be transformed into uniform variables, $\{\hat{u}_{it}\}$, and then empirical

[6] Gumbel copula has upper tail dependence only.

marginals, $\widehat{F}_i(x_{it})$, can be obtained. Second, we estimate the copula parameter, $\hat{\delta}$, by maximizing a *pseudo log-likelihood function*.

$$\hat{\delta} = \arg\max \sum_{t=1}^{T} \ln c\left(\widehat{F}_1(x_{1t}), \widehat{F}_2(x_{2t}), \dots \dots \widehat{F}_n(x_{nt}); \delta\right) \qquad (9)$$

3. Empirical results

For each of the sample countries, we first summarized their sovereign CDS spreads for the periods before and during the Argentina crisis. As can be seen in the descriptive statistics shown in Table 1, before the crisis, the highest CDS spread was for Argentina. During the crisis, all sovereign CDS spreads increased simultaneously while Argentina's remained the highest. We also calculated the ratios of changes in sovereign CDS spreads over the crisis period for sample countries. Argentina was found to have the greatest change, followed by Brazil. Mexico changed the least. Hence, markets observed higher sovereign risk during the crisis and requested more credit spreads, presumably because the number of protection buyers exceeded the number of protection sellers in the CDS market. A simultaneous increase in all sovereign CDS spreads indicates the higher possibility of joint defaults. In particular, the large increase in Brazil and small increase in Mexico reflect the relationships described in dependence structures we found, which will be discussed below.

[Insert Table 1here]

To study the relationship of CDS spreads between Argentina and other sovereigns, their scatter diagrams were plotted in Figure 1. We observed two relevant findings. First, before the crisis period, the relationship of spreads between Argentina and Brazil was almost linear, while no clear relationship was seen between Argentina and Mexico or Venezuela. Second, we found that during the crisis period there was tail dependence for CDS spreads, no matter which country was paired with Argentina. The clusters appeared in both right and left tails. This finding is consistent with results from the non-linear contagious models recently developed by Longin and Solnik (2001), Bae et. al. (2003), Dungey and Tambakis (2003).

[Insert Figure 1here]

We performed Jarque-Bera test to access the normality of distribution of the CDS spread (Table 1). Our samples were found to have non-normal distributions, consistent with the result of previous studies. Because we observed both non-normal and non-linear properties, we calculated Pearson's rho[7], Kendall's tau and Spearman's rho to further analyze the biases (Table 2). Pearson's rho, compared with the other two measures, seems to overstate all the correlations during the crisis period, indicating possible misspecifications of the dependence structures. Meanwhile, the association between Argentine CDS spreads and those of any other country was higher during the

[7] We understand that Pearson correlation indicates the strength of a linear relationship between two variables. Its value alone is not sufficient to evaluate the relationship in our dataset. We use it to enquire whether correlations are under- or overstated, if data are nonlinear. Similarly, the nonparametric rank correlations, Kendall and Spearman measures, are less sensitive to the observations in the tails. We calculate all these measures as preliminary tests of correlations and mainly for the purpose of comparison. It strengthens the need for copula analysis.

crisis than before it, supporting Forbes and Rigobon's (2002) argument that contagion exists if cross-market comovement increases significantly after the shock.

[Insert Table 2 here]

Because of the non-normal property of our data, we used the semi-parametric *Canonical Maximum Likelihood* (CML) procedure to estimate and calibrate the parameters in copula models. Both before and during the crisis, all three models had positive copula parameters (Panel A Table 3), suggesting that sovereign CDS spreads of Argentina positively comoved with those of other countries in Latin America. Furthermore, the degree of this association increased more during the crisis period than before. For example, ρ_{Gau} of the Gaussian copula increased from 0.579 to 0.729 for Argentina with Brazil, from 0.174 to 0.701 with Mexico and from 0.293 to 0.772 with Venezuela. Results were similar when the Student's t or the Gumbel copula was used.

[Insert Table 3 here]

Financial integration and mutual trading among Latin American countries may be the reason for the strong comovement during the crisis. Most of the effects of the Argentine debt crisis were transmitted through financial channels, because these countries have common lenders and foreign investors (Kaminsky and Reinhart, 2002). The default of Argentine sovereign bond may have caused correlated defaults of other sovereign bonds. Once the crisis occurred in Argentina, the investors started adjusting their holdings in other related countries to respond to changes in liquidity and asset quality.

As a result, sovereign CDS spreads can serve as one of the leading indicators for externally-induced financial crisis. Therefore, this spread can be used by policymakers to prepare their countries for imminent turmoil and mitigate it. The IMF need consider the impact of credit contagion when assessing the effectiveness of interventions for a particular country. It can also be expected that banks and fund managers will ask higher credit premiums to compensate for potential correlated default.

Moreover, regardless of the sample periods and copula functions, estimated parameters of dependence for Brazil are larger than those for Mexico or Venezuela, meaning that Brazil would be more vulnerable to credit contagion from Argentina. During the crisis period, the Brazilian currency devaluation against the dollar accelerated. The Brazilian real fell 2.3 percent in June, 5.5 percent in July and 10 percent in late September. Although there were five increases of interest rate that occurred during 2001, the Brazilian real fell by 23 percent. The big drop in exchange rate devastated Brazil's dollar-denominated debt. Hence, Brazil's vulnerability during the financial crisis was very similar to that of Argentina.

In contrast, Mexico was better able to maintain its overall economic growth since it is related to the United States more through the North American Free Trade Agreement than to other countries in Latin America. This link has made its economy the brightest in the Latin American region. Our results showed that Mexico stayed on the sideline of turbulence. Regardless of the copula functions used, the estimated parameter of dependence appeared to be the smallest for Mexico during the crisis period.

Moody's rating of Mexico's sovereign credit was upgraded to Baa3 in early 2000. Since that time, comovements between Mexico's sovereign bonds and those of other Latin American countries were less correlated (Rigobon, 2002). Actually, investors could have expanded their Mexican holdings for portfolio reasons[8] despite the shocks in Argentina. Due to this relative immunity to the contagion from Argentine crisis, three rating agencies rated Mexico's long-term foreign currency sovereign debt as investment grade in 2002[9].

The choice of the best fit of copula function is based on the value of Akaike information criterion (AIC)[10]. From the maximized log-likelihood values (lnL) in Panel A of Table 3, we compute the AIC for each copula, and then rank the copula models accordingly. Panel B of Table 3 shows the AIC values for three chosen copulas. For the sample period before the crisis, we found that the Gaussian copula showed the lowest AIC value for each pair of dependences. They were -42.217, -9.877 and -7.226, respectively, indicating that the Gaussian copula was the best fitting model before the crisis, and that there was no tail dependence between CDS spreads of Argentina and those of other countries. During the crisis period, however, the Gumbel copula represented the lowest AIC value for Brazil and Venezuela, but not for Mexico. The consistent results can also be found using Schwartz Bayesian Criteria (SBC). The evidence suggests that the right tail dependence is presented for Brazil and Venezuela. The sovereign CDS of Brazil and Venezuela were found to be significantly dependent on those of Argentina with such extreme increases in Argentina's sovereign spread.

In contrast, for Mexico where the Gaussian was still the best model, there was no tail dependence with Argentina, even during that crisis. The right tail dependences we observed for Brazil and Venezuela indicate that once contagion happens, these two countries will be more severely affected than Mexico. The impact will be underestimated if only Pearson correlation or OLS regression are used. The insignificant spillover from Argentina to Venezuela found in Chan-Lau (2003) may be caused by such conventional methods.

To further examine the dependence in the tails, we compared the coefficients of tail dependence in the Student's t and the Gumbel copulas computed based on proposition 2 and 3. Since the t distribution was symmetric, its estimated coefficients capture the tail dependence on both sides. The coefficients from the Gumbel copula, on the other hand, represent only the upper tail dependence. As shown in Table 4, tail dependences were not significant before the crisis. However, during the crisis, we found remarkable Gumbel coefficients of 0.629 and 0.541 for Brazil and Venezuela, respectively. We conjecture that sovereign bond investors perceive these countries as a group when crisis occurs.

[Insert Table 4 here]

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[8] Investment-grade rating promotes holdings from investors such as mutual funds or pension funds with restricted investment policies.

[9] Fitch first upgraded Mexican sovereign bond from double B plus to triple B minus in January 2002, while Moody's upgraded it from Baa3 to Baa2 in February 2002. S&P reacted promptly the next day after Moody's announcement.

[10] $AIC = -2L(\widehat{\theta}\,; x) + 2q$. where q is the number of parameters needed to be estimated in each specific model. Both the Gaussian and the Gumbel copulas need to estimate one parameter, i.e., ρ_{Gau} and θ, respectively, while the Student's t copula has two correlation parameters ρ_t and degree of freedom $\boldsymbol{v}$.

Given the estimated copula parameters, the surface of the copula densities can be expressed by equation (1), (2) and (3). Comparing the densities for Argentina and Brazil before the crisis (Figure 2) and during the crisis (Figure 3), we could clearly observe their joint probability distributions and dependence structures. For all copula densities, there were no tail dependences before the crisis. However, remarkable spikes in the right tails for all copulas were observed during the crisis. As can be seen in Figure 4, where the Gumbel copula for each pair of countries is plotted, there was notable right tail dependence for Brazil, whereas, as we have expected, none for Mexico.

[Insert Figure 2 here]

[Insert Figure 3 here]

[Insert Figure 4 here]

4. Conclusion

Research on sovereign CDS has important implications for a better understanding of sovereign risk behavior. Because default expectation can be extracted from CDS spreads, their dependence structures help us specify how sovereign risks are correlated. Increasing integration of international markets makes credit contagion more common than before, especially in times of financial crisis. In this study, we measured the dependence structure of sovereign defaults using the copula method, a method able to consider the non-linear relationship and evaluate the different impacts from extreme observations. Our results should be useful for policymakers, foreign investors as well as the international bankers.

Using daily closing quotes of sovereign CDS of Argentina, Brazil, Mexico and Venezuela for the periods before and during the crisis, we found that dependences between sovereign CDS spreads increased significantly during the crisis period. Before the crisis, there was no tail dependence between Argentina and other countries, making the Gaussian copula the best fitting model for that period. However, during the crisis, the Gumbel copula performs best for Brazil and Venezuela, but not for Mexico, reflecting the different credit risk relationship. The right tail dependence we observed indicated Brazil and Venezuela was more seriously impacted by the Argentina crisis than Mexico once contagion started. This effect would have been underestimated had it been specified by the linear correlation. The difference in credit dependence among these countries is related to sovereign's creditworthiness. The higher the credit ranking the country has, the milder the contagion effect it suffers.

Understanding the correlated default at sovereign level is important in pricing sovereign bond, designing sovereign risk derivatives, managing country risk, analyzing portfolio allocations, and supervising financial markets. Besides the nature of correlation, how is the credit relationship affected? What are the factors determining this dependence structure? How long does this contagious effect take place? These are interesting issues left to be explored in future studies.

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Table 1. Summary statistics of CDS spreads before and during the crisis

	Argentina			*Brazil*			*Mexico*			*Venezuela*		
	Pre-crisis period	Crisis period	Ratio of change	Pre-crisis period	Crisis period	Ratio of change	Pre-crisis period	Crisis period	Ratio of change	Pre-crisis period	Crisis period	Ratio of change
Min	470	1288	1.740	140	655	3.679	80.5	142.5	0.770	557.5	612.5	0.099
Q1[a]	1050	1999	0.904	438.8	691.3	0.575	162.5	155	-0.046	572.5	710.6	0.241
Median	1121	1999	0.783	512.5	751.9	0.467	175	158.8	-0.093	590	715	0.212
Mean	1150	2548	1.216	479.3	812.7	0.696	164.5	178.6	0.086	587.8	734.4	0.249
Q3[b]	1263	3325	1.633	572.5	917.5	0.603	175	200	0.143	595	813.4	0.367
Max	2025	3775	0.864	720	1046	0.453	175	246.3	0.407	662.5	815	0.230
p-value[c]	0	0.02		0	0.01		0	0.005		0.004	0.596	

[a] Q1 represents the first and the third quantiles of CDS spread distribution

[b] Q3 represents the first and the third quantiles of CDS spread distribution

[c] p-value is for normality test in CDS spread distribution of each country.

Table 2. Measures of association between pair countries before and during the crisis

	Pre-crisis Period			Crisis Period		
Paired		*Argentina v.s.*			*Argentina v.s.*	
countries	*Brazil*	*Mexico*	*Venezuela*	*Brazil*	*Mexico*	*Venezuela*
Pearson ρ^{a}	0.556	0.205	0.303	0.883	0.900	0.889
Kendall τ^{b}	0.443	0.267	0.188	0.671	0.570	0.723
Spearman ρ^{c}	0.587	0.336	0.267	0.800	0.758	0.840

[a] Pearson's rho is a measure of linear dependence

[b] $\tau = 4 \iint_{I^2} C(u_1, u_2) d\, C(u_1, u_2) - 1$

[c] $\rho = 12 \iint_{I^2} u_1 u_2 \, dC(u_1, u_2) - 3$

Table 3. Parameter estimations and goodness-of-fit test for copula functions

	Pre-Crisis Period			Crisis Period		
Paired	*Argentina v.s.*			*Argentina v.s.*		
countries	*Brazil*	*Mexico*	*Venezuela*	*Brazil*	*Mexico*	*Venezuela*
Panel A: Copula estimation						
Gaussian						
ρ_{Gau} [a]	0.579 (0.0000)	0.174 (0.0005)	0.293 (0.0024)	0.729 (0.0000)	0.701 (0.0101)	0.772 (0.0023)
$\ln L$	22.108	5.939	4.613	28.292	23.767	36.544
Student's t						
ρ_t [b]	0.443 (0.0005)	0.267 (0.0023)	0.188 (0.0471)	0.671 (0.0000)	0.570 (0.0041)	0.723 (0.0014)
v	114	114	114	5	86	86
$\ln L$	19.818	3.952	3.845	28.689	21.278	35.645
Gumbel						
θ [c]	1.427 (0.0002)	1.054 (0.099)	1.070 (0.654)	2.198 (0.0000)	1.615 (0.0052)	1.834 (0.0013)
$\ln L$	14.483	3.991	0.501	38.067	13.661	37.517
Panel B: Goodness-of-fit test (AIC)[d]						
Gaussian	-42.217	-9.877	-7.226	-54.584	-45.535	-71.088
Student's t	-35.637	-3.905	-3.691	-53.379	-38.556	-67.290
Gumbel	-26.967	-5.982	0.998	-74.134	-25.321	-73.034
Panel C: Goodness-of-fit test (SBC)[e]						
Gaussian	-39.479	-7.141	-4.489	-52.129	-43.079	-68.633
Student's t	-34.899	-3.167	-2.953	-52.923	-38.101	-66.835
Gumbel	-24.229	-3.245	3.734	-71.679	-22.867	-70.579

[a] ρ_{Gau} is the correlation parameter of Gaussian copula.

[b] ρ_t is the correlation parameter of Student's t copula. $v$is the degree of freedom of the Student's t copula.

[c] θ is the dependence parameter of Gumbel copula.

[d] The choice of the best fit in Panel B is based on the value of Akaike information criterion (AIC), $AIC = -2L(\hat{\theta}\,; x) + 2q$, where q is the number of parameters to be estimated in each specific model.

[e] The choice of the best fit in Panel C is based on the value of Schwartz Bayesian criterion (SBC), $SBC = -2L(\hat{\theta}\,; x) + q\ln T$, where q is the number of parameters to be estimated in each specific model and T is the sample size.

Table 4. Coefficients of tail dependence

	Pre-Crisis Period			**Crisis Period**		
Paired	*Argentina v.s.*			*Argentina v.s.*		
countries	*Brazil*	*Mexico*	*Venezuela*	*Brazil*	*Mexico*	*Venezuela*
Student's t λ_t [a]	0.000	0.000	0.000	0.319	0.000	0.000
Gumbel λ_U [b]	0.375	0.070	0.089	0.629	0.464	0.541

[a] $\lambda_t = 2 - 2t_{v+1}(\sqrt{v+1}\sqrt{\frac{1-\rho_t}{1+\rho_t}})$

[b] $\lambda_U = 2 - 2^{\frac{1}{\theta}}$, where θ is its dependence parameter. If $\lambda_U > 0$, Gumbel copula has upper tail dependence

Figure 1. Scatter plots for pairs of sovereign CDS spreads

(A). Pre-Crisis period (B). Crisis period

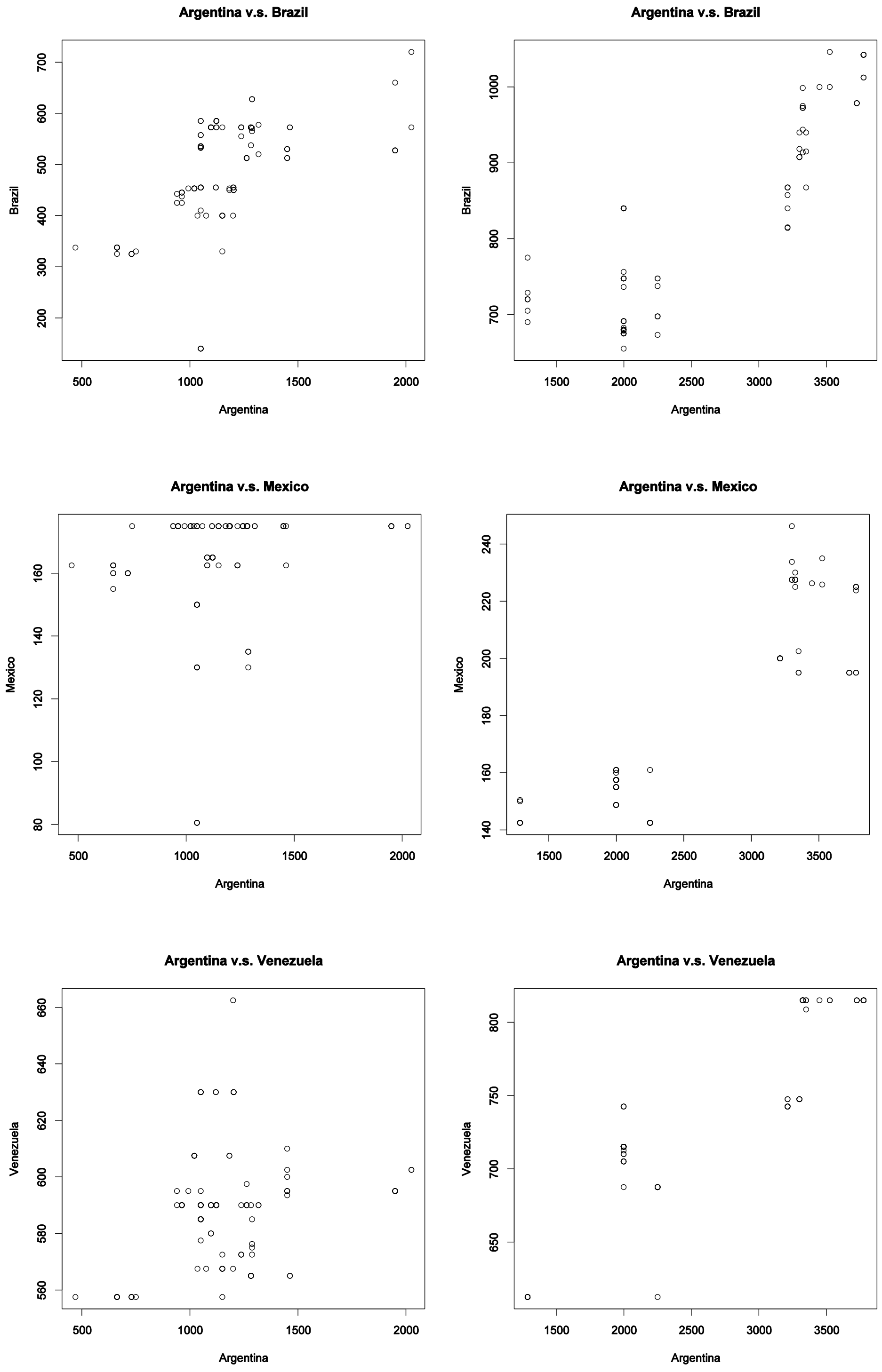
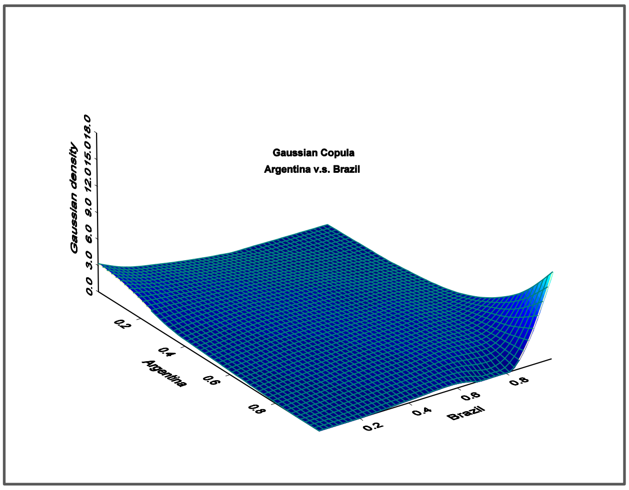
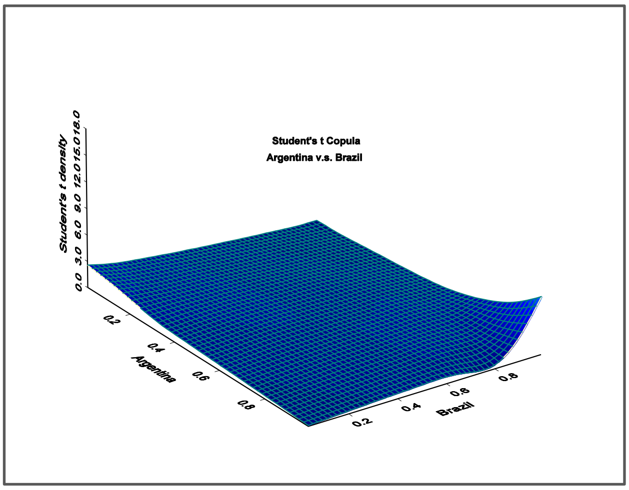


Fig. 1(A) shows the relationship of CDS spreads between Argentina and other sovereigns during pre-crisis period, while Fig. 1(B) shows their relationships during the crisis period.

Figure 2. Copula density plots for the pre-crisis period





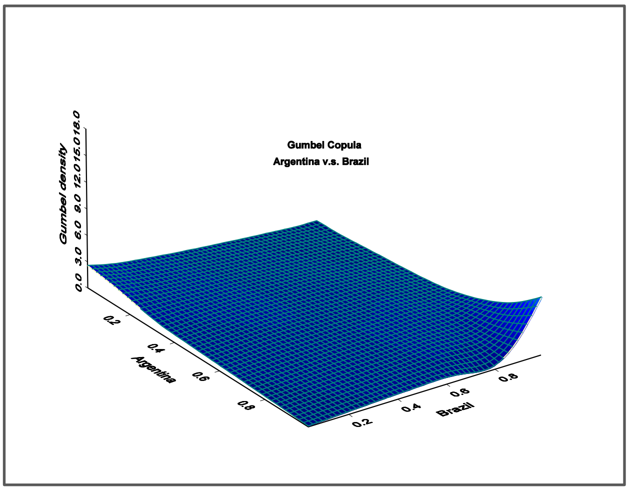


Fig. 2 is a three dimensional figure which contains Argentine empirical marginals in X axis, Brazilian empirical marginals in Y axis, and their joint default probabilities, specified by the Gaussian, Student's t and Gumbel copulas, respectively, in Z axis for the pre-crisis period.

Figure 3. Copula density plots for the crisis period

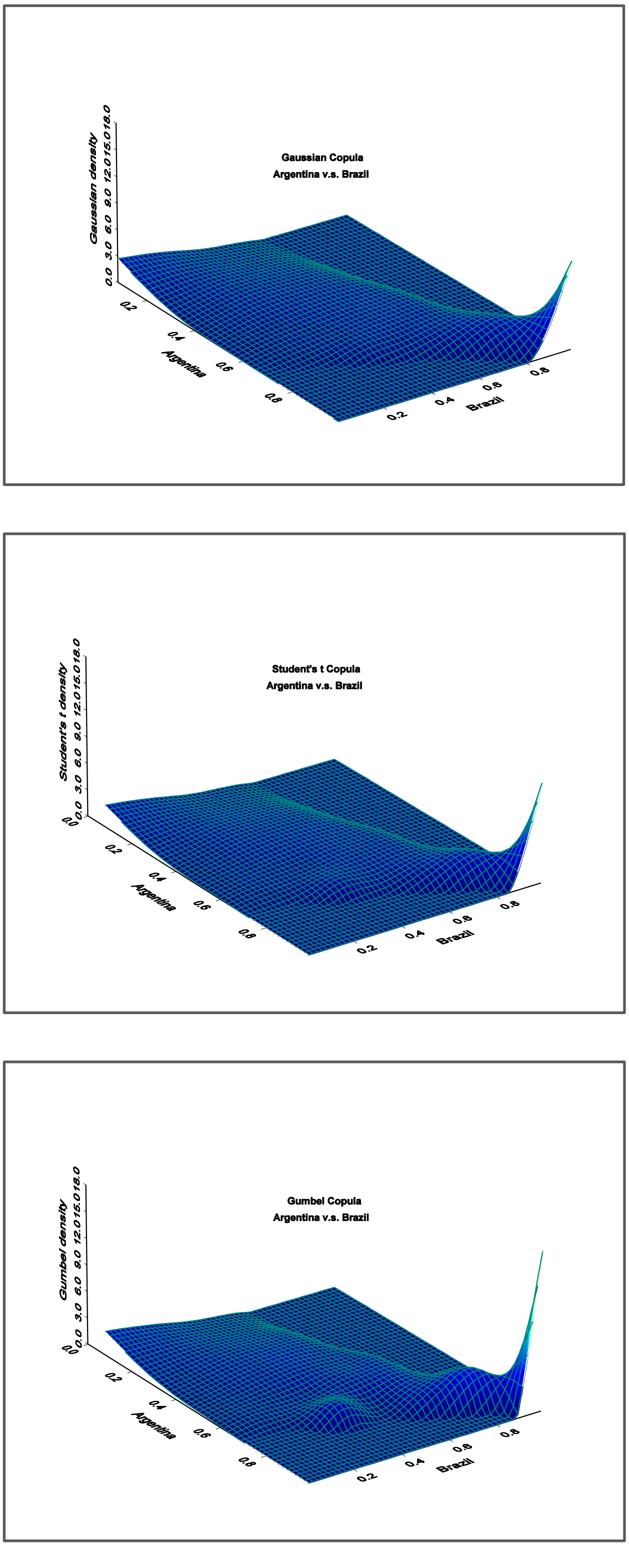


Fig. 3 is a three dimensional figure which contains Argentine empirical marginals in X axis, Brazilian empirical marginals in Y axis, and their joint default probabilities, specified by the Gaussian, Student's t and Gumbel copulas, respectively, in Z axis for the crisis period.

