ESSAYS ON TAIL BEHAVIOR AND EXTREME DEPENDENCE PATTERNS IN EAST ASIAN FINANCIAL MARKETS

by

FANGXIA LIN

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Terence Agbeyegbe

Date

Chair of Examining Committee

Merih Uctum

Date

Executive Officer

Professor Terence D. Agbeyegbe

Professor Thom B. Thurston

Distinguished Professor Michael Grossman

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

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Adviser: Professor Terence Agbeyegbe

This dissertation comprises of three essays organized into three separate chapters on tail behavior and extreme dependence patterns, with each chapter focusing on a specific aspect of the financial markets in several East Asian economies. In chapter one, "Tail Behavior in East Asian Stock Index Returns and Foreign Exchange Rate Movements", I analyze the tail behavior of the daily stock index returns and foreign exchange rate movements of six East Asian markets: Hong Kong, Indonesia, South Korea, Malaysia, Singapore, and Taiwan. I use extreme value theory (EVT), in particular, the generalized Pareto distribution (GPD), to understand the probability of extreme events and estimate the level of fatness in the tails of stock index returns as well as foreign exchange rate returns. Empirically, I find that, whether stock index returns and currency movements of a country have fatter left or right tail is very country specific. And for countries in the same geographical region, the tails of the returns distribution do not behave similarly as often claimed in the literature.

In chapter two, "Tail Dependence between Stock Index Returns and Foreign Exchange Rate Returns: A Copula Approach", I apply the concept of copula to model the

dependence patterns, especially in the tail area, between stock index returns and foreign exchange rate returns for five East Asian economies: Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. I first filter the raw returns series using AR(k)−GARCH(p, q) type models to make sure the probability integral transforms are i.i.d Uniform (0,1), and then I fit the resulting series to the copula models. Some major empirical findings are, for the two more advanced markets, namely Hong Kong and Singapore, there exists neither left nor right tail dependence between stock index returns and exchange rate returns for the period under examination. Two of the three emerging markets (Indonesia and South Korea) have much stronger left tail dependency than right tail dependency, indicating that the higher probability of double extreme losses than double extreme gains. Taiwan has symmetric tail dependence with similar right and left tail dependence coefficients.

In chapter three, "Extreme Dependence across East Asian Financial Markets: Evidence in Equity and Currency Markets", I investigate pairwise extreme dependencies across regional financial markets by directly estimating the degree of tail dependence via unconditional and conditional copulas. I apply the two-step inference functions for margins (IFM) method to model the extreme dependence patterns across stock markets as well as across currency markets. Empirically, I find significant asymmetric tail dependence in equity markets, with a larger left tail dependence coefficient than the right tail dependence coefficient. Mixed results are found for extreme co-movements in the foreign exchange markets. Extreme co-movements in the currency markets are much weaker, in several cases, with larger right tail coefficients. Using conditional copula, I also find significant changes in the degree of tail dependence for most of the equity pairs.

These results serve as evidence that the degree of tail dependence in these stock markets changes over time, suggesting that these stock markets are in the process of becoming more integrated.

In chapter four, “Summary of Findings”, I summarize the empirical results of this study and discuss the potential implications of these findings.

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Chapter 1

Tail Behavior in East Asian Stock Index Returns and Foreign Exchange Rate Movements

1.1 Introduction

This chapter is concerned with modeling the tail behavior of the foreign exchange rate movements and stock index returns in six East Asian economies (Hong Kong, Indonesia, South Korea, Malaysia, Singapore, and Taiwan) using extreme value theory (EVT)[1]. In particular, I use the generalized Pareto distribution (GPD) to investigate the question of fat tails and study how tail behavior varies between markets within a country and across countries in the same geographical region. The observed empirical distribution of financial returns is far from normal, often characterized as skewed and leptokurtotic, or fat-tailed relative to the normal distributions. This tail-fatness[2] of financial price changes was first pointed out by Mandelbrot (1963a, 1963b) and subsequently by Fama

[1] Extreme value theory is a branch of statistics dealing with the extreme deviations from the median of probability distributions. EVT is important for assessing risk for highly unusual events. There are basically two approaches often used in finance literature, one is to model extreme value using block maxima method, the other is to model them using the peaks-over-threshold method (POT).

[2] Fat tails are defined as tails of the distribution that have a higher density than what is predicted under the Gaussian assumption. For instance, a distribution that has a power decay of the density function in the tails is considered a fat tailed distribution, while a distribution that has an exponential decay, as in the normal or log-normal, as well as a distribution with a finite endpoint is considered thin tailed in the literature.

(1965). Stable distributions[3] were suggested in these earlier works as an alternative to the normal one. Though few question the notion of fat tails in the distribution of financial returns, there is no unique way to define the exact distributions in the finance literature. Rather than fitting a single distribution for the entire sample under examination, it is quite possible to investigate only the tails of the return distributions using limit laws, given that only the tails are important to the task at hand, such as value-at-risk (VaR)[4] in risk management practice. And the body of research in this direction has been growing.

EVT allows us to use tail observations to measure the density in the tail area. This measure can be extrapolated to parts of the distribution that have yet to be observed in the empirical data. It can also be mapped onto distributions with specific tail behavior. In this way we can simulate a theoretical process that captures the extreme features of the empirical data and improve the accuracy of estimated probabilities of extraordinary market movement, in the hope that we can better manage and hedge market risk.

In this chapter, I strive to answer the following questions: 1) are returns distributions in currency market and equity market asymmetric? I aim to demonstrate that if tail fatness is statistically different between extreme positive and negative realizations of the log difference distribution; 2) are fat tails more prevalent in currency market or

[3] In probability theory, a random variable is said to have stable distribution if it has the property that a linear combination of two independent copies of the variable has the same distribution, up to location and scale parameters.

[4] Value at Risk (VaR) is a widely used market risk measure of the risk of loss on a specific portfolio of financial assets, i.e. an equity portfolio. For a given portfolio, probability and time horizon, VaR is defined as a threshold value such that the probability that the loss on the portfolio over the given time horizon exceeds the value is the given probability level. For example, if a portfolio of equity has a one-week 99% VaR of $1 million, there is a 0.01 probability that the portfolio will fall in value by more than $1 million over a one-week period, assuming markets are normal.

equity market? Evidence of this would be consistent with the common view that currency returns have fatter tails than equity returns; 3) do markets in the same region exhibit similar tail behavior?

Extreme value theory (EVT) is initially applied in hydrology and climatology. Work applying extreme value theory in investigating the tail behavior of financial return can be traced back to early 1990s and the literature in this area has been growing ever since then. The study of tail behavior of foreign exchange rate returns are done by Koedijk et al. (1990) and Hols and de Vries (1991). Müller et al. (1998) and Pictet et al. (1998) study the probability of exceedances for the foreign exchange rates and compare them with GARCH models. The potentials and limitations of the EVT are investigated by Embrechts (1999, 2000a). Hartmann et al. (2003) use extreme value theory to analyze the behavior of currencies during crisis periods and their results show that Latin American currencies have less extreme dependence than East Asia currencies do. Jansen and de Vries (1991) investigate the distribution of extreme stock prices via non-parametric approach. They use daily data from 10 S&P 500 stocks spanning from 1962 to 1986 to exploit the asymptotic normality of the hill index. Loretan and Phillips (1994) use extreme value theory to analyze stock returns in the US and their results indicate the existence of second moments and possibly third and fourth moments, but not much more than the fourth moment. Longin (1996) examines the extreme movements of the U.S. stock market over a century of daily observations (1885−1990) and shows that the distribution of minima and maxima is a Fréchet distribution. Susmel (2001) uses extreme value theory to investigate the tail distributions for a group of international markets including developed markets and Latin American emerging markets and documents that the emerging markets have significantly fatter left tails than developed markets. Agbeyegbe (2002) studies the tail behavior of the Jamaican stock index returns and confirms a heavier left tail than a right one. Longin and Solnik (2001) use equity index data from developed markets to test for multivariate normality in both lower and upper tails via parametric multivariate approach. They document that tail correlations may reach zero in the upper tail but not in the lower tail. They also find that correlation is not related to market volatility per se but to the market trend, further implying the asymmetric tail distributions. Jondeau and Rockinger (2003) find almost no significant difference in the tail index either between tails or across markets. Their results relied on direct estimation of the scale, location and shape parameters of the extreme value observations. They construct likelihood ratio tests to estimate the significance of parameter differences. LeBaron and Samanta (2004) apply EVT and use non-parametric techniques to assess the significance of differences in tail thickness between the positive and negative tails of a given stock market and in the tail behavior of the developed and emerging regions. They find that lower tails are statistically significantly fatter than upper tails for a subset of markets in both regions. They also show that the tail index is statistically similar across countries within the same region. Kittiakarasakun and Tse (2010) apply the extreme value theory to characterize the returns distribution of Asian stock indices for the period 1989−2009. They show that the return distributions of the Asian market indices are fat-tailed with finite variance and conclude that the shape parameter in emerging markets is not significantly different from those of developed markets as represented by the S&P 500 index and the MSCI World index). For a comprehensive source of the extreme value theory to the finance and insurance literature, interested readers can refer to Embrechts et al. (1997) and Embrechts (2000a).

Similarity of this study to the existing literature lies in that it also investigates the tail behavior of international financial market returns. It is different from and contributes to the literature in the following ways: first, the data used in this study are different, which cover the 1997 Asian financial crisis started in Thailand and the most recent global financial crisis originated in the U.S.; secondly, I examine the tail behavior in the stock index returns as well as that of foreign exchange rate movements for the same countries. This allows us to compare the tail behavior across markets for each individual country. Many East Asian countries are experiencing rapid economic growth and this provides an attractive opportunity for global investors from industrialized countries to diversify their portfolio into this important geographical region. The empirical results of this study have potential implications for international diversification and portfolio construction, but I do not explore them here in this research.

My key empirical result indicates that the unconditional daily log difference distributions have different left and right tail behavior and the amount of tail mass is country specific in the same geographical region. The remainder of the chapter is organized as follows. Next section briefly reviews the basic concepts of extreme value theory. In section 1.3, I describe the data and methodology used in this chapter, and Section 1.4 summarizes the empirical results regarding the tail estimation for each country. I discuss the empirical evidence and offer concluding remarks in section 1.5.

1.2 The Methodology

In this section I present the parametric framework for my analysis. There are basically two approaches to model extreme events in the finance literature. One is directly modeling the distribution of block minima or maxima by the generalized extreme value distribution, and the other one is to model the excess of a high threshold in a dataset by the generalized Pareto distribution (GPD), a method commonly referred to as the Peaks-Over-Threshold (POT). The generalized Pareto distribution (GPD) was first introduced by Pickands (1975). Ever since then, it has been applied in many fields, including, but not limited to, use in the analysis of environmental extreme events and extreme financial returns. In this study I apply the generalized Pareto distribution to model extreme observations in stock index returns and foreign exchange rate returns.

1.2.1 The generalized extreme value distribution

The generalized extreme value (GEV) combines three simpler distributions into a single form, usually used to model the smallest or largest value among a large set of independent and identically distributed random observations. The three cases covered by the GEV are often referred to as the Type I, Type II, and Type III. Each type corresponds to the limiting distribution of block maxima from a different class of underlying distributions. Distributions whose tails decrease exponentially, such as the normal, lead to the Type I (Gumbel). Distributions whose tails decrease as a polynomial, such as Student’s t, belongs to the Type II (Frechet). Distributions with finite tails, such as the beta, lead to the Type III (Weibull).

The probability density function for the generalized extreme value distribution with location parameter θ, scale parameter σ, and shape parameter k is

$$f(x|k,\theta,\sigma) = \begin{cases} \left(\frac{1}{\sigma}\right) \exp\left(-\left(1+\mathrm{k}\frac{(\mathrm{x}-\theta)}{\sigma}\right)^{-\frac{1}{\mathrm{k}}}\right)\left(1+\mathrm{k}\frac{(\mathrm{x}-\theta)}{\sigma}\right)^{-1-\frac{1}{\mathrm{k}}}, & k \neq 0 \\ \left(\frac{1}{\sigma}\right) exp\left(-exp\left(-\frac{(x-\theta)}{\sigma}\right)-\frac{(x-\theta)}{\sigma}\right), & k = 0 \end{cases} \tag{1.1}$$

for $1 + k\frac{(\mathrm{x}-\theta)}{\sigma} > 0$.

1.2.2 The generalized Pareto distribution (GPD)

The generalized Pareto distribution (GPD) is a right-skewed limiting distribution and usually used to model the tails of another distribution. Let $(Y_1, \ldots, Y_n)$ be a sequence of independent and identically (i.i.d) random variables from an unknown distribution F. the distribution function of the excesses over the threshold u, is given by

$$F_u(x) = P\{X - u \leq x | Y > u\} = \frac{F(x+u) - F(u)}{1 - F(u)} \tag{1.2}$$

for $0 \leq x \leq x_0 - u$. $F_u(x)$ is the probability that a return exceeds the threshold u by no more than amount x, given that the threshold is exceeded. x_0 is defined as the finite or infinite right end point of the distribution. The resulting distribution from above is the generalized Pareto distribution (GPD). The GPD has three basic forms, each corresponding to a limiting distribution of exceedance data from a different class of underlying distributions. Distributions whose tails decrease exponentially, such as the normal, lead to a GPD shape parameter of $k = 0$. Distributions whose tail decreases as a polynomial, such as Student's t, lead to a positive shape parameter. Distributions whose tails are finite, such as the beta, lead to a negative shape parameter.

The probability density function for the generalized Pareto distribution (GPD) with shape parameter *k*, scale parameter σ, and threshold value u, is

$$f(x|k,\sigma,u) = \begin{cases} \frac{1}{\sigma}\left(1 + k\frac{(x-u)}{\sigma}\right)^{-1-1/k} & k \neq 0 \\ \frac{1}{\sigma}exp\left(-\frac{(x-u)}{\sigma}\right) & k = 0 \end{cases} \quad (1.3)$$

x is the exceedance data and the range of *x* is $u \leq x < +\infty$ for $k \geq 0$, and for $k < 0$, $u \leq x \leq u - \frac{\sigma}{k}$.

A number of other distributions are embedded in the generalized Pareto distribution. When *k* > 0, it takes the form of the ordinary Pareto distribution, which is the fat-tail case and most relevant for financial return analysis. The existence of moments is up to the integer of 1/*k*. For example, if *k* > 0.5, the exceedance data have an infinite variance. If the estimated shape parameter is less than 0.5, the returns have finite variance in the tail distribution (Dacorogna *et al.* 2001). In case of *k* = 0, the GPD corresponds to the exponential distribution with no upper bound, such as the normal. Notice that, for *k* < 0, the distribution has zero probability density for x > $-\frac{\sigma}{k}$, indicating a finite tail of the distribution. For the shapes of the GPD and its important properties, see Hosking and Wallis (1987). The shapes of generalized Pareto distributions for different values of *k* are also illustrated in Figure 1.1 in Appendix 1.

1.2.3 Estimation method

In the literature there are several estimators of the parameters in the GPD. Provided that the shape parameter $k < -0.5$, Hosking and Wallis (1987) shows that maximum likelihood method can be applied and the ML estimates are asymptotically normally distribution, and standard errors of the estimators can be computed through maximum likelihood estimation. And this is the method I adopt in estimating the tail parameters. The generalized Pareto distribution (GPD) is fitted to the exceedance data by the maximum likelihood method. Theoretically, the MLEs are most preferable because of their asymptotic efficiency. Other estimation methods include likelihood moment estimation (LME) and probability weighted moments (PWM). For a discussion of the different estimation methods, see Hosking and Wallis (1987). The key issue when applying EVT is the choice of threshold. I follow Agbeyegbe (2002), among others, to choose the threshold as 2.0 standard deviations away from the empirical mean of the return series for each country [5]. In particular, Extreme observations are defined as observations which are outside of two standard deviations. Exceedance data are obtained by subtracting the respective threshold from the extreme returns and then I fit the GPD model to these exceedance data.

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[5] There is no consensus on the best method to select the optimal threshold. Neftci (2000) defines the threshold as 1.645 of the unconditional variance of the data, which represents 5% of the observations under normal distributions. Longin and Solnik (2001) use Monte Carlo simulation method to select the threshold by optimizing the trade-off between variance and bias. In Frey and McNeil (2000), they apply the mean-excess plot to choose the optimal threshold.

I use the method of maximum likelihood to estimate the parameters. The log–likelihood function for a sample $x = \{x_1, \ldots, x_n\}$ is

$$\log L\,(x; k, \sigma) = -n\log\sigma - (1-k)\sum_{i=1}^{n} -k^{-1}\log(1 - \frac{kx_i}{\sigma}) \tag{1.4}$$

where x is the exceedance data, k is the shape parameter and σ is the scale parameter, n is the sample size.

1.3 Data

1.3.1 The data

The aim of this chapter is to provide cross-market as well as cross-country evidence for extreme returns. I don't make any assumption about what distribution of the returns series might follow. What I attempt to do is to obtain the shape parameter of the tail observations for the returns on the stock index and foreign exchange rate of several East Asian countries. The data used in this study consist of daily observations of the foreign exchange rate and stock index for the following six East Asian economies: Hong Kong, Indonesia, South Korea, Malaysia, Singapore, and Taiwan. The foreign exchange rate data are US$/HKD for the Hong Kong dollars, US$/IDR for Indonesian Rupiah, US$/KRW for South Korean Won, US$/MYR for Malaysian Ringgit, US$/SGD for Singapore dollar, and US$/TWD for Taiwanese dollar. All exchange rates are quoted in units of US$ per local currency. The stock index data are the Jakarta SE Composite Index of Indonesia, the Hang Seng Stock Index of Hong Kong, the Korea Stock Exchange Stock Price Index (KOSPI) of South Korea, the Kuala Lumpur Stock Exchange

Composite of Malaysia, the Singapore Strait Times Stock Index of Singapore, and the Taiwan Stock Exchange Capitalization Weighted Index of Taiwan[6].

