Extreme Dependence across East Asian Financial Markets: Evidence in equity and currency markets

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ABSTRACT

Using unconditional and conditional copulas, this paper investigates pair-wise extreme dependence across equity markets and currency markets by directly modeling the tail dependence behavior. Empirically, we find significant asymmetric tail dependence in equity markets, with a large lower tail dependence coefficient than upper tail dependence coefficient, implying that international diversification is limited since the equity pairs tend to crash together when diversification is most needed. Mixed results are found for currency co-movements. Co-movements in the currency markets are much weaker, in several cases, with larger upper tail coefficients. This study has important implications in portfolio selection and risk management strategies in international diversification.

INTRODUCTION

In this paper, we focus on five East Asian countries: Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. We examine the tail dependence behavior across the equity markets as well as across the currency markets. We endeavor to answer the following questions: 1) is there extreme dependence across the equity market? 2) is there extreme dependence across the currency market? 3) are the tail dependence behavior similar? By answering these questions we hope to better understand the extreme co-movements across these two important markets and provide some insight on risk management strategies involving hedging and potential diversification benefits.

Co-movement across international financial markets of the same or different types has been widely studied in the finance community, as it has very important implications in portfolio selection and risk management. Earlier research is conducted along the line of correlations and conditional correlations. Kaplanis (1988) examines the stability of the co-movements among monthly stock index returns for ten industrial countries between 1967 and 1982 and finds stability in correlations but not in covariances. Using a dynamic simultaneous equations model, Koch and Koch (1991) study co-movements of daily returns in six developed and two developing countries over three different years: 1972, 1980, and 1987. They find growing market interdependence within the same geographical region over time. Chung and Liu (1994) find that the US and five East Asian countries have co-integrated stock prices.

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Using bivariate GARCH model on data over the period 1960−1990 for seven OECD countries, Longin and Solnik (1995) conclude that both covariances and correlations are unstable and they also find that the correlation rises in periods of high volatility. Karolyi and Stulz (1996) investigate daily return co-movements between Japanese and U.S. stocks. They find strong evidence that covariances are higher when there are large contemporaneous return shocks in the national markets. Forbes and Rigobon (2002) conclude that there was virtually no increase in unconditional correlation coefficients during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. stock market crash and they argue that increased correlation during more volatile periods could be an artifact. They term the high level of market co-movement as interdependence, instead of financial contagion.

Some other works attempt to examine the co-movements between financial markets using extreme value theory. Examples include Longin and Solnik (2001) and Hartmann et al. (2004), among others. Longin and Solnik (2001) explicitly model the multivariate distribution of large returns and estimate the correlation for increasing threshold values. They find that correlation increases in bear markets but not in bull markets. Hartmann et al. (2004) also use extreme-value analysis to capture the dependence structure between stock and bond returns for pairs of G5 countries. They find that extreme dependence between stocks and bonds is much lower than extreme dependence between stock markets or bond markets.

Discussions of the limitations of correlation measures in risk management by Embrechts et al. (1999, 2001) turn more and more researchers and practitioners to apply copula framework in modeling dependence structure and co-movements between financial variables. Applications of copula methods in finance can be found in Cherubini et al. (2004), and Patton (2009) gives an excellent survey within time series framework. Other references include Li (2000), Hu (2006), Rodriguez (2007), Ning (2009, 2010) among others. Using likelihood ratio-based methods, Mashal and Zeevi (2002) investigate the potential for extreme co-movements between financial assets (equities, currencies, and commodities markets) and find the presence of extreme co-movements is statistically significant in the three markets.More recent works allow some dynamics in dependence using conditional copula. Using conditional copula, Patton (2004) examines dependence between small and large cap US stocks. He documents evidence of asymmetric dependence in the stock returns and indicates that knowledge of this asymmetry can lead to significant gains for investors who do not face short sales constraints. Patton (2006) investigates the dependence structure between Deutsche mark and Japanese yen. He finds evidence that the mark-dollar and yen-dollar have asymmetric dependence structure in the tail area.Jondeau and Rockinger (2006) capture the time-varying volatilities of univariate returns by a GARCH model and introduce Markov-switching Student t-copula for pairwise dependence in international financial returns. Chollete et al. (2009) propose a model of multivariate regime-switching copulas to capture asymmetric dependence in international financial markets.