Figure 4. Tail dependence display from the Gumbel copula (crisis period)

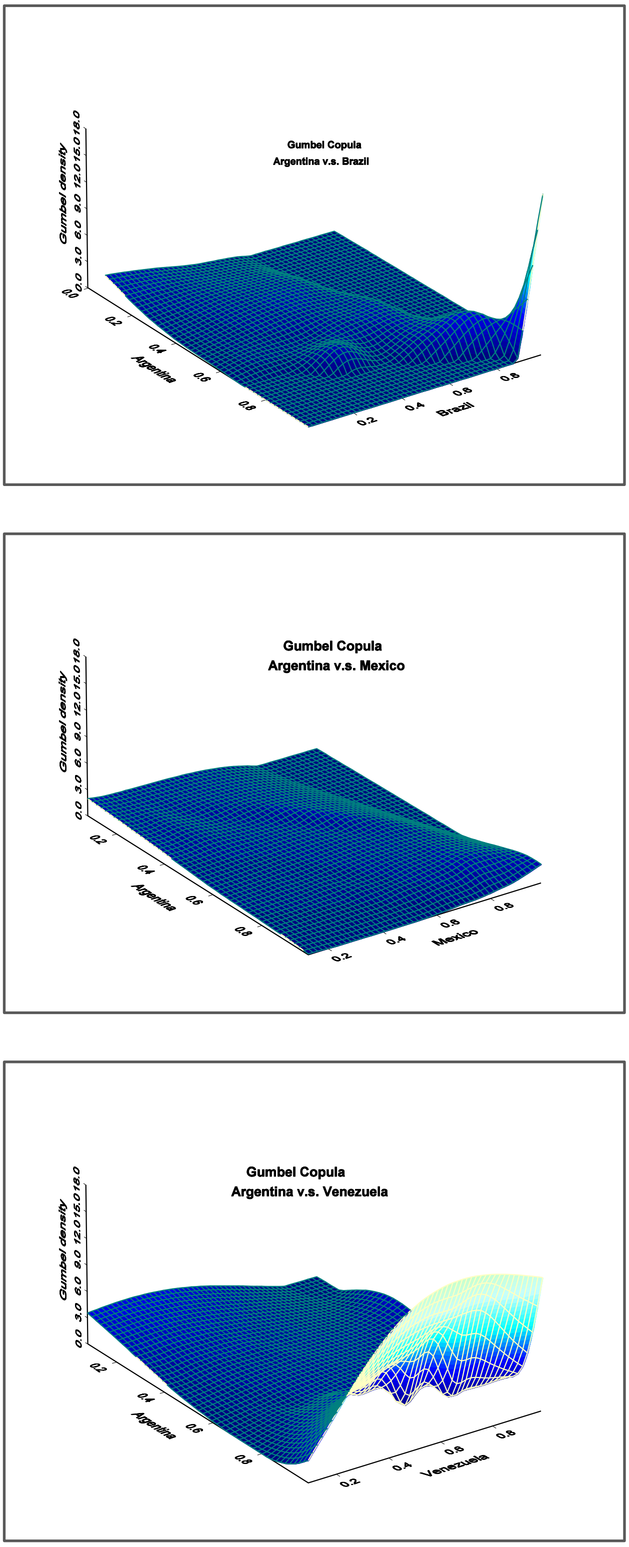


Fig. 4 focuses on the Gumbel copula in the crisis period where Argentine empirical marginals in X axis, other sovereigns' empirical marginals in Y axis, and their joint default probabilities in Z axis.

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

年　　月　　日

附件

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	97年7月6日至97年7月9日 奧蘭多，佛羅里達，美國	本會核定補助文號	NSC 96-2415-H-216-002
會議名稱	（中文）第十五屆多國籍財務學會研討會 （英文）15th annual conference of the multinational finance society		
發表論文題目	（中文）中國股票市場與國際財務市場的動態相依性結構之研究與檢視 （英文）Re-investigating the International Financial Market Dependence: the Role of China		

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 10 “Asian Financial Markets”，報告順序為第三，並且本人亦評論同一場次的論文

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

Re-investigating the international financial market dependence: The role of China

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Abstract

This study emphasizes the dynamic dependence between the Chinese financial market and other major markets in the world as China is being influential and integrated with the global economy. We provide a comprehensive analysis of the dynamic market dependence for the period 2002-2007 by estimating time-varying copula models between indices of those stock markets and the findings are further interpreted. It will provide more implications for portfolio diversification, risk management and international asset allocation than those based on a static model.

Keywords: International finance; Dependence structure; Copula; GARCH

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1. Introduction

The integration and dependence of financial markets has been an issue of interest for both financial economists in academia and investment practitioners in industry (Bartram and Dufey, 2001) Research on dependence of financial markets has gained wide response in literatures because of its implications on international diversification as well as market integration. Recent studies have shown evidence of contagion in equity markets (Jondeau and Rockinger, 2006; Bekaert et al., 2005; Poon et al., 2004; Longin and Solnik, 2001; Forbes and Rigobon, 2002). However, these researches have mainly emphasized the developed countries such as U.S., U.K., Germany, France and Japan. Relatively few studies have investigated the financial market of China for its role in the international dependence.

By the end of year 2006, the total market capitalization in China remarkably increased from US$2,028 million by 1991 to US$ 786 billion, the largest of all emerging markets. 1,517 companies had been listed in the stock markets of China by the end of September 2007, and the volume of equity market capitalization ranked fourth in the world. According to a recent IMF report[1], China may replace German to be the third largest in near future. The dramatic growth of China's stock market has allured the

[1] Global Economic Outlook 2007, IMF

attention of speculators, investors as well as the scholars, notwithstanding the worries of the sensitive stock market crash driven by panics or underlying economic factors.

Chinese stock market took a major hit on Feb 27, 2007. The Shanghai Stock Exchange's Composite Index unexpectedly dropped 8.8%, the largest one-day decline in 10 years. The same day, the Dow Jones Industrial Average tumbled 3.3% and the NASDAQ declined 3.9%, the sharpest falls since 911 crisis. This may be an evidence of the integration of China's financial markets into the world and indicates that an event in China might trigger reactions around the world.

China's growing economy has attracted huge foreign investment. A crash in the stock market may prompt the investors for abrupt withdrawals from China. As a consequence, financial contagion may be erupted. Our study especially concerns about the relationship between the Chinese market and other major markets of the world. It can provide implications for portfolio diversification, risk management and international asset allocation.

To demonstrate the market correlation between China and other countries, we provide a comprehensive analysis of the market dependence during the period 2002-2007 by estimating time-varying copula dependence models between indices of these stock markets. In a time-varying copula setting, the dependence parameters in the copula function are modeled as a dynamic process conditional on currently available information to allow non-linear, time dependant relationship.

Our study makes two contributions. First, although the capital market of China has noticeably grown and it has significant impact on other financial markets, few studies have focused on the role of China in the international dependence. By and large, researches are confined to its regional roles (Cheng, H., Glascock, 2005; Cheng, H., Glascock, 2006; Baur, 2007; Chang et al., 2000). Since its production and trade also have significant global influence, the regional constraint should be extended world-wide. Moreover, Bekaert et al. (2005) and Goetzmann et al. (2005) find a positive causality from market integration to market dependence. Does China integrate into international financial market with higher dependence after opening its market to world?

The second contribution is to show how a conditional copula model can be applied. In fact, a copula-based measure can specify the structure and the degree of dependence to examine correlations, which takes the non-linear property into account and allows a more comprehensive understanding as well. 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 correlation or tail dependence (Patton, 2006a). Patton(2006a) is the first to apply a time-varying copula to exchange rate dependence.

Bartram et al. (2007) use the same method to examine the Euro and European financial market dependence, but they do not explore any time-varying tail dependence. Our copula model investigates both conditional dependence structures and conditional tail dependences between stock market of China and other stock markets.

The daily stock indices for MSCI China, MSCI Japan, MSCI Unite States, MSCI Europe, MSCI emerging markets, MSCI world and MSCI AcWorld are collected over the period 2002 - 2007. We consistently find that, irrespective of the assumed copula function; the emerging, the Pacific and the Japanese markets experience a higher degree of dependence persistence with the Chinese market. The Rotated Gumbel copula is the best fitting model, thus existence of time-varying lower tail dependence in each pair is evident. Given that the bubbles in Chinese stock market are pricked, higher probability of a joint market crash in Japan, in Pacific and in the emerging countries could be conjectured.

The remainder of this paper is structured as follows: Section 2 discusses our empirical methodology of a time-varying copula model. Section 3 reports the data and summary statistics. Empirical results are presented and discussed in Section 4, while Section 5 is the conclusion.

2. Empirical methodology

It is evident that multivariate normality is not suitable for measuring the dependence structure of equity returns (Lognin and Solnik, 2001; Poon et al., 2004). Researchers are concerned about the methodology used to specify comovement or contagion effect, especially for their asymmetric part, between the stock markets. Lognin 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.[2] The dependence function used for estimating the threshold may not be well defined[3]. Further, the determination of the number of parameters in the dependence structures[4] is also a problem.

Kroner and Ng(1998), Engle(2002) and Cappiello et al.(2006) have developed GARCH models with time-varying covariances and correlations. Engle(2002) provides a univarite GARCH model which is capable of allowing conditional asymmetries in both volatilities and correlations. Cappiello et al.(2006) extend Engel's (2002) model to

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

[3] Typically, logistic function is used to make this estimation, though the solution is not good.

[4] For bivariate model in the EVT, there are typically seven parameters to be estimated: two tail probabilities, two dispersion parameters, two tail indexes, and the dependence parameter.

two dimensional environments. Both 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.

Recently, copula method has been emphasized because of its capability of modeling the contemporaneous interdependence between either univariate time series or innovations of univariate parametric time series models. It is being more and more popular because it can analyze dependence structure beyond linear correlation and provide a higher degree of flexibility in estimation by separating marginal and joint distributions. Furthermore, it can be extended to a time-varying specification in order to capture changes in the dependence structure. Patton (2006a,b) introduces the method of time-varying copula and applies it to measure conditional asymmetries in the exchange rate dependence. Bartram et al. (2007) employ it to measure dependences between some European stock indices. Following their settings, our empirical time-varying copula is modeled as below.

2.1. The models for the marginal distribution

In this study, the marginal distribution for each index return is assumed to be characterized by an AR(1)-GARCH(1,1) model. Let $R_{i,t}$ and $h_{i,t}$ denote index i's return and its conditional variance for period t, respectively. The AR(1)-GARCH(1,1) model for the index return is:

$$
\begin{aligned}
R_{i,t} &= u_i + \emptyset_i R_{i,t-1} + \varepsilon_{i,t} \\
h_{i,t} &= \omega_i + \beta_i h_{i,t-1} + \alpha_i \varepsilon_{i,t}^2 \\
\varepsilon_{i,t} | \Omega_{t-1} &\sim \mathrm{N}(0, h_{i,t})
\end{aligned} \tag{1}
$$

Fisher(1932) and Rosenblatt(1952) showed that random variable $U_{i,t} = F_{i,t}(\varepsilon_{i,t}|\Omega_{t-1})$ has *Uniform(0,1)* distribution, regardless what unconditional distribution is. Thus, the value of the random variable from conditional marginal distribution $\mathrm{F}_{\mathrm{i,t}}(\varepsilon_{\mathrm{i,t}}|\Omega_{t-1})$ should be between zero and one. Typically, the technique of "probability integral transform[5]" for conditional random variables, $\varepsilon_{i,t}|\Omega_{t-1}$, can be applied to satisfy this requirement.

2.2. The models for the copula

Equity returns have been found 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 direction of the return distribution. We therefore employ the Gaussian, the Gumbel and the Rotated Gumbel copula for specification and calibration, all with and without time variation. The Gaussian copula is generally viewed as a benchmark for comparison, while the

---

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

Gumbel and the Rotated Gumbel copula are used to capture the upper and lower tail dependence, respectively.

The Gaussian copula function is the density of joint standard uniform variables (u_t, z_t), as the random variables $\{R_{i,t}\}$ are bivariate normal with a time-varying correlation, ρ_t. Moreover, let $x_t = \Phi^{-1}(u_t)$ and $y_t = \Phi^{-1}(z_t)$, where $\Phi^{-1}(.)$ denotes the inverse of the cumulative density function of the standard normal distribution. The density of the time-varying Gaussian copula can be shown as

$$c_t^{Gau}(u_t, z_t|\Omega_{t-1}) = \frac{1}{\sqrt{1-\rho_t}} exp\left\{\frac{2\rho_t x_t y_t - x_t^2 - y_t^2}{2(1-\rho_t^2)} + \frac{x_t^2 + y_t^2}{2}\right\} \quad (2)$$

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 are pricked. The Gumbel and the Rotated Gumbel copula can efficiently capture the tail dependence arising from the extreme observations caused by asymmetry. The density of the time-varying Gumbel copula is

$$C_{\delta_t^U}^{Gum}(u_t, z_t|\Omega_{t-1}) = \frac{(-\ln u_t)^{\delta_t^U-1}(-\ln z_t)^{\delta_t^U-1}}{u_t z_t} \exp\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\frac{1}{\delta_t^U}}\right\}$$
$$\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\left(\frac{1-\delta_t^U}{\delta_t^U}\right)^2} + (\delta_t^U - 1)\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\left(\frac{1-2\delta_t^U}{\delta_t^U}\right)}\right\} \quad (3)$$

where $\delta_t^U \in [1, \infty)$ measures the degree of dependence between u_t and z_t. $\delta_t^U = 1$ implies an independent relationship and $\delta_t^U \to \infty$ represents perfect dependence.

Cherubini et al. (2004) show that the Gumbel family has upper tail dependence, with $\lambda_t^U = 2 - 2^{1/\delta_t^U}$. Rotated Gumbel copula has a similar density function to that of Gumbel copula and its time-varying version is

$$c_{\delta_t^L}^{R.Gum}(1-u_t, 1-z_t) =$$

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

$$\left\{-\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-z_t))^{\delta_t^L-1}\right]^{\left(\frac{1-\delta_t^L}{\delta_t^L}\right)^2} + (\delta_t^L - 1)\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-z_t))^{\delta_t^L-1}\right]^{\left(\frac{1-2\delta_t^L}{\delta_t^L}\right)}\right\} \quad (4)$$

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

In reality, time-invariant dependence seems unreasonable. So, a conditional copula with a time-varying dependence parameter is prevalent (Patton, 2006a; Patton, 2006b; Bartram et al., 2007; Jondeau and Rochinger, 2006; Rodriguez, 2007). Following the studies of Patton(2006a) and Bartram et al.(2007), we assume that the dependence parameter is determined by the 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 one are rarely different from zero (Bartram et al.[6], 2007; Samitas et al., 2007). The dependence process of Gaussian copula is therefore:

$$\rho_t = \Lambda(\beta\rho_{t-1} + \omega + \gamma|u_{t-1} - z_{t-1}|) \tag{5}$$

The conditional dependence, ρ_t , depends on its previous dependence, ρ_{t-1} , and historical absolute difference, $|u_{t-1} - z_{t-1}|$. In this way the persistence and the variation in the dependence process can both be captured. $\Lambda(x)$ 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 time (Patton, 2006a). The estimation of copula parameters, $\theta_c = (\beta, \omega, \gamma)'$, 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:

$$\delta_t^U = \beta_U\delta_{t-1}^U + \omega + \gamma|u_{t-1} - z_{t-1}| \tag{6}$$

$$\delta_t^L = \beta_L\delta_{t-1}^L + \omega + \gamma|u_{t-1} - z_{t-1}| \tag{7}$$

where $\delta_t^U \in [1, \infty)$ measures the degree of dependence in the Gumbel copula and has a lower bound equal to one which indicates an independent relationship, while $\delta_t^L \in [1, \infty)$ measures the degree of dependence in the Rotated Gumbel copula. After

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

estimating the Gumbel copula parameters $\theta_c = (\beta_U, \omega, \gamma)'$, the conditional upper tail dependence coefficents, $\{\lambda_t^U | \Omega_{t-1}\}$, are obtained by

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

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

2.4. Estimating and calibrating copula models

Calibrating copula parameters using real market data has involved much interest in recent statistical literatures (Meneguzzo and Vecchiato, 2004; Mashal and Zeevi, 2002; Dias and Embrechts, 2003; Galiani, 2003). *Exact Maximum Likelihood Method* (EML) is a well-known parametric method for estimation. However, the EML need to estimate the parameters of the marginals and 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 of copula models are naturally decomposed into two steps: the first for the marginals and the second for the copula, which is the concept of *Inference function for Margins* method (IFM). 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 prior to those of copula functions. The efficiency is therefore enhanced.

$$\hat{\theta}_i = \arg\max \sum_{t=1}^{T} \ln f_i(x_{it}|\Omega_{t-1}, \theta_i) \quad (9)$$

$$\hat{\theta}_c^{IFM} = \arg\max \sum_{t=1}^{T} \ln c\left(F_1\left(x_{1t}\middle|\hat{\theta}_1\right), F_2\left(x_{2t}\middle|\hat{\theta}_2\right), \dots \dots F_n\left(x_{nt}\middle|\hat{\theta}_n\right)|\Omega_{t-1}, \hat{\theta}_i\right) \quad (10)$$

3. Data and summary statistics

The daily stock indices provided by Morgan Stanley Capital International (MSCI) are obtained from Datastream database over the period from1 January 2002 to 30 June 2007. 1433 daily observations for each index are collected. Maghyereh (2004) states the reasons why MSCI indices are better than other local stock indices. For country's level, MSCI China, MSCI United States, MSCI Japan indices are selected. In order to specify which regional stock market is more correlated to China's, possibly due to their geographic ties or trade relationship, we use MSCI Europe and MSCI Pacific. To detect whether emerging markets have severer impacts than developed markets do, both MSCI world index and MSCI emerging markets index are collected. MSCI world index contains market indices of 23 developed countries, while MSCI emerging market index includes market indices of 25 emerging countries. Moreover, MSCI AcWorld index, which combines market indices of 48 developed and developing countries, is collected to measure the worldwide-level dependence.

The summary statistics of each index return are reported in Table 1. Table 2 shows the Pearson, Spearman and Kendall correlations for each index return paired with China's. Pearson 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, Kendall's tau and Spearman's rho, are less sensitive to the observations in the tails. As shown in Table 2, no matter which measurement is used, China-Emerging pair has the greatest correlation, followed by China-Pacific pair and China-Japan pair. The parameters of the marginal distributions for each index return are estimated and presented in Table 3. They are assumed to be characterized by an AR(1)-GARCH(1,1) model given by equation (1). As shown in Table 3, most parameters are at least significant at 5 percent level. Furthermore, 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. Results of unconditional copula models

For comparison, results of unconditional copula model are presented in Table 4. Since marginal distributions are assumed to be an AR(1)-GARCH(1,1) model, Table 4 reports the estimated parameters and results of goodness-of-fit test for static Gaussian, Gumbel and Rotated Gumbel copula functions. As shown in Panel A of Table 4, all copula functions have positive parameters, indicating that index return of China positively commoves with all index returns. We can consistently find that, irrespective of assumed copula function, the dependence between index return of an emerging market and market of China is the highest, followed by China-Pacific pair and China-Japan pair. Bekaert et al. (2005) and Goetzmann et al. (2005) claim that capital market integration and increased trade are embedded with a prediction about the dependence between markets. Therefore, we contend that an emerging market has a severer impact on dependence than a developed market[7] does. This may be attributed to the high trade frequency since the emerging countries are usually key suppliers of China for energy, mine, cropper and various commodities. Once the growth of Chinese economy is unexpectedly decayed, emerging markets may suffer severely. Also, the high degree dependence between China and Pacific or Japan may be attributed to their geographic ties and trade frequencies. Furthermore, this finding will be more evident as China proposes to join ASEAN Free Trade Area (AFTA) in 2010 to strengthen their cooperative and competitive abilities through eliminating tariffs and non-tariff barriers.

[7] Which is measured by MSCI world index

The choice of the best fit of copula function is based on the value of Akaike information criterion (AIC)[8]. From the maximized log-likelihood values (lnL) in Panel A of Table 4, we compute the AIC for each copula, and then rank the copula models accordingly. Panel B of Table 4 shows the AIC values for three chosen copulas. The lowest AIC value from the Rotated Gumbel copula indicates that the it is the best fitting model and the lower tail dependence exists in each pair. This finding is consistent with the literature that equity returns have been found exhibiting more joint negative extremes than joint positive extremes, leading to the observation that stocks tend to crash, but not to boom, together.

[Insert Table 4 here]

4.2. Results of conditional copula model

Given that the marginal distributions follow an AR(1)-GARCH(1,1) model, the estimated parameters of time-varying correlations in the Gaussian copula are reported in the Panel A of Table 5. The time-varying dependence model in equation (5) is estimated and calibrated for each pair of index returns. The parameter, β, captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. The initial value of the dependence, measured by ρ_1, is esimated

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

as well. It can be seen in the Panel A of Table 5 that the emerging, the Pacific and the Japanese markets experience a higher degree of dependence persistence with the Chinese market. Meanwhile, the log-likelihood functions for these areas are higher than those for others. Figure 1 depicts the implied time path of conditional correlations for each pair of index returns across sample period. Obviously, China-Pacific pair, China-Japan pair and China-emerging-markets pair all demonstrate greater conditional correlation, which is consistent with that of unconditional model.

[Insert Table 5 here]

4.3. Results of conditional tail dependence

Panel B and C of the Table 5 report the estimated parameters of time-varying tail dependence specified by the Rotated Gumbel and the Gumbel copula, respectively. It can be seen in both tables that the emerging, the Pacific and the Japanese markets show higher degrees of dependent persistence with the Chinese market. Both time-varying lower and upper tail dependences can be obtained by employing equation (8) where estimated conditional dependences, δ_t^U and δ_t^L, are from equation (6) and (7). In Figure 2 and 3 we present the plots of conditional lower and upper tail dependence specified by the time-varying Rotated Gumbel and Gumbel copula model, respectively. Overall, the value of the copula log-likelihood function of the Rotated Gumbel is the highest and that of the Gaussian is the lowest, indicating that the Rotated Gumbel copula is the best fitting model, and time-varying lower tail dependence exists in each pair. This finding is consistent with the unconditional model and the literature as well. Especially, the emerging, the Pacific and the Japanese markets experience higher degrees of lower tail dependent persistence with the Chinese market. Therefore, if the bubbles in Chinese stock markets burst, the probability of a joint market crash in Japan, in Pacific and in the emerging countries will be high.

[Insert Figure 1 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

5. Conclusions

Researches of international dependence have mainly focused on the developed markets. Relatively few have enquired the role of China despite of its noticeable growth in its capital market and distinctive impacts on global economy. In this study, we emphasize the dynamic dependence between the Chinese financial market and other major markets of the world. By estimating time-varying copula models between indices of these stock markets, we provide a comprehensive analysis of the time-varying market dependence for the period 2002-2007.

Regardless of the assumed copula functions, we consistently find that the Chinese market experiences a higher degree of dependence with markets in Japan, in the Pacific, and in the emerging countries. Geographic ties and close trading relationship may be attributed to this high dependence. 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. As China proposes to join ASEAN Free Trade Area, this threat will be strengthened further. With this understanding, some decisions on international diversification, portfolio allocation and risk management should be reconsidered.

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Table 1 Summary statistics

This table shows summary statistics of the returns of MSCI China, MSCI World, MSCI U.S., MSCI Europe, MSCI Japan, MSCI AcWorld, MSCI Pacific and MSCI Emerging. The sample period covers 1 January 2002 to 30 June 2007. 1433 daily observations for each index are collected.