1.3.2 Descriptive statistics

TABLE 1.1 provides univariate descriptive statistics of the log difference of the data series. Panel A shows the descriptive statistics for the log difference of stock index returns and Panel B shows those of the log difference of the foreign exchange rate returns. In the table I also display for the countries the starting dates of the data as well as the number of observations. All series end on June 4, 2010. The sample size ranges from 3034 for Indonesia up to 5497 for Hong Kong. The daily stock returns for country *i* is computed as

$$r_{i,t} = \log(\frac{p_{i,t}}{p_{i,t-1}}) \qquad (1.5)$$

where $P_{i,t}$ is the stock index level at time *t* and $P_{i,t-1}$ is the stock index level at time *t*-1 for country *i*.

The currency returns for country *i* is computed as:

$$e_{i,t} = \log(\frac{S_{i,t}}{S_{i,t-1}}) \qquad (1.6)$$

[6] These national stock indices are the representative stock market index of the corresponding countries, just like the S&P 500 in the U.S. and they are the main indicator of the overall stock market performance for the countries. Since we have different starting dates for the indices, in total, Hong Kong has 5497 observations, Indonesia has 3034 observations, South Korea has 3037 observations, Malaysia has 3951 observations, Singapore has 5437 observations, and Taiwan has 3066 observations.

where $S_{i,t}$ is the spot exchange rate at time *t* for country *i* expressed as units of US$ per unit of local currency, and $S_{i,t-1}$ is the spot exchange rate at time *t-1* for the exchange rate of country *i*.

Stock index returns

The average daily equity returns is positive for all countries except Taiwan (−0.0064 percent). Indonesia has the highest average daily return of 0.043 percent, followed by Hong Kong (0.0351 percent). These two countries have similar standard deviations around 1.8 percent. Korea and Singapore have similar average daily returns (0.02 percent), with Korea having a much higher standard deviation than Singapore (2.12 percent vs. 1.32 percent). The sample skewness shows that all the sample daily returns have asymmetric distribution. All countries except Malaysia have negative skewness, with values ranging from −2.44 for Hong Kong to −0.12 for Indonesia and Singapore. The sample skewness measure is 0.40 for Malaysia. This indicates that the asymmetric tail extends more towards negative values for most returns series. The highest (Max) and lowest (Min) one day return are also reported in the table for each country. Highest returns are in the range of 8.5 percent (Taiwan) to 20.8 percent (Malaysia), while the lowest returns spread from a striking −24.52 percent (Hong Kong) to −9.9 percent (Taiwan).

According to the sample kurtosis estimates, the daily log differences are far from normally distributed. For the stock index returns, the lowest kurtosis estimates are 5.4 (Taiwan) and 6.7 (Korea) while the highest estimates are Malaysia (37.3) and 18.5 (Hong

Kong). Based on the sample kurtosis estimates, returns data all confirm the fat-tailness. Study of the QQ-plots of each return series also confirms that the return distributions have fat tails. Furthermore, I test for normality using the Jarque-Bera test, J-B stat, which follows a chi-squared distribution with two degrees of freedom. In all cases the Jarque-Bera statistics is very large implying non-normality of the series.

Foreign exchange rate returns

Since the foreign exchange rate is measured in USD per local currency, therefore, a positive (negative) change indicates appreciation (depreciation) of the local currency. For my sample period, on average, most of the emerging market currencies depreciated against U.S. dollars, with Indonesian Rupiah (−0.041 percent) depreciated the most over the sample period. Singapore dollar has a positive average return. Taiwan dollar and Hong Kong dollar have zero average return over their respective sample period. Indonesia Rupiah and South Korea Won are the most volatile as measured by the standard deviation, with the highest standard deviation of 1.92 percent for Indonesia currency, followed by 1.15 percent for Korean Won. Sample skewness measures are mixed for the currencies, with Hong Kong, Indonesia, South Korea, and Taiwan having more negative observations and Malaysia, and Singapore positively skewed. Sample kurtosis measures are especially high for Hong Kong (167.92) and South Korea (102.75). Singapore (16.19) and Taiwan (19.46) had the least sample kurtosis measures. Again, Jarque-Bera stat rejects the normality test for all the currency returns.

1.3.3 Tail observations

TABLE 1.2 focuses on the extreme observations in my sample data. Extreme observations are defined as observations outside of two standard deviations. The mean, standard deviation values of the lower and upper tail observations along with the respective thresholds are presented in the table. n is the number of extreme observations in the corresponding series. Exceedances are obtained by subtracting the respective threshold from the extreme returns and then I fit the GPD model to these exceedance data. The following section discusses the estimation results.

1.4 Empirical Results

TABLE 1.3 lists the maximum likelihood estimates of the parameters of the generalized Pareto distribution (GPD), along with the maximized log likelihood values for each return series. The top panel reports the estimation results for stock index returns and bottom panel reports the results for currency returns. Overall, the standard errors indicate that the relative precision of the estimate for shape parameter, k, is lower than that for the scale parameter, σ. All the estimates for the scale parameter are statistical significant at one percent level. I discuss the estimated shape parameters for the two markets in more details below.

Tail behavior of equity returns

Inspection of the point estimates of the left tail and right tail shape parameters and associated standard errors reveals that not all emerging stock market returns have fat tail distributions as often claimed in the literature. For the upper tail, the estimated shape parameter ranges from −0.1795 for Taiwan to 0.5991 for Malaysia. For the lower tail, the estimated shape parameter ranges from −0.0087 for Korea and 0.4302 for Hong Kong. For Hong Kong, Malaysia and Singapore, the estimated shape parameters of the lower and upper tails are significantly positive, indicating that their stock index returns all have significant fat right and left tails, though the degree of fatness is different for these countries as gauged by the shape parameter. Malaysia has a fatter right tail (0.5991) compared to the left tail (0.3842), whereas Hong Kong has similar tails, with a left tail shape parameter estimate of 0.3274 and a right tail estimate of 0.3436. The point estimates for both tails (left tail is 0.2354 and right tail is 0.1861) of Singapore stock index returns imply a fatter left tail relative to the right tail, but they are not significantly different from each other. It is a different story for the rest of the countries. Even though the sample excess kurtosis is different from zero for South Korea and Indonesia stock index returns, both left and right tail estimates are not statistically significantly different from zero, implying that they have thin-tailed return distributions. As for Taiwan, it seems to exhibit a truncated upper tail (−0.1795) though theoretically returns have no upper limit. This might be explained by the limited price movements imposed by the regulations on the country's stock market[7]. The estimated shape parameter of its left tail is not significantly different from zero, indicating a thin left tail.

[7] It is said that there is a seven percent limit in the daily stock price movements in the Taiwan Stock Exchange and the limit on Korean Stock Exchange is twelve percent. The minimum and maximum of the sample data are −12.80 percent and 12.06 percent for Korea stock index returns and −9.94 percent and 8.52 percent for Taiwan stock index returns.

Tail behavior of currency returns

Bottom panel of TABLE 1.3 presents the estimated parameters of the GPD for the currency returns of the selected markets along with the maximized likelihood values. Hong Kong, Singapore, and Taiwan have significant fat tails on both sides of the return distributions. The point estimates of the two tails for Hong Kong and Taiwan are very close. For Singapore, the estimated shape parameter for the upper tail is higher than that of the lower tail, implying a fatter right tail, but they are not significantly different from each other. For Indonesia and Malaysia, it seems that the right tail is fatter than the left tail, while I don't have enough evidence to support a lower fat tail. For South Korean Won, there is evidence to support a lower fat tail but not the upper tail.

By comparing the fatness of the tails based on the point estimates across markets, I can draw the following conclusions: the right tails of currency returns for Indonesia and Singapore are fatter than that of the stock index returns; Hong Kong, South Korea, and Taiwan have both fatter tails in the currency returns than stock index returns; in the case of Malaysia, its stock index returns has both a fatter left and right tail than the currency returns. There are very important implications from these findings. Financial returns for different emerging markets exhibit very different tail behavior and it is country specific. For an investor interested in international diversification, attention to the specific tail behavior of any individual market is warranted. He/she needs to explicitly calibrate the tail behavior of each market and allow for differing levels of tail fatness between markets and across different countries. From this study, the empirical results don't support the statement that emerging market financial returns have fatter tails than developed ones, as often claimed in the literature.

1.5 Conclusion

The aim of this chapter is to use the extreme value theory to analyze six East Asian financial markets: two advanced markets (Hong Kong and Singapore) and four emerging markets (Indonesia, South Korea, Malaysia, and Taiwan). The main objective is to identify what is the tail behavior in the stock market returns and foreign exchange rate fluctuations in this geographical region. Understanding the influence of extreme market events on financial returns is of great importance to market risk managers. By modeling the extreme observations separately from observations under normal market conditions, risk managers are able to obtain a more conservative measure of value at risk (VaR) of the portfolio.

My empirical results indicate that the generalized Pareto distribution (GPD) fits the tails of the return distributions in these markets reasonably well. The results also indicate that the daily return distributions have different left and right tail characteristics. Therefore, the risk and reward are not equally likely in the financial markets of these economies. Regarding the three questions in the introduction section, I don’t have a clear yes or no answer to any one of them. The following conclusions can be drawn from this study: 1) the daily price movements have different characteristics at left and right tails across country and across markets; 2) not all return series exhibit fat tail behavior, judged by the estimated shape parameter; 3) as I have shown in this study, markets in the same geographical region and across markets in the same country have variant tail behavior.

In this chapter I consider the individual behavior of stock index returns and foreign exchange rate movements. I find for nearly all returns series a tail behavior compatible with the existence of the first and second moments. For some even higher moments seem to exist. In the area of risk management for emerging market investments, an accurate measure and understanding of market specific tail behavior is critical to hedging risk in these markets. For an investor interested in international diversification the study of cross-market co-movement may also be of great importance because it will affect the portfolio returns. Therefore, a natural extension of this study will on be the co-movements between financial markets within a country, especially in the tail area. I will focus on this task in the following chapter.

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Appendix 1: Tables and Figures for Chapter 1

TABLE 1.1: Summary statistics of the log difference of the stock index and foreign exchange rate

Country	Hong Kong	Indonesia	Korea	Malaysia	Singapore	Taiwan
Starting date	11/2/1987	7/2/1997	7/2/1997	12/3/1993	12/28/1987	7/2/1997
Obs	5497	3034	3074	3951	5437	3066
Panel A: Stock index						
Mean	0.0004	0.0004	0.0002	0.0001	0.0002	−0.0001
Std	0.0175	0.0187	0.0217	0.0159	0.0134	0.0169
Max	0.1725	0.1313	0.1206	0.2082	0.1287	0.0852
Min	−0.2452	−0.1273	−0.1280	−0.1925	−0.1054	−0.0994
Skew	−0.4794	−0.0749	−0.0970	0.8129	−0.0673	−0.1416
Kurtosis	18.5473	8.9916	6.6713	37.3242	11.3275	5.3880
J-B stat	***55574.5	***4541.1	***1731.2	***194388.7	***15714.3	***738.7
LB(20)	***63.1	***131.6	***43.7	***42.6	***92.1	**36.7
$LB^2(20)$	***1471.7	***1007.5	***1636.4	***1012.1	***2233.1	***673.0
Panel B: Currency						
Mean	0.0000	−0.0004	−0.0001	−0.0001	0.0001	0.0000
Std	0.0005	0.0197	0.0105	0.0057	0.0036	0.0032
Max	0.0127	0.2332	0.1100	0.1282	0.0404	0.0336
Min	−0.0130	−0.3019	−0.1344	−0.0709	−0.0272	−0.0340
Skew	−0.0979	−1.4193	−0.9425	2.8303	0.6700	−0.4944
Kurtosis	167.9241	53.5803	40.6763	102.7384	15.8255	21.0622
J-B stat	***6229934.0	***324438.9	***182269.4	***1642924.0	***37671.7	***41802.3
LB(20)	***495.7	***144.0	***434.0	***350.5	***113.1	***81.1
$LB^2(20)$	***1313.7	***2904.7	***4872.9	***1744.7	***3486.7	***410.0

Note: This table presents summary statistics for the log difference of the stock index and foreign exchange rates for the selected East Asian economies. All data series end with June 4, 2010. The first line of the table indicates the date when the series start. Obs is the number of observations in each series. The Jarque-Bera (JB) test, which follows a chi-square distribution with two degrees of freedom, was used to determine normality of the returns distribution. The J-B stat rejects the normality test of the return series. LB(20) and $LB^2(20)$ denote the Ljung-Box test statistics for up to the 20^{th} order autocorrelation of the raw and squared returns, respectively.

and * indicates 5% and 1% statistical significance level, respectively.

TABLE 1.2: Summary statistics of the tail observations.

	Lower tail				Upper tail			
Country	n	Mean	Std	Threshold	n	Mean	Std	Threshold
Stock Index								
Hong Kong	147	−0.0518	0.0251	−0.0346	120	0.0523	0.0229	0.0354
Indonesia	90	−0.0535	0.0183	−0.0370	78	0.0562	0.0186	0.0379
Korea	87	−0.0608	0.0176	−0.0432	91	0.0606	0.0159	0.0437
Malaysia	83	−0.0511	0.0284	−0.0318	77	0.0563	0.0367	0.0319
Singapore	144	−0.0398	0.0157	−0.0267	138	0.0402	0.0154	0.0271
Taiwan	96	−0.0454	0.0116	−0.0339	80	0.0457	0.0103	0.0337
Currency								
Hong Kong	76	−0.0019	0.0015	−0.0010	86	0.0019	0.0015	0.0010
Indonesia	55	−0.0857	0.0499	−0.0399	54	0.0722	0.0414	0.0390
Korea	61	−0.0418	0.0243	−0.0211	47	0.0414	0.0227	0.0209
Malaysia	84	−0.0215	0.0112	−0.0116	64	0.0240	0.0185	0.0114
Singapore	130	−0.0104	0.0038	−0.0071	125	0.0115	0.0056	0.0072
Taiwan	72	−0.0105	0.0052	−0.0065	72	0.0100	0.0045	0.0064

Note: This table presents the summary statistics of the extreme movements in the stock and currency markets. n is the corresponding number of observations above each respective threshold. Sample Maxima and Minima are the observations the two standard deviations away from the estimated mean value of the log difference. Std stands for standard deviation. Threshold is defined as two standard deviations above/below the mean of the log difference.

TABLE 1.3: Maximum Likelihood Estimates (MLE) of the parameters of the GPD model.

	Panel A: Left Tail *k*	S.E.	σ	S.E	*llv*	Panel B: Right Tail *k*	S.E.	σ	S.E.	*llv*
Stock Index										
Hong Kong	0.3274	0.1114	0.0116	0.0016	−459.6	0.3436	0.1283	0.0113	0.0018	−376.4
t-stat	***(2.9391)		***(7.3553)			***(2.6780)		***(6.4799)		
Indonesia	0.1256	0.1292	0.0145	0.0024	−280.0	0.0106	0.1248	0.0181	0.0031	−234.1
t-stat	(0.9727)		***(6.0171)			(0.0853)		***(5.9339)		
Korea	−0.0087	0.1106	0.0178	0.0027	−264.3	−0.0837	0.1042	0.0184	0.0027	−280.2
t-stat	(−0.0784)		***(6.4918)			(−0.8031)		***(6.7768)		
Malaysia	0.3842	0.1495	0.0122	0.0022	−250.9	0.5991	0.1949	0.0118	0.0025	−218.9
t-stat	***(2.5693)		***(5.5358)			***(3.0744)		***(4.6471)		
Singapore	0.2354	0.1131	0.0102	0.0014	−482.5	0.1861	0.1133	0.0107	0.0015	−461.9
t-stat	***(2.0812)		***(7.1892)			*(1.6430)		***(7.1010)		
Taiwan	0.0006	0.1141	0.0115	0.0018	−332.6	−0.1795	0.0937	0.0141	0.0020	−275.2
t-stat	(0.0057)		***(6.5333)			*(-1.9155)		***(6.9205)		
Currency										
Hong Kong	0.4652	0.1741	0.0005	0.0001	−464.8	0.4781	0.1623	0.0005	0.0001	−531.1
t-stat	***(2.6727)		***(4.9625)			***(2.9453)		***(5.3208)		
Indonesia	0.0888	0.1617	0.0419	0.0088	−114.7	0.2286	0.1691	0.0258	0.0055	−131.2
t-stat	(0.5488)		***(4.7566)			(1.3517)		***(4.6545)		
Korea	0.2446	0.1847	0.0159	0.0035	−176.8	0.1658	0.2121	0.0172	0.0044	−136.0
t-stat	(1.3245)		***(4.4940)			(0.7819)		***(3.9025)		
Malaysia	0.1460	0.1395	0.0085	0.0015	−303.8	0.3620	0.1849	0.0082	0.0018	−219.9
t-stat	(1.0467)		***(5.6687)			**(1.9579)		***(4.5760)		
Singapore	0.2472	0.1570	0.0026	0.0005	−611.5	0.3222	0.1406	0.0030	0.0005	−560.0
t-stat	(1.5743)		***(5.6010)			**(2.2914)		***(6.0931)		
Taiwan	0.2641	0.1428	0.0030	0.0005	−355.1	0.2552	0.1612	0.0027	0.0005	−335.6
t-stat	(1.8495)		***(5.5633)			(1.5835)		***(5.0660)		

Note: Top panel of this table reports the maximum likelihood estimates of the scale (σ) and shape (*k*) parameters of the generalized Pareto distribution of the equity returns. The column labeled *llv* presents the maximized log likelihood value. SE is the standard error of the estimates. Bottom panel of this table reports the maximum likelihood estimates of the scale (σ) and shape (*k*) parameters of the generalized Pareto distribution of the currency data. The column labeled *llv* is the maximized log likelihood value. S.E. is the standard error of the estimates. The numbers in parentheses are t-statistics.
***indicates 1% statistical significance level. **indicates 5% statistical significance level. *indicates 10% statistical significance level.