One of our major findings is that, across stock markets, there is an obvious asymmetry between the dependencies in bear markets and bull markets, consistent with previous research results. An important implication of this finding for practice work is the warning against using bivariate normality or correlation coefficients as a guide for risk management and international asset allocation. Given a constant correlation, the underlying dependence structure could be very different. We also find that co-movements across the currency markets of the countries are quite different from stock market co-movements. In many cases, the upper tail dependent coefficient is higher than the lower tail dependence coefficient.

The layout of this paper is as follows. In section 2, we introduce some conventional measures of dependence and copula measures of dependence. In section 3, the models are specified for the marginal distributions and for the joint distributions. We describe the data used in the study and discuss our empirical results in section 4. Section 5 concludes.

DEPENDENCE MEASURES AND COPULA CONCEPTS

In finance, the most popular measure of dependence is linear correlation. Under the assumption of multivariate normal distribution, the linear correlation is the canonical measure of dependence. However, empirical evidence in finance has proved the inadequacy of the multivariate normal distribution. Therefore, linear correlation as a measure of dependence can often lead to misleading results. Over the past decade, copulas have experienced a surging popularity in modeling dependency between financial variables and risk factors. Copula functions represent a methodology to handle the co-movement between financial markets and other variables relevant in financial economics, independent of the underlying marginal distributions.

Classical measures of dependence

Linear correlation

Linear correlation is the most popular measure of dependence, and it is also known as Pearson's product moment correlation.

Definition1 Let $(X, Y)^T$ be a vector of random variables with nonzero finite variance. The linear correlation coefficient for $(X, Y)^T$ is

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}} \quad (1)$$

where $Cov(X,Y) = E(XY) - E(X)E(Y)$is the covariance of $(X, Y)^T$, *Var*(*X*) and *Var*(*Y*) are the variances of *X* and *Y*, respectively, and $-1 \le \rho(X,Y) \le 1$. In the case $\rho(X,Y) = 1$, we say that *X* and *Y* are perfectly positively correlated, in the case of $\rho(X,Y) = -1$, *X* and *Y* are perfectly negatively correlated. The value of 0 indicates that there is no linear correlation between *X* and *Y*. As explained by Embrechts et al. (1999), the linear correlation is a dependence measure only in the case of multivariate normal distributions.

Kendall's tau

The Kendall's tau rank correlation coefficient, developed by Maurice Kendall in 1938, is a non-parametric statistic used to measure the degree of correspondence between two rankings.

Definition 2 Let F be a continuous bivariate cdf and let $(X_1, X_2), (X_1', X_2')$be independent random pairs with distribution F. Then Kendall's tau is

$$\tau = \Pr\left((X_1 - X_1')(X_2 - X_2') > 0\right) - \Pr\left((X_1 - X_1')(X_2 - X_2') < 0\right)$$
$$= 2\Pr\left((X_1 - X_1')(X_2 - X_2') > 0\right) - 1 = 4\int\int F\,dF - 1 \qquad (2)$$

Kendall's tau is a bivariate measure of dependence for continuous variables that are invariant with respect to strictly increasing transformations.

Spearman's rho

Spearman's rho, named after Charles Spearman and denoted by the Greek letter ρ_s (rho), is also a non-parametric measure of correlation. As with Kendall's tau, Spearman's rho is also a bivariate measure of dependence. Both Kendall's tau and Spearman's rho provide distribution free measure of dependence between two variables, and known as concordance measures of dependence.

Definition 3 Let F be a continuous bivariate cdf with univariate margins F_1 , F_2 and let $(X_1 , X_2) \sim F$; then Spearman's rho is the correlation of $F_1(X_1)$ and $F_2(X_2)$. Since $F_1(X_1)$ and $F_2(X_2)$ are U(0,1) random variables, their expectations are 1/2, their variances are 1/12, and Spearman's rho is

$$\rho_s = 12\int\int F_1(X_1)F_2(X_2)\,dF(F_1, X_2) - 3 = 12\int\int\,F\,dF_1dF_2 - 3 \qquad (3)$$

For bivariate data, ρ_s is the rank correlation and the rank transformation is like the probability transform of a random variable to U(0, 1).