	Mean	Standard Deviation	Skewness	Kurtosis
China	0.00092	0.01375	-0.24097	1.88839
World	0.00022	0.00812	0.06665	4.01935
U.S.	0.00018	0.00982	0.19883	3.52405
Europe	0.00020	0.01078	-0.13120	4.20785
Japan	0.00038	0.01133	-0.25321	1.23256
AcWorld	0.00025	0.00797	0.06665	3.87711
Pacific	0.00042	0.00920	0.02574	1.52761
Emerging	0.00070	0.00832	-0.64147	2.36938

Table 2 Association measurement

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

China versus	Pearson Correlation	Spearman Correlation	Kendall Correlation
World	0.26387	0.26792	0.18310
U.S.	0.10788	0.11032	0.07409
Europe	0.26673	0.25095	0.17222
Japan	0.44507	0.41799	0.29013
AcWorld	0.29341	0.29720	0.20407
Pacific	0.58330	0.55533	0.39476
Emerging	0.67998	0.63421	0.46171

Table 3 Estimated parameters for AR(1)-GARCH(1,1) marginal distributions

This table shows the estimated parameters of the marginal distributions for each index return. They are assumed to be characterized by an AR(1)-GARCH(1,1) model given by equation (1). The numbers in brackets ( ) are *p*-values.

	AR(1)	GARCH constant	Lagged variance	Lagged residual
China	0.0906	4.277e-06	0.9249	0.05202
	(0.0006)	(0.00261)	(0.0000)	(0.0000)
World	0.1059	5.683e-07	0.9275	0.06087
	(0.0001)	(0.00035)	(0.0000)	(0.0000)
U.S.	-0.0544	7.631e-07	0.9418	0.04731
	(0.0397)	(0.00011)	(0.0000)	(0.0000)
Europe	-0.0193	1.358e-06	0.8938	0.08985
	(0.4653)	(0.00010)	(0.0000)	(0.0000)
Japan	0.0273	2.383e-06	0.9023	0.08109
	(0.3009)	(0.00127)	(0.0000)	(0.0000)
AcWorld	0.1209	5.858e-07	0.9233	0.06458
	(0.000)	(0.00036)	(0.0000)	(0.0000)
Pacific	0.0411	2.067e-06	0.8952	0.08209
	(0.1204)	(0.00050)	(0.0000)	(0.0000)
Emerging	0.2008	2.034e-06	0.8866	0.08338
	(0.0000)	(0.00052)	(0.0000)	(0.0000)

Table 4 Parameter estimations and goodness-of-fit test for unconditional copula model

This table reports the estimated results of unconditional copula model in the Panel A. ρ is the correlation parameter of Gaussian copula. δ^{U} and δ^{L} are dependence parameters of Gumbel and 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, Gumbel and Rotated Gumbel copula functions are shown in the Panel B. $AIC = -2L(\widehat{\theta};x) + 2q$, where q is the number of parameters to be estimated in each specific model.

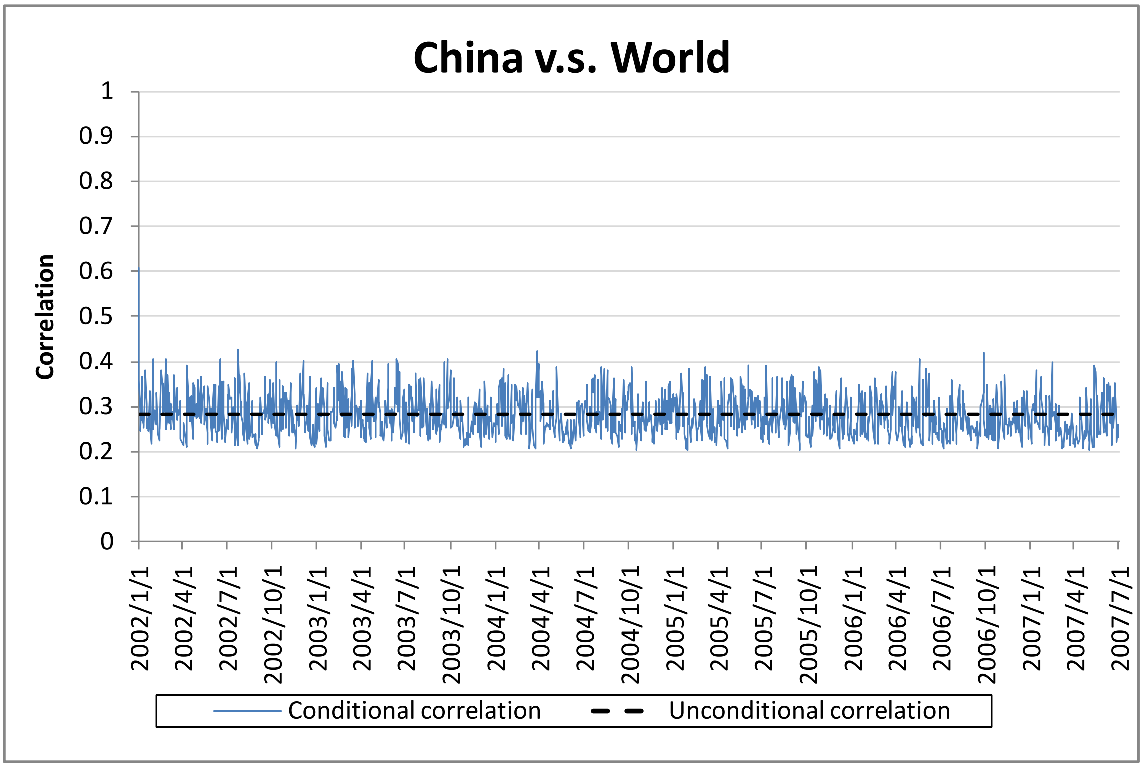
Unconditional Copula Model							
Paired				*China v.s.*			
Indices	*World*	*U.S.*	*Europe*	*Japan*	*AcWorld*	*Pacific*	*Emerging*
Panel A: Copula estimation							
Gaussian							
ρ	0.282	0.111	0.286	0.434	0.314	0.576	0.667
ln L	58.624	8.691	60.141	147.631	73.418	273.776	405.782
Gumbel							
δ^{U}	1.184	1.050	1.190	1.348	1.214	1.559	1.758
λ^{U}	0.204	0.065	0.210	0.328	0.230	0.440	0.517
ln L	45.670	5.701	50.149	126.326	58.664	252.248	375.204
R.Gumbel							
δ^{L}	1.206	1.071	1.205	1.369	1.237	1.583	1.797
λ^{L}	0.223	0.090	0.222	0.341	0.249	0.451	0.529
ln L	60.415	9.568	61.433	147.402	75.783	274.907	406.959
Panel B: Goodness-of-fit test (AIC)							
Gaussian	-115.248	-15.382	-118.282	-293.262	-144.836	-545.552	-809.564
Gumbel	-89.34	-9.402	-98.298	-250.652	-115.328	-502.496	-748.408
R.Gumbel	-118.83	-17.136	-120.866	-292.804	-149.566	-547.814	-811.918

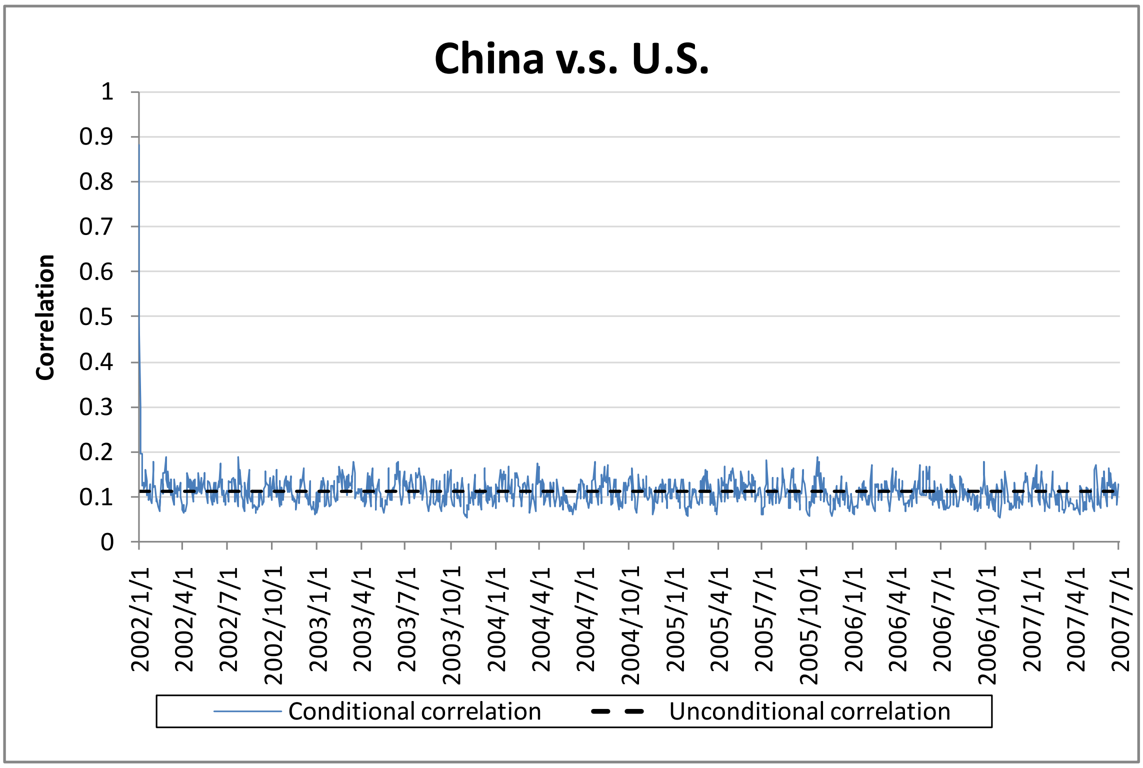
Table 5 Estimated parameters of time-varying dependences in the chosen copulas

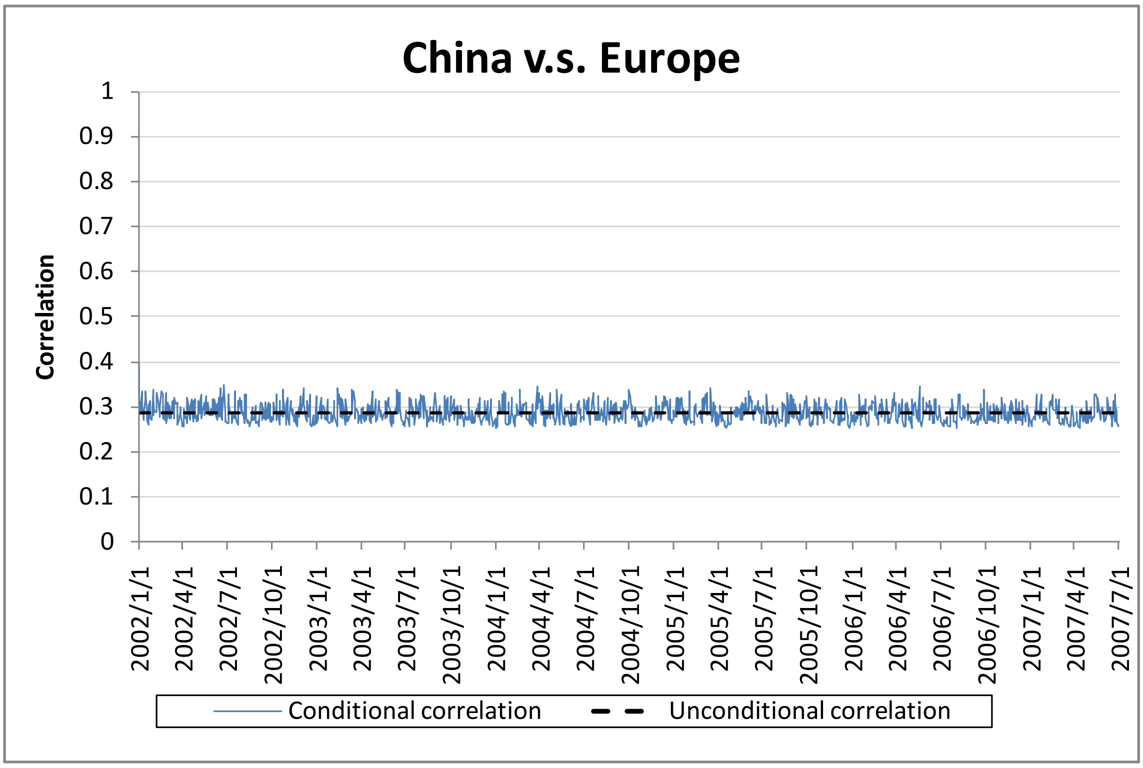
This table shows the estimated parameters of time-varying dependences in the chosen copulas. The time-varying dependence models in equation (5), (6), (7) are estimated and calibrated for each pair of index returns. The parameter, β, captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. The initial value of the dependence is estimated as well. LLF(c) is the maximum of the copula component of the log-likelihood function.

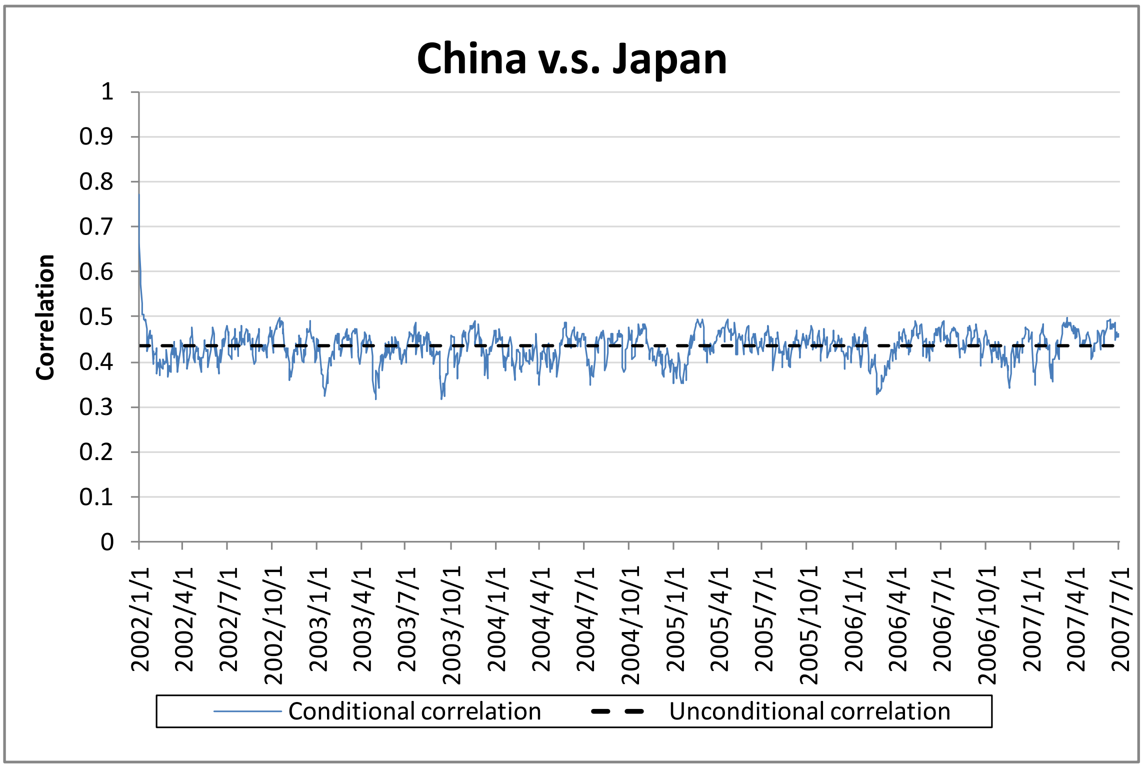
China versus	β	ω	γ	Initial value	LLF(c)
Panel A: Gaussian copula					
World	0.31945	0.13538	0.22749	0.60793	60.75699
U.S.	0.56739	0.01781	0.09516	0.87929	10.08956
Europe	0.34985	0.16647	0.09658	0.39344	60.55184
Japan	0.99990	0.05737	-0.10777	0.77259	149.3346
AcWorld	0.27147	0.181184	0.21209	0.59932	75.2125
Pacific	0.99990	0.12581	-0.21283	0.63262	281.2017
Emerging	0.99990	0.17462	-0.19900	0.80974	409.1492
Panel B: Rotated Gumbel copula					
World	0.38781	0.68741	0.18189	1.95735	62.30450
U.S.	0.37218	0.64788	0.07926	3.69468	11.13930
Europe	0.42159	0.67766	0.06901	1.44933	61.78139
Japan	0.92767	0.12652	-0.11190	1.50332	150.61170
AcWorld	0.35824	0.74466	0.18093	1.96737	77.45485
Pacific	0.95300	0.11094	-0.16929	1.39997	283.0431
Emerging	0.96375	0.09432	-0.15127	1.20698	414.9552
Panel C: Gumbel copula					
World	0.19345	0.90657	0.17268	1.29830	47.05787
U.S.	0.43248	0.58589	0.03316	2.51917	6.76919
Europe	0.55675	0.51727	0.03869	1.00000	50.47848
Japan	0.89806	0.16567	-0.11484	1.44770	128.61650
AcWorld	0.16640	0.96713	0.16552	1.28228	59.81751
Pacific	0.93504	0.14005	-0.17935	1.29072	258.90430
Emerging	0.95090	0.12672	-0.21067	1.23979	384.14260

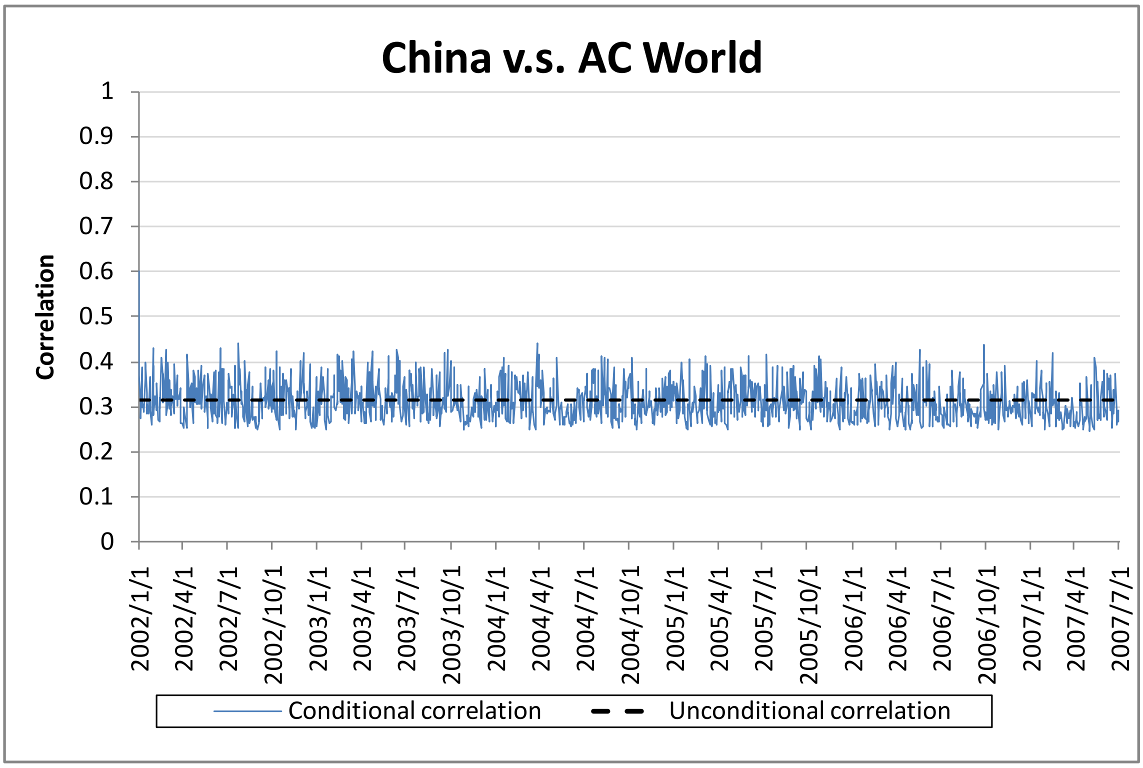
Figure 1 Conditional correlation estimation from the Gaussian copula






China v.s. Europe
Correlation
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2002/1/1
2002/4/1
2002/7/1
2002/10/1
2003/1/1
2003/4/1
2003/7/1
2003/10/1
2004/1/1
2004/4/1
2004/7/1
2004/10/1
2005/1/1
2005/4/1
2005/7/1
2005/10/1
2006/1/1
2006/4/1
2006/7/1
2006/10/1
2007/1/1
2007/4/1
2007/7/1
Conditional correlation
Unconditional correlation


China v.s. Japan
Correlation
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2002/1/1
2002/4/1
2002/7/1
2002/10/1
2003/1/1
2003/4/1
2003/7/1
2003/10/1
2004/1/1
2004/4/1
2004/7/1
2004/10/1
2005/1/1
2005/4/1
2005/7/1
2005/10/1
2006/1/1
2006/4/1
2006/7/1
2006/10/1
2007/1/1
2007/4/1
2007/7/1
Conditional correlation
Unconditional correlation


China v.s. AC World
Correlation
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2002/1/1
2002/4/1
2002/7/1
2002/10/1
2003/1/1
2003/4/1
2003/7/1
2003/10/1
2004/1/1
2004/4/1
2004/7/1
2004/10/1
2005/1/1
2005/4/1
2005/7/1
2005/10/1
2006/1/1
2006/4/1
2006/7/1
2006/10/1
2007/1/1
2007/4/1
2007/7/1
Conditional correlation
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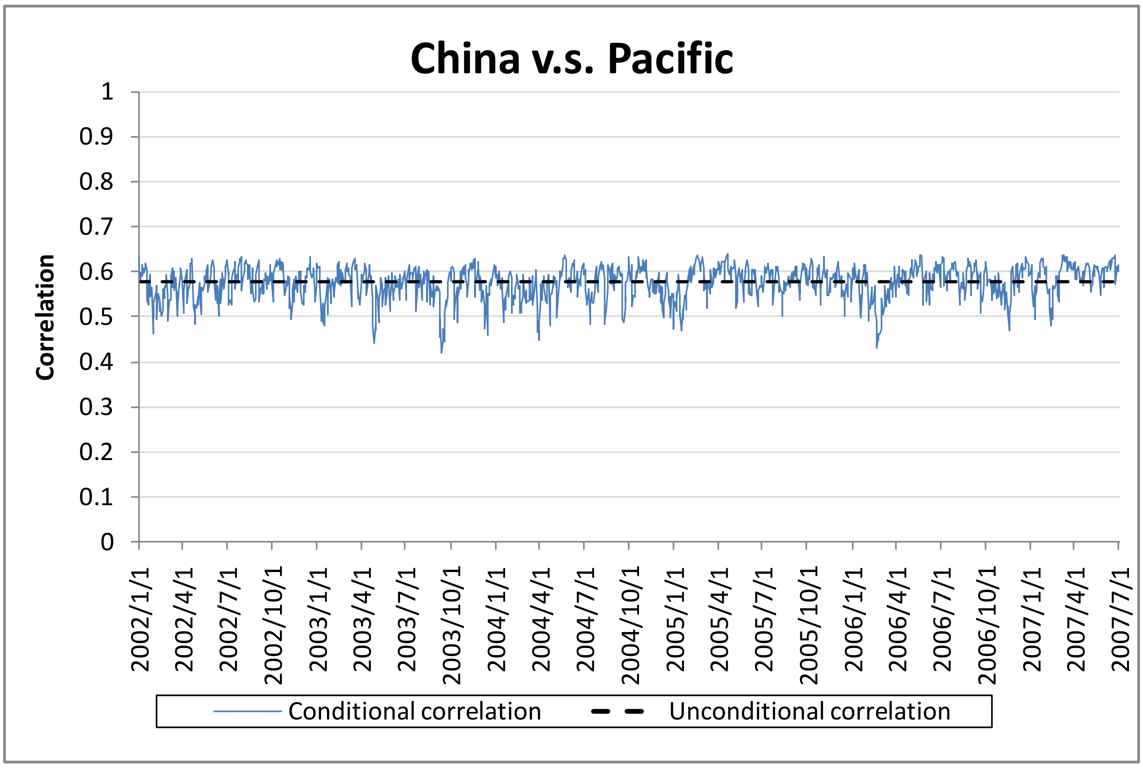
China v.s. Pacific
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Conditional correlation
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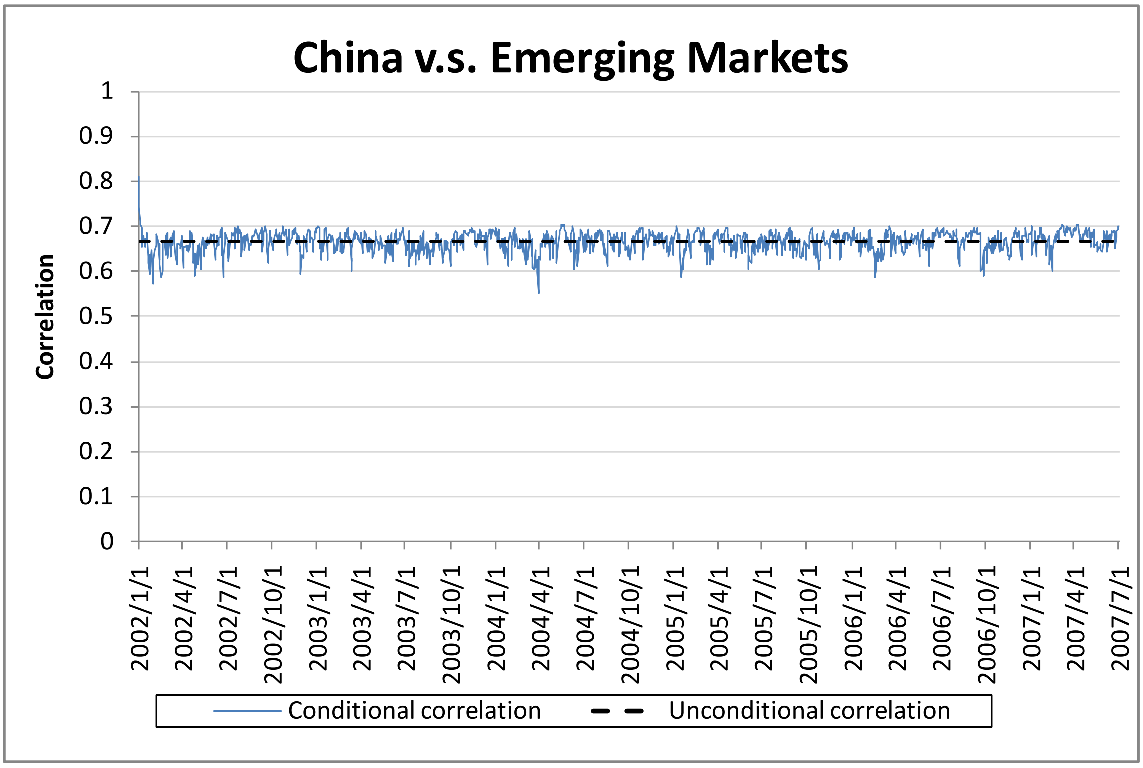