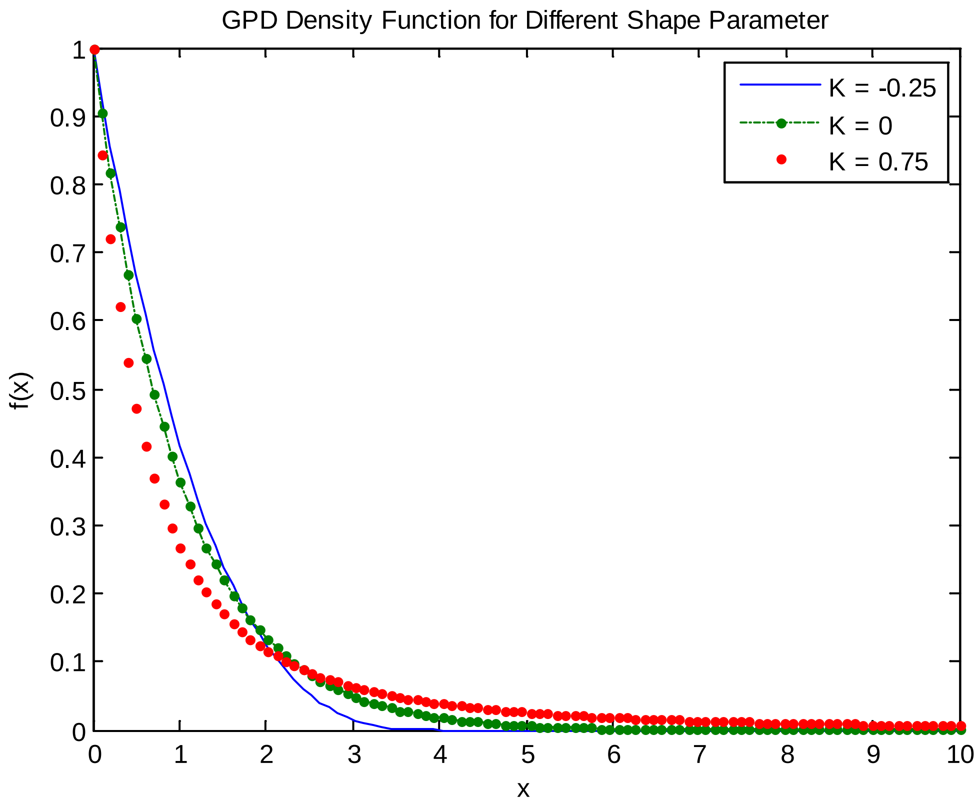

Figure 1.1

Note: Figure 1.1: This figure plots the GPD density functions for 3 different shape parameter, given that $\sigma = 1$ and $\mu = 0$. Notice that, for $k < 0$, the distribution has zero probability density for $x > -\sigma/k$, and for $k \geq 0$, there is no upper bound.

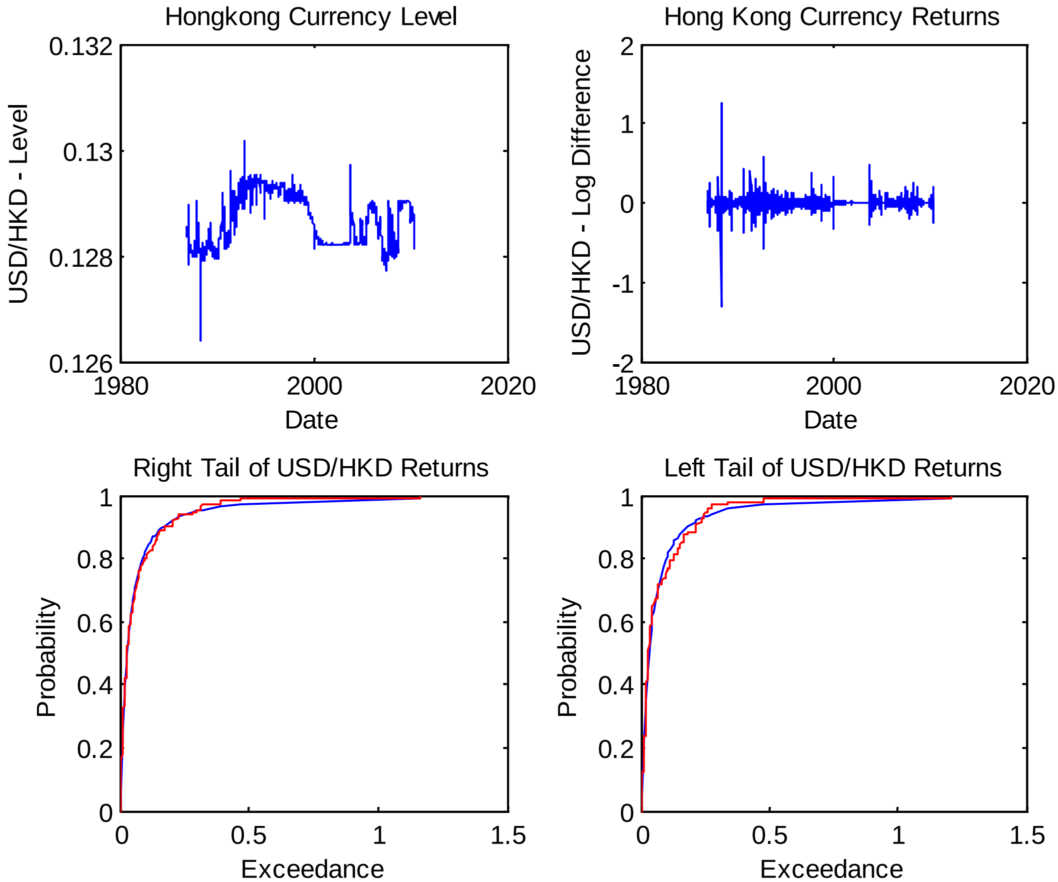

Figure 1.2a

Note: Figure 1.2a: Top panel shows Hong Kong currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Hong Kong currency extreme returns. The left plot is for the right tail of returns whereas the right side plot corresponds to the left tail.

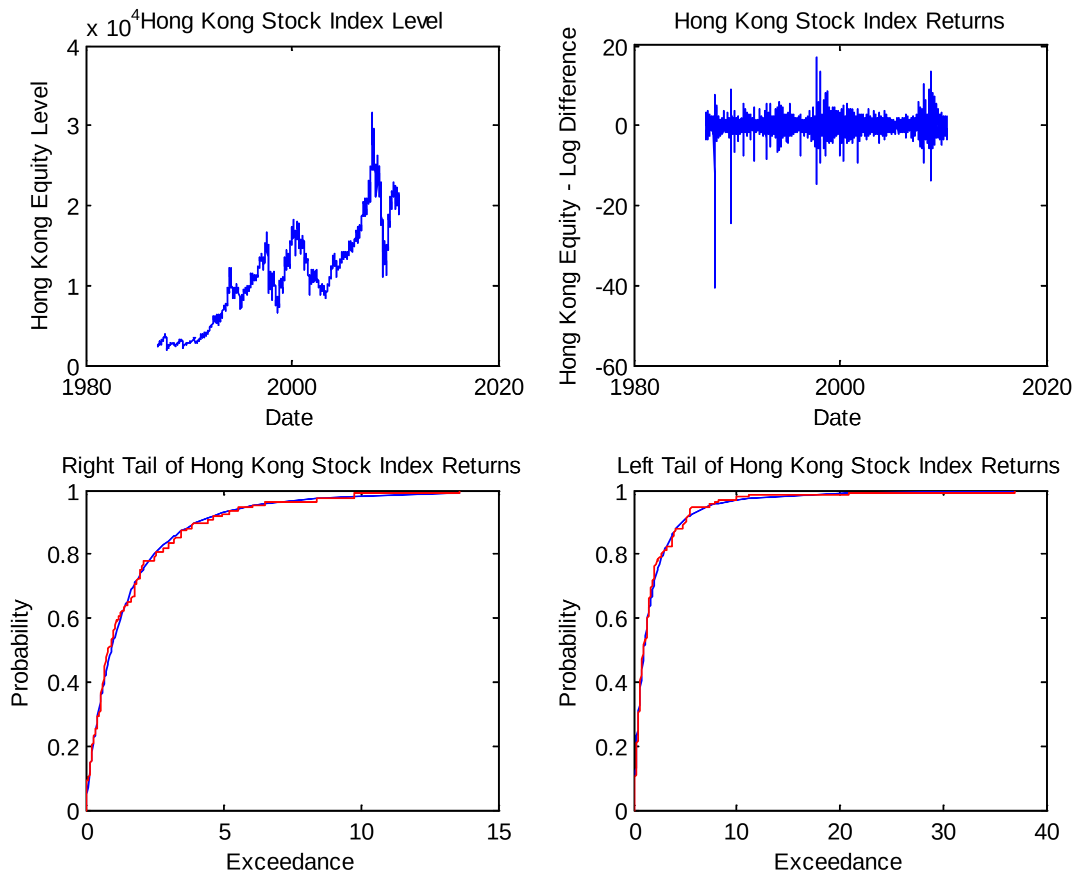

Figure 1.2b

Note: Figure 1.2b: Top panel shows Hong Kong equity market level and log difference. The Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Hong Kong equity extreme returns. The left plot is for the right tail of returns whereas the right side plot corresponds to the left tail.

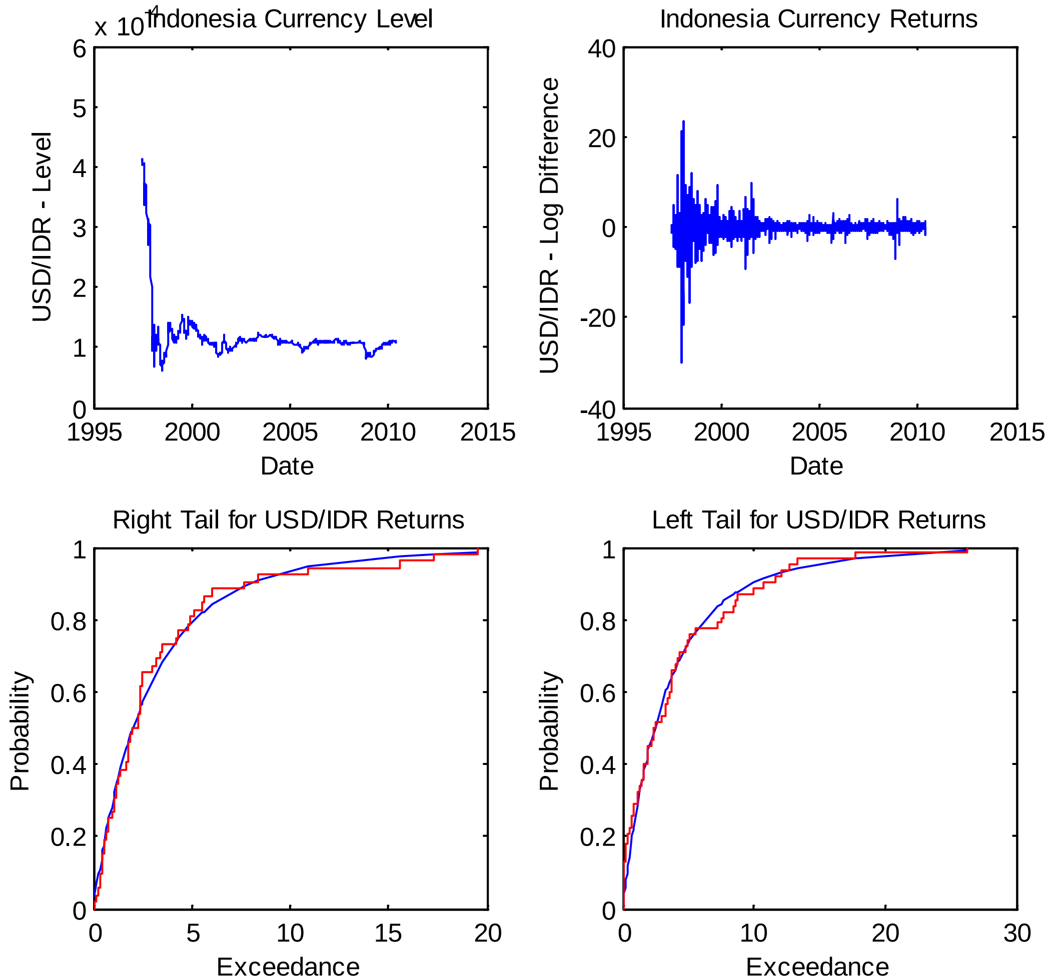

Figure 1.3a

Note: Figure 1.3a: Top panel shows Indonesia currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Indonesia currency extreme returns. The left plot is for the right tail of returns whereas the right side plot corresponds to the left tail.

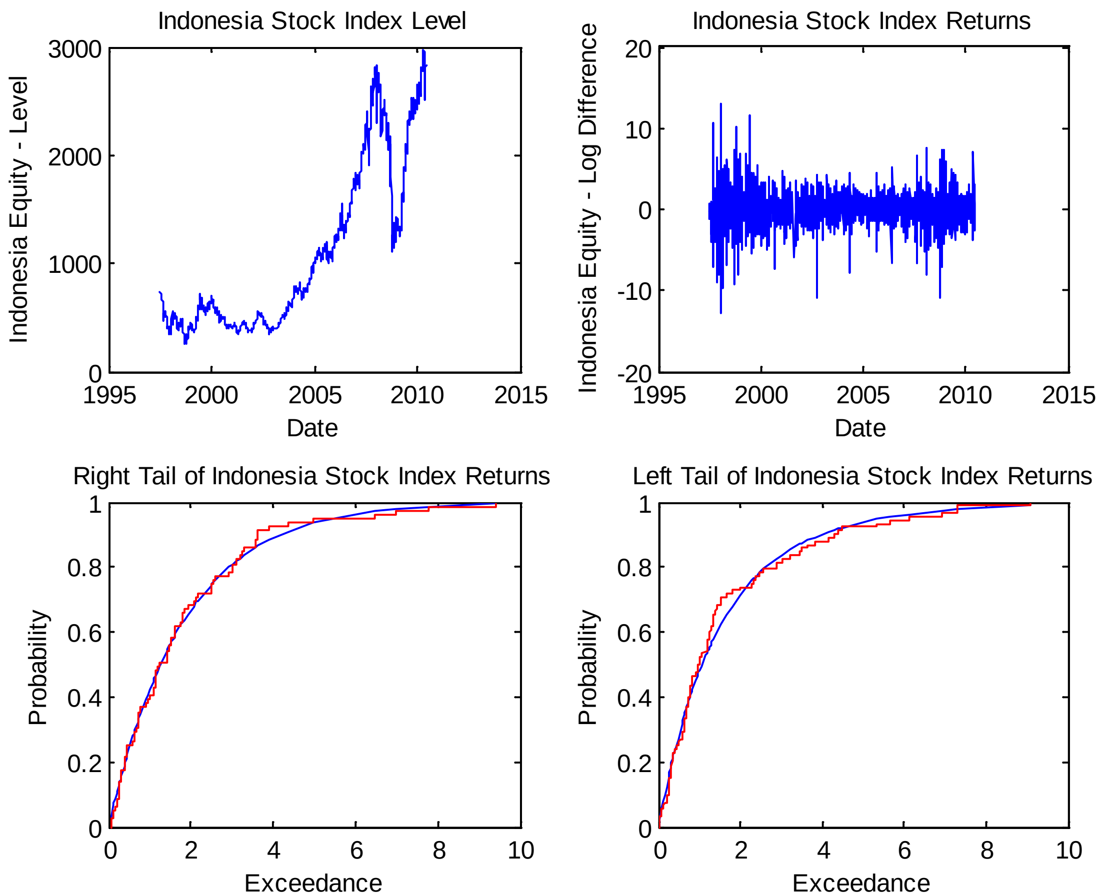

Figure 1.3b

Note: Figure 1.3b: Top panel shows Indonesia equity market level and log difference. The Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Indonesia equity extreme returns. The left plot is for the right tail of returns whereas the right side plot corresponds to the left tail.