Kendall's tau and Spearman's rho coefficient lie inside the interval $[-1, 1]$. The value of -1 indicates the disagreement between the two rankings is perfect, and one ranking is the reverse of the other. The value of 0 indicates the rankings are completely independent, and if the agreement between the two rankings is perfect, the rank correlation coefficient is +1. Concordance correlation measures like Kendall's tau and Spearman's rho are independent of the univariate marginal distributions. They provide the best alternatives to the linear correlation coefficient as a measure of dependence for non-elliptical distributions. The advantage of rank correlations over linear correlation is that they are invariant under monotonic transformations.

Copula measures of dependence

Dependence between random variables can also be modeled by copula (coined by Sklar (1959)) method, an ever increasingly popular way to model the dependency between financial risk factors. As described in Joe (1997), a copulais a multivariate distribution function that is used to bind each marginal distribution function to form the joint distribution function. Copulas parameterize the dependence between the margins, while the parameters of each marginal distribution function can be estimated separately. The advantages of copula method presents over the traditional methods to measure dependence are as follows. One is that copulas allow modeling nonlinear dependence structure; secondly, no assumption required regarding the marginal distribution, which is particularly suitable for financial returns data, as there is no known exact distribution; lastly, we can use copulas to model tail events, which can never be over-emphasized in financial risk management practice.

The Gaussian copula

The Gaussian copula is derived from the bivariate normal distribution. With Φ_ρ being the standard bivariate normal cumulative distribution function with correlation ρ, The Gaussian copula is

$$C_\rho^{Ga}(u,v) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right) \quad (4)$$

where the variables u and v are the CDFs of the standardized residuals from the marginal models, with $0 \leq u, v \leq 1$, Φ_ρ is the joint distribution function of a 2-dimensional standard normal vector, with linear correlation coefficient ρ, Φ is the standard normal distribution function. The density function of a Gaussian copula can be represented by the following

$$c_\rho(u,v) = \frac{\varphi_{X,Y,\rho}(\Phi^{-1}(u),\Phi^{-1}(v))}{\varphi\left(\Phi^{-1}(u)\right)\varphi(\Phi^{-1}(v))} \quad (5)$$

where

$$\varphi_{X,Y,\rho}(x,y) = \frac{1}{2\pi\sqrt{1-\rho^2}} exp\left(-\frac{1}{2(1-\rho^2)}[x^2+y^2-2\rho xy]\right)$$

is the density function for the standard bivariate Gaussian distribution with Pearson's product moment correlation ρ and φ is the standard normal density. If two return series have a bivariate normal copula, then both upper and lower tail dependence coefficients are zero, implying that there is no tail dependence.

Gumbel copula

Gumbel copula is another member of the Archimedean copula family and can be used to describe upper tail dependence. The bivariate Gumbel copula is given by the following

$$C_\theta^{Gu}(u,v) = exp\{-\left[(-lnu)^\theta + (-lnv)^\theta\right]^{1/\theta}\} \quad (6)$$

where $0 < \theta \leq 1$ is a parameter controlling the dependence, $\theta \rightarrow 0^+$ implies perfect dependence, and $\theta = 1$ implies dependence. Gumbel copula has upper tail dependence and has no lower tail dependence.

To avoid repetition, the copulas we use in this study are introduced in section 3. The functional forms for the three static copula models will be given in subsection and the conditional copula function is introduced in subsections. We use three Archimedean copula models (static and conditional Symmetrized Joe-Clayton (SJC) and Clayton) and one elliptical copula (Student's t-copula), each with a different tail dependence behavior.

MODEL SPECIFICATION AND ESTIMATION

Our estimation procedure include the following steps: first, we filter the original returns series with a GARCH model, secondly, we check to make sure that the marginal models are correctly specified before we transform the standardized residuals into i.i.d. Uniform (0,1). In the final step, we plug the probability integral transforms of the standardized residuals from the marginal models to the choice copulas. In the literature, this estimation method is referred to as the inference functions for the margins (IFM) method proposed by Joe and Xu (1996). The marginal distributions can be estimated either parametrically or non-parametrically. Joe (1997) points out that the IFM is a highly efficient method, and he proves that the IFM estimator is consistent and asymptotically normal under standard conditions. Because of its computational tractability, IFM method, either parametrically or semi-parametrically, has been widely used for multivariate copula applications.