China v.s. Emerging Markets
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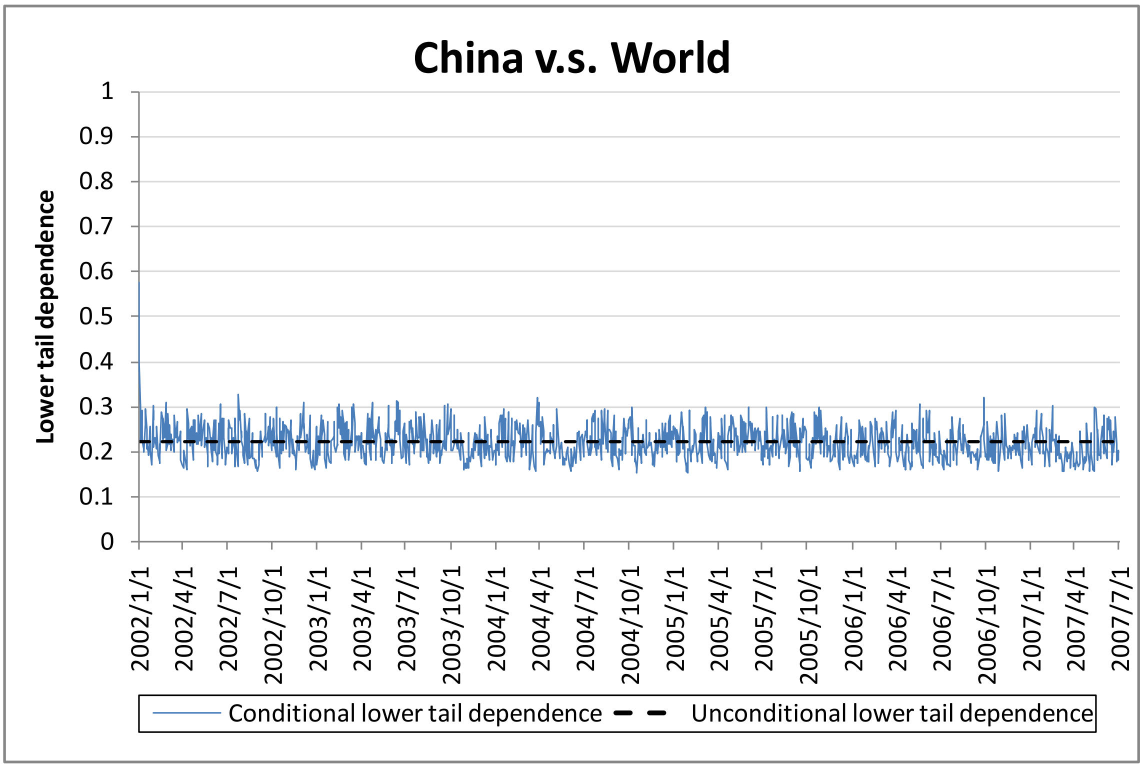
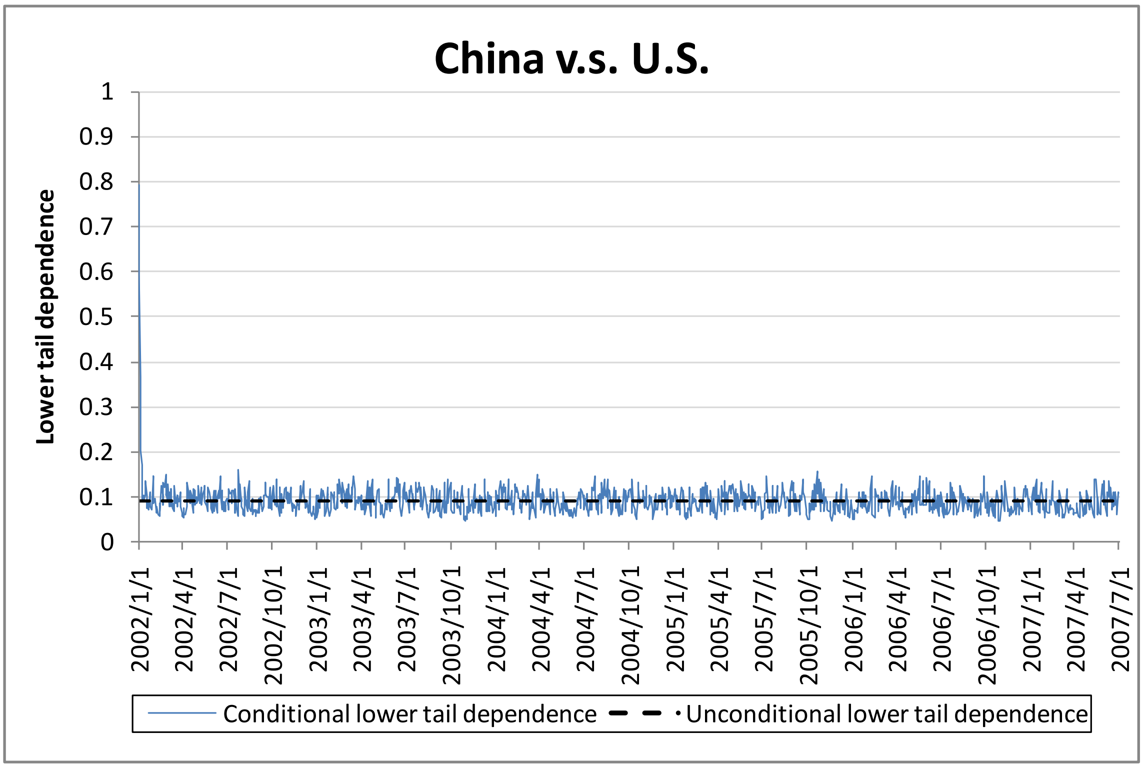
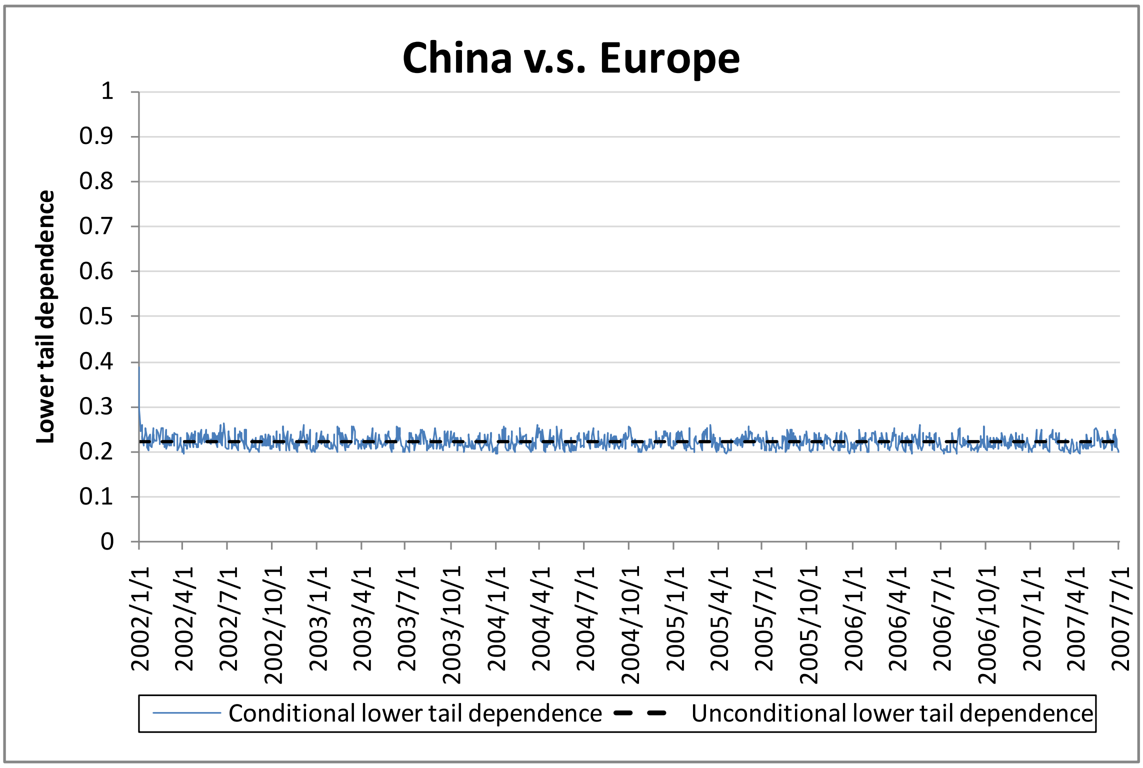
Conditional correlation
Unconditional correlation

Figure 2. Conditional lower tail dependence estimation from the Rotated Gumbel copula






China v.s. Europe
Lower tail dependence
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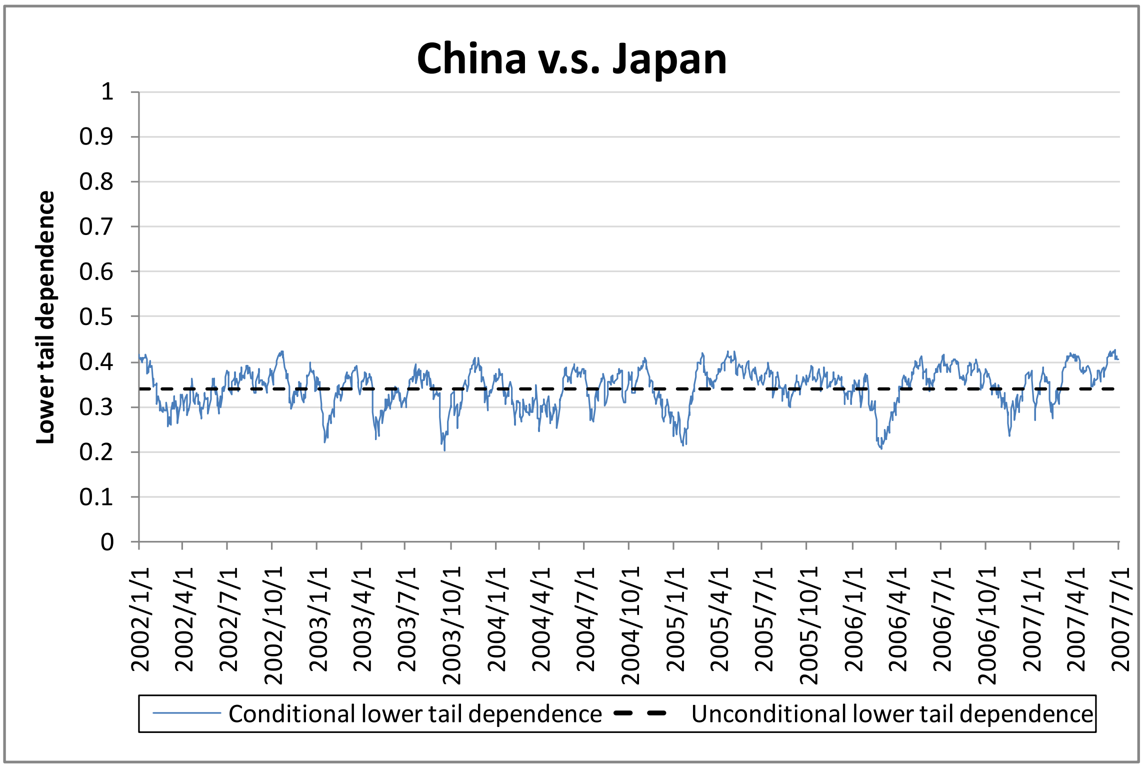
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Japan
Lower tail dependence
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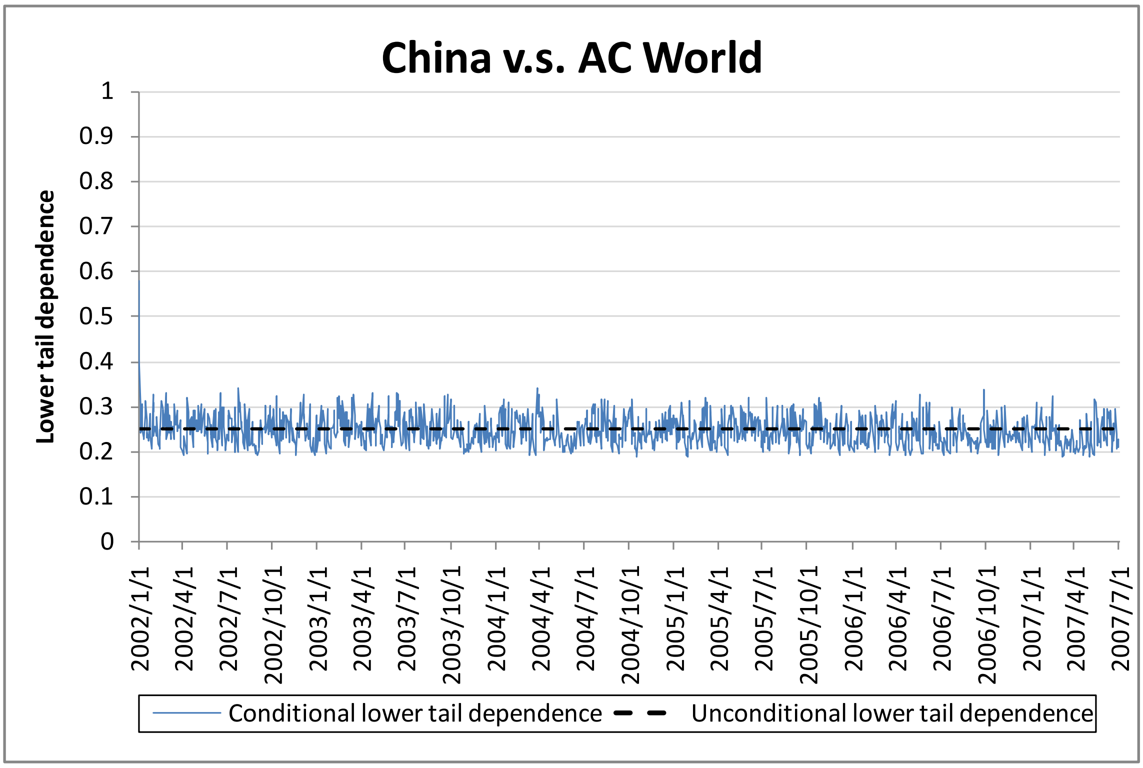
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. AC World
Lower tail dependence
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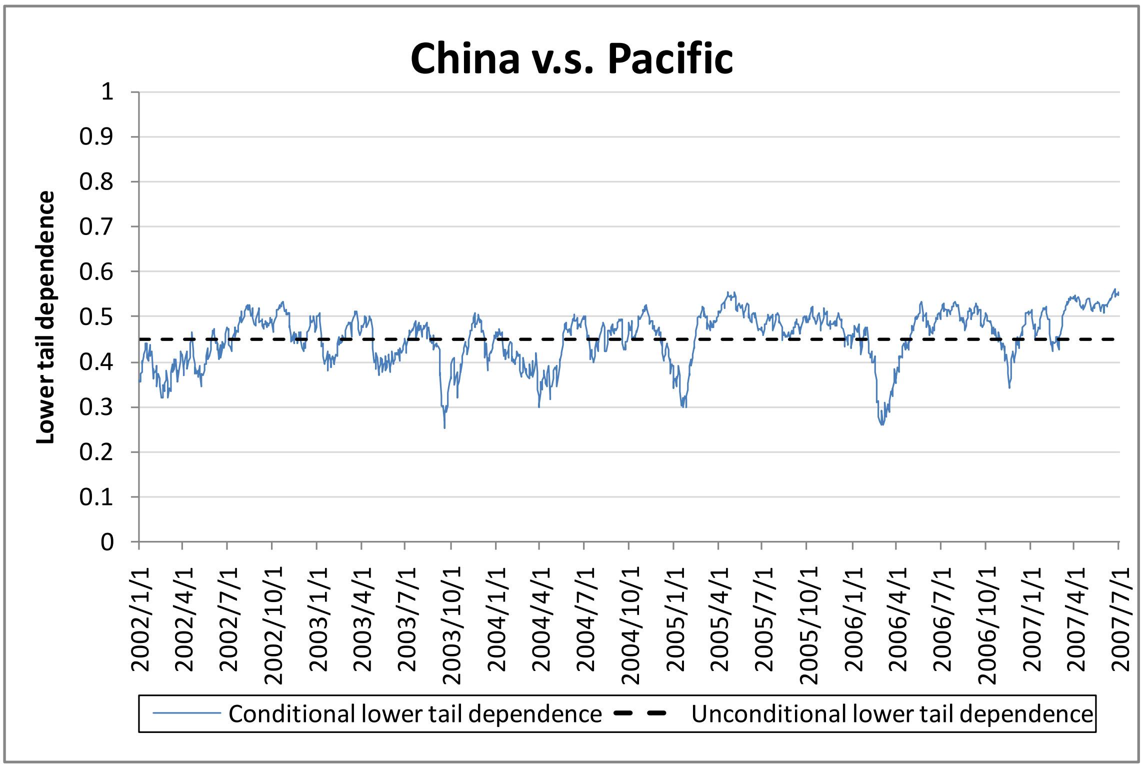
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Pacific
Lower tail dependence
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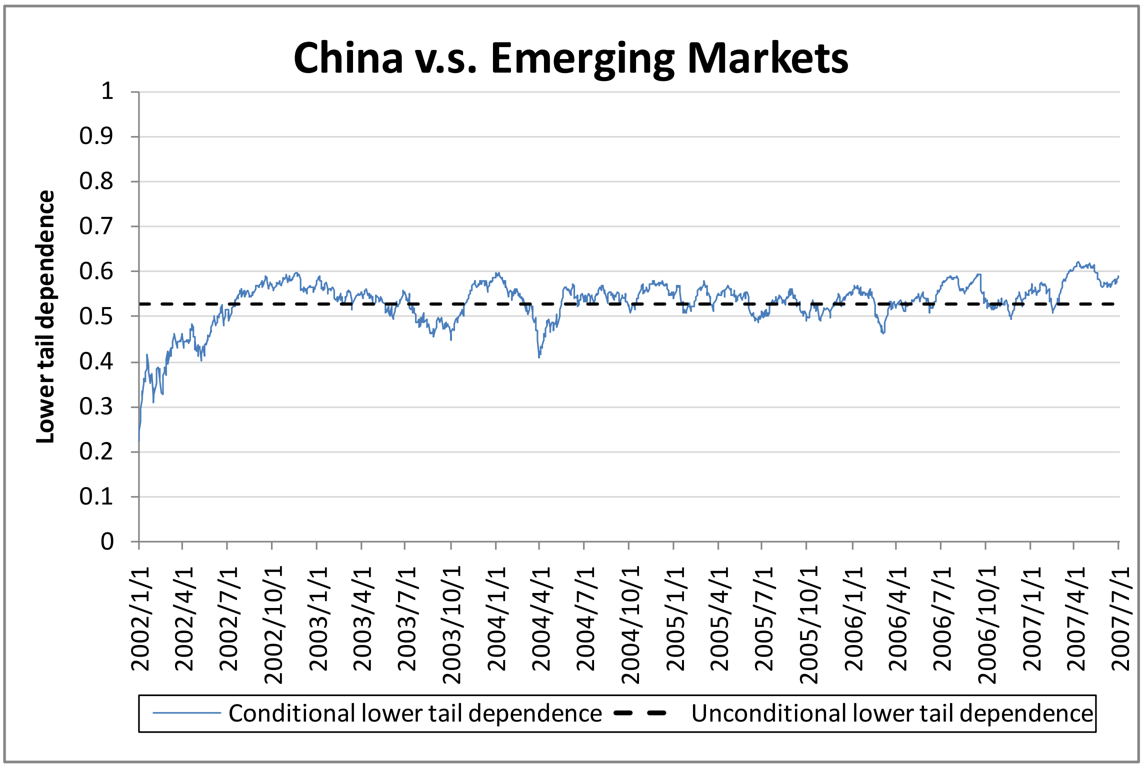
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Emerging Markets
Lower tail dependence
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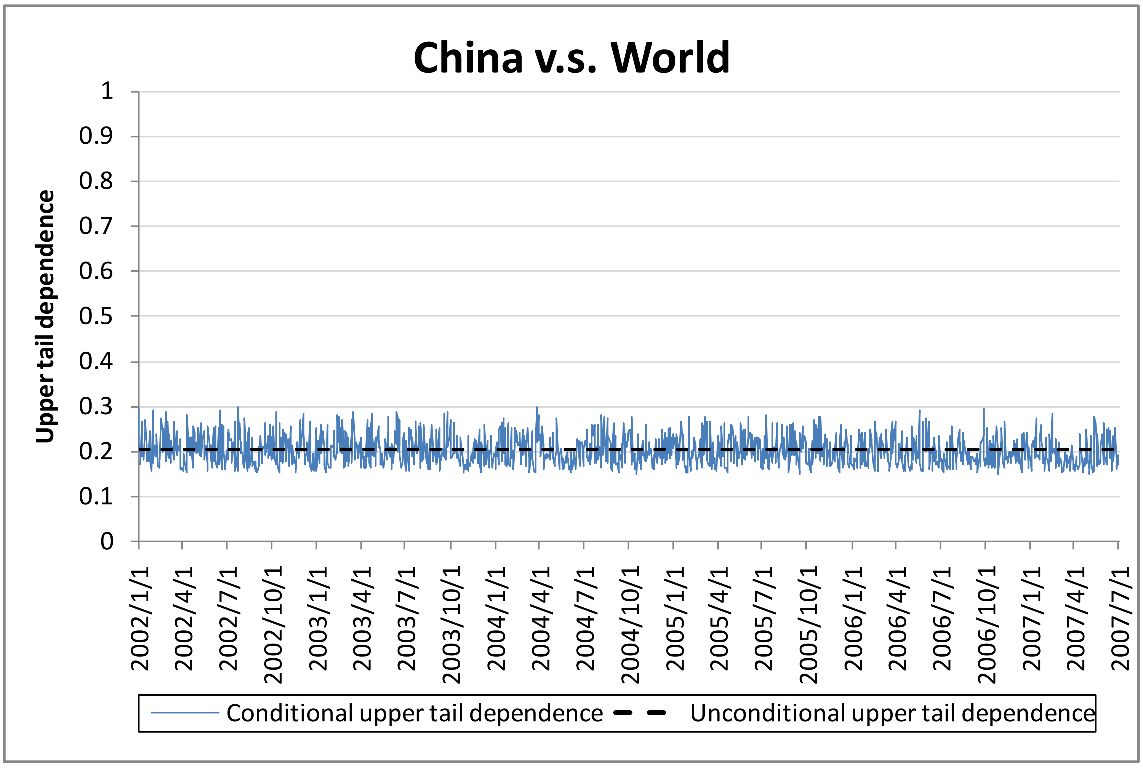
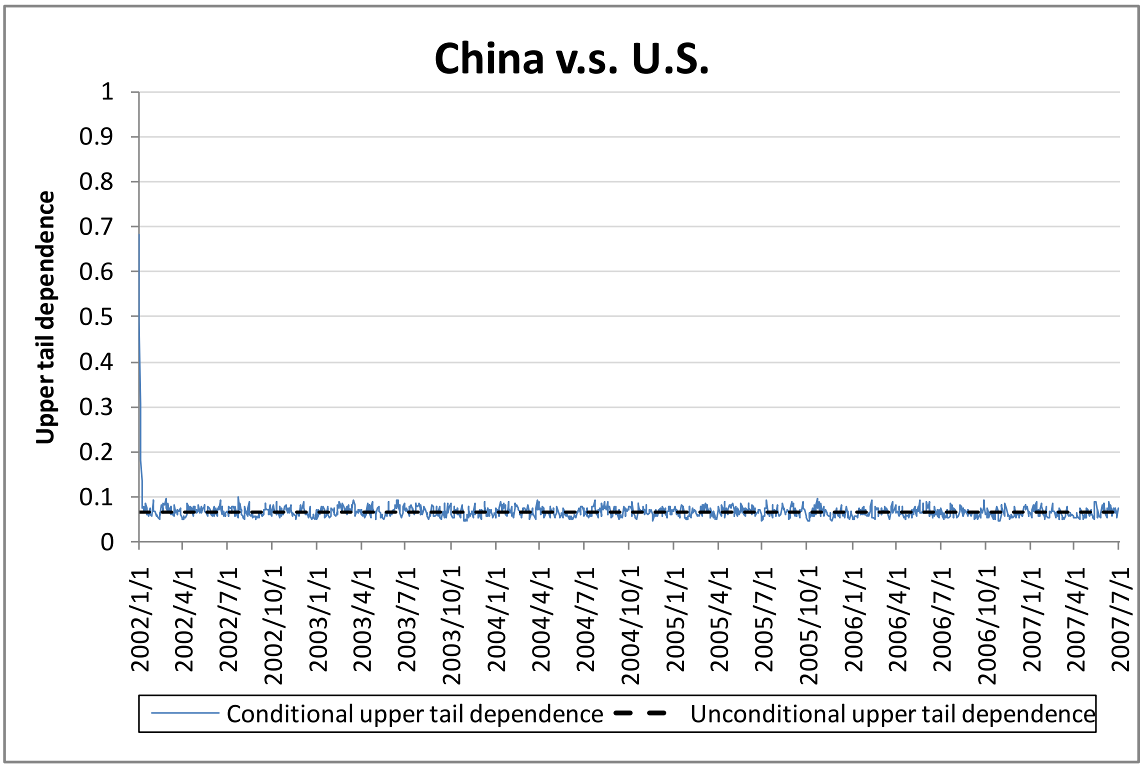
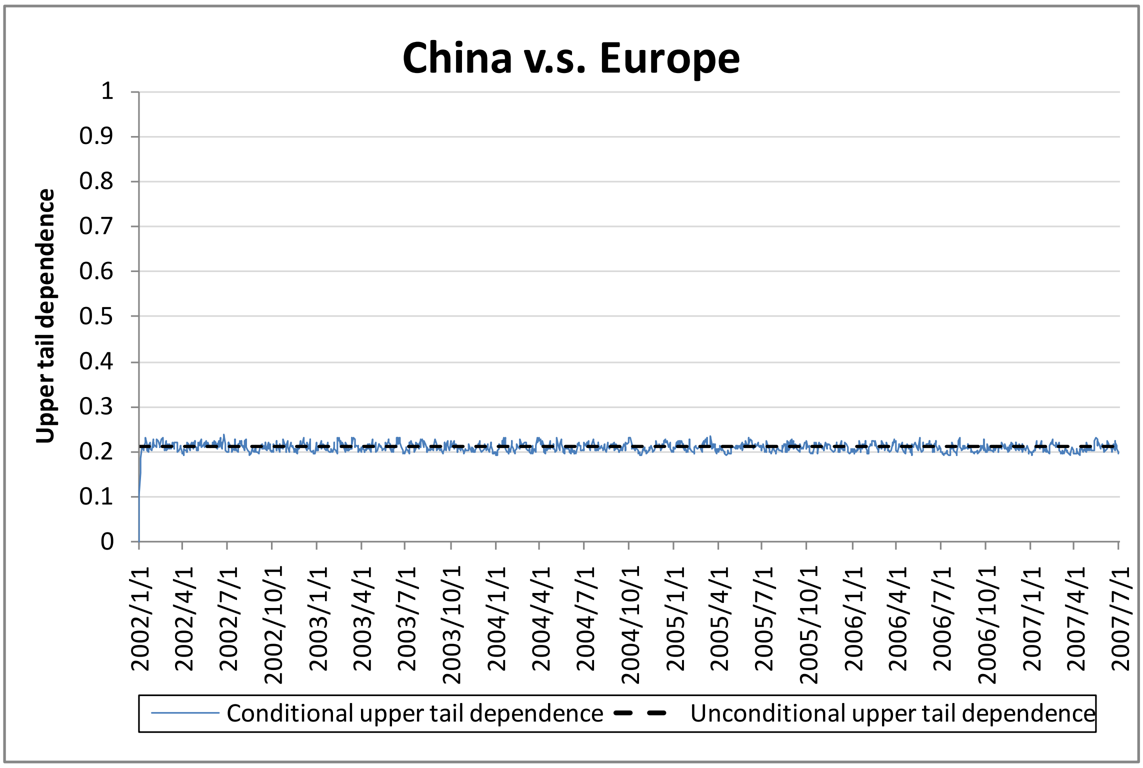
Conditional lower tail dependence
Unconditional lower tail dependence