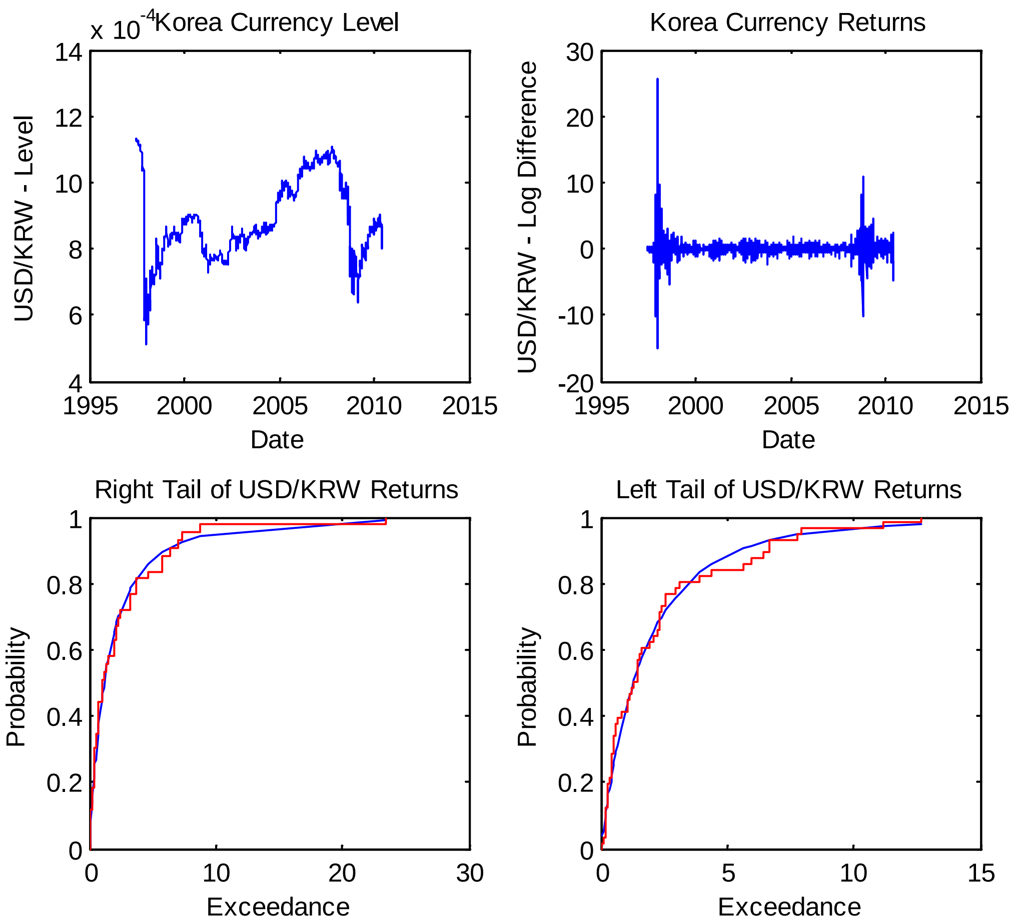

Figure 1.4a

Note: Figure 1.4a: Top panel shows Korea currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Korea currency extreme returns. The left plot is for the right tail of returns whereas the right side plot corresponds to the left tail.

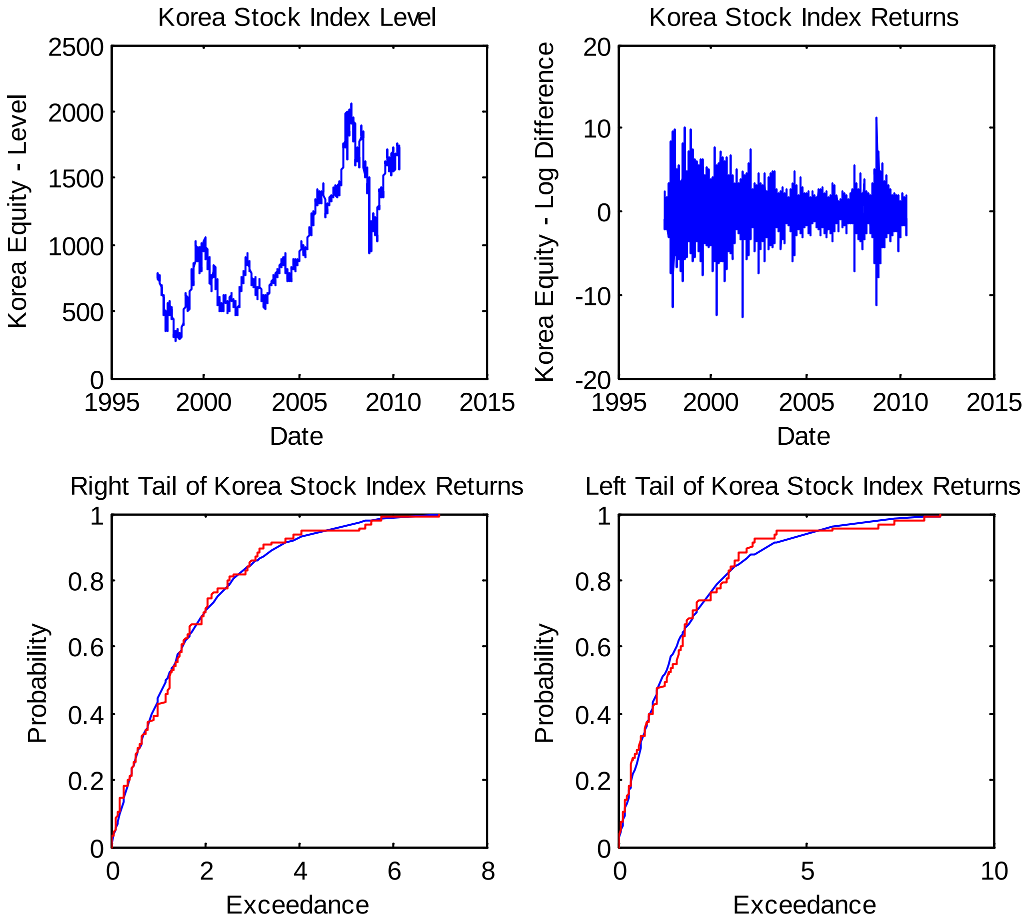

Figure 1.4b

Note: Figure 1.4b: Top panel shows Korea equity market level and log difference. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Korea equity extreme returns. The left graph is for the right tail of returns whereas the right side graph corresponds to the left tail.

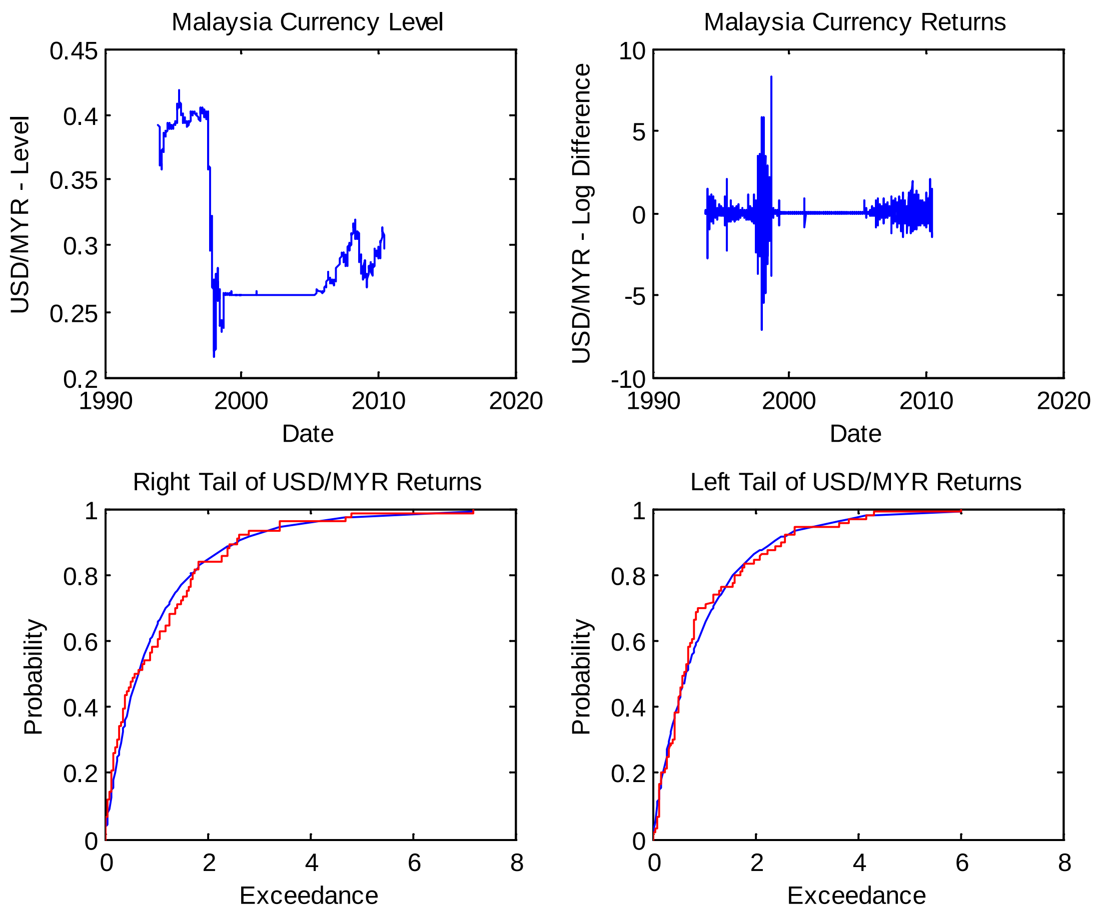

Figure 1.5a

Note: Figure 1.5a: Top panel shows Malaysia currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line against the empirical distribution function for Malaysia currency extreme returns. The left plot is for the right tail of returns whereas the right plot corresponds to the left tail.

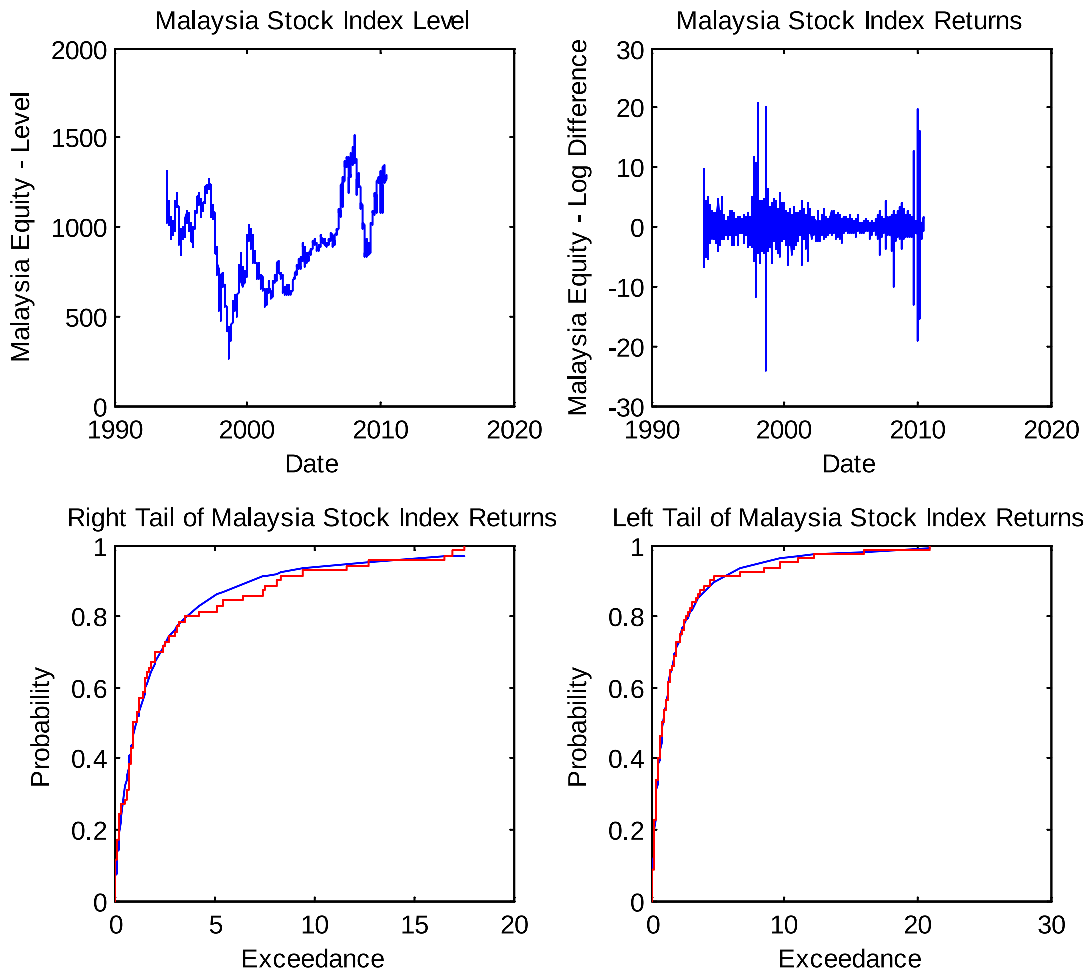

Figure 1.5b

Note: Figure 1.5b: Top panel shows Malaysia equity market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Malaysia equity extreme returns. The left graph is for the right tail of returns whereas the right side plot corresponds to the left tail.

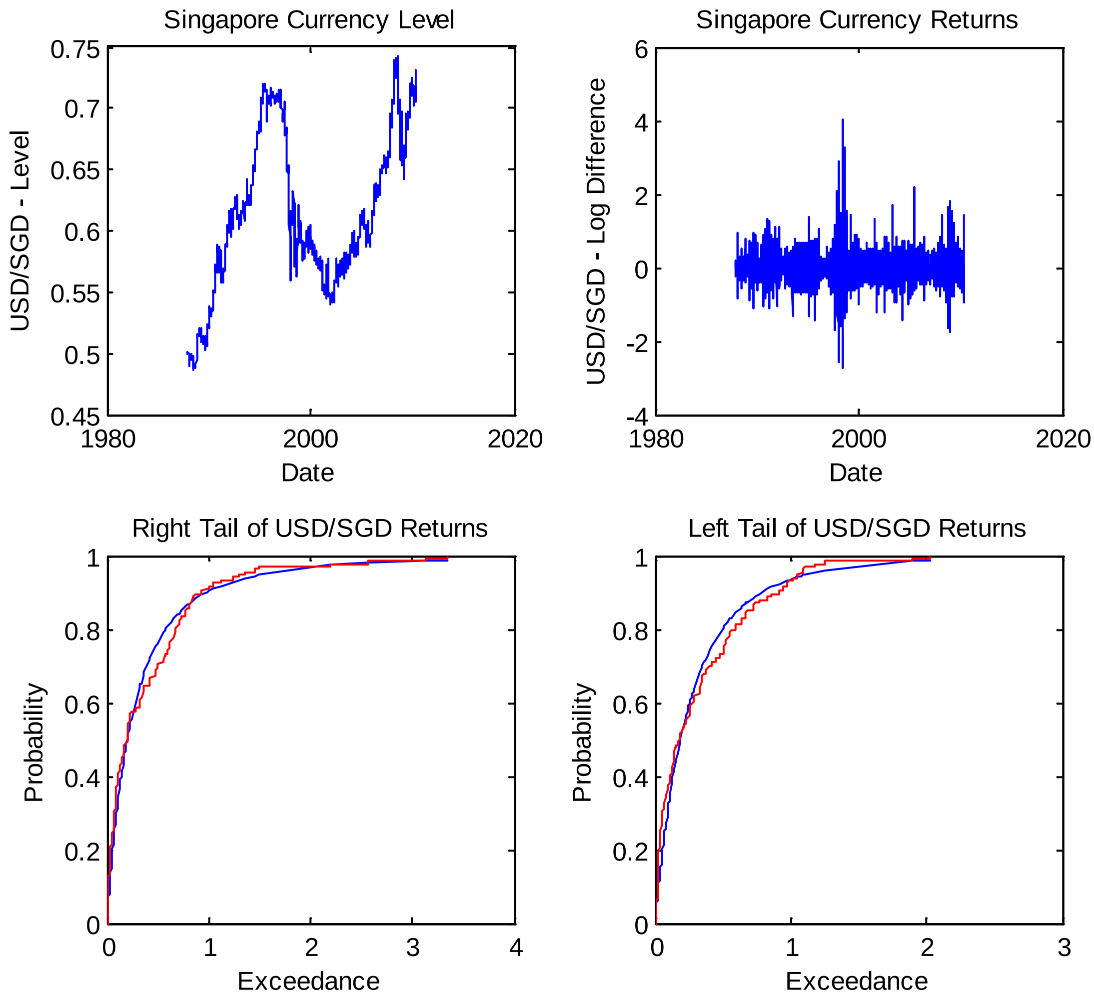

Figure 1.6a

Note: Figure 1.6a: Top panel shows Singapore currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Singapore currency extreme returns. The left graph is for the right tail of returns whereas the right side graph corresponds to the left tail.

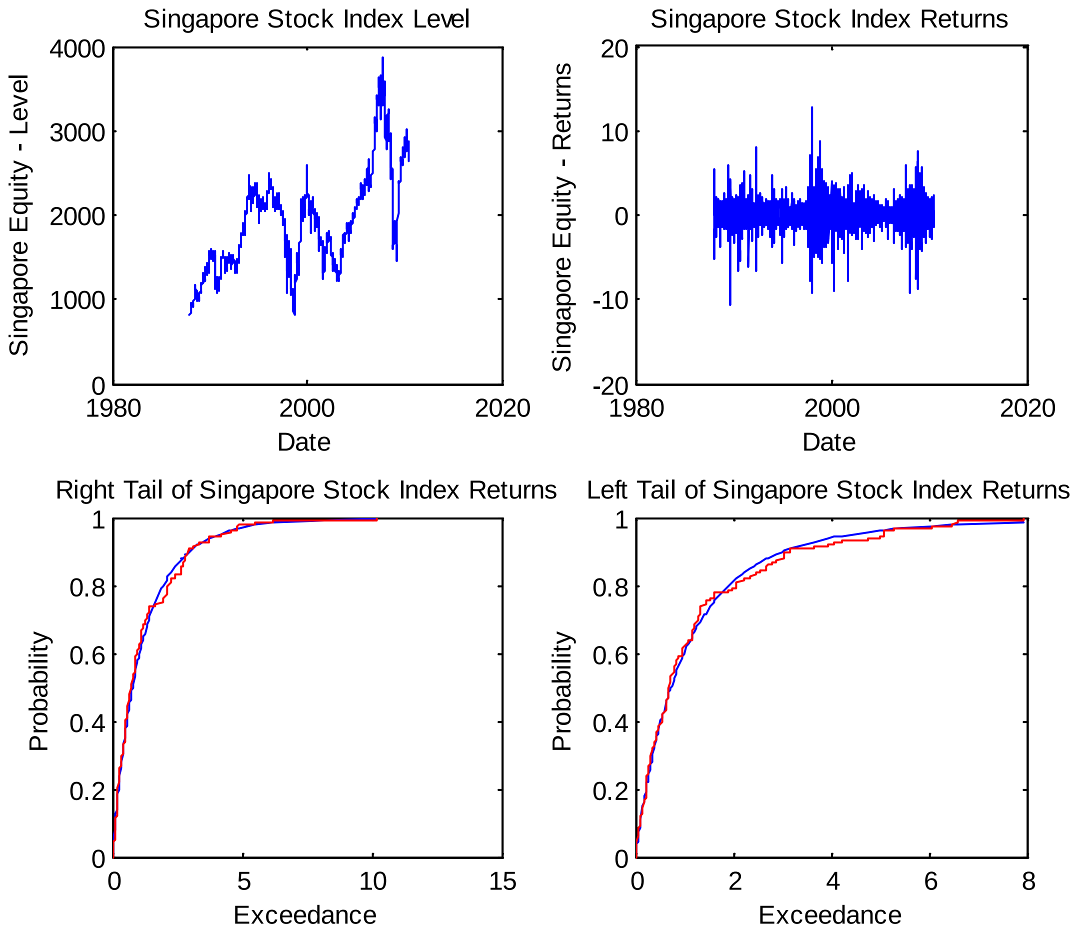

Figure 1.6b

Note: Figure 1.6b: Top panel shows Singapore equity market level and log difference. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Singapore equity extreme returns. The left graph is for the right tail of returns whereas the right side graph corresponds to the left tail.