The procedure we apply in stock markets is the same as in foreign exchange markets. We compare the performance of the copula models by examining the Akaike's information criterion and/or Bayesian information criterion.

Marginal models

We model the marginal distributions parametrically using GARCH type models. In the finance literature, a very common approach to model time series is the generalized autoregressive conditional heteroskedasticity (GARCH) model. In particular, we filter the raw returns data with a AR(*k*)-GARCH(*p*, *q*)or AR(*k*)-*t*-GARCH(*p*, *q*) type models. This type of models has been used in Bollerslev (1987), Patton (2006), and Ning (2010) among others. The marginal model is specified as follows:

$$r_{i,t} = C_i + \sum_k AR_{i,k} \times r_{i,t-k} + \varepsilon_{i,t} \tag{7}$$

$$\sigma_{i,t}^2 = Arch0_i + \sum_p Garch(p)_i \times \sigma_{t-p}^2 + \sum_q Arch(q)_i \times \varepsilon_{i,t-q}^2 \tag{8}$$

where $r_{i,t}$ is the returns for country *i* at time *t*, $\sigma_{i,t}^2$ is the variance of $\varepsilon_{i,t}$term in the mean equation (equation (7)). Estimation results of the marginal models are discussed in section 4.

Static copula models

Symmetrized Joe-Clayton copula (SJC)

Symmetrized Joe-Clayton (SJC) copula allows both upper and lower tail dependence and symmetric dependence as a special case. The SJC copula is a modified version of the Joe-Clayton copula (Joe 1997), as proposed by Patton (2006) and it is defined as follows.

$$\begin{aligned} &C_{SJC}(u, v|\lambda_r, \lambda_l) \\ &= 0.5 \cdot (C_{JC}(u, v|\lambda_r, \lambda_l) + C_{JC}(1-u, 1-v|\lambda_r, \lambda_l) + u + v - 1) \end{aligned} \tag{9}$$

where $C_{JC}(u, v|\lambda_r, \lambda_l)$ is the Joe-Clayton copula defined as follows:

$$\begin{aligned} &C_{JC}(u, v|\lambda_r, \lambda_l) \\ &= 1 - \left(1 - \{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma}\right)^{1/k} \end{aligned} \tag{10}$$

where $k = 1/\log_2(2 - \lambda_r)$, $\gamma = -1/\log_2(\lambda_l)$, and $\lambda_r \in (0,1)$, $\lambda_l \in (0,1)$. The drawback of the Joe-Clayton copula is discussed in Patton (2006).

SJC copula belongs to the Archimedean family of copulas and is very flexible since it allows for both asymmetric upper and lower tail dependence and symmetric tail dependence as a special case.

Clayton copula

Clayton copula belongs to the Archimedean Copula family and is known to have tail dependence. The bivariate Clayton copula can be written as the following

$$C_\theta^{Cl}(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \tag{11}$$

where $0 < \theta < \infty$ is a parameter controlling the dependence, $\theta \to 0^+$ implies independence, and $\theta \to \infty$ implies perfect dependence. Clayton copula can be used to describe lower (left) tail dependence and no upper (right) tail dependence. Like SJC copula, Clayton copula also belongs to Archimedean copula family.

Student's t-copula

The Student's t- copula is based on the multivariate t distribution, in the same way as the Gaussian copula is derived from the multivariate normal distribution. The copula of the bivariate Student's t-distribution with a degree of freedom of v and correlation ρ is

$$C_{v,\rho}^t(u,v) = \int_{-\infty}^{t_v^{-1}(u)} \int_{-\infty}^{t_v^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left\{1 + \frac{(s^2+t^2-2\rho st)}{v(1-\rho^2)}\right\}^{-(v+2)/2} dsdt \tag{12}$$

As the value of *v* increases, say *v* = 100, it approximates a Gaussian distribution. The bivariate Student's t-copula exhibits symmetric tail dependence and has the tail independent Gaussian copula as a special case. Student's t-copula belongs to the elliptical copula family, as does the Gaussian copula.

Dynamic copula model

To examine time-varying tail dependence in the returns series, we use the time-varying SJC copula, as proposed in Patton (2006).

$$\lambda t = \Lambda(\omega + \beta\lambda_{t-1} + \alpha \cdot \frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|), \tag{13}$$

where Λ denotes the logistic transformation to keep the tail dependency parameter of the SJC copula in [0,1] and it is defined as $\Lambda(x) = (1 + e^{-x})^{-1}$.