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






China v.s. Europe
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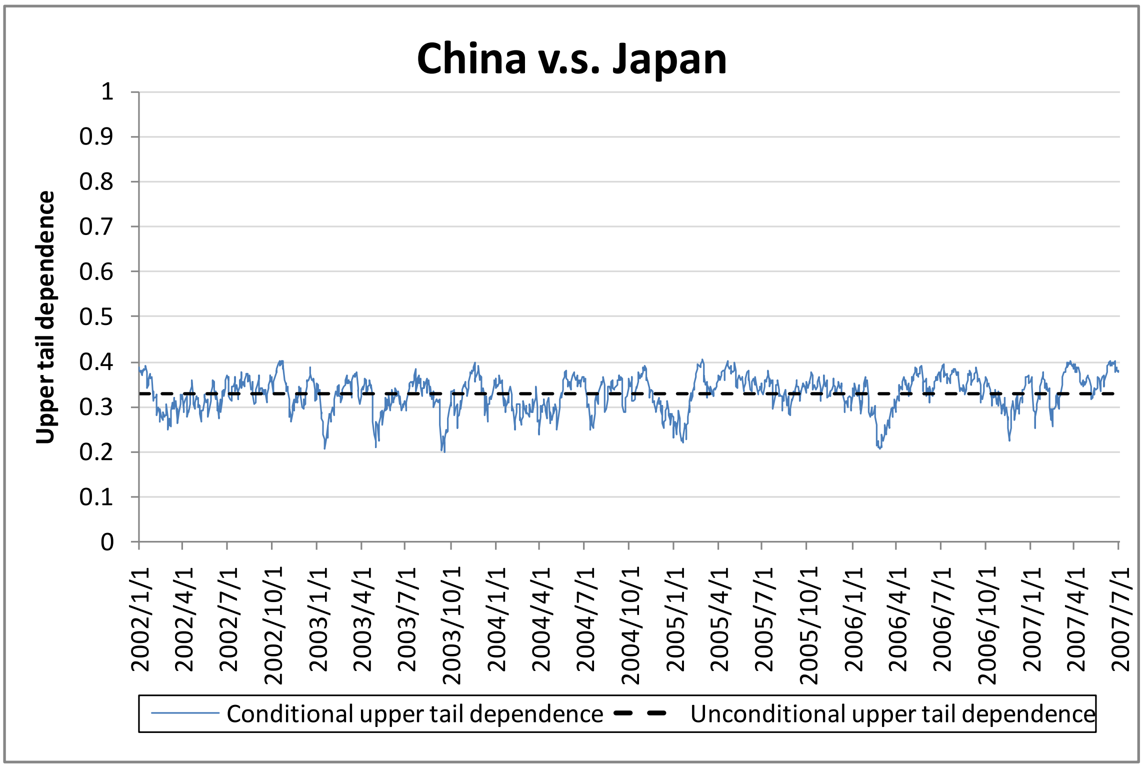
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Japan
Upper tail dependence
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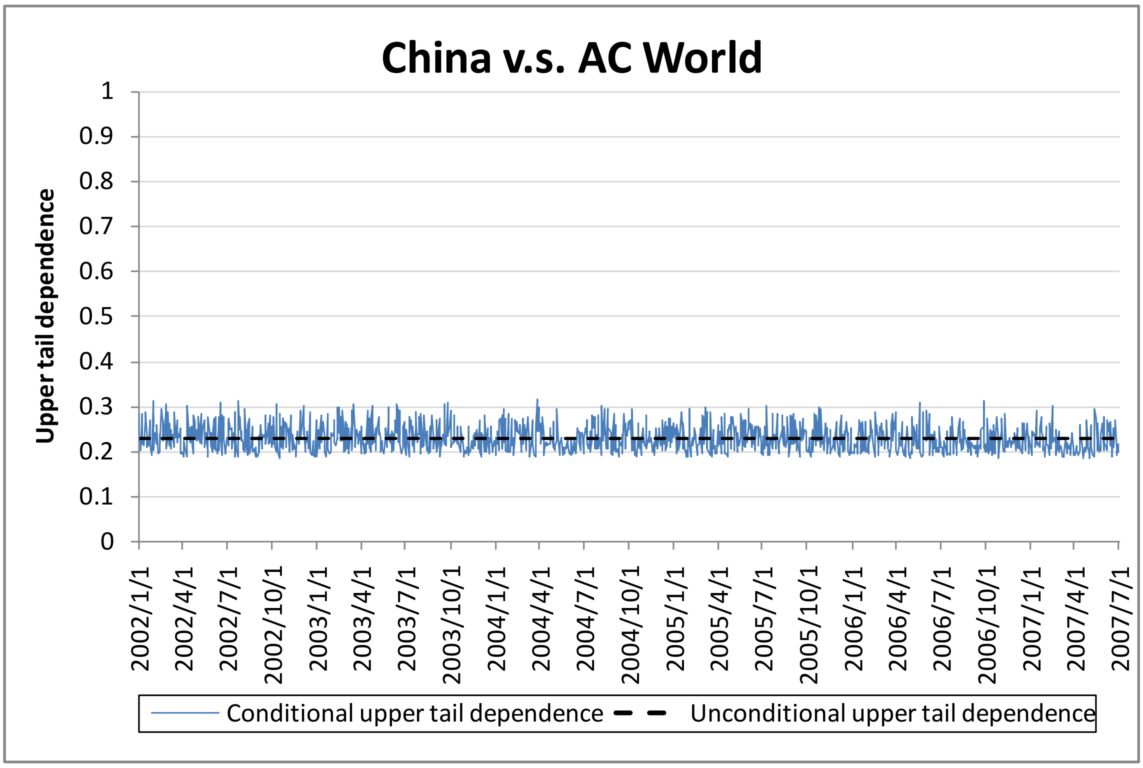
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. AC World
Upper tail dependence
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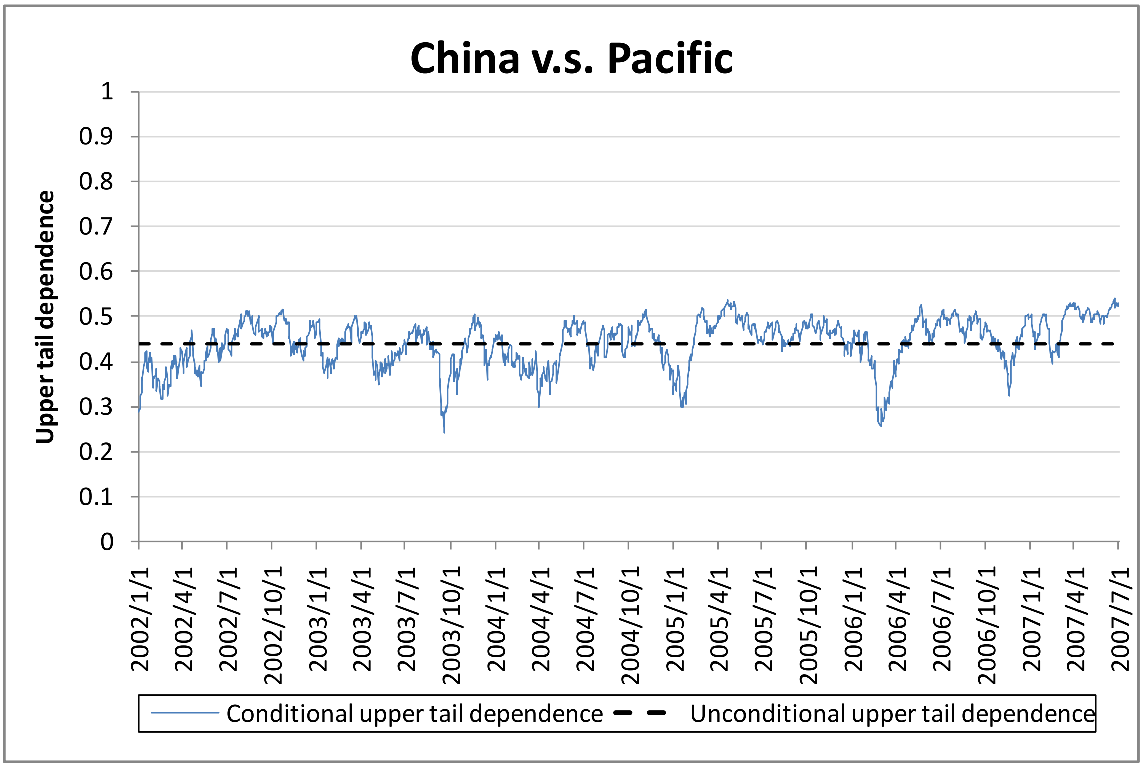
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Pacific
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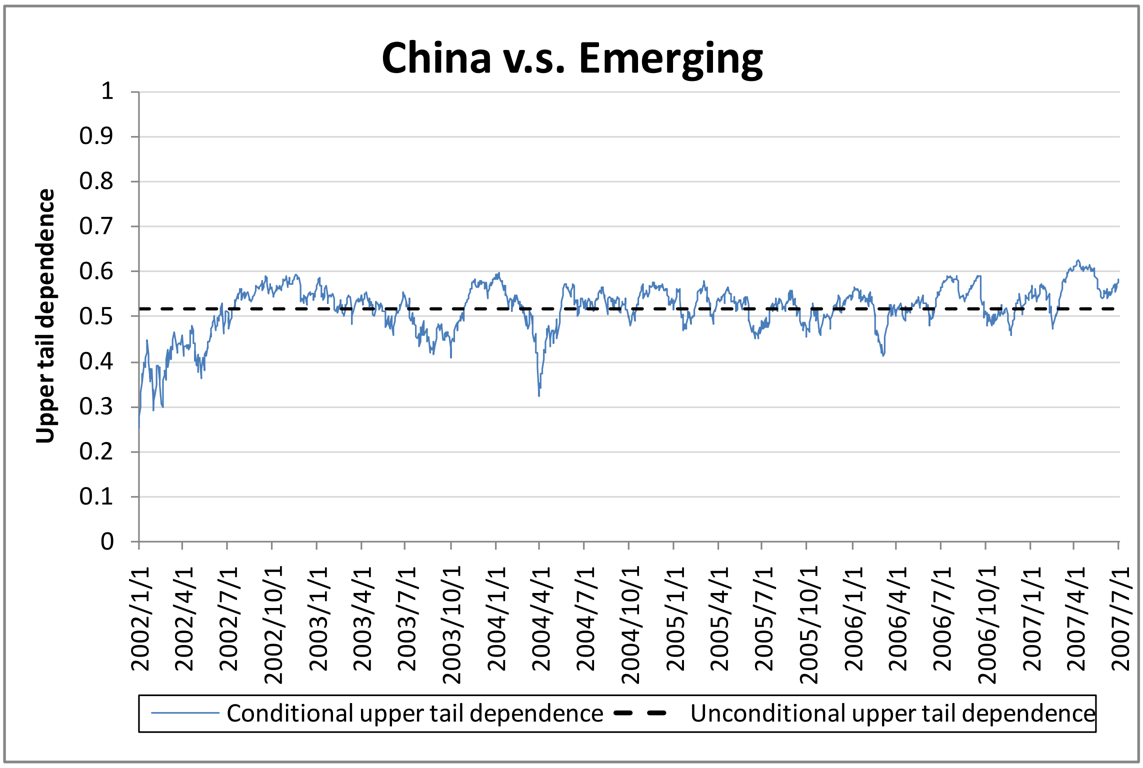
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Emerging
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Conditional upper tail dependence
Unconditional upper tail dependence

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

年　　月　　日

附件

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	97年7月6日至97年7月9日 奧蘭多，佛羅里達，美國	本會核定補助文號	NSC 96-2415-H-216-002
會議名稱	(中文)第十五屆多國籍財務學會研討會 (英文) 15th annual conference of the multinational finance society		
發表論文題目	(中文)中國股票市場與國際財務市場的動態相依性結構之研究與檢視 (英文)Re-investigating the International Financial Market Dependence: the Role of China		

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 10 "Asian Financial Markets"，報告順序為第三，並且本人亦評論同一場次的論文

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

表 Y04

Re-investigating the international financial market dependence: The role of China

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Abstract

This study emphasizes the dynamic dependence between the Chinese financial market and other major markets in the world as China is being influential and integrated with the global economy. We provide a comprehensive analysis of the dynamic market dependence for the period 2002-2007 by estimating time-varying copula models between indices of those stock markets and the findings are further interpreted. It will provide more implications for portfolio diversification, risk management and international asset allocation than those based on a static model.

Keywords: International finance; Dependence structure; Copula; GARCH

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1. Introduction

The integration and dependence of financial markets has been an issue of interest for both financial economists in academia and investment practitioners in industry (Bartram and Dufey, 2001) Research on dependence of financial markets has gained wide response in literatures because of its implications on international diversification as well as market integration. Recent studies have shown evidence of contagion in equity markets (Jondeau and Rockinger, 2006; Bekaert et al., 2005; Poon et al., 2004; Longin and Solnik, 2001; Forbes and Rigobon, 2002). However, these researches have mainly emphasized the developed countries such as U.S., U.K., Germany, France and Japan. Relatively few studies have investigated the financial market of China for its role in the international dependence.

By the end of year 2006, the total market capitalization in China remarkably increased from US$2,028 million by 1991 to US$ 786 billion, the largest of all emerging markets. 1,517 companies had been listed in the stock markets of China by the end of September 2007, and the volume of equity market capitalization ranked fourth in the world. According to a recent IMF report[1], China may replace German to be the third largest in near future. The dramatic growth of China's stock market has allured the

[1] Global Economic Outlook 2007, IMF

attention of speculators, investors as well as the scholars, notwithstanding the worries of the sensitive stock market crash driven by panics or underlying economic factors.

Chinese stock market took a major hit on Feb 27, 2007. The Shanghai Stock Exchange's Composite Index unexpectedly dropped 8.8%, the largest one-day decline in 10 years. The same day, the Dow Jones Industrial Average tumbled 3.3% and the NASDAQ declined 3.9%, the sharpest falls since 911 crisis. This may be an evidence of the integration of China's financial markets into the world and indicates that an event in China might trigger reactions around the world.

China's growing economy has attracted huge foreign investment. A crash in the stock market may prompt the investors for abrupt withdrawals from China. As a consequence, financial contagion may be erupted. Our study especially concerns about the relationship between the Chinese market and other major markets of the world. It can provide implications for portfolio diversification, risk management and international asset allocation.

To demonstrate the market correlation between China and other countries, we provide a comprehensive analysis of the market dependence during the period 2002-2007 by estimating time-varying copula dependence models between indices of these stock markets. In a time-varying copula setting, the dependence parameters in the copula function are modeled as a dynamic process conditional on currently available information to allow non-linear, time dependant relationship.

Our study makes two contributions. First, although the capital market of China has noticeably grown and it has significant impact on other financial markets, few studies have focused on the role of China in the international dependence. By and large, researches are confined to its regional roles (Cheng, H., Glascock, 2005; Cheng, H., Glascock, 2006; Baur, 2007; Chang et al., 2000). Since its production and trade also have significant global influence, the regional constraint should be extended world-wide. Moreover, Bekaert et al. (2005) and Goetzmann et al. (2005) find a positive causality from market integration to market dependence. Does China integrate into international financial market with higher dependence after opening its market to world?

The second contribution is to show how a conditional copula model can be applied. In fact, a copula-based measure can specify the structure and the degree of dependence to examine correlations, which takes the non-linear property into account and allows a more comprehensive understanding as well. 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 correlation or tail dependence (Patton, 2006a). Patton(2006a) is the first to apply a time-varying copula to exchange rate dependence.

Bartram et al. (2007) use the same method to examine the Euro and European financial market dependence, but they do not explore any time-varying tail dependence. Our copula model investigates both conditional dependence structures and conditional tail dependences between stock market of China and other stock markets.

The daily stock indices for MSCI China, MSCI Japan, MSCI Unite States, MSCI Europe, MSCI emerging markets, MSCI world and MSCI AcWorld are collected over the period 2002 - 2007. We consistently find that, irrespective of the assumed copula function; the emerging, the Pacific and the Japanese markets experience a higher degree of dependence persistence with the Chinese market. The Rotated Gumbel copula is the best fitting model, thus existence of time-varying lower tail dependence in each pair is evident. Given that the bubbles in Chinese stock market are pricked, higher probability of a joint market crash in Japan, in Pacific and in the emerging countries could be conjectured.

The remainder of this paper is structured as follows: Section 2 discusses our empirical methodology of a time-varying copula model. Section 3 reports the data and summary statistics. Empirical results are presented and discussed in Section 4, while Section 5 is the conclusion.

2. Empirical methodology

It is evident that multivariate normality is not suitable for measuring the dependence structure of equity returns (Lognin and Solnik, 2001; Poon et al., 2004). Researchers are concerned about the methodology used to specify comovement or contagion effect, especially for their asymmetric part, between the stock markets. Lognin 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.[2] The dependence function used for estimating the threshold may not be well defined[3]. Further, the determination of the number of parameters in the dependence structures[4] is also a problem.

Kroner and Ng(1998), Engle(2002) and Cappiello et al.(2006) have developed GARCH models with time-varying covariances and correlations. Engle(2002) provides a univarite GARCH model which is capable of allowing conditional asymmetries in both volatilities and correlations. Cappiello et al.(2006) extend Engel's (2002) model to

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

[3] Typically, logistic function is used to make this estimation, though the solution is not good.

[4] For bivariate model in the EVT, there are typically seven parameters to be estimated: two tail probabilities, two dispersion parameters, two tail indexes, and the dependence parameter.

two dimensional environments. Both 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.

Recently, copula method has been emphasized because of its capability of modeling the contemporaneous interdependence between either univariate time series or innovations of univariate parametric time series models. It is being more and more popular because it can analyze dependence structure beyond linear correlation and provide a higher degree of flexibility in estimation by separating marginal and joint distributions. Furthermore, it can be extended to a time-varying specification in order to capture changes in the dependence structure. Patton (2006a,b) introduces the method of time-varying copula and applies it to measure conditional asymmetries in the exchange rate dependence. Bartram et al. (2007) employ it to measure dependences between some European stock indices. Following their settings, our empirical time-varying copula is modeled as below.

2.1. The models for the marginal distribution

In this study, the marginal distribution for each index return is assumed to be characterized by an AR(1)-GARCH(1,1) model. Let $R_{i,t}$ and $h_{i,t}$ denote index i's return and its conditional variance for period t, respectively. The AR(1)-GARCH(1,1) model for the index return is:

$$
\begin{aligned}
R_{i,t} &= u_i + \emptyset_i R_{i,t-1} + \varepsilon_{i,t} \\
h_{i,t} &= \omega_i + \beta_i h_{i,t-1} + \alpha_i \varepsilon_{i,t}^2 \\
\varepsilon_{i,t} &| \Omega_{t-1} \sim \mathrm{N}(0, h_{i,t})
\end{aligned}
\tag{1}
$$

Fisher(1932) and Rosenblatt(1952) showed that random variable $U_{i,t} = F_{i,t}\left(\varepsilon_{i,t} | \Omega_{t-1}\right)$ has *Uniform(0,1)* distribution, regardless what unconditional distribution is. Thus, the value of the random variable from conditional marginal distribution $\mathrm{F}_{i,t}\left(\varepsilon_{i,t} | \Omega_{t-1}\right)$ should be between zero and one. Typically, the technique of "probability integral transform[5]" for conditional random variables, $\varepsilon_{i,t} | \Omega_{t-1}$, can be applied to satisfy this requirement.

2.2. The models for the copula

Equity returns have been found 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 direction of the return distribution. We therefore employ the Gaussian, the Gumbel and the Rotated Gumbel copula for specification and calibration, all with and without time variation. The Gaussian copula is generally viewed as a benchmark for comparison, while the

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

Gumbel and the Rotated Gumbel copula are used to capture the upper and lower tail dependence, respectively.

The Gaussian copula function is the density of joint standard uniform variables (u_t, z_t), as the random variables $\{R_{i,t}\}$ are bivariate normal with a time-varying correlation, ρ_t. Moreover, let $x_t = \Phi^{-1}(u_t)$ and $y_t = \Phi^{-1}(z_t)$, where $\Phi^{-1}(.)$ denotes the inverse of the cumulative density function of the standard normal distribution. The density of the time-varying Gaussian copula can be shown as

$$c_t^{Gau}(u_t, z_t|\Omega_{t-1}) = \frac{1}{\sqrt{1-\rho_t}} exp\left\{\frac{2\rho_t x_t y_t - x_t^2 - y_t^2}{2(1-\rho_t^2)} + \frac{x_t^2 + y_t^2}{2}\right\} \quad (2)$$

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 are pricked. The Gumbel and the Rotated Gumbel copula can efficiently capture the tail dependence arising from the extreme observations caused by asymmetry. The density of the time-varying Gumbel copula is

$$C_{\delta_t^U}^{Gum}(u_t, z_t|\Omega_{t-1}) = \frac{(-\ln u_t)^{\delta_t^U-1}(-\ln z_t)^{\delta_t^U-1}}{u_t z_t} \exp\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\frac{1}{\delta_t^U}}\right\}$$
$$\left\{-\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\left(\frac{1-\delta_t^U}{\delta_t^U}\right)^2} + (\delta_t^U - 1)\left[(-\ln u_t)^{\delta_t^U-1} + (-\ln z_t)^{\delta_t^U-1}\right]^{\left(\frac{1-2\delta_t^U}{\delta_t^U}\right)}\right\} \quad (3)$$

where $\delta_t^U \in [1, \infty)$ measures the degree of dependence between u_t and z_t. $\delta_t^U = 1$ implies an independent relationship and $\delta_t^U \to \infty$ represents perfect dependence.