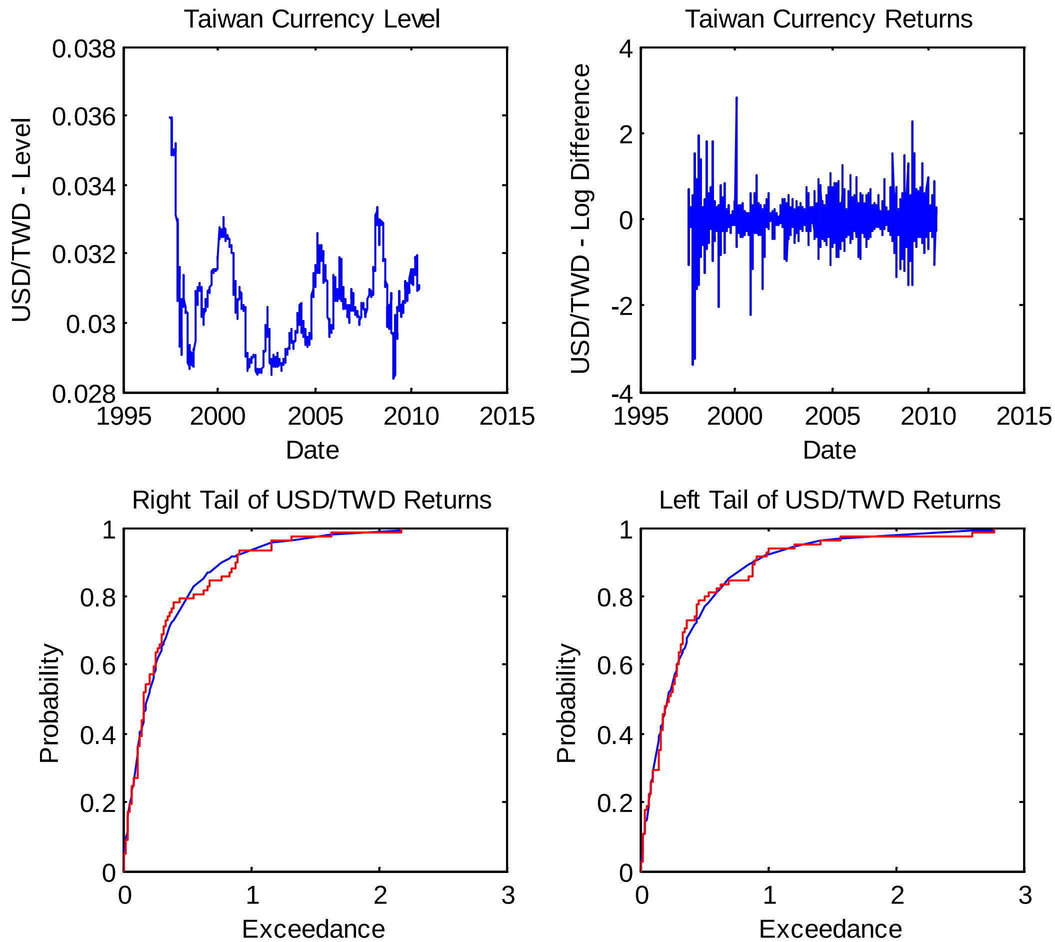

Figure 1.7a

Note: Figure 1.7a: Top panel shows Taiwan currency market level and log difference. The impact of the massive devaluation of the Thailand Baht in July 1997 is visible in the graph. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Taiwan currency extreme returns. The left graph is for the right tail of returns whereas the right side graph corresponds to the left tail.

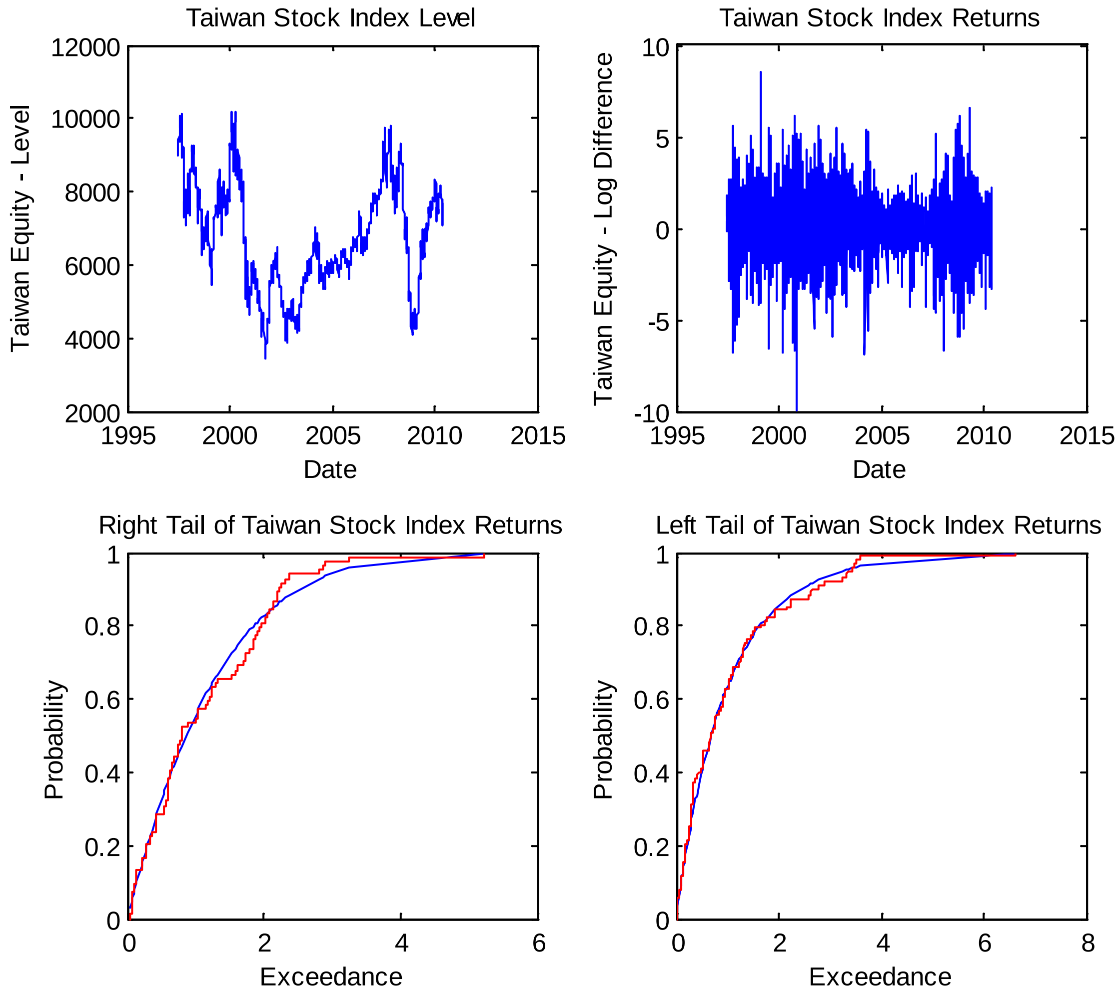

Figure 1.7b

Note: Figure 1.7b: Top panel shows Taiwan equity market level and log difference. Bottom panel traces the estimated GPD (smooth line) against the empirical distribution function for Taiwan equity extreme returns. The left graph is for the right tail of returns whereas the right side graph corresponds to the left tail.

Chapter 2

Tail Dependence between Stock Index Returns and Foreign Exchange Rate Returns: A Copula Approach

2.1 Introduction

Understanding the dependence between risk factors is crucial in risk management and asset allocation. This chapter aims to examine the tail dependence between the stock index returns and exchange rate returns of five East Asian economies: Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. Tail behavior of random variables during extreme events, such as financial crisis, can be captured via measures of tail dependence. In this case, tail dependence measures the probability that we will observe extremely large gain in the stock market, given that the local currency also has had a large appreciation against the USD. For a U.S. investor seeking international diversification, he/she will experience double large gains, one in the equity market, and the other in the currency market when translating the local currency investment into U.S. dollars. Likewise, when the stock market crashes, the international investor not only suffers big loss in the stock market, but also in the currency market. Therefore, goal of risk reduction cannot be achieved due to this possibility.

The questions I attempt to answer in this chapter are the following three: 1) can investing in East Asian stock markets provide any diversification benefits? If I find positive tail dependence between the two markets, then I can claim that, for a U.S. investor, investing in the East Asian equity markets can't provide any risk reduction benefits when it is most needed (correlation breakdown); 2) is the tail dependency similar for the countries? 3) do the tails exhibit symmetric or asymmetric dependency in that economic region? By answering these questions I hope to better understand the co-movements of equity-currency markets for the selected countries in this geographical region.

Extensive research has been done on the relationship between these two markets, both theoretically and empirically. On the theoretical ground, there are two models explaining the causal relationship between the equity and currency markets: one is the "stock-oriented"[8] model of exchange rate and the other is "flow-oriented"[9] model of exchange rate. From the microeconomic point of view, local currency appreciation can cause exporting firms competitive disadvantage, therefore lowering their stock prices, indicating negative relationship between stock returns and exchange rate. While on the other hand, importing firms can benefit from home currency appreciation, suggesting a positive relationship between these two markets. From the macroeconomic point of view,

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[8] "Stock-oriented" models view exchange rates as equating the supply and demand for assets such as stocks and bonds (e.g. Branson (1983) and Frankel (1983)).

[9] "Flow-oriented" models focus on the current account or the trade balance. Changes in exchange rates affect international competitiveness and trade balances, thereby influencing real income and output (e.g. Dornbusch and Fisher (1980)).

if domestic interest rate is higher relative to the rest of the world, the higher demand for home currency leads to its appreciation. In the meantime, higher interest rates also increase domestic firms' borrowing cost, causing lower stock prices. This suggests a negative relationship between these two markets. Mixed results have been documented on the causal relationship between these two markets. Using the ordinary least squares (OLS) estimation, Solnik (1987) finds weak positive relationship for monthly data but negative relationship for quarterly data for eight western markets. Based on error correction model (ECM), Ajayi and Mougoué (1996) find that, in the short run, the relationship between stock prices and home currency is negative, but positive in the long run. Using a GARCH approach, Patro et al. (2002) find significant currency risk exposure in country equity index returns for 16 OECD countries. Using Granger causality test, Pan et al. (2007) study the dynamic linkages between exchange rates and stock prices for several East Asian countries. They find a significant causal relationship from exchange rates to stock prices before the 1997 Asian financial crisis.

The conventional dependence measure is constructed as an average of deviations from the mean and it doesn't distinguish between large or small realizations or between positive and negative returns. And it is based on assumptions of a linear relationship and a multivariate Gaussian distribution. Since the research of Embrechts et al. (2002) identified the limitations of correlation-based models in risk management, copula method has become more and more popular an approach in modeling dependence structure between financial variables. Copulas can capture dependence throughout the entire distribution of asset returns, independent of the univariate returns distribution. Not only can copulas model the degree of dependence, but also the structure of dependence. Works using copulas include Mashal and Zeevi (2002), Hu (2006), Chollete et al. (2006, 2009), and Rodriguez (2007) on the dependence structure across international equity markets, Patton (2006) on dependence structure in currency markets, Ning and Wirjanto (2008) on extreme return-volume dependence, and Ning (2010) on the dependence between equity-currency markets for several developed countries, just to name a few.

The study undertaken in this chapter is different from previous literature and contributes to the literature in finance and economics in the following ways. Besides the difference in data used, it studies the degree of tail dependence using different copula models by focusing on countries from the same geographical region. The key empirical result reveals that the tail dependence structure is significant for the three East-Asian emerging markets (asymmetric tail dependence for Indonesia and South Korea and symmetric tail dependence for Taiwan), and for the more advanced countries, there isn't enough evidence to support the existence of any tail dependency between the currency returns and stock index returns. My findings have important implications in risk management and asset pricing. For global investors seeking to diversify their portfolio into emerging markets, ignoring the joint downside risk would underestimate the value-at-risk (VaR), which is a common market risk measure in risk management practice. My findings should also affect the pricing of assets. As pointed out in Phylaktis and Ravazzolo (2004), an international capital asset pricing model (ICAPM) will be mis-specified if currency risk[10] is omitted. Poon et al. (2004) states that, tail dependence is a true measure for systematic risk in times of financial crisis and global investors should be compensated for exposure to such risk during joint market downturns.

The remainder of this chapter is organized as follows. Section 2.2 introduces copula concepts and measure of tail dependence. Section 2.3 specifies the models and estimation method. In section 2.4, I describe the data used and present the empirical evidence of extreme co-movements between stock index returns and foreign exchange rate fluctuations. Concluding remarks are offered in section 2.5.

2.2 Copula[11] Concepts and Tail Dependence

Dependence between random variables can be modeled by copula method. In this section I introduce the general concept of copulas and some copulas used to model tail dependence in finance literature. Copulas represent a new tool to measure the dependence structures between financial markets, risk factors and other relevant financial variables. Copula method to model dependence is becoming more and more popular among academics and practitioners in the field of finance due to the inability of the linear correlation to handle the fat-tail problem in financial returns. There are some advantages of copula method over traditional methods: one is that copulas allow modeling nonlinear

[10] Currency risk is a form of risk that arises from the change in price of one currency against another and it is a key element in foreign investment. International investors face currency risk if their positions are not hedged.

[11] Copulas, derived from the Latin word *copulare*, meaning to connect or to join, are first introduced by Sklar (1959) to study probabilistic metric spaces. In statistics, copula is a function linking marginal variables into a multivariate distribution. Copula method has become a very popular tool to model financial risk factors in the past decade or so.

dependence structure; secondly, no assumption required regarding the marginal distributions; lastly, we can also use copulas to model tail events, which is often a paramount concern in financial risk management.

As described in Joe (1997), a copula is 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.

2.2.1 Sklar's Theorem and copulas

The theorem central to the theory of copulas is called Sklar's theorem. In 1959, A. Sklar (1959) created a new class of functions now famously known as copulas, which couple a joint distribution function to its univariate marginals. I will present this theorem mainly by following Nelson (1999).

Sklar's Theorem[12] (Sklar1959) Let H be a joint distribution function with marginals F and G. then there exists a copula C such that for all x, y in R,

$$H(x, y) = C\big(F(x), G(y)\big) \tag{2.1}$$

[12] As stated in Patton (2006, pp.533), Sklar Theorem implies that we may link any two univariate distributions, of type, not necessarily from the same family, with any copula, to define a valid bivariate distribution. With a corollary to Sklar's Theorem, as given in Nelson (1999) for example, we are able to extract the copula from any given multivariate distributions and use it independently of the marginal distributions of the original distribution. For example, we are able to extract the normal copula from a standard bivariate normal distribution.

If F and G are continuous, then C is unique; otherwise, C is uniquely determined on RanF ×RanG. Conversely, if C is a copula and F and G are distribution functions, then the function H defined by the above equation is a joint distribution function with marginals F and G.

Definition 2.1 A two-dimensional copula is a function $C: [0,1]^2 \rightarrow [0,1]$ which satisfies the following properties:

(a) Grounded: for every u, v in [0,1], $C(u, 0) = 0 = C(0, v)$;

(b) $C(u, 1) = u$ and $C(1, v) = v$ for all $(u, v) \in [0,1]^2$;

(c) 2-increasing: for every u_1, u_2, v_1, v_2 in [0,1] such that $u_1 \leq u_2$ and $v_1 \leq v_2$, $C(u_2, v_2) - C(u_2, v_1) - C(u_1, v_2) + C(u_1, v_1) \geq 0$.

Hence, any bivariate distribution function whose margins are standard uniform distributions is a copula. From the definition, we know that copulas are joint distribution functions of standard uniform random variables:

$$C(u, v) = \Pr(U_1 \leq u, U_2 \leq v)$$

The following probabilities of uniform variates can be written via copulas:

$$\Pr(U_1 \leq u, U_2 > v) = u - C(u, v)$$

$$\Pr(U_1 > u, U_2 \leq v) = v - C(u, v)$$

$$\Pr(U_1 \leq u | U_2 \leq v) = C(u, v)/2$$

$$\Pr(U_1 \leq u | U_2 > v) = \frac{u - C(u,v)}{(1-v)}$$

$$C_{1|2}(u,v) \equiv \Pr(U_1 \leq u | U_2 = v) = \frac{\partial C(u,v)}{\partial v}$$

$$C_{2|1}(u,v) \equiv \Pr(U_2 \leq v | U_1 = u) = \frac{\partial C(u,v)}{\partial v}$$

For further properties of copula functions, see Joe (1997) and Nelson (1999). For an overview of copula applications in finance, see Cherubini et al. (2004), and Patton (2009) for copula applications in financial time series.