The dynamic copula model contains an autoregressive term designed to capture persistence in dependence and a forcing variable which is the mean absolute difference between *u* and *v*. The forcing variable is positive when the two probability integral transforms are on the same side of the extremes of the joint distribution and close to zero when they are on the same side of the extremes.

DATA AND EMPIRICAL RESULTS

Data

The dataset used consists of daily closing stock index returns and foreign exchange rate movements for five East Asian economies: Hong Kong, Indonesia, South Korea, Singapore and Taiwan. The stock indices are the Hang Seng Index of Hong Kong, the Jakarta SE Composite Index of Indonesia, the Korea Stock Exchange Stock Price Index (KOSPI), the Strait Times Stock Exchange of Singapore, and the Taiwan Stock Exchange Capitalization Weighted Index. The corresponding exchange rates are Hong Kong dollar (USD/HKD), Indonesia Rupiah (USD/IDR), Korean Won (USD/KRW), Singapore dollar

(USD/SGD), and Taiwanese dollar (USD/TWD). The returns datastart on 7/3/1997, and end on June 4, 2010. There are a total of 2772 observations for stock index returns and 3227 observations for the exchange rate returns. The bilateral spot exchange rates for the selected countries are expressed as units of U.S. dollar per unit of local currency. The stock index return is computed as:

$$\mathrm{r_t} = \ln(\frac{P_t}{P_{t-1}}) \tag{14}$$

where P_t is the stock index level at time *t*, and P_{t-1} is the stock index level at time t-1. The currency movement is computed as

$$e_t = \ln(\frac{\mathrm{S_t}}{\mathrm{S_{t-1}}}) \tag{15}$$

where $\mathrm{S_t}$ is the spot exchange rate at time *t* expressed as units of USD per unit of local currency, and $S_{t-1}$is the spot exchange rate at time t-1.The stock index returns from each country should represent the stock market performance of the country. We discuss the summary statistics and some properties of the returns distribution below.

TABLE 1 presents summary statistics of the log differences of stock index levels and exchange rate movements for each country. Panel A of the table presents the summary statistics of the stock index returns and Panel B reports those of the exchange rate returns. The high risk in the stock markets can be manifested from the table, ranging from 1.65% (Singapore) to 2.27% (South Korea), compared with much smaller mean returns for the sample period. Generally, the standard deviation of stock index returns is higher than that of exchange rate returns. All countries experienced positive average returns in the equity market except Taiwan. But the skewness measures all point to the fact that more negative returns are observed. The returns distribution in the currency market is more peaked than the stock market, as judged by the kurtosis measure for the returns series. In the table we also report the Jarque-Bera and Ljung-Box statistics. For all the cases, the Jarque-Bera test statistic strongly rejects the hypothesis of normally distributed stock index returns and currency movements at 5% significance level. The Ljung-Box statistic for raw returns, LB(20) is significant for all cases, implying serial dependencies in these returns. For squared returns, $\mathrm{LB}^2(20)$ is significant for all cases, showing significant evidence in support of GARCH effects. All these test statistics further confirm non-normality in our returns series and volatility clustering observed in most financial markets. We employ GARCH models to the return series to capture this property.

The unconditional linear correlation matrix and Kendall's tau for the stock index returns and foreign exchange rate returns are presented in Panel A and Panel B of TABLE2, respectively. The linear correlation coefficients observed for the stock index returns, ranging from 0.3435 (Indonesia and Taiwan) to 0.6953 (Hong Kong and Singapore), indicating that a rather large dependency between the stock markets is expected. For the exchange rate returns, the correlation is the smallest between Hong Kong dollar and Indonesian Rupiah (0.0340), and the largest between the Singapore dollar and Taiwanese dollar (0.3583).