Cherubini et al. (2004) show that the Gumbel family has upper tail dependence, with $\lambda_t^U = 2 - 2^{1/\delta_t^U}$. Rotated Gumbel copula has a similar density function to that of Gumbel copula and its time-varying version is

$$c_{\delta_t^L}^{R.Gum}(1-u_t, 1-z_t) =$$

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

$$\left\{-\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-z_t))^{\delta_t^L-1}\right]^{\left(\frac{1-\delta_t^L}{\delta_t^L}\right)^2} + (\delta_t^L - 1)\left[(-\ln(1-u_t))^{\delta_t^L-1} + (-\ln(1-z_t))^{\delta_t^L-1}\right]^{\left(\frac{1-2\delta_t^L}{\delta_t^L}\right)}\right\} \quad (4)$$

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

In reality, time-invariant dependence seems unreasonable. So, a conditional copula with a time-varying dependence parameter is prevalent (Patton, 2006a; Patton, 2006b; Bartram et al., 2007; Jondeau and Rochinger, 2006; Rodriguez, 2007). Following the studies of Patton(2006a) and Bartram et al.(2007), we assume that the dependence parameter is determined by the 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 one are rarely different from zero (Bartram et al.[6], 2007; Samitas et al., 2007). The dependence process of Gaussian copula is therefore:

$$\rho_t = \Lambda(\beta\rho_{t-1} + \omega + \gamma|u_{t-1} - z_{t-1}|) \tag{5}$$

The conditional dependence, ρ_t , depends on its previous dependence, ρ_{t-1} , and historical absolute difference, $|u_{t-1} - z_{t-1}|$. In this way the persistence and the variation in the dependence process can both be captured. $\Lambda(x)$ 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 time (Patton, 2006a). The estimation of copula parameters, $\theta_c = (\beta, \omega, \gamma)'$, 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:

$$\delta_t^U = \beta_U \delta_{t-1}^U + \omega + \gamma|u_{t-1} - z_{t-1}| \tag{6}$$

$$\delta_t^L = \beta_L \delta_{t-1}^L + \omega + \gamma|u_{t-1} - z_{t-1}| \tag{7}$$

where $\delta_t^U \in [1, \infty)$ measures the degree of dependence in the Gumbel copula and has a lower bound equal to one which indicates an independent relationship, while $\delta_t^L \in [1, \infty)$ measures the degree of dependence in the Rotated Gumbel copula. After

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

estimating the Gumbel copula parameters $\theta_c = (\beta_U, \omega, \gamma)'$, the conditional upper tail dependence coefficents, $\{\lambda_t^U | \Omega_{t-1}\}$, are obtained by

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

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

2.4. Estimating and calibrating copula models

Calibrating copula parameters using real market data has involved much interest in recent statistical literatures (Meneguzzo and Vecchiato, 2004; Mashal and Zeevi, 2002; Dias and Embrechts, 2003; Galiani, 2003). *Exact Maximum Likelihood Method* (EML) is a well-known parametric method for estimation. However, the EML need to estimate the parameters of the marginals and 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 of copula models are naturally decomposed into two steps: the first for the marginals and the second for the copula, which is the concept of *Inference function for Margins* method (IFM). 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 prior to those of copula functions. The efficiency is therefore enhanced.

$$\hat{\theta}_i = \arg\max \sum_{t=1}^{T} \ln f_i(x_{it} | \Omega_{t-1}, \theta_i) \quad (9)$$

$$\hat{\theta}_c^{IFM} = \arg\max \sum_{t=1}^{T} \ln c\left(F_1\left(x_{1t}\middle|\hat{\theta}_1\right), F_2\left(x_{2t}\middle|\hat{\theta}_2\right), \ldots\ldots F_n\left(x_{nt}\middle|\hat{\theta}_n\right) | \Omega_{t-1}, \hat{\theta}_i\right) \quad (10)$$

3. Data and summary statistics

The daily stock indices provided by Morgan Stanley Capital International (MSCI) are obtained from Datastream database over the period from1 January 2002 to 30 June 2007. 1433 daily observations for each index are collected. Maghyereh (2004) states the reasons why MSCI indices are better than other local stock indices. For country's level, MSCI China, MSCI United States, MSCI Japan indices are selected. In order to specify which regional stock market is more correlated to China's, possibly due to their geographic ties or trade relationship, we use MSCI Europe and MSCI Pacific. To detect whether emerging markets have severer impacts than developed markets do, both MSCI world index and MSCI emerging markets index are collected. MSCI world index contains market indices of 23 developed countries, while MSCI emerging market index includes market indices of 25 emerging countries. Moreover, MSCI AcWorld index, which combines market indices of 48 developed and developing countries, is collected to measure the worldwide-level dependence.

The summary statistics of each index return are reported in Table 1. Table 2 shows the Pearson, Spearman and Kendall correlations for each index return paired with China's. Pearson 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, Kendall's tau and Spearman's rho, are less sensitive to the observations in the tails. As shown in Table 2, no matter which measurement is used, China-Emerging pair has the greatest correlation, followed by China-Pacific pair and China-Japan pair. The parameters of the marginal distributions for each index return are estimated and presented in Table 3. They are assumed to be characterized by an AR(1)-GARCH(1,1) model given by equation (1). As shown in Table 3, most parameters are at least significant at 5 percent level. Furthermore, 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. Results of unconditional copula models

For comparison, results of unconditional copula model are presented in Table 4. Since marginal distributions are assumed to be an AR(1)-GARCH(1,1) model, Table 4 reports the estimated parameters and results of goodness-of-fit test for static Gaussian, Gumbel and Rotated Gumbel copula functions. As shown in Panel A of Table 4, all copula functions have positive parameters, indicating that index return of China positively commoves with all index returns. We can consistently find that, irrespective of assumed copula function, the dependence between index return of an emerging market and market of China is the highest, followed by China-Pacific pair and China-Japan pair. Bekaert et al. (2005) and Goetzmann et al. (2005) claim that capital market integration and increased trade are embedded with a prediction about the dependence between markets. Therefore, we contend that an emerging market has a severer impact on dependence than a developed market[7] does. This may be attributed to the high trade frequency since the emerging countries are usually key suppliers of China for energy, mine, cropper and various commodities. Once the growth of Chinese economy is unexpectedly decayed, emerging markets may suffer severely. Also, the high degree dependence between China and Pacific or Japan may be attributed to their geographic ties and trade frequencies. Furthermore, this finding will be more evident as China proposes to join ASEAN Free Trade Area (AFTA) in 2010 to strengthen their cooperative and competitive abilities through eliminating tariffs and non-tariff barriers.

[7] Which is measured by MSCI world index

The choice of the best fit of copula function is based on the value of Akaike information criterion (AIC)[8]. From the maximized log-likelihood values (lnL) in Panel A of Table 4, we compute the AIC for each copula, and then rank the copula models accordingly. Panel B of Table 4 shows the AIC values for three chosen copulas. The lowest AIC value from the Rotated Gumbel copula indicates that the it is the best fitting model and the lower tail dependence exists in each pair. This finding is consistent with the literature that equity returns have been found exhibiting more joint negative extremes than joint positive extremes, leading to the observation that stocks tend to crash, but not to boom, together.

[Insert Table 4 here]

4.2. Results of conditional copula model

Given that the marginal distributions follow an AR(1)-GARCH(1,1) model, the estimated parameters of time-varying correlations in the Gaussian copula are reported in the Panel A of Table 5. The time-varying dependence model in equation (5) is estimated and calibrated for each pair of index returns. The parameter, β, captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. The initial value of the dependence, measured by ρ_1, is esimated

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

as well. It can be seen in the Panel A of Table 5 that the emerging, the Pacific and the Japanese markets experience a higher degree of dependence persistence with the Chinese market. Meanwhile, the log-likelihood functions for these areas are higher than those for others. Figure 1 depicts the implied time path of conditional correlations for each pair of index returns across sample period. Obviously, China-Pacific pair, China-Japan pair and China-emerging-markets pair all demonstrate greater conditional correlation, which is consistent with that of unconditional model.

[Insert Table 5 here]

4.3. Results of conditional tail dependence

Panel B and C of the Table 5 report the estimated parameters of time-varying tail dependence specified by the Rotated Gumbel and the Gumbel copula, respectively. It can be seen in both tables that the emerging, the Pacific and the Japanese markets show higher degrees of dependent persistence with the Chinese market. Both time-varying lower and upper tail dependences can be obtained by employing equation (8) where estimated conditional dependences, δ_t^U and δ_t^L, are from equation (6) and (7). In Figure 2 and 3 we present the plots of conditional lower and upper tail dependence specified by the time-varying Rotated Gumbel and Gumbel copula model, respectively. Overall, the value of the copula log-likelihood function of the Rotated Gumbel is the highest and that of the Gaussian is the lowest, indicating that the Rotated Gumbel copula is the best fitting model, and time-varying lower tail dependence exists in each pair. This finding is consistent with the unconditional model and the literature as well. Especially, the emerging, the Pacific and the Japanese markets experience higher degrees of lower tail dependent persistence with the Chinese market. Therefore, if the bubbles in Chinese stock markets burst, the probability of a joint market crash in Japan, in Pacific and in the emerging countries will be high.

[Insert Figure 1 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

5. Conclusions

Researches of international dependence have mainly focused on the developed markets. Relatively few have enquired the role of China despite of its noticeable growth in its capital market and distinctive impacts on global economy. In this study, we emphasize the dynamic dependence between the Chinese financial market and other major markets of the world. By estimating time-varying copula models between indices of these stock markets, we provide a comprehensive analysis of the time-varying market dependence for the period 2002-2007.

Regardless of the assumed copula functions, we consistently find that the Chinese market experiences a higher degree of dependence with markets in Japan, in the Pacific, and in the emerging countries. Geographic ties and close trading relationship may be attributed to this high dependence. 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. As China proposes to join ASEAN Free Trade Area, this threat will be strengthened further. With this understanding, some decisions on international diversification, portfolio allocation and risk management should be reconsidered.

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Table 1 Summary statistics

This table shows summary statistics of the returns of MSCI China, MSCI World, MSCI U.S., MSCI Europe, MSCI Japan, MSCI AcWorld, MSCI Pacific and MSCI Emerging. The sample period covers 1 January 2002 to 30 June 2007. 1433 daily observations for each index are collected.

	Mean	Standard Deviation	Skewness	Kurtosis
China	0.00092	0.01375	-0.24097	1.88839
World	0.00022	0.00812	0.06665	4.01935
U.S.	0.00018	0.00982	0.19883	3.52405
Europe	0.00020	0.01078	-0.13120	4.20785
Japan	0.00038	0.01133	-0.25321	1.23256
AcWorld	0.00025	0.00797	0.06665	3.87711
Pacific	0.00042	0.00920	0.02574	1.52761
Emerging	0.00070	0.00832	-0.64147	2.36938

Table 2 Association measurement

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

China versus	Pearson Correlation	Spearman Correlation	Kendall Correlation
World	0.26387	0.26792	0.18310
U.S.	0.10788	0.11032	0.07409
Europe	0.26673	0.25095	0.17222
Japan	0.44507	0.41799	0.29013
AcWorld	0.29341	0.29720	0.20407
Pacific	0.58330	0.55533	0.39476
Emerging	0.67998	0.63421	0.46171

Table 3 Estimated parameters for AR(1)-GARCH(1,1) marginal distributions

This table shows the estimated parameters of the marginal distributions for each index return. They are assumed to be characterized by an AR(1)-GARCH(1,1) model given by equation (1). The numbers in brackets ( ) are *p*-values.

	AR(1)	GARCH constant	Lagged variance	Lagged residual
China	0.0906	4.277e-06	0.9249	0.05202
	(0.0006)	(0.00261)	(0.0000)	(0.0000)
World	0.1059	5.683e-07	0.9275	0.06087
	(0.0001)	(0.00035)	(0.0000)	(0.0000)
U.S.	-0.0544	7.631e-07	0.9418	0.04731
	(0.0397)	(0.00011)	(0.0000)	(0.0000)
Europe	-0.0193	1.358e-06	0.8938	0.08985
	(0.4653)	(0.00010)	(0.0000)	(0.0000)
Japan	0.0273	2.383e-06	0.9023	0.08109
	(0.3009)	(0.00127)	(0.0000)	(0.0000)
AcWorld	0.1209	5.858e-07	0.9233	0.06458
	(0.000)	(0.00036)	(0.0000)	(0.0000)
Pacific	0.0411	2.067e-06	0.8952	0.08209
	(0.1204)	(0.00050)	(0.0000)	(0.0000)
Emerging	0.2008	2.034e-06	0.8866	0.08338
	(0.0000)	(0.00052)	(0.0000)	(0.0000)

Table 4 Parameter estimations and goodness-of-fit test for unconditional copula model

This table reports the estimated results of unconditional copula model in the Panel A. ρ is the correlation parameter of Gaussian copula. δ^U and δ^L are dependence parameters of Gumbel and 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, Gumbel and Rotated Gumbel copula functions are shown in the Panel B. $AIC = -2L(\hat{\theta};x) + 2q$, where q is the number of parameters to be estimated in each specific model.

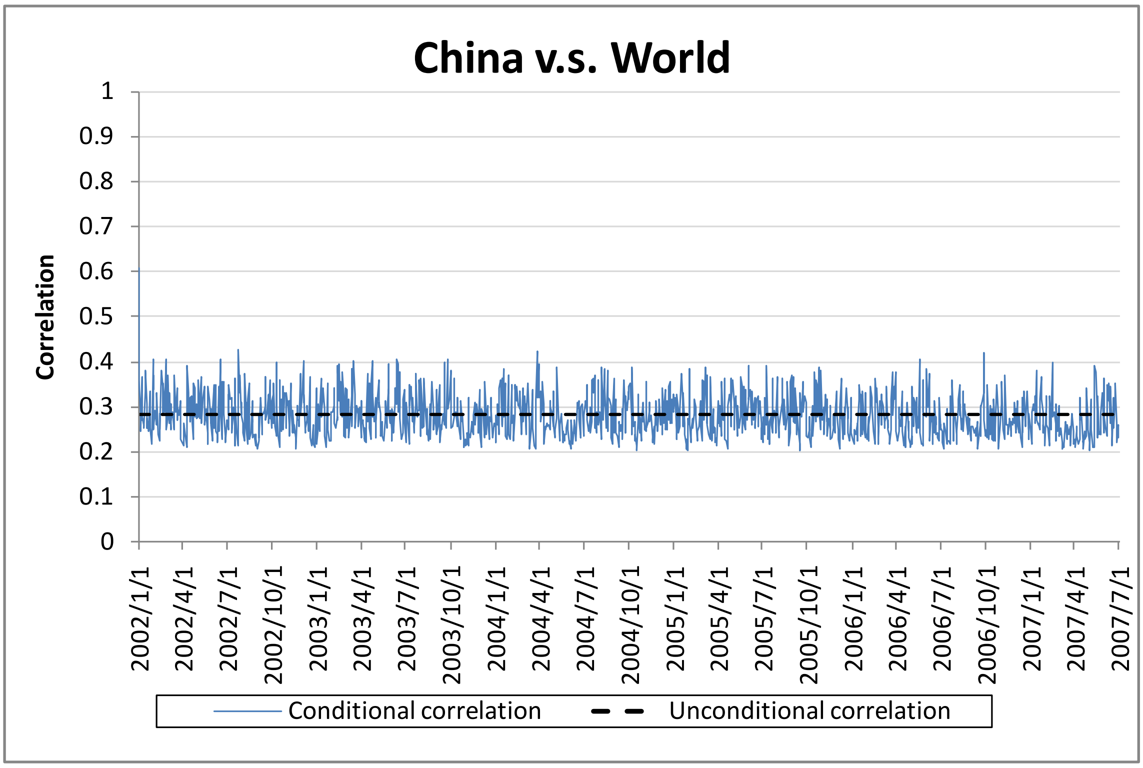
Unconditional Copula Model							
Paired				*China v.s.*			
Indices	*World*	*U.S.*	*Europe*	*Japan*	*AcWorld*	*Pacific*	*Emerging*
Panel A: Copula estimation							
Gaussian							
ρ	0.282	0.111	0.286	0.434	0.314	0.576	0.667
ln L	58.624	8.691	60.141	147.631	73.418	273.776	405.782
Gumbel							
δ^U	1.184	1.050	1.190	1.348	1.214	1.559	1.758
λ^U	0.204	0.065	0.210	0.328	0.230	0.440	0.517
ln L	45.670	5.701	50.149	126.326	58.664	252.248	375.204
R.Gumbel							
δ^L	1.206	1.071	1.205	1.369	1.237	1.583	1.797
λ^L	0.223	0.090	0.222	0.341	0.249	0.451	0.529
ln L	60.415	9.568	61.433	147.402	75.783	274.907	406.959
Panel B: Goodness-of-fit test (AIC)							
Gaussian	-115.248	-15.382	-118.282	-293.262	-144.836	-545.552	-809.564
Gumbel	-89.34	-9.402	-98.298	-250.652	-115.328	-502.496	-748.408
R.Gumbel	-118.83	-17.136	-120.866	-292.804	-149.566	-547.814	-811.918

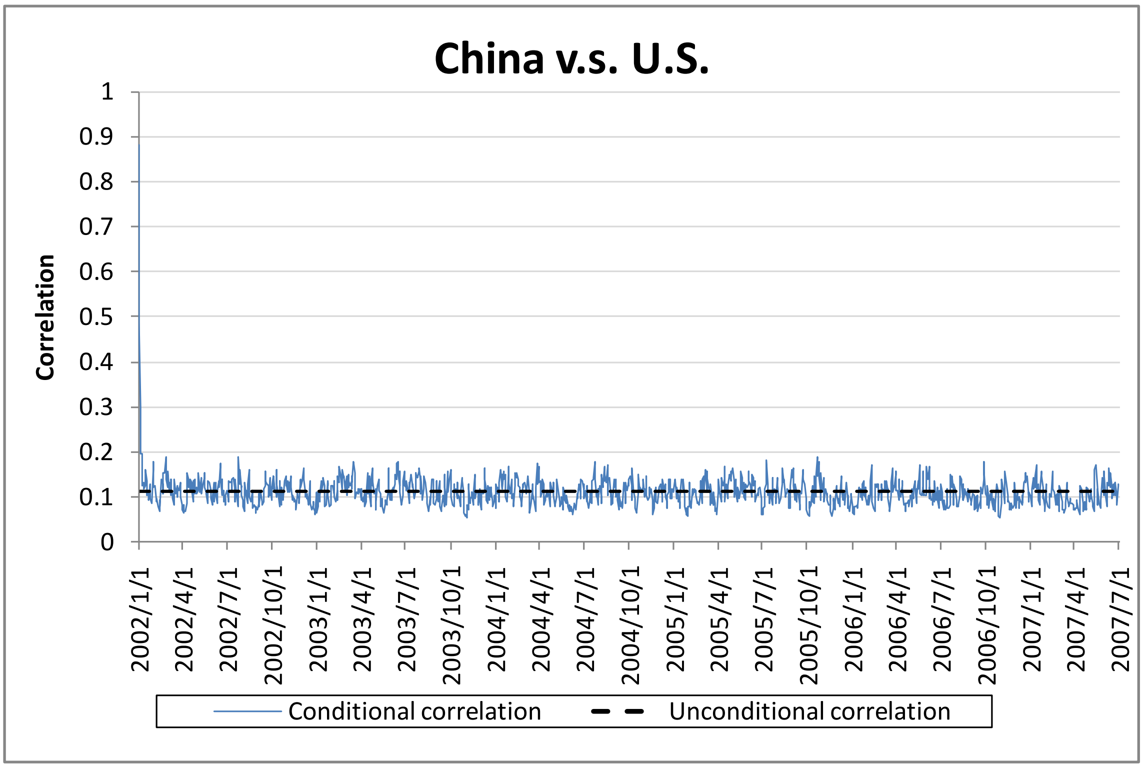
Table 5 Estimated parameters of time-varying dependences in the chosen copulas

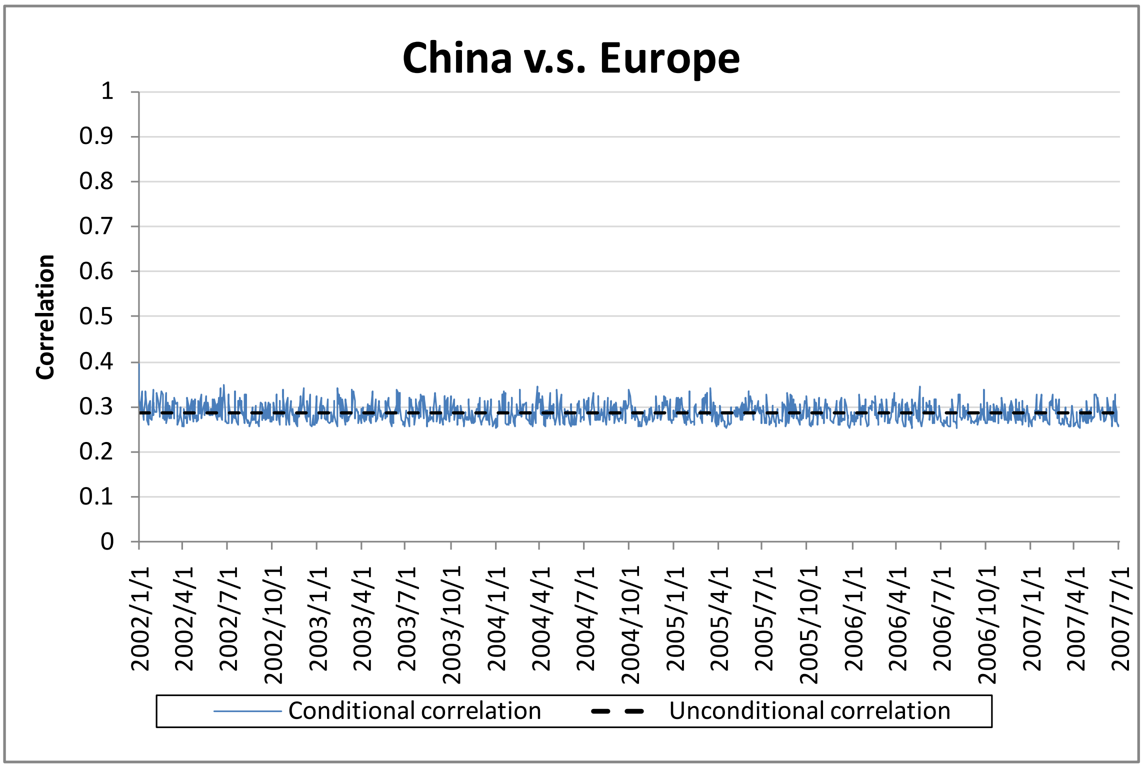
This table shows the estimated parameters of time-varying dependences in the chosen copulas. The time-varying dependence models in equation (5), (6), (7) are estimated and calibrated for each pair of index returns. The parameter, β, captures the degree of persistence in the dependence and γ captures the adjustment in the dependence process. The initial value of the dependence is estimated as well. LLF(c) is the maximum of the copula component of the log-likelihood function.