2.2.2 Measure of tail dependence[13]

Tail dependence refers to the amount of dependence in the tails of a bivariate distribution or alternatively the dependence in the corner of the lower-left quadrant or upper-right quadrant of a bivariate distribution. Tail dependence between two random variables is a copula property and hence the amount of tail dependence is invariant under strictly increasing transformations of X and Y. For two random variables X and Y with marginal distributions $F_X(x)$ and $F_Y(y)$, the upper tail dependence[14] is

$$\lambda_r = \lim_{u \to 1} \Pr[F_Y(y) \geq u | F_X(x) \geq u] = \lim_{u \to 1} \frac{1-2u+C(u,u)}{1-u} \qquad (2.2)$$

---

[13] Tail dependence allows investors to measure the probability of simultaneous large losses or gains. It is extremely important for safety-first investors since the lower tail dependence between stock returns and exchange rate fluctuations measures the likelihood of large loss in foreign investment.

[14] In the text, I use left tail or lower tail and right tail or upper tail interchangeably.

and the lower tail dependence is

$$\lambda_l = \lim_{u \to 0} \Pr[F_Y(y) \le u | F_X(x) \le u] = \lim_{u \to 0} \frac{C(u,u)}{u} \tag{2.3}$$

where λ_r and $\lambda_l \in [0,1]$. Positive λ_l or λ_r indicates that X and Y are to be tail dependent. If the tail dependence coefficient is zero, the variables are asymptotically independent. However, tail independency does not mean that the variables are independent. The copulas with different tail dependency applied in this study are introduced in the next section.

2.3 Estimation Method and Model Specification

Generally speaking, there are two approaches to estimate copula models, one is the one-stage full maximum likelihood estimation method, and the other is the two-stage inference functions for margins (IFM) method proposed by Joe and Xu (1996). The one-stage approach jointly estimates the parameters of the marginal models and parameters of the copula models simultaneously. Given the large number of parameters, this method can be computationally intensive and make the numerical maximization of the log likelihood function difficult. Therefore, in practice, the two-stage IFM method is preferred due to its computational tractability. Under the IFM approach, the first step models the marginal models, either parametrically or non-parametrically. If estimation is done non-parametrically, then the method is a semi-parametric two-step estimation method, also known as Canonical Maximum Likelihood, or CML method. Copula parameters are estimated in the second step. For more details on this estimation method, interested reader can refer to Cherubuni et al. (2004). Joe (1997) points out that the IFM method is a highly efficient method, and he proves that the IFM estimator is consistent and asymptotically normal under standard conditions[15].

2.3.1 The marginal models

I 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, I 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 (2006a), and Ning (2010) among others. The marginal model is specified as follows:

$$r_{i,t} = C_i + \sum_k AR_{i,k} \times r_{i,t-k} + \varepsilon_{i,t} \quad (2.4)$$

$$\sigma_{i,t}^2 = Arch0_i + \sum_p Garch(p)_i \times \sigma_{i,t-p}^2 + \sum_q Arch(q)_i \times \varepsilon_{i,t-q}^2 \quad (2.5)$$

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 (2.4)). Estimation results of the marginal model are discussed in the following section.

2.3.2 The copula models

[15] Joe and Xu (1996) compared the efficiency of the IFM estimator with ML estimator via simulation and find that the ratio of the mean square errors of the IFM estimator to the ML estimator is close to 1, indicating the high efficiency of the IFM estimator.

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

$$C_{v,\rho}^{t}(u_1, u_2) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left\{1 + \frac{(s^2+t^2-2\rho st)}{v(1-\rho^2)}\right\}^{-(v+2)/2} dsdt \qquad (2.6)$$

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 independence Gaussian copula 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

$$C_{\theta}^{Cl}(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \qquad (2.7)$$

where $0 < \theta < \infty$ is a parameter controlling the dependence, $\theta \to 0^{+}$ implies independence, and $\theta \to \infty$ implies perfect dependence. *u* and *v* are standard uniformly distributed i.i.ds. Clayton copula can be used to model lower tail dependency and it exhibits no upper tail dependency.

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 (2006a) and it is defined as follows.

$$C_{SJC}(u, v|\lambda_r, \lambda_l)$$

$$= 0.5 \cdot (C_{JC}(u, v|\lambda_r, \lambda_l) + C_{JC}(1-u, 1-v|\lambda_r, \lambda_l) + u + v - 1) \quad (2.8)$$

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

$$C_{JC}(u, v|\lambda_r, \lambda_l)$$

$$= 1 - \left(1 - \{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma}\right)^{1/k} \quad (2.9)$$

where $k = 1/\log_2(2 - \lambda_r)$, $\gamma = -1/\log_2(\lambda_l)$, and $\lambda_r \in (0,1)$, $\lambda_l \in (0,1)$. As pointed out in Patton (2006), the main drawback in Joe-Clayton copula is that, even when λ_l and λ_r are equal, there is still slight asymmetry in the copula. Given the way SJC copula is constructed, it is a better copula model to determine the presence or absence of asymmetry based on the empirical tail dependence measures. I discuss the empirical results based on SJC copula model in the following section.

2.4 Data and Empirical Results

2.4.1 Data

The dataset used in this chapter consists of daily 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 (US$/HKD), Indonesia Rupiah (US$/IDR), South Korean Won (US$/KRW), Singapore dollar (US$/SGD), and Taiwanese dollar (US$/TWD). The dataset has different starting dates, but all end on June 4, 2010. The stock index return is computed as

$$\mathrm{r_{i,t}} = \ln(\frac{P_{i,t}}{P_{i,t-1}}), \qquad (2.10)$$

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

$$e_{i,t} = \ln(\frac{\mathrm{S_{i,t}}}{\mathrm{S_{i,t-1}}}), \qquad (2.11)$$

where $S_{i,t}$ is the spot exchange rate at time *t* for currency *i*, and $S_{i,t-1}$ is the spot exchange rate level at time *t*-1 for country *i*, expressed as units of US$ per unit of local currency.

TABLE 2.1 presents the summary statistics of the continuously compounded stock index returns and currency movements for each country, and all returns are in percentage terms. As manifested from the table, East Asian equity markets did provide higher returns (with the exception of Taiwan for the sample period), at the expense of higher risk, as measured by the sample standard deviation. I observe that the standard deviation of equity returns is higher than that of currency movements, with the exception of Indonesia. On average, Indonesian Rupiah, South Korean Won, and Taiwanese dollar experienced depreciation against U.S. dollar. The negative skewness measure of the equity returns shows that most returns slightly skew to the left. For the foreign exchange rate returns, Singapore dollar has more positive observations than negative observations. The rest of the countries under study have negative skewness measures. The fourth moment measure for the currency returns (range from 15.8 (Singapore) to 167.9 (Hong Kong)) is generally higher than that of the equity returns (range from 5.4 (Taiwan) to 18.50 (Hong Kong)). The nonzero skewness measure and excess kurtosis all point to the non-normality of the returns. The Jarque-Bera tests further confirm the non-normality of the returns data (not reported in the table). J-B test is based on both skewness and excess kurtosis and is χ^2 distributed with two degrees of freedom.

I check for serial correlation with the Ljung-Box statistics (not reported in the table). The Ljung-Box statistic on 20 lags for the raw returns is significant for all cases (not reported in the table), implying serial dependencies in these returns. For squared returns, the Ljung-Box statistic is also significant for all cases, showing significant evidence in support of GARCH effects. All these test statistics further confirm non-normality in return series and volatility clustering observed in most stock and foreign exchange markets. I employ GARCH models which are well known to capture this property in the return series.

The different unconditional correlation measures are presented in TABLE 2.2: Pearson's linear correlation, the Kendall's tau, and Spearman's rho rank correlation coefficients. The correlation coefficients measure the degree of dependence between the equity returns and exchange rate changes for the selected countries. The correlation coefficients observed for the three emerging markets range from 0.2107 (Indonesia pair) to 0.3373 (South Korea pair), indicating that the increase (decrease) of the local stock market is associated with the appreciation (depreciation) of the local currency, a hallmark of emerging market finance. Correlation coefficients between the two financial market returns (stock index and exchange rate) for the more advanced economies (Hong Kong and Singapore) are lower. I also observe that the dependency between the Korea pair is the strongest, and that the Hong Kong pair has the weakest dependency among them all.

2.4.2 Results of the GARCH models

In order to make sure that a series of i.i.d Uniform(0,1) observations are fitted to the copula models, I need to correctly specify the marginal models: I model each asset return series using $AR(k)-GARCH(p, q)$ or $AR(k)-t-GARCH(p, q)$ type models, whichever is suitable to the specific return series. I experiment with different terms of AR and GARCH until I find the best fit for the data on hand. The parameter estimates and standard errors for marginal distribution models are reported in TABLE 2.3 and TABLE 2.4. Only the highly significant (with 5 percent significance level at least) autoregressive terms and GARCH terms are reported in the table. Serial correlation in the raw stock index returns and currency returns can generally be captured with up to an AR(5) term, except Indonesia stock index returns (with a significant AR(10) term) and Indonesia currency returns (with a significant AR(9) term), indicating a long memory in the raw returns series. For most of the return series, GARCH(1,1) is sufficient to model the conditional heteroskedasticity, but some require higher Arch/Garch terms. This is shown by a significant Arch2, Arch3, and Garch8 terms for Indonesia currency returns, Garch2 for Hong Kong equity returns. A Gaussian conditional probability is sufficient for most of the marginal models, except for the returns of Hong Kong dollar and that of the stock index returns of South Korea. The estimated degree of freedom is reported in the respective tables for those returns more suitable for t-GARCH models. I also perform goodness-of-fit tests to test for serial independence of the standardized residuals and the probability integral transforms. I employ Ljung-Box Q-statistic lack-of-fit hypothesis test which is based on the Q-statistic

$$Q = N(N+2)\sum_{k=1}^{L}\frac{r_k^2}{(N-k)} \tag{2.12}$$

where N = sample size, L = number of autocorrelation lags included in the statistic, and r_k^2 is the squared sample autocorrelation at lag k. Q-statistic is asymptotically Chi-square distributed under the null hypothesis. TABLE 2.5 presents the results of the goodness-of-fit tests on the first four moments of the probability integral transforms. The p-values from the Ljung-Box tests are from 0.08 to 0.98, implying that I cannot reject the null hypothesis that the probability integral transforms are serially independent, and thus the marginal models are not mis-specified. In the next subsection, I discuss the results of the copula models.

2.4.3 Empirical results of the joint copula models

Parameter estimates of the SJC copula, Student's t-copula, and Clayton copula models are presented in TABLE 2.6. I observe significant estimates of the parameters of the lower tail dependence as well as upper tail dependence for the three emerging markets, namely, Indonesia pair, South Korea pair and Taiwan pair. For the two more advanced economies (Hong Kong and Singapore), there is no evidence on tail dependence, i.e. the tail dependence parameters are not significant at either tail. Whereas Indonesia pair (λ_l = 0.1318, λ_r = 0.0528) and South Korea pair (λ_l = 0.1992, λ_r = 0.0501) have asymmetric tail dependence, Taiwan pair has symmetric tail dependence measure as the estimated parameters are not significantly different, with λ_l = 0.0872 (0.024) and λ_r = 0.0846 (0.022). The estimated degree of freedom (*v*) of the Student's t-copula ranges from 6.74 (Korea) to 16.06 (Taiwan), indicating bivariate non-normality between the returns distributions of the two markets for the countries under study. This further confirms that linear correlation coefficient as a measure of dependence between financial returns can give misleading results. For Hong Kong and Singapore, even though not enough evidence to show that there exists extreme co-movement between the equity−currency markets, but the estimated degree of freedom parameter ranges from 12.12 (Singapore) to 15.14 (Hong Kong), indicating that bivariate normal distribution is not reasonably a good assumption in modeling the dependence between the two returns series. Judged by the information criteria, Clayton copula is not a good candidate to model the tail dependence between stock index returns and foreign exchange rate returns.

Next I look at the dynamics of the tail dependence measures. Since the copula results indicate no tail dependence in the two more developed markets, here I focus on the three emerging markets. I apply Patton (2006) time-varying SJC copula to examine the conditional bivariate distribution of the returns series for Indonesia, South Korea, and Taiwan. TABLE 2.7 reports the parameter estimates along with the static SJC copula results for convenience. The evolution of the dependency parameter (upper and lower tail dependence coefficients), as defined in Patton (2006), is as follows

$$\lambda t = \Lambda(\omega + \beta\lambda_{t-1} + \alpha \cdot \frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|), \tag{2.13}$$

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

Equation (2.13) includes an autoregressive term and a forcing variable, which is the mean absolute difference between u_t and v_t over the previous 10 observations. The second term on the right hand side of equation (2.13) is the autoregressive term designed to capture persistence in dependence. My empirical results show that the autoregressive term for both tails of Korea pair (lower tail β = 0.8947, upper tail β = 0.9737), upper tail of Indonesia pair (β = 0.9210), and lower tail for Taiwan pair (β = 0.9079), is significant, indicating the high persistence in the dependence level. The parameter values for the lower tail dependence coefficient of Indonesia pair are not significantly different from zero, indicating that there is no significant change in the degree of the tail dependence.

To illustrate the evolving time path of the degree of tail dependence coefficients, in Figure 2.1, Figure 2.2, and Figure 2.3, I plot the conditional lower and upper tail dependence implied by the time-varying SJC copula model. In the figures (bottom plot in each figure), I also plot the time varying difference between lower tail and upper tail coefficients, as calculated by $\lambda_l - \lambda_r$. Under symmetry, this difference should be zero. From the bottom plot of Figures 2.1 and 2.2, I note that conditional lower tail dependence is greater than conditional upper tail dependence almost all the time for Indonesia pair and South Korea pair, supporting my conclusion of asymmetry in tail dependencies for these two pairs. In the case of Taiwan (Figure 2.3), the difference between the lower tail coefficient and upper tail coefficient fluctuates around zero, indicating that it is not significantly different in the lower and upper tail dependence coefficients, as I have concluded earlier based on unconditional copula results.

I compare the relative performance of the competing copula models using Akaike's information criterion (AIC). For the three pairs, I find a reduction of the AIC in the time-varying SJC model (Korea pair decreased the most and Taiwan pair decreased the least), indicating the dynamic copula model performs better than its static counterpart.

2.5 Conclusion

In this chapter, using a relatively new method, namely the copula framework, I examine the degree of dependence at the extremes of the distribution between the stock index returns and foreign exchange fluctuations in five East Asian economies (Hong Kong, Indonesia, South Korea, Singapore, and Taiwan). First I apply AR-GARCH or

AR-t-GARCH type models to filter the raw returns data to ensure the copula inputs are serially independent, then I fit different copula models to detect any tail dependence behavior between the stock index returns and foreign exchange rate fluctuations for the selected countries. My major findings are the following: 1) for the two advanced economies, namely Hong Kong and Singapore, there is no evidence of tail dependence between the two returns series; 2) for the three emerging markets, Indonesia and South Korea have significantly higher left tail dependency than right tail dependency, thus asymmetric tail dependencies. For Taiwan, the tail dependence is significant and similar between the lower and upper tail, suggesting symmetric tail dependence behavior. Examination of the time path of the tail dependence coefficients also confirms my results.

My findings have important finance implications in risk management and asset pricing. For global investors seeking to diversify their portfolio into emerging markets, ignoring the joint downside risk would underestimate the value-at-risk (VaR), which is a common market risk measure in risk management. Tail dependence serves as a true measure for systematic risk in times of financial crisis and global investors should be compensated for exposure to such risk during joint market downturns. These results can provide important guidance for investors who consider international diversification into this geographical region. For those investors seeking international diversification into Indonesia and South Korea stock markets, it is more likely for them experiencing higher double losses (one in the stock market and the other in the currency market when translating into home currency returns) than higher double gains. Therefore hedging equity investments with currency derivatives is highly recommended. For investments made in the two more advanced markets, namely Hong Kong and Singapore, currency hedging does not seem quite necessary.

Now I have examined the tail dependence between the stock index returns and foreign exchange rate returns for each of the selected countries. The next chapter will focus on the extreme dependence patterns across the stock markets as well as across the currency markets for these selected economies to investigate if international investment made into this geographical region can provide any diversification benefits, especially when it is most needed.

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Appendix 2: Tables and Figures for Chapter 2

TABLE 2.1: Summary statistics (%)

Country	mean	std	skewness	kurtosis
Panel A:				
Stock index				
Hong Kong	0.0399	1.7524	−0.4794	18.5473
Indonesia	0.0446	1.8707	−0.0749	8.9916
Korea	0.0248	2.1706	−0.0970	6.6713
Singapore	0.0225	1.3440	−0.0673	11.3275
Taiwan	−0.0066	1.6898	−0.1416	5.3880
Panel B:				
Foreign exchange				
Hong Kong	0.0000	0.0508	−0.0979	167.9241
Indonesia	−0.0436	1.9711	−1.4193	53.5803
Korea	−0.0099	1.0490	−0.9425	40.6763
Singapore	0.0064	0.3565	0.6700	15.8255
Taiwan	−0.0048	0.3230	−0.4944	21.0622

Note: the five East Asian countries used in this study are Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. This table reports the first four moments of the stock index returns and foreign exchange returns measured in percentage terms (as calculated as 100 times the logarithm differences of the price levels). The data series has different starting dates, but all data end on 6/4/2010. Hong Kong data span from 11/2/1987 with 5497 daily observations, Indonesia, Korea, and Taiwan data span from 7/2/1997 with 3034, 3074, and 3066 daily observations, respectively, Singapore data span from 12/28/1987 with 5437 daily returns.