Results of the marginal models

Given the stylized fact that financial market returns exhibit volatility clustering and are non-normally distributed, it is a crucial step to model the marginal distributions correctly to make sure that we have non-serially correlated probability integral transforms as copula model inputs. For all the stock index returns, in the mean model we set k = 10, and in the variance model, we set p = 1, and q = 1. TABLE 3 presents the GARCH model estimates for the stock index returns. Numbers in parentheses are standard errors. Serial correlation in the raw returns can be captured with up to an AR4 term for Hong Kong, Singapore and Taiwan, but higher terms are required for Indonesia (with significant AR6, AR9, and AR10 terms) and South Korea (AR7 is significant). GARCH(1,1) is sufficient to model the conditional heteroskedasticity for all the stock index returns series. Since the intercept term in the variance model is less than 0.0001 for all cases, and therefore not reported in the table.

The marginal models for the exchange rate returns are presented in TABLE 4. For the mean model of exchange rate returns, AR term is set to equal 10 for all cases except Indonesia (k = 5) to deal with serial correlation, and in the variance model, higher order of p and q terms are generally required to model the conditional variance. Hong Kong dollar returns series has significant Arch terms up to Arch10, but only the first three are reported in the table. For Indonesian Rupiah series, not only are the Arch1, Arch2, and Arch3 terms significant, but also is Garch8 term. The intercept term of both the mean and variance models are less than 0.0001 and thus not reported in the table. Only the highly significant autoregressive terms and GARCH terms (with a t-stat greater than 2.0) are reported in the tables.

For each marginal model, we perform goodness-of-fit test to test for serial independence of the standardized residuals and of the probability integral transforms. Ljung-Box Q-statistic is employed in conducting the tests and the test results on the first four moments of the probability integral transforms are reported in TABLE 5. For the stock index returns, the p-values range from 0.0796 to 0.9947 on the first four moments, indicating that the copula models will not be mis-specified. For the currency returns, most series past the test with p-value ranging from 0.1064 to 0.9268 except Hong Kong (p-value is 0.0004 for the fourth moment). We discuss the copula models in the following subsection.

Results of static copula models

Parameter estimates for the copula models, along with the log-likelihood values and the AIC (Akaike's information criterion) and BIC (Schwarz's Bayesian information criterion) are presented in tables from TABLE 6 to TABLE 9. We discuss the empirical results across the two financial markets separately.

Co-movements in stock markets

Why international stock markets move together? As put by Karolyi and Stulz (1996, pp.953), one possibility is "market contagion". Contagion effects occur when enthusiasm for stocks in one country brings about enthusiasm for stocks in other countries, regardless of the evolution of market fundamentals. Co-movements across international stock markets can also be explained using information hypothesis. The changes of stock prices in one market may reveal information on the fundamentals underlying the worldwide equity market and these price movements serve as signals to investors in other markets. It has been found that the co-movements during market downturns are different from market upward movements.

Our study covers five national stock markets and thus we have in total ten pairs. We report results for all ten pairs. The estimated tail dependence coefficients and degree of freedom parameters and the respective standard errors are presented in TABLE 6a, top panels of TABLE 7, TABLE 8, and TABLE 9. From the tables, we observe that in all ten pairs, there is obvious asymmetry between the dependencies in bear markets and bull markets. For example, our SJC copula results suggest that, the limiting probability of the Singapore stock market and Hong Kong stock market crashes together is about 34% greater than for the two stock markets booming together. The average tail coefficients range from 0.1628 (Indonesia-Taiwan pair) to 0.4428 (Hong Kong-Singapore pair), implying that the diversification benefits, if any, are much smaller by investing in the two more advanced markets (i.e. Hong Kong and Singapore) than two emerging markets (i.e. Indonesia and Taiwan).To explain this asymmetry, one possible reason is that investors are more sensitive to bad news than good news in other markets. Investors are loss aversion,and when a stock market crash occurs in a foreign country, they tend to take cautious action in domestic market as well. The estimated degrees of freedom from Student's t-copula range from 4.41 (Hong Kong-Indonesia pair) to 7.18 (Taiwan-Indonesia pair) are small, indicating that bivariate distribution is far from normal.

Co-movements in foreign exchange markets

Empirical studies of co-movements in foreign exchange markets usually focus on currency crisis, such as the 1997-1998 Asian currency crisis originated in Thailand (Corsetti et al. (1998)). There are multiple channels that currency crisis can be transmitted from one country to others. Two main channels are discussed in Eichengreen et al. (1996): trade links and similarity in macroeconomic and political situations. Countries having strong trade links are likely to transmit currency crises. Regarding the second point, it may be explained by the confidence of currency traders. Currency traders in one country may become skeptical if another country with similar economic and political situations suffers from crises.