China versus	β	ω	γ	Initial value	LLF(c)
Panel A: Gaussian copula					
World	0.31945	0.13538	0.22749	0.60793	60.75699
U.S.	0.56739	0.01781	0.09516	0.87929	10.08956
Europe	0.34985	0.16647	0.09658	0.39344	60.55184
Japan	0.99990	0.05737	-0.10777	0.77259	149.3346
AcWorld	0.27147	0.181184	0.21209	0.59932	75.2125
Pacific	0.99990	0.12581	-0.21283	0.63262	281.2017
Emerging	0.99990	0.17462	-0.19900	0.80974	409.1492
Panel B: Rotated Gumbel copula					
World	0.38781	0.68741	0.18189	1.95735	62.30450
U.S.	0.37218	0.64788	0.07926	3.69468	11.13930
Europe	0.42159	0.67766	0.06901	1.44933	61.78139
Japan	0.92767	0.12652	-0.11190	1.50332	150.61170
AcWorld	0.35824	0.74466	0.18093	1.96737	77.45485
Pacific	0.95300	0.11094	-0.16929	1.39997	283.0431
Emerging	0.96375	0.09432	-0.15127	1.20698	414.9552
Panel C: Gumbel copula					
World	0.19345	0.90657	0.17268	1.29830	47.05787
U.S.	0.43248	0.58589	0.03316	2.51917	6.76919
Europe	0.55675	0.51727	0.03869	1.00000	50.47848
Japan	0.89806	0.16567	-0.11484	1.44770	128.61650
AcWorld	0.16640	0.96713	0.16552	1.28228	59.81751
Pacific	0.93504	0.14005	-0.17935	1.29072	258.90430
Emerging	0.95090	0.12672	-0.21067	1.23979	384.14260

Figure 1 Conditional correlation estimation from the Gaussian copula






China v.s. Europe
Correlation
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2002/1/1
2002/4/1
2002/7/1
2002/10/1
2003/1/1
2003/4/1
2003/7/1
2003/10/1
2004/1/1
2004/4/1
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2007/1/1
2007/4/1
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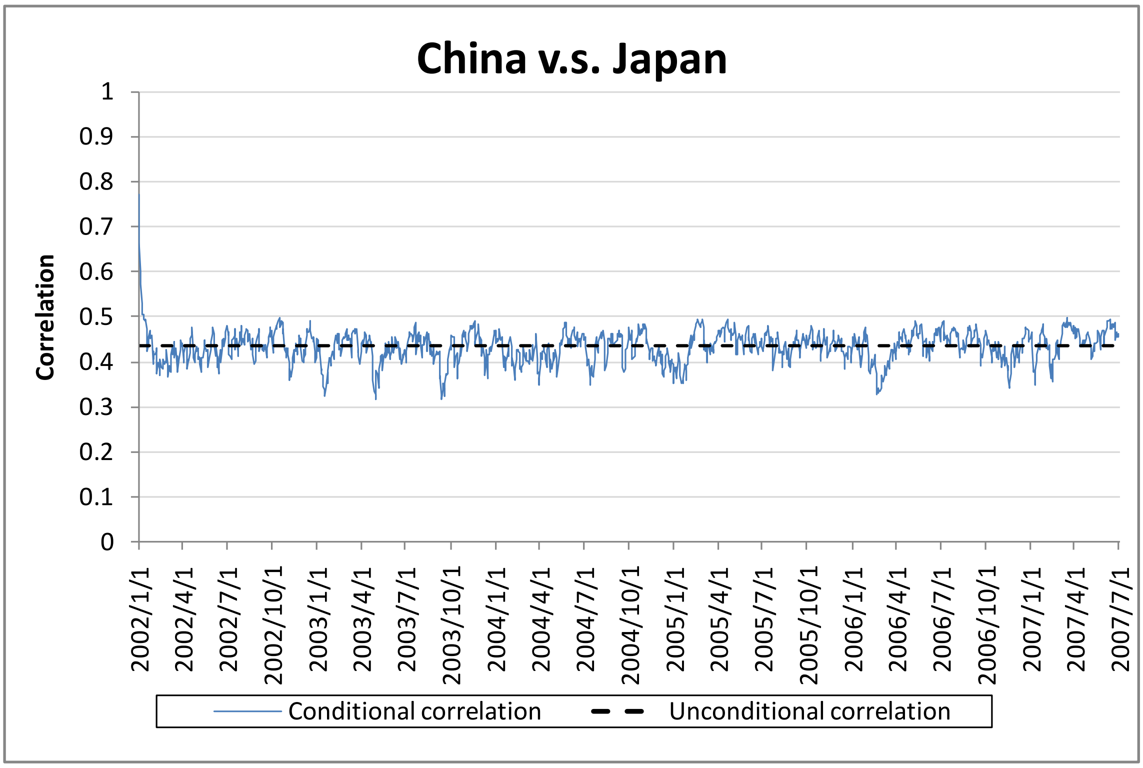
Conditional correlation
Unconditional correlation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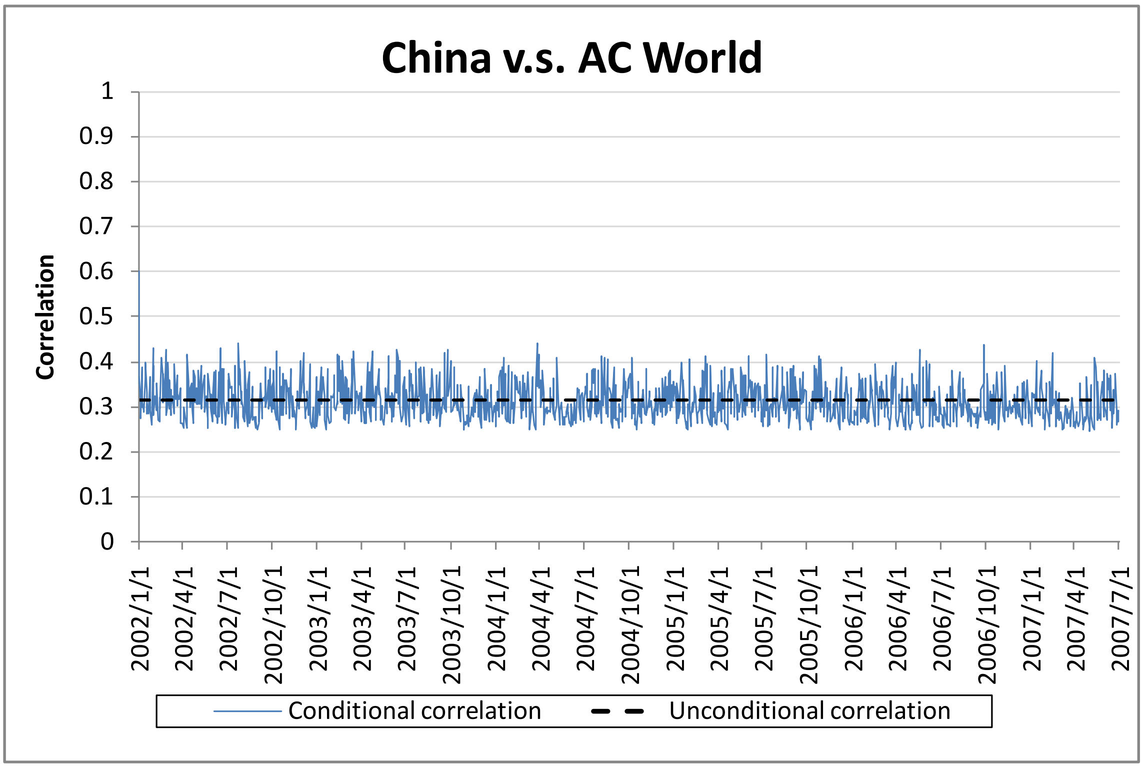
Conditional correlation
Unconditional correlation


China v.s. AC World
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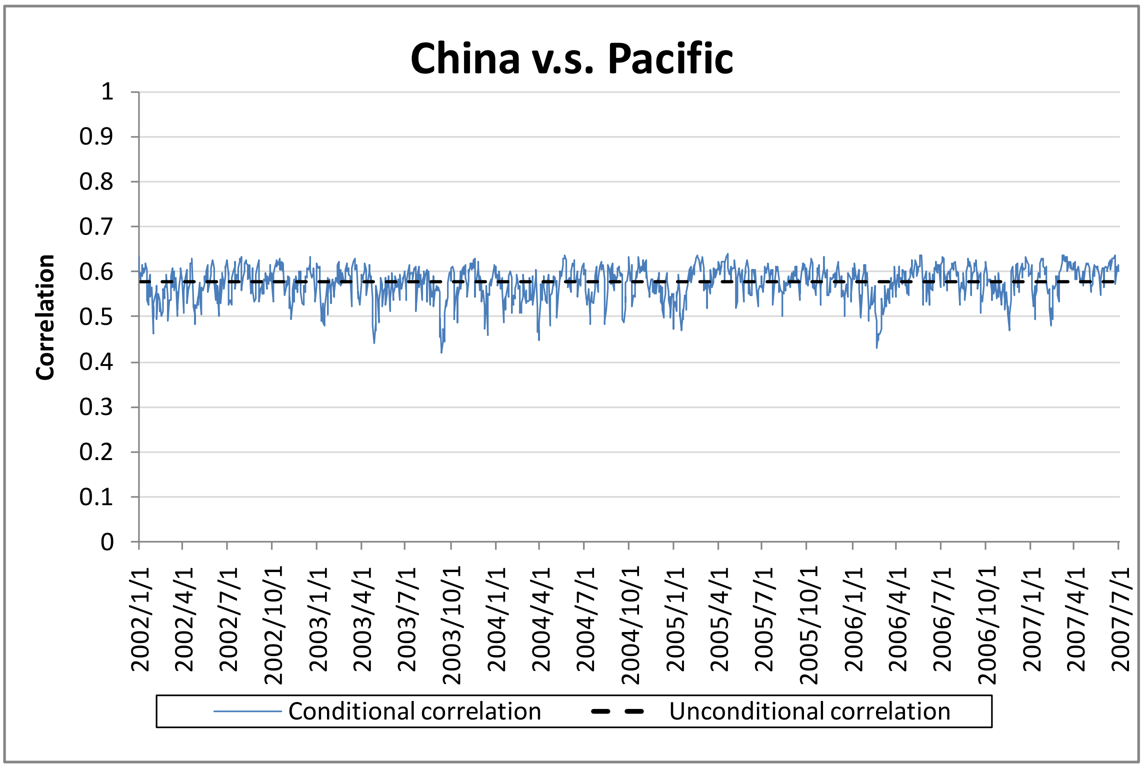
Conditional correlation
Unconditional correlation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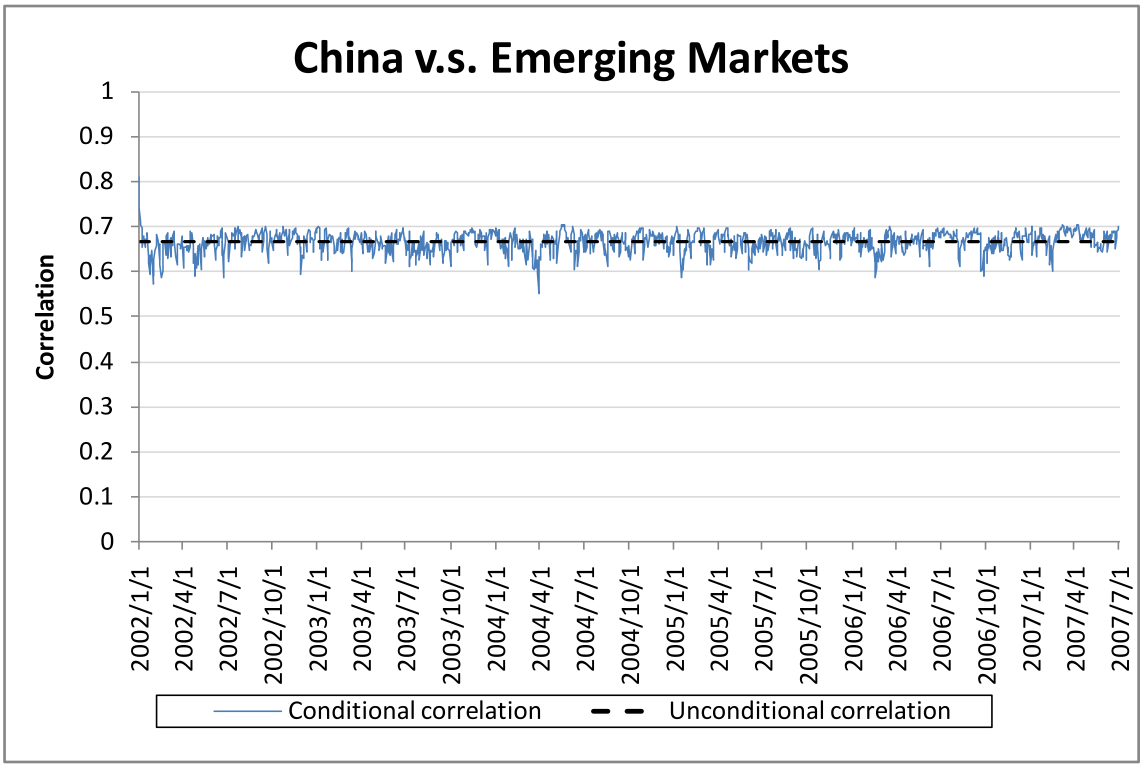
Conditional correlation
Unconditional correlation


China v.s. Emerging Markets
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2006/1/1
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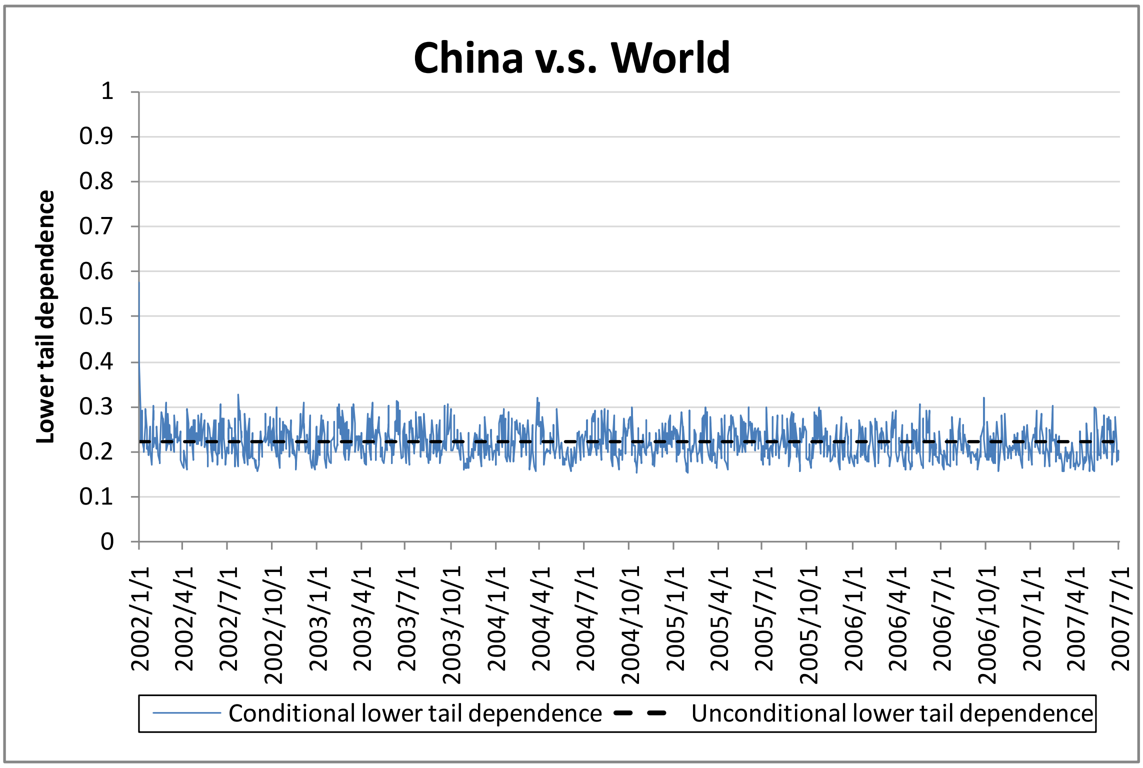
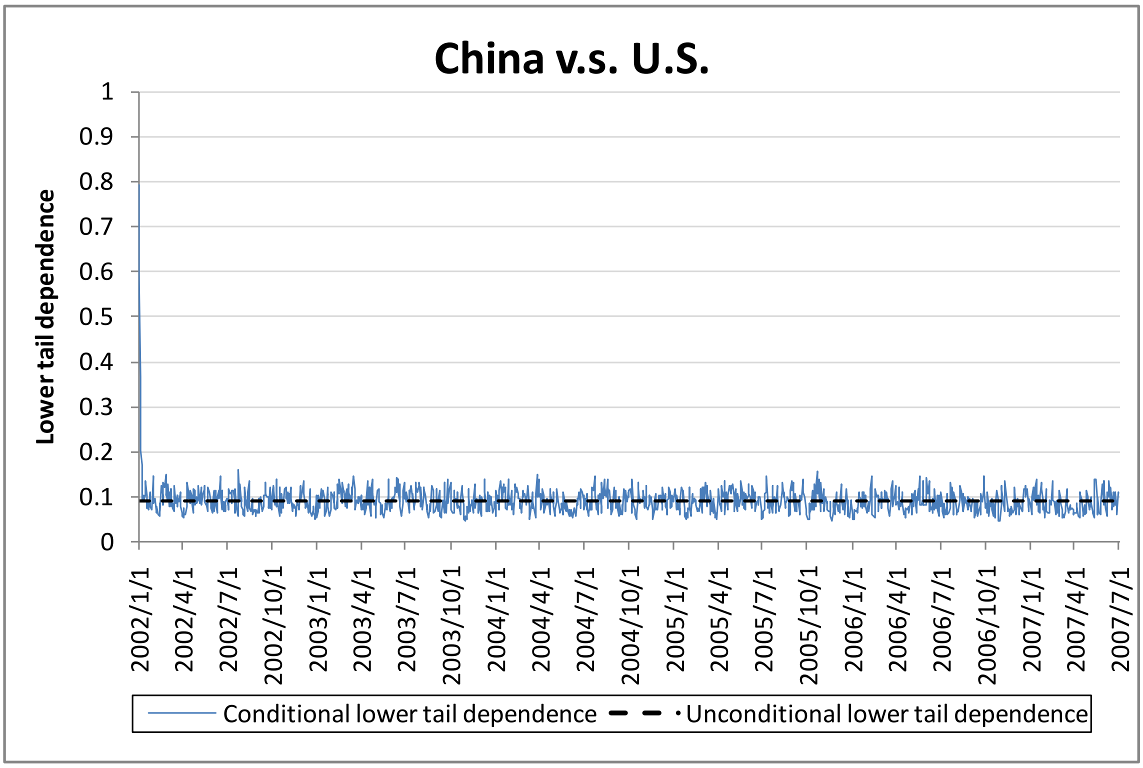
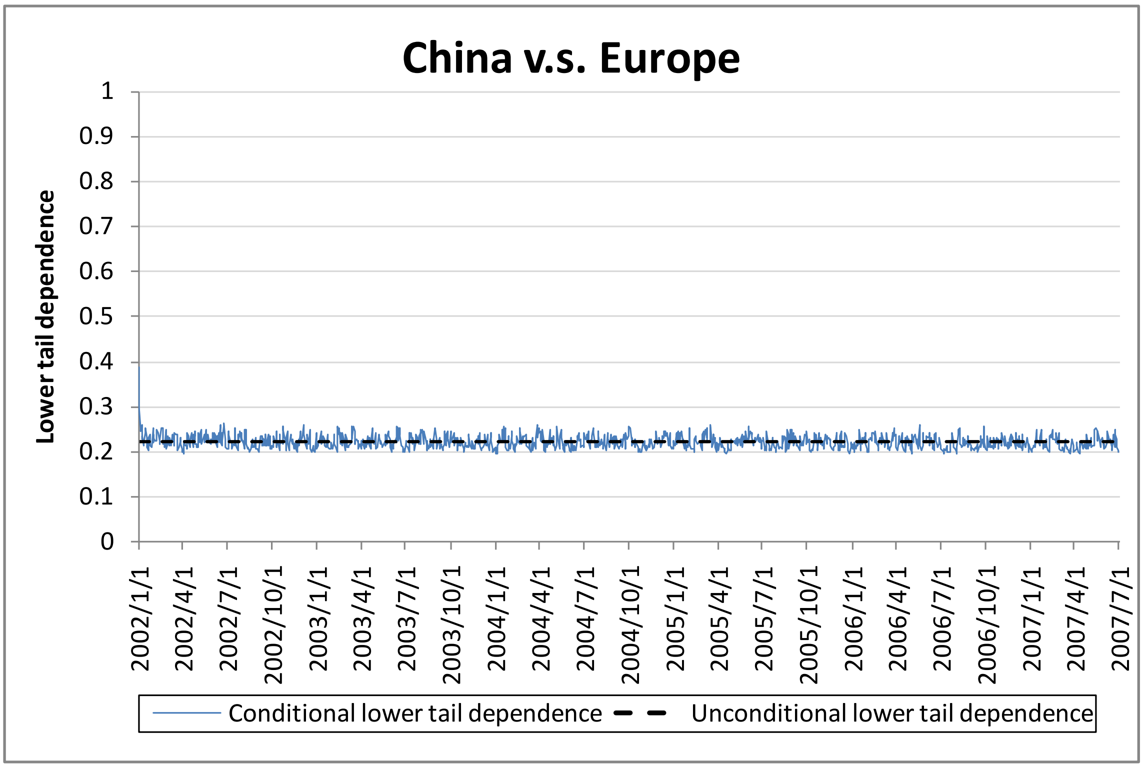
2007/7/1
Conditional correlation
Unconditional correlation

Figure 2. Conditional lower tail dependence estimation from the Rotated Gumbel copula



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Lower tail dependence
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0
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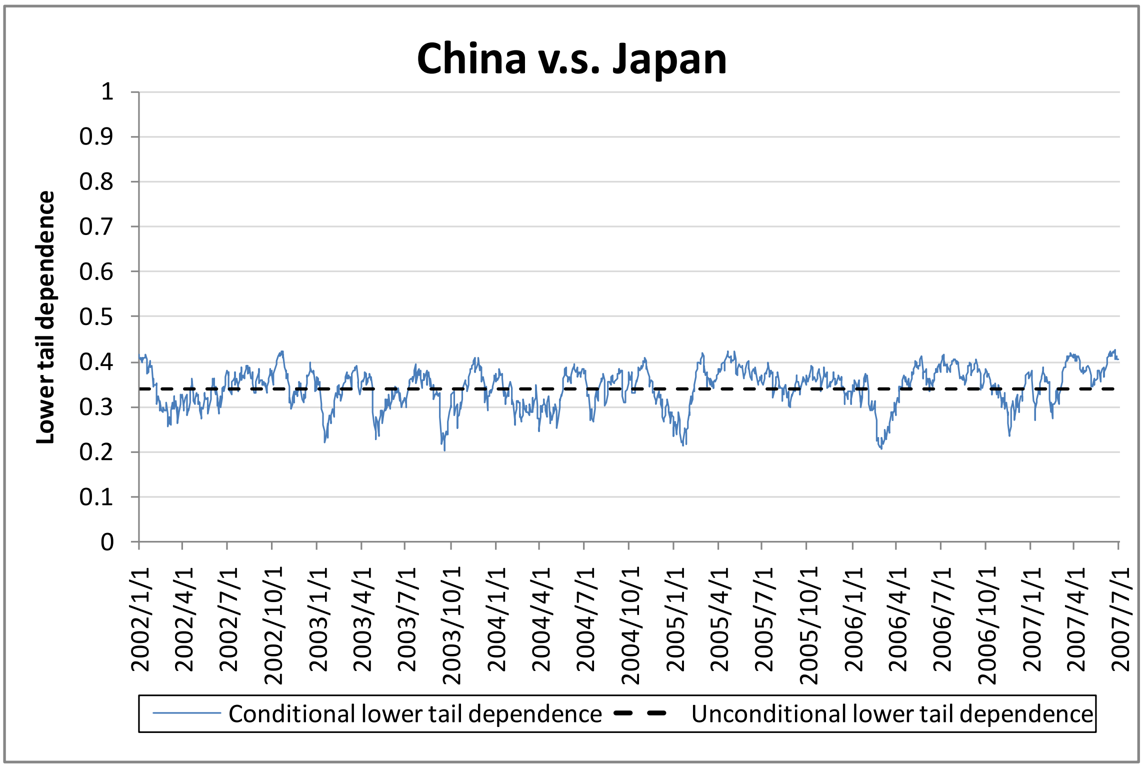
2007/7/1
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Japan
Lower tail dependence
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0
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2005/7/1
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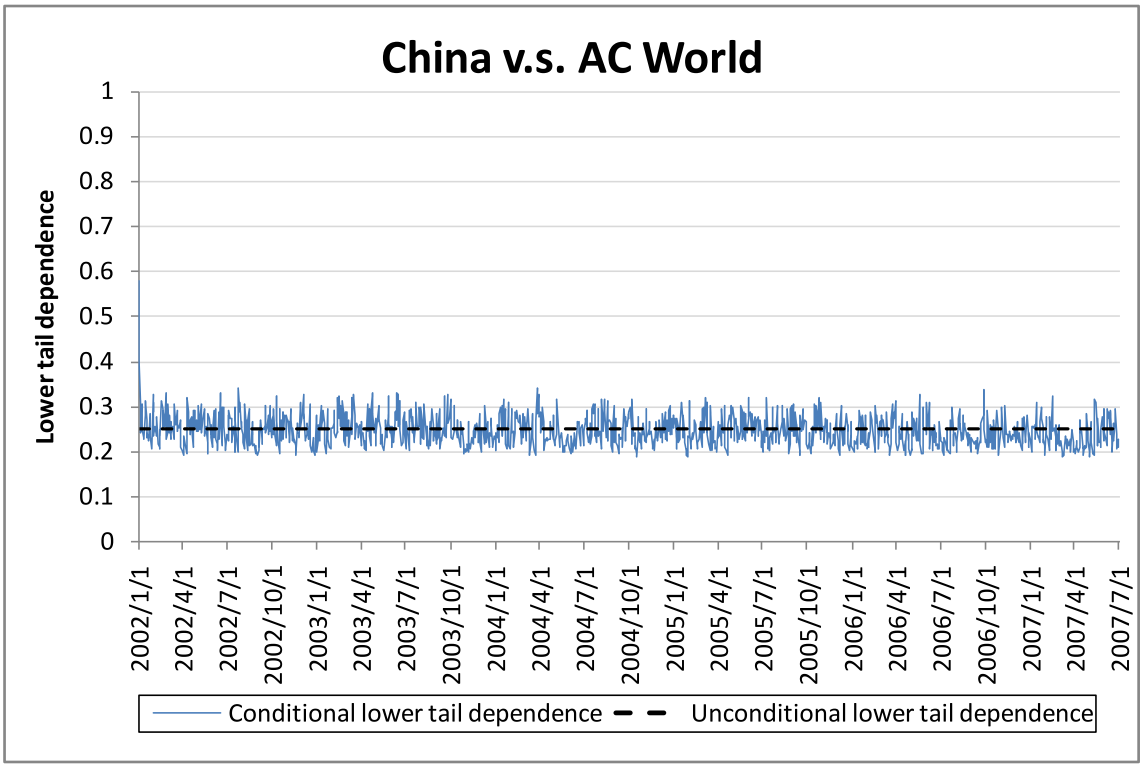
2006/10/1
2007/1/1
2007/4/1
2007/7/1
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. AC World
Lower tail dependence
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0
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2002/4/1
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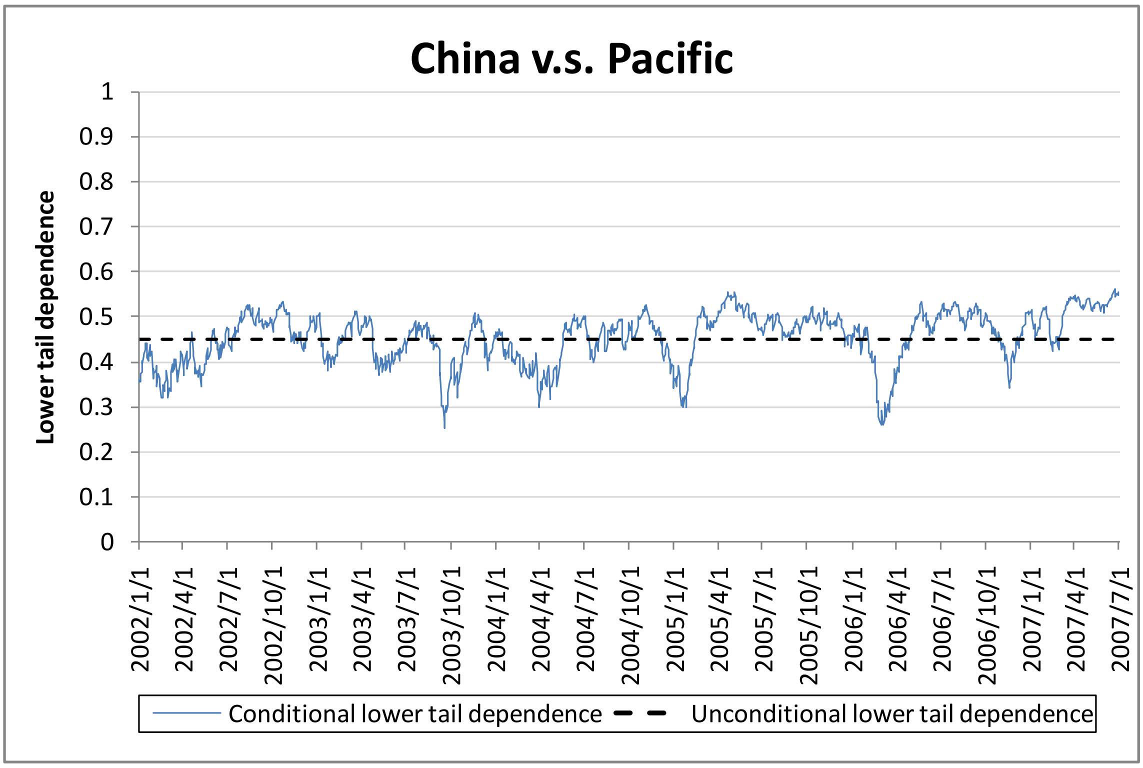
2007/7/1
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Pacific
Lower tail dependence
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0.3
0.2
0.1
0
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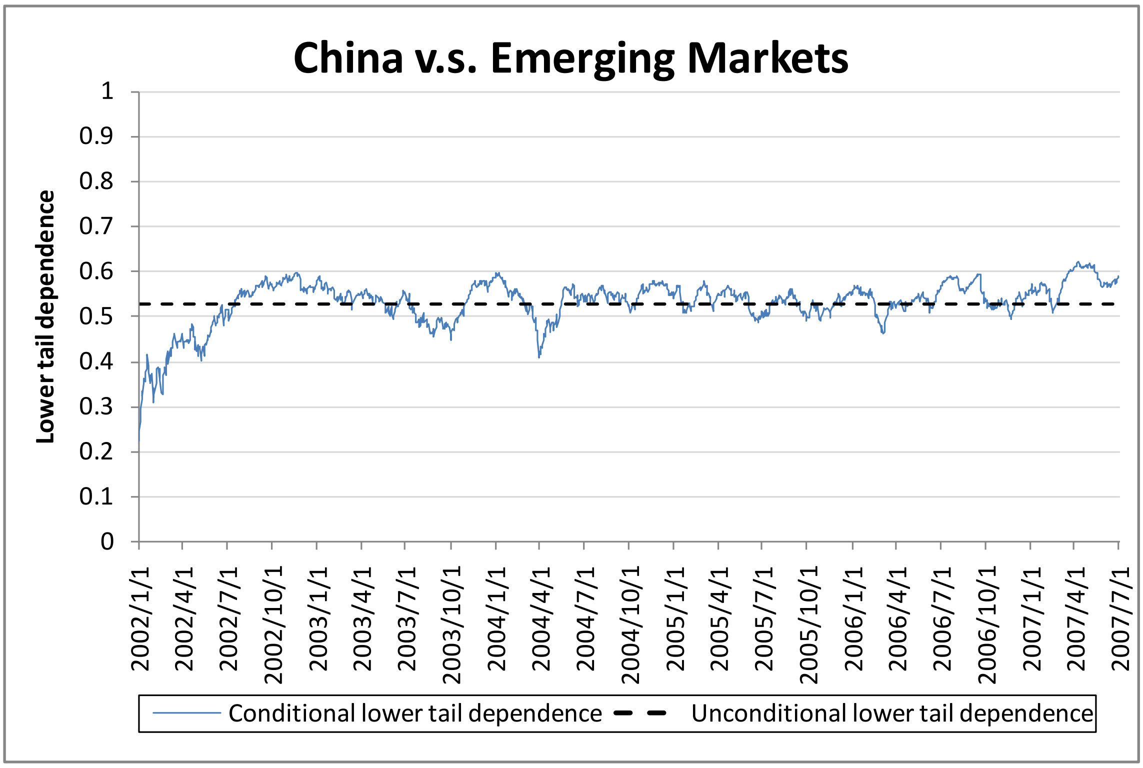
Conditional lower tail dependence
Unconditional lower tail dependence