TABLE 2.2: Correlation Coefficients:

Pairs	Pearson's rho	Kendall's tau	Spearman's rho
Hong Kong	0.0352	0.0254	0.0370
Indonesia	0.2107	0.1408	0.2032
Korea	0.3373	0.1956	0.2823
Singapore	0.1486	0.0677	0.0996
Taiwan	0.2422	0.1610	0.2388

Note: this table presents the different correlation coefficients between the local stock index returns and foreign exchange rate fluctuations for the selected five East Asian economies.

TABLE 2.3: GARCH models for stock index returns.

Variable	C	AR1	AR3	AR5	AR10	Arch1	Garch1	Garch2	DoF
Equity									
Hong Kong	0.0008	0.0753	0.0348	−0.0432		0.1544	0.3249	0.4985	
	(0.0002)	(0.0150)	(0.0133)	(0.0140)		(0.0083)	(0.0564)	(0.0533)	
Indonesia	0.0010	0.1363			0.0419	0.1317	0.8465		
	(0.0003)	(0.0194)			(0.0176)	(0.0090)	(0.0085)		
S. Korea	0.0012					0.0779	0.9205		7.19
	(0.0003)					(0.0099)	(0.0093)		(0.91)
Singapore	0.0004	0.0991		−0.0307		0.1487	0.8270		
	(0.0001)	(0.0151)		(0.0138)		(0.0072)	(0.0073)		
Taiwan	0.0005	0.0500				0.0735	0.9204		
	(0.0003)	(0.019)				(0.0061)	(0.0064)		

Note: this table reports the estimation results of GARCH models for the stock index returns. All estimates are based on the log differences of the stock index levels. The intercept term in the variance equation is not reported as it is less than 0.0001 in all the cases. All the coefficients are significant at 1% level. Estimation is based on log differences.

TABLE 2.4: GARCH models for foreign exchange rate returns.

Variable	Hong Kong	Indonesia	S. Korea	Singapore	Taiwan
C				0.0001	
				(0.00004)	
AR1	−0.2440	−0.0994	0.0415	−0.0480	
	(0.0127)	(0.0217)	(0.0199)	(0.0148)	
AR2	−0.0974				
	(0.0116)				
AR3	−0.0284				
	(0.0105)				
AR4	−0.0223			0.0402	
	(0.0105)			(0.0145)	
AR5	0.0362				0.0662
	(0.0087)				(0.0212)
AR9		0.0405			
		(0.0195)			
Arch1	0.5277	0.1183	0.1636	0.0779	0.1230
	(0.0066)	(0.0140)	(0.0078)	(0.0040)	(0.0069)
Arch2		0.0611			
		(0.0179)			
Arch3		0.0995			
		(0.0181)			
Garch1	0.4723	0.2221	0.8364	0.9053	0.8162
	(0.0123)	(0.1054)	(0.0065)	(0.0040)	(0.0080)
Garch8		0.4990			
		(0.0518)			
DoF	2.6608				
	(0.0030)				

Note: this table presents the estimation results of the GARCH models for the foreign exchange rate fluctuations. All estimates are based on the log differences of the exchange rate levels, instead of percentage returns. Only Singapore has an intercept term in the mean model. The intercept in the variance mode is less than 0.0001 in all the cases, therefore none is reported in the table. All the coefficients are significant at 1% level. Estimation is based on log differences.

TABLE 2.5: Goodness-of-fit test for copula marginal models.

Copula Margins	1st moment test	2nd moment test	3rd moment test	4th moment test
Hong Kong stock	0.9181	0.6700	0.3440	0.2167
US$/HKD	0.2099	0.2123	0.1689	0.1566
Indonesia stock	0.9824	0.9419	0.8009	0.6715
US$/IDR	0.5191	0.8111	0.8873	0.7715
Korea stock	0.9997	0.9153	0.3588	0.1257
US$/KRW	0.5175	0.5980	0.7588	0.8466
Singapore stock	0.8518	0.9799	0.9360	0.8756
US$/SGD	0.2633	0.2175	0.2336	0.3263
Taiwan stock	0.9807	0.7058	0.2295	0.0842
US$/TWD	0.0897	0.4969	0.6697	0.1908

Note: this table presents the goodness-of-fit test results for the copula marginals for serial correlation on 10 lags of the probability transforms. The reported numbers are the p-values of the test, ranging from 0.08 to 0.98, indicating they all pass the Ljung-Box test for serial correlation at 5% significance level.

TABLE 2.6: Estimation of copula parameters and tail dependence:

Pairs	Parameters	SJC copula	t-copula	Clayton copula
Hong Kong	v		15.14** (3.42)	
	λ_l	0.0003 (0.001)		0.024** (0.007)
	λ_r	0.0000		
	llv	8.87	16.22	6.4
	AIC	−13.73	−30.43	−10.80
	BIC	−0.51	−23.82	−4.19
Indonesia	v		10.46** (2.32)	
	λ_l	0.1318** (0.022)		0.1345** (0.010)
	λ_r	0.0528** (0.020)		
	llv	115.34	109.46	96.87
	AIC	−226.69	−216.92	−191.74
	BIC	−214.65	−210.90	−185.72
South Korea	v		6.74** (0.95)	
	λ_l	0.1992** (0.023)		0.1641** (0.011)
	λ_r	0.0501** (0.022)		
	llv	156.03	160.09	138.12
	AIC	−308.06	−318.18	−274.23
	BIC	−296.00	−312.15	−268.20
Singapore	v		12.12** (2.17)	
	λ_l	0.0258 (0.016)		0.0526** (0.008)
	λ_r	0.0000		
	llv	31.5700	37.5400	28.1200
	AIC	−59.1300	−73.0700	−54.2400
	BIC	−45.9300	−66.4700	−47.6400
Taiwan	v		16.06** (5.38)	
	λ_l	0.0872** (0.024)		0.1213** (0.011)
	λ_r	0.0846** (0.022)		
	llv	104.15	105.05	73.62
	AIC	−204.31	−208.10	−145.24
	BIC	−192.25	−202.07	−139.22

Note: This table presents the three copula results: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC, BIC, and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are the asymptotic standard errors.

**indicates significance at 1% level.

TABLE 2.7: SJC copula and time-varying SJC copula results:

Market	Parameter	SJC copula λr	SJC copula λ_l	Time-varying SJC copula λr	Time-varying SJC copula λ_l
Indonesia		0.0528**	0.1318**		
		(0.020)	(0.022)		
	ω			0.232	1.2622
				(0.918)	(2.376)
	α			−1.611	−10.000
				(7.010)	(19.563)
	β			0.9210**	0.0667
				(0.335)	(1.806)
	AIC	−226.686		−247.877	
	llv	115.343		129.939	
Korea		0.0501**	0.1992**		
		(0.022)	(0.023)		
	ω			0.0719*	0.3709
				(0.039)	(0.266)
	α			−0.5201	−1.8048
				(0.350)	(1.390)
	β			0.9737**	0.8947**
				(0.026)	(0.098)
	AIC	−308.062		−366.918	
	llv	156.031		189.459	
Taiwan		0.0846**	0.0872**		
		(0.022)	(0.024)		
	ω			0.7174	0.1261
				(0.677)	(0.173)
	α			−10.000**	−1.1337
				(0.001)	(0.680)
	β			0.0051	0.9079**
				(0.361)	(0.045)
	AIC	−204.3076		−208.866	
	llv	104.154		110.433	

Note: this table reports the maximum likelihood estimates, with asymptotic standard errors in parentheses, of the parameters of the constant SJC copula and time varying SJC copula. *AIC and llv* correspond to Akaike's information criterion and log-likelihood value, respectively.
** and * indicate significance at 1% and 5% level respectively.

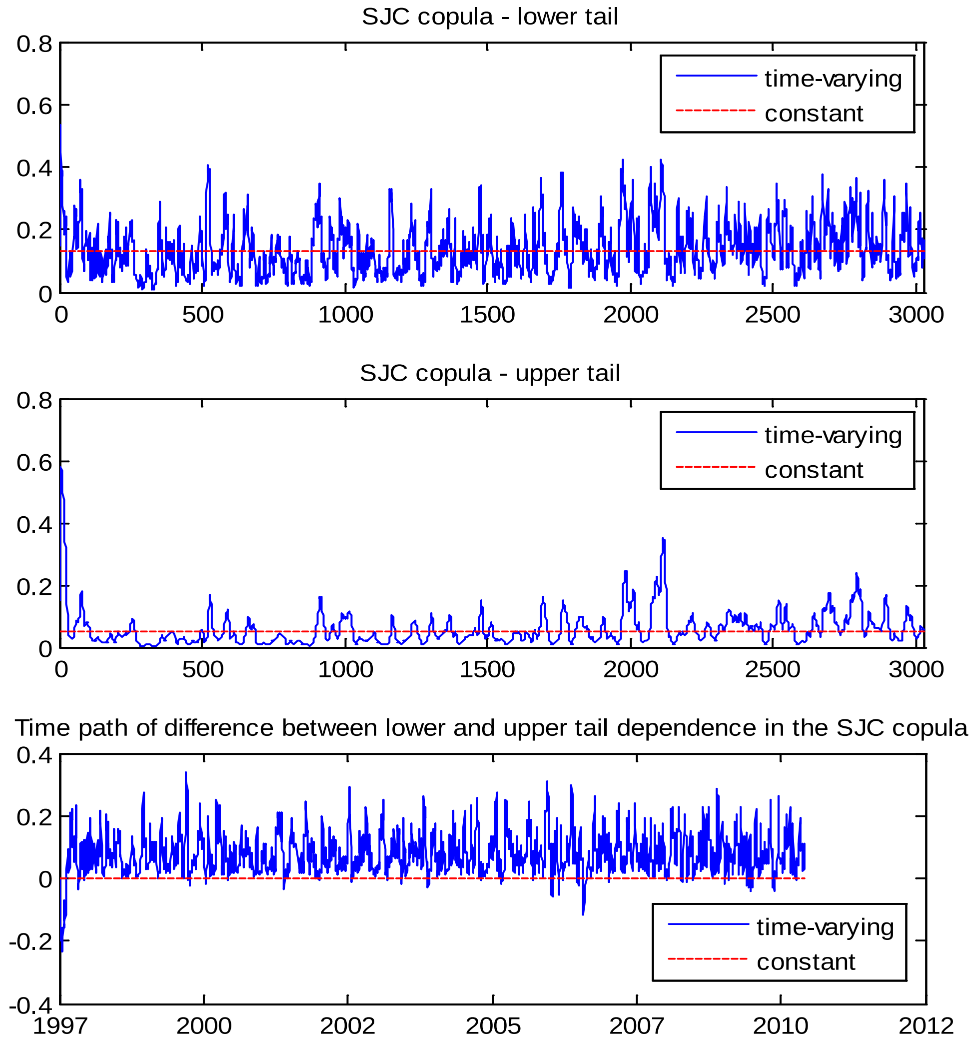

Figure 2.1

Note: Figure 2.1 shows the time path of conditional tail dependence coefficients of the time-varying SJC copula for Indonesia pair. The red dashed line in the top two plots are the estimated lower and upper tail dependence coefficients, respectively. The bottom plot shows the time path of difference between lower and upper tail coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

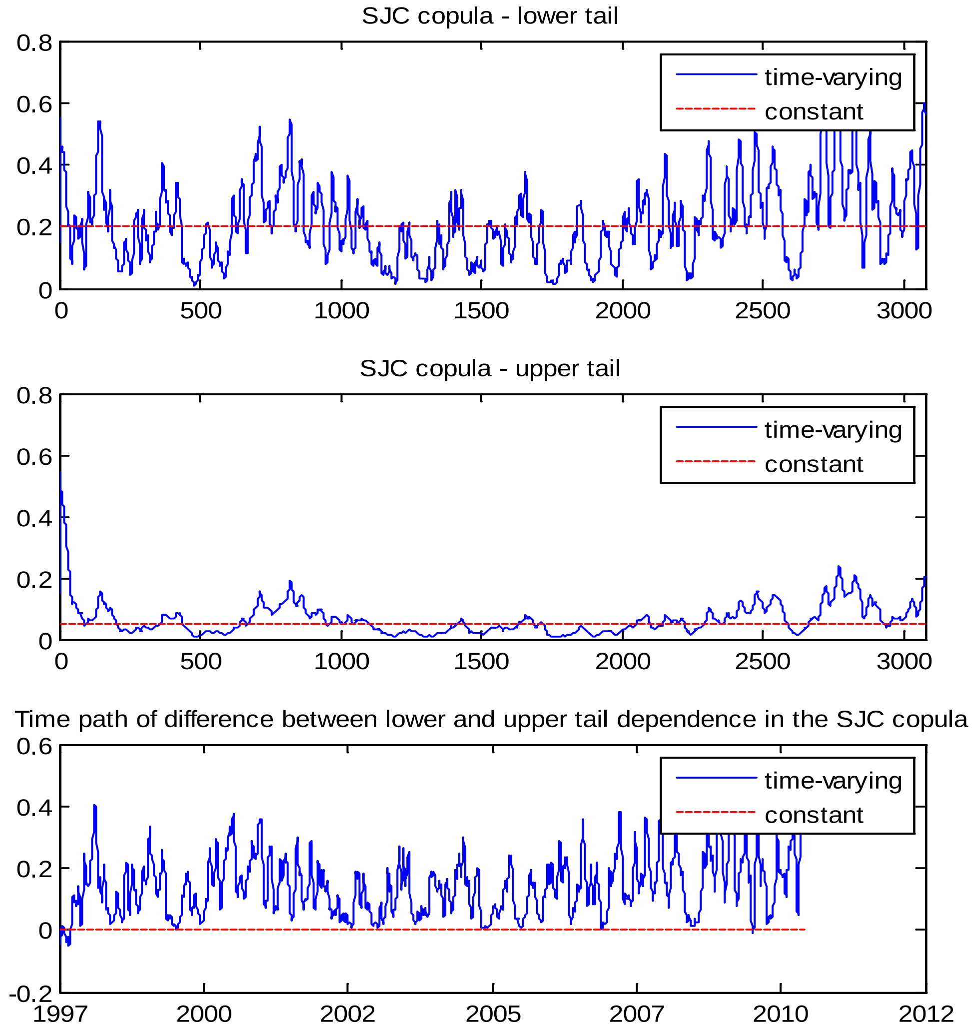

Figure 2.2

Note: Figure 2.2 shows the time path of conditional tail dependence coefficients of the time-varying SJC copula for Korea pair. The red dashed line in the top two plots are the estimated lower and upper tail dependence coefficients, respectively. The bottom plot shows the time path of difference between lower and upper tail coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

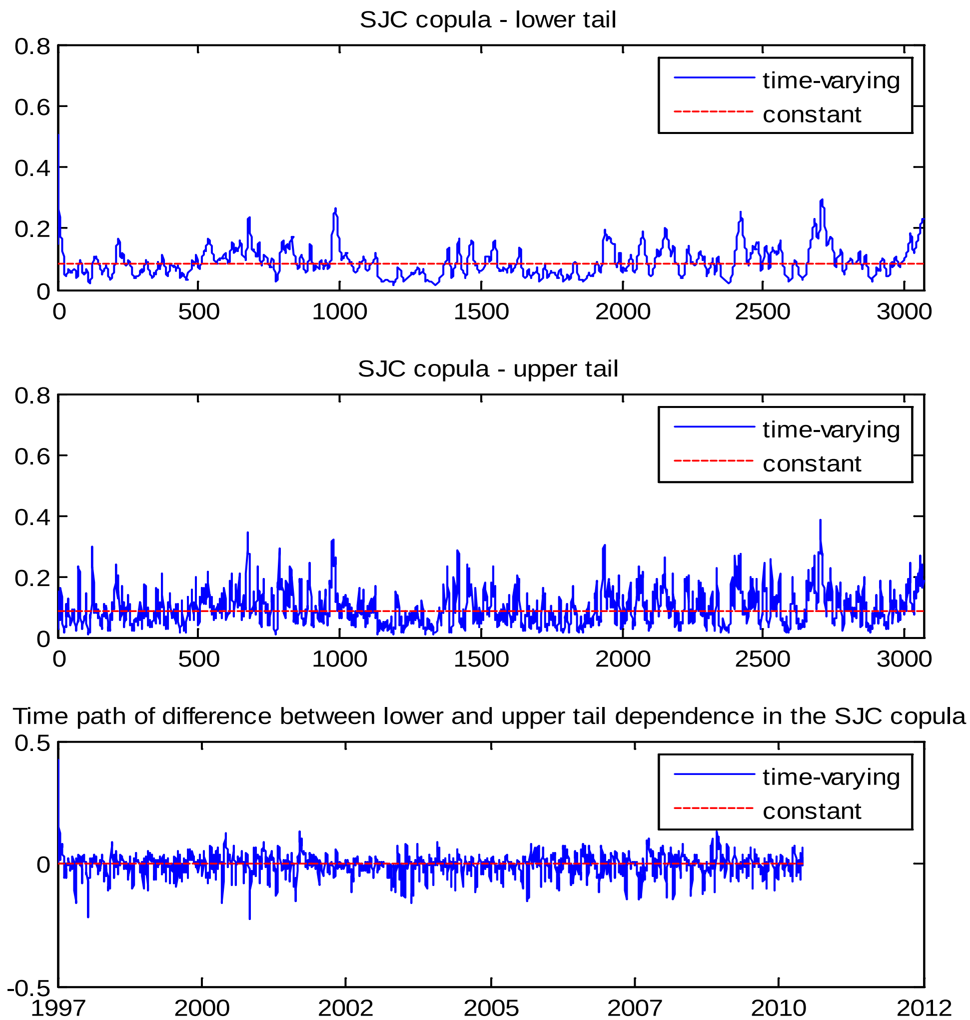

Figure 2.3

Note: Figure 2.3 shows the time path of conditional tail dependence coefficients of the time-varying SJC copula for Taiwan pair. The red dashed line in the top two plots are the estimated lower and upper tail dependence coefficients, respectively. The bottom plot shows the time path of difference between lower and upper tail coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

Chapter 3

Extreme Dependence across East Asian Financial Markets: Evidence in Equity and Currency Markets

3.1 Introduction

The premise for investing in international financial markets is typically driven by the potential benefits that the diversification offers to global investors. Can international investment really offer diversification benefits to a global investor? Most past research is based on the simple measure of linear correlation, which assumes multivariate Gaussian distribution. While this seems to be generally accepted in finance theory, a more in-depth investigation in the dependence structure often provides some compelling evidence that this is not always the case, especially when global financial markets are in turmoil when diversification is most needed. In financial economics, the classical measure of dependency is the Pearson correlation coefficient, commonly known as linear correlation. But linear correlation does not provide precise information on the dependence structure between financial variables or risk factors. Any inference based on linear correlation can be misleading given the fact that financial returns often exhibit fat tails and volatility clustering (heteroskedasticity). Financial crisis and other extreme events often create high turbulences (large drops in asset prices and increased market volatility) in global financial markets, causing potential changes in the dependence structure between markets during crisis period. The high likelihood of extreme co-movements is of paramount importance to investors who wish to diversify their portfolio globally. In this chapter, I use unconditional and conditional copula models to investigate the dependence patterns across international financial markets by focusing on tail dependence (extreme co-movement). Tail dependency can be viewed as the probability of the worst event happening in one market (i.e. one stock/currency market) given that the worst event occurs in another market (i.e. another stock/currency market).