Co-movements across the currency markets of the countries are quite different from stock market co-movements, as manifested from our empirical estimates. Copula results are reported in TABLE 6b, bottom panels of TABLE 7, TABLE 8, and TABLE 9. In the currency case, Hong Kong currency pairs stand out. We only detect weak lower tail dependency between US$/HKD and US$/SGD. There is not enough evidence to support extreme co-movements in the Hong Kong currency pairs. The estimated degrees of freedom parameter in the Student's t-copula also suggest a much thinner bivariate distribution tails than corresponding stock markets. The bivariate pairs for South Korea, Singapore and Taiwan exhibit strongest tail dependency with greater upper tail coefficients than lower tail coefficients. For Indonesia pairs, only the extreme co-movements between US$/IDR and US$/SGD are significant, with higher probability depreciating than appreciating together against U.S. dollar.

Dynamic tail dependence – time-varying SJC copula

TABLE 10 reports the result for the time-varying SJC copula models for the equity pairs and some selected currency pairs. For the equity pairs, most dynamic parameters are significant, indicating significant changes in the degree of tail dependence across pairwise stock markets. These results serve as evidence that the degree of tail dependence in these stock markets changes over time. We find insignificant change in the lower tail dependence of Hong Kong−South Korea pair and the upper tail dependence of Singapore−Taiwan pair. To illustrate how the degree of tail dependence evolves over time, we plot the lower and upper tail dependence coefficients, along with the estimated parameter value using static SJC copula, in Figures 1−10. The bottom plot in each figure shows the difference between lower and upper tail coefficients over time. The percentage of time that lower tail coefficient is greater than upper tail coefficient ranges from 62 percent (Hong Kong – Korea pair) to 90 percent (Hong Kong – Singapore pair), showing asymmetry of tail dependence with greater lower tail dependency than upper tail dependency overall. We observe the increasing degree of dependence in the upper tail (e.g. Hong Kong−Indonesia pair, Singapore−Indonesia pair) and/or lower tail (e.g. most Taiwan pairs) for some equity pairs since 2007, suggesting that these stock markets are in the process of becoming more integrated.

By examining the time path of the tail dependence coefficients for the selected currency pairs, we find no significant change in the lower and upper tail dependence of Korea−Taiwan pair and in the lower tail dependence of Singapore−Taiwan pair, as shown in Figure 12 and Figure 13. The conditional tail coefficients fluctuate around their respective mean value (the horizontal dashed line). The time path in the difference further confirms our earlier conclusion of asymmetry in the tail as 98 percent of the time that the upper tail coefficient is greater than the lower tail coefficient. In terms of asymmetry, this is also the case for Singapore−Taiwan currency pair. It is more likely that Taiwanese dollar tends to appreciate together with Korea Won and Singapore dollar than they depreciate together against USD. For the Singapore pairs (vs. Korea and Indonesia), there is not enough evidence to support asymmetry in the tail dependencies, even though there is significant change in the dynamics of tail coefficients (see Figure 11 and Figure 14).

Comparing the static and time-varying SJC models, we find the latter perform better than the former, as judged by the decreased Akaike's information criterion. By the same token, the dynamic SJC model performs slightly better than the static SJC model in modeling the currency co-movements. These two models produced very similar results regarding the degree of tail dependence.

CONCLUSION

In this paper we model the tail dependence structure across international financial markets. Specifically we use copula functions to model the pairwise extreme co-movements across the equity markets as well as across the currency markets of five East Asian economies over the period 1997−2010.

An important property of the copula function is that it is defined over i.i.d. uniform marginals. To ensure that we have the required inputs for the copula functions, we first filter the raw returns series using GARCH-type models and then we get the standardized residuals from this first step. Copula models inputs are the probability integral transforms of the i.i.d. standardized residuals from the marginal models. Comparisons of model performance are based on the Akaike information criterion and/or Bayesian information criterion.

The extreme co-movement across the five East Asian stock markets is found to be significant in both tails, with a larger lower tail dependence coefficient than an upper tail dependence coefficient. This is not the case in the currency markets. Our findings have important implications in international finance, especially for those investors who seek international diversification to improve asset allocation and overall portfolio returns.

ENDNOTES

1. The tables and figures are available from the author upon request.

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