China v.s. Emerging Markets
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0
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2006/1/1
2006/4/1
2006/7/1
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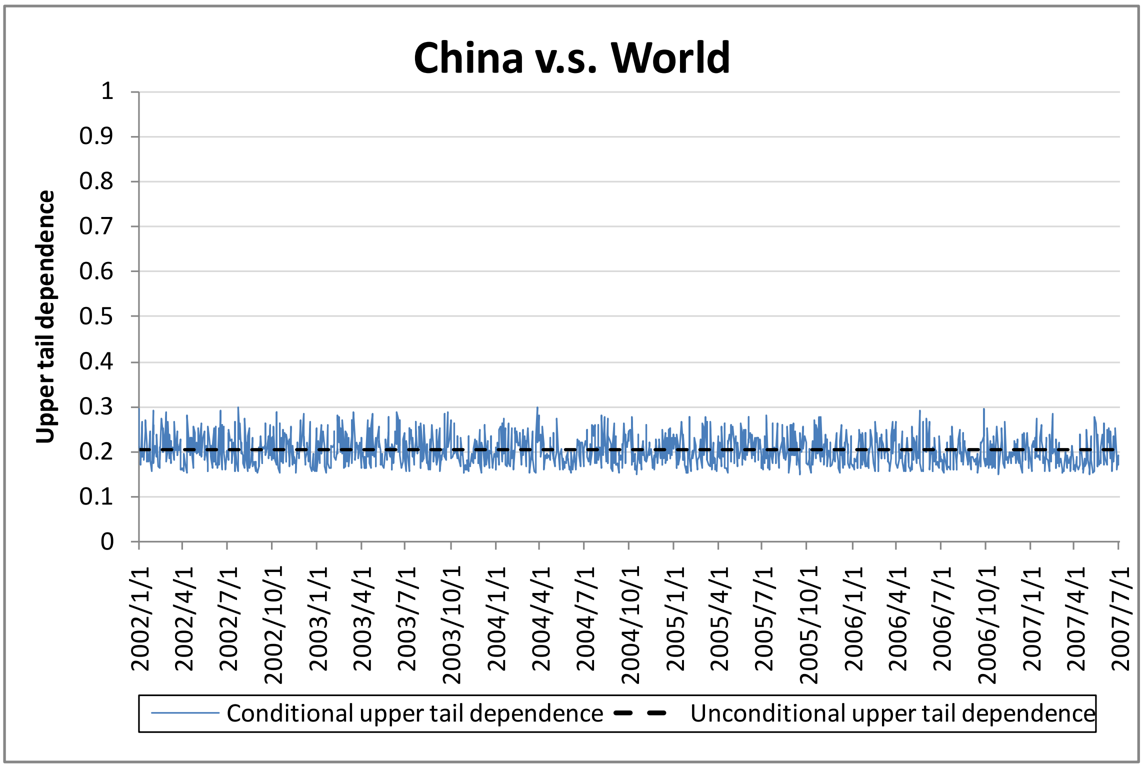
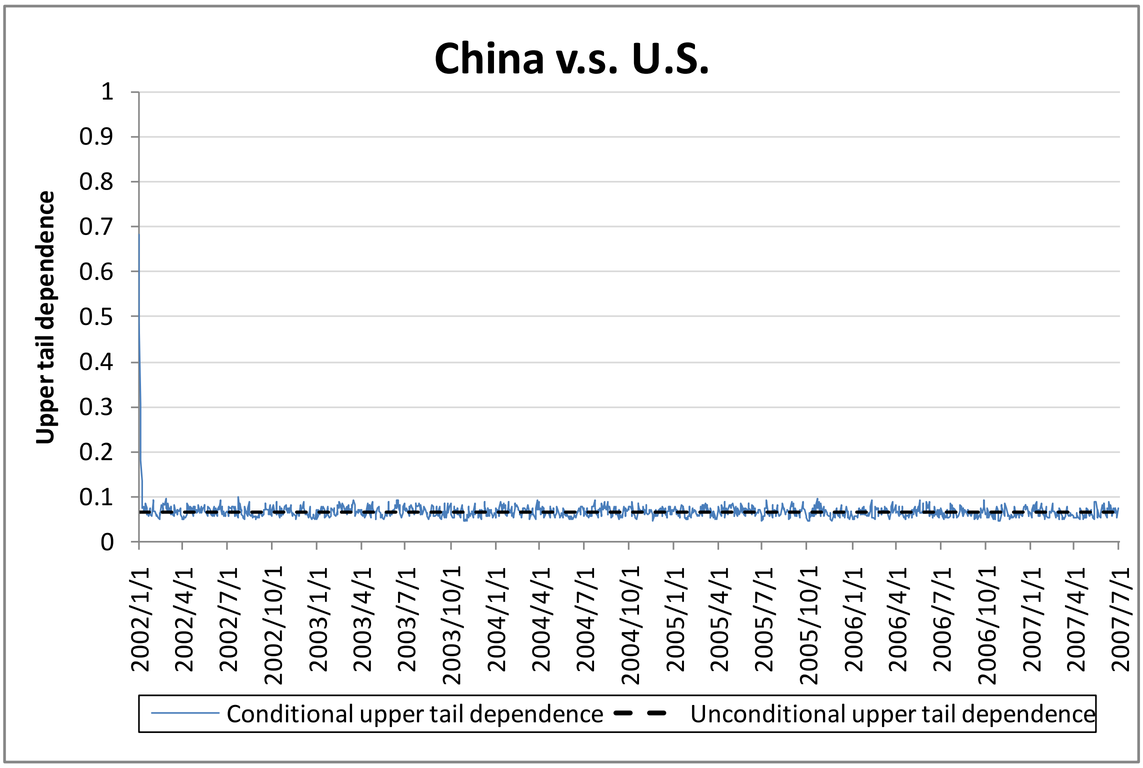
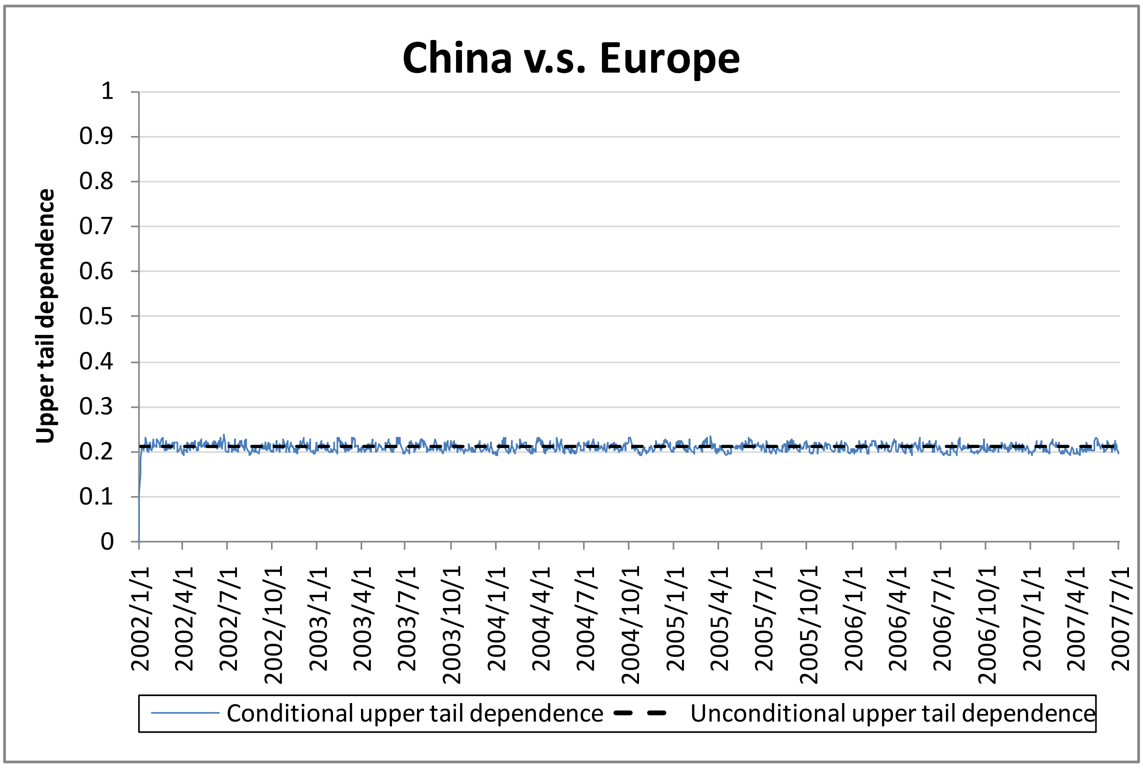
2007/4/1
2007/7/1
Conditional lower tail dependence
Unconditional lower tail dependence

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






China v.s. Europe
Upper tail dependence
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0.3
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0.1
0
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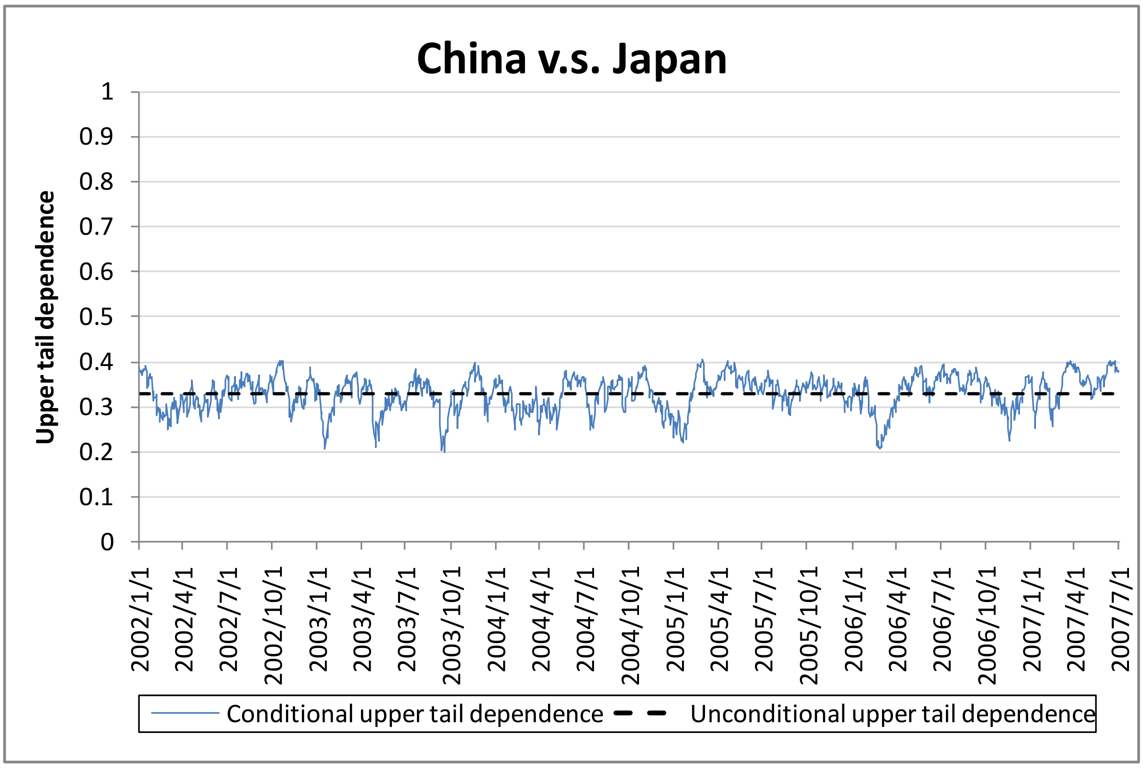
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Japan
Upper tail dependence
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0.3
0.2
0.1
0
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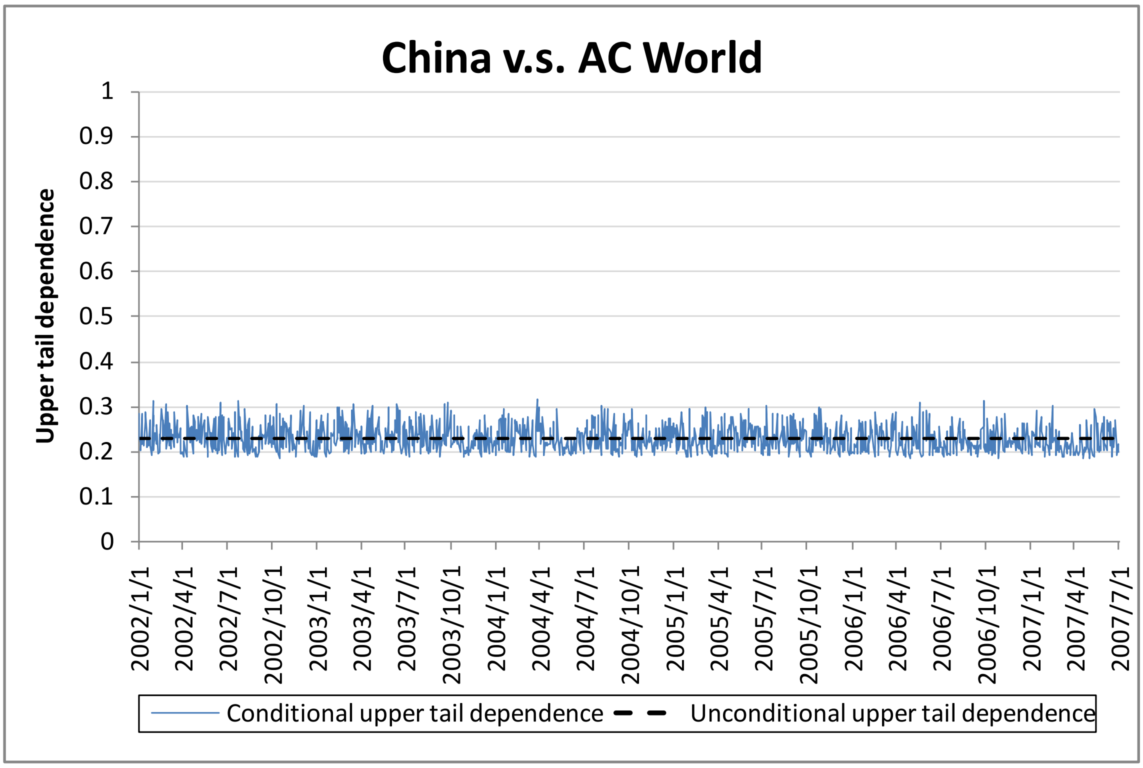
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. AC World
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0.3
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0
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2002/4/1
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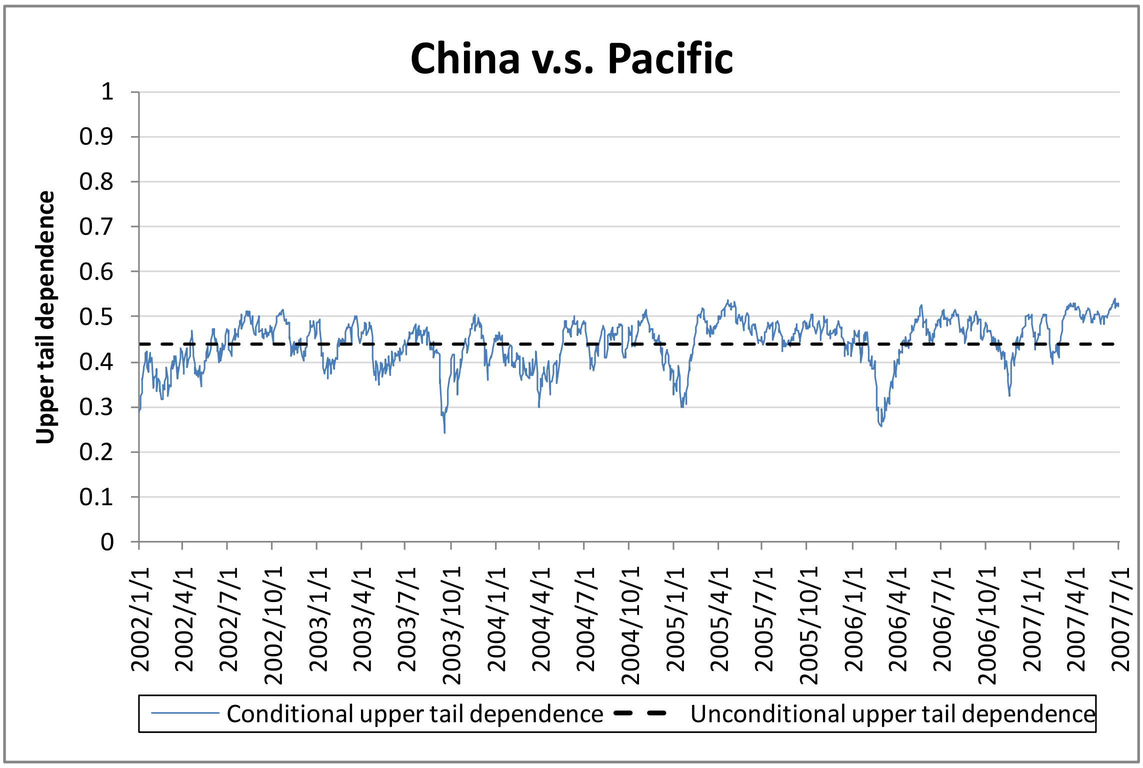
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Pacific
Upper tail dependence
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0
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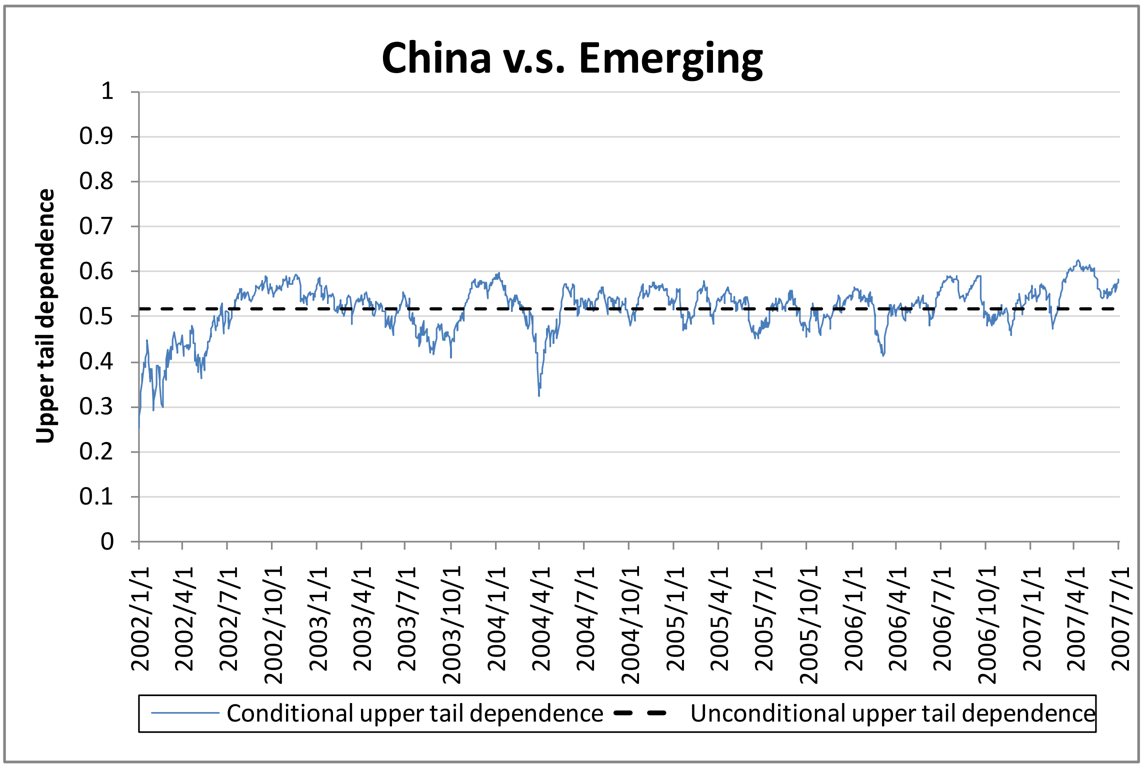
Conditional upper tail dependence
Unconditional upper tail dependence


China v.s. Emerging
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2007/7/1
Conditional upper tail dependence
Unconditional upper tail dependence