Since early 2000s, some Asian equity markets fully opened their stock market to foreign investors and entered the post-financial liberalization period. Most existing studies using copula methods on extreme dependence measures have focused on developed financial markets, few have focused on Asian markets. Therefore, to model the extreme dependence patterns across international financial markets, I focus on five East Asian countries: Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. I examine the tail dependence behavior across the equity markets as well as across the currency markets. The questions I endeavor to answer in this chapter are the following: 1) is there any extreme dependency across the equity market? 2) is there any extreme dependency across the currency market? 3) is the tail dependence bahavior similar? By answering these questions I hope to better understand the extreme co-movements across these two important markets and provide some insight on risk management strategies 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. 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 returns 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[16] 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 and risk factors. 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

[16] G5 nations are five of the world's leading economies−−France, Germany, Japan, the United Kingdom, and the United States.

(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.

This study is similar to the previous literature in the sense that it also models dependence in international financial market returns. It is different from the existing literature and contributes to the literature in the following: firstly, the countries and data period are different; secondly, the copula models are different, that is, unconditional copulas as well as conditional copulas are applied in this study. One of my major empirical 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 practical finance work is the warning against using bivariate normality or linear correlation coefficients as a guide for risk management and international asset allocation. Given a constant correlation, the underlying dependence structure could be very different. I also find that extreme co-movements across the currency markets of the countries are quite different from stock market extreme co-movements. In several cases, the right tail dependence coefficient is higher than the left tail dependence coefficient.

The layout of this chapter is as follows. In section 3.2, I introduce some conventional measures of dependence as well as some copula measures of dependence. In section 3.3, the models are specified for the marginal distributions and for the joint distributions. I describe the data used in the study and discuss the empirical results in section 3.4. Section 3.5 concludes this chapter.

3.2 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-movements between financial markets and other variables relevant in financial economics, independent of the underlying marginal distributions.

3.2.1 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.

Definition 3.1 Let $(X, Y)^T$ be a vector of random variables with nonzero finite variance. The linear correlation coefficient for $(X, Y)^T$ is

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}} \tag{3.1}$$

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 $-1 \leq \rho(X,Y) \leq 1$. 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 3.2 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

$$\tau = \Pr\big((X_1 - X_1')(X_2 - X_2') > 0\big) - \Pr((X_1 - X_1')(X_2 - X_2') < 0)$$

$$= 2\Pr\big((X_1 - X_1')(X_2 - X_2') > 0\big) - 1 = 4\int\int F\,dF - 1 \qquad (3.2)$$

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 3.3 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 Uniform(0,1) random variables, their expectations are 1/2, their variances are 1/12, and Spearman's rho is

$$\rho_S = 12\int\int F_1(X_1)F_2(X_2)\,dF(F_1, X_2) - 3 = 12\int\int\ F\,dF_1 dF_2 - 3 \qquad (3.3)$$

For bivariate data, ρ_S is the rank correlation and the rank transformation is like the probability transform of a random variable to Uniform (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.

3.2.2 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 variables and risk factors. As described in Joe (1997), a copula is 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.

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

$$C_\rho^{Ga}(u,v) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right) \tag{3.4}$$

where the variables *u* and *v* are the CDFs of the standardized residuals from the marginal models, with $0 \le u, v \le 1$, 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

$$c_\rho(u,v) = \frac{\varphi_{X,Y,\rho}(\Phi^{-1}(u),\Phi^{-1}(v))}{\varphi(\Phi^{-1}(u))\varphi(\Phi^{-1}(v))} \tag{3.5}$$

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

$$C_{\theta}^{Gu}(u,v) = exp\{-\left[(-lnu)^{\theta} + (-lnv)^{\theta}\right]^{1/\theta}\} \quad (3.6)$$

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 (right) tail dependence and has no lower (left) tail dependence. In the text I use upper or right tail and lower or left tail interchangeably.

The copulas I use in this study are introduced in section 3.3. The functional forms for the three static copula models will be given in subsection 3.3.2, and the conditional copula function is introduced in subsection 3.3.3. I use three Archimedean copula models (Symmetrized Joe-Clayton (SJC), time-varying Symmetrized Joe-Clayton, and Clayton) and one elliptical copula (Student's t-copula), each with a different tail dependence behavior[17].

[17] Student's t-copula assumes symmetric tail dependence, Clayton copula has lower (left) tail dependence, and SJC copula is symmetric when lower/left tail parameter is equal to upper/right tail parameter, otherwise, it is asymmetric.

3.3 Model Specification

The estimation procedure applied in this chapter include the following few steps: first, I filter the original returns series with a GARCH model, secondly, I check to make sure that the marginal models are correctly specified before I transform the standardized residuals into i.i.d Uniform(0,1). In the final step, I 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 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 I apply in stock markets is the same as in foreign exchange markets. I compare the performance of the copula models by examining the Akaike's information criterion and/or Bayesian information criterion.

3.3.1 Marginal models

I 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, I 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:

$$r_{i,t} = C_i + \sum_k AR_{i,k} \times r_{i,t-k} + \varepsilon_{i,t} \tag{3.7}$$

$$\sigma_{i,t}^2 = Arch0_i + \sum_p Garch(p)_i \times \sigma_{t-p}^2 + \sum_q Arch(q)_i \times \varepsilon_{i,t-q}^2 \tag{3.8}$$

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 (3.7)). Estimation results of the marginal models are discussed in section 4.

3.3.2 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.

$$\begin{aligned} &C_{SJC}(u, v|\lambda_r, \lambda_l) \\ &\quad = 0.5 \cdot (C_{JC}(u, v|\lambda_r, \lambda_l) + C_{JC}(1-u, 1-v|\lambda_r, \lambda_l) + u + v - 1) \end{aligned} \tag{3.9}$$

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

$$\begin{aligned} &C_{JC}(u, v|\lambda_r, \lambda_l) \\ &\quad = 1 - \left(1 - \{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma}\right)^{1/k} \end{aligned} \tag{3.10}$$

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

$$C_\theta^{Cl}(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \tag{3.11}$$

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.

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

$$C_{v,\rho}^{t}(u_1,u_2) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left\{1 + \frac{(s^2+t^2-2\rho st)}{v(1-\rho^2)}\right\}^{-(v+2)/2} dsdt \tag{3.12}$$

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.

3.3.3 Dynamic copula model: Time-varying SJC copula

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

$$\lambda t = \Lambda(\omega + \beta\lambda_{t-1} + \alpha \cdot \frac{1}{10}\sum_{i=1}^{10}|u_{t-i} - v_{t-i}|), \tag{3.13}$$

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 opposite side of the extremes of the joint distribution and close to zero when they are on the same side of the extremes.

3.4 Data and Empirical Results

3.4.1 Data

The dataset used in this chapter 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 Stock Exchange 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 (US$/HKD), Indonesia Rupiah (US$/IDR), Korean Won (US$/KRW), Singapore dollar (US$/SGD), and Taiwanese dollar (US$/TWD). The returns data start 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:

$$\mathrm{r}_{\mathrm{i,t}} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{3.14}$$

where $P_{i,t}$ is the stock index level at time t, and $P_{i,t-1}$ is the stock index level at time t-1, for country i. The currency movement is computed as

$$e_{i,t} = \ln\left(\frac{S_{i,t}}{S_{i,t-1}}\right) \tag{3.15}$$

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

TABLE 3.1 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 percent (Singapore) to 2.27 percent (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 I 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 percent 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, $LB^2(20)$ is significant for all cases, showing significant evidence in support of GARCH effects. All these test statistics further confirm non-normality in the returns series and volatility clustering observed in most financial markets. I 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 TABLE 3.2, 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).

3.4.2 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 I have non-serially correlated probability integral transforms as copula model inputs[18]. For all the stock index returns, in the mean model I set $k = 10$, and in the variance model, I set $p = 1$, and $q = 1$. TABLE 3.3 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. The estimated intercept term in the variance model is less than 0.0001 for all cases.

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[18] As stated in Patton (2006, pp.539), modeling conditional copula requires that the models for the marginal distributions are indistinguishable from the true marginal distribution. If a mis-specified model for the marginals is used, then the probability integral transforms will not be Uniform(0,1), and any copula model will automatically be mis-specified. Therefore, it is a crucial step to test for serial independence of the probability integral transforms.

The marginal models for the exchange rate returns are presented in TABLE 3.4. 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, so is the Garch8 term. Note that the intercept term of both the mean and variance models are less than 0.0001. 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, I 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 3.5. 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). I discuss the copula models in the following subsection.

3.4.3 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 3.6 to TABLE 3.9. I 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.

This study covers five national stock markets and thus there are in total ten equity pairs. I report the results for all ten pairs. The estimated tail dependence coefficients and degree of freedom parameters and the respective standard errors are presented in TABLE 3.6a, top panels of TABLE 3.7, TABLE 3.8, and TABLE 3.9. From the tables, I observe that in all ten pairs, there is obvious asymmetry between the dependencies in bear markets and bull markets. For example, the SJC copula results suggest that, the limiting probability of the Singapore stock market and Hong Kong stock market crashes together is about 34 percent 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)[19], 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 (see Hu (2002)). 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 crisis. 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 crisis.

[19] The average tail coefficients are calculated as $(\lambda_r + \lambda_l) \div 2$.

Co-movements across the currency markets of the countries are quite different from stock market co-movements, as manifested from the empirical estimates. Copula results are reported in TABLE 3.6b, bottom panels of TABLE 3.7, TABLE 3.8, and TABLE 3.9. In the currency case, Hong Kong currency pairs stand out. I 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 right tail coefficients than left 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.

3.4.4 Dynamic tail dependence – time-varying SJC copula

TABLE 3.10 and TABLE 3.11 report the results for the time-varying SJC copula models for the equity pairs and some selected currency pairs, respectively. For the equity pairs, most dynamic parameters are significant, indicating significant changes in the degree of tail dependence across pairwise stock market co-movements. These results serve as evidence that the degree of tail dependence in these stock markets changes over time. I 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, I plot the lower and upper tail dependence coefficients, along with the estimated parameter value using static SJC copula, in figures from Figures 3.1 to Figure 3.10. The bottom plot in each figure shows time path of the difference between lower and upper tail coefficients over the sample period. 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 overall asymmetry of tail dependence with greater left tail dependency than right tail dependency. I 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, I 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 3.12 and Figure 3.13. The conditional tail coefficients fluctuate around their respective mean value (the horizontal dashed line). The time path in the difference further confirms my 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 3.11 and Figure 3.14).

Comparing the static and time-varying SJC models, the latter models 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 extreme co-movements.

3.5 Conclusion

In this chapter I model the tail dependence patterns across international financial markets by directly estimating the tail dependence coefficients. Specifically I 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 I have the required inputs for the copula functions, I first filter the raw returns series using GARCH−type models and then I get the standardized residuals from this first step. Copula model 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 left tail dependence coefficient than a right tail dependence coefficient. This asymmetry between the dependencies in bear markets and bull markets is consistent with previous research results. Extreme co-movements in the corresponding currency markets are quite different. The bivariate currency pairs for

South Korea, Singapore and Taiwan exhibit strongest tail dependency with higher right tail coefficients than left tail coefficients. For Indonesia currency pairs, only the extreme co-movement between US$/IDR and US$/SGD is significant, with higher probability depreciating than appreciating together against U.S. dollars. Using conditional SJC copula model I also examine the dynamics of tail dependence coefficients 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 stock markets. These results serve as evidence that the degree of tail dependence in these stock markets changes over time, suggesting that these stock markets are in the process of becoming more integrated. My findings have important implications in international finance, especially for those investors who seek international diversification to improve asset allocation and overall portfolio returns. These empirical findings also imply that advantages from international diversification may be offset since the equity pairs are more likely to crash together than boom together.

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Appendix 3: Tables and Figures for Chapter 3

TABLE 3.1: Summary statistics of stock index returns and foreign exchange rate returns

Country	Hong Kong	Indonesia	Korea	Singapore	Taiwan
Panel A: Stock index					
N=2772					
Mean	0.0001	0.0005	0.0003	0.0001	−0.0001
Std. dev.	0.0200	0.0200	0.0227	0.0165	0.0178
Min	−0.1597	−0.1360	−0.1298	−0.1244	−0.0994
Max	0.1725	0.1908	0.1282	0.1106	0.0852
Skewness	−0.1337	−0.2615	−0.1560	−0.1730	−0.2036
Kurtosis	12.54	12.04	6.93	9.88	6.10
J-B stat	10509.15**	9472.98**	1797.24**	5487.97**	1128.08**
LB(20)	34.90**	89.87**	74.84**	62.16**	43.57**
$LB^2(20)$	690.94**	617.83**	1411.15**	991.93**	541.87**
Panel B: forex					
N=3227					
Mean	0.0000	−0.0004	−0.0001	0.0000	0.0000
Std. dev.	0.0003	0.0192	0.0115	0.0040	0.0031
Min	−0.0033	−0.3019	−0.1500	−0.0272	−0.0340
Max	0.0049	0.2332	0.2570	0.0404	0.0280
Skewness	1.6408	−1.5070	2.0675	0.7942	−0.5906
Kurtosis	39.73	56.10	112.30	15.47	19.40
J-B stat	182830.46**	380382.17**	1608490.09**	21258.56**	36332.88**
LB(20)	178.27**	163.90**	241.55**	72.83**	59.13**
$LB^2(20)$	569.53**	2904.09**	1707.82**	1862.94**	335.56**

Note: This table presents summary statistics of the daily stock index returns and foreign exchange rate returns for the selected East-Asian economies. N is the number of observations in each return series.
forex denotes the foreign exchange rate returns. Panel A shows summary statistics of the daily stock index returns, and Panel B shows summary statistics of the daily foreign exchange rate returns. p-value for the J-B stat is less than 0.001 in all cases. **indicates 5% significance level. The data span from 7/3/1997 to 6/4/2010, resulting a total of 2772 observations for the daily stock index returns and 3227 observations for the daily exchange rate returns.

TABLE 3.2: Correlation coefficients.

Country	Hong Kong	Indonesia	Korea	Singapore	Taiwan
Panel A: Pearson's rho					
stock index					
Hong Kong	1.0000				
Indonesia	0.4811	1.0000			
Korea	0.4960	0.3550	1.0000		
Singapore	0.6953	0.4882	0.4792	1.0000	
Taiwan	0.4405	0.3435	0.4518	0.4614	1.0000
forex					
US$/HKD	1.0000				
US$/IDR	0.0340	1.0000			
US$/KRW	0.0508	0.1188	1.0000		
US$/SGD	0.1127	0.3278	0.2089	1.0000	
US$/TWD	0.0935	0.1861	0.2375	0.3583	1.0000
Panel B: Kendall's tau					
stock index					
Hong Kong	1.0000				
Indonesia	0.2695	1.0000			
Korea	0.3443	0.2259	1.0000		
Singapore	0.4471	0.2848	0.3305	1.0000	
Taiwan	0.3045	0.2101	0.3366	0.2980	1.0000
forex					
US$/HKD	1.0000				
US$/IDR	0.0316	1.0000			
US$/KRW	0.0543	0.1084	1.0000		
US$/SGD	0.0886	0.2006	0.2256	1.0000	
US$/TWD	0.0807	0.1232	0.2732	0.2414	1.0000

Note: this table reports the Pearson’s product moment and Kendall’s *tau* correlation coefficients between stock returns and between foreign exchange rate returns for the selected countries. Panel A shows the linear correlation coefficients between stock index returns and between foreign exchange rate returns for the countries. Panel B shows the corresponding Kendall’s tau measure of correlation. forex denotes foreign exchange rate, measured as the price of US$ per local currency.

TABLE 3.3: GARCH results for stock index returns.

Variable	C	AR1	AR3	AR4	AR6	AR7	AR9	AR10	Arch0	Arch1	Garch1
Stock index											
Hong Kong	0.0006		0.0435						9.74E-07	0.0527	0.9473
	(0.0003)		(0.020)						(2.65E-07)	(0.004)	(0.003)
Indonesia	0.0009	0.1089			−0.04467		0.0465	0.0508	1.25E-05	0.1279	0.8478
	(0.0003)	(0.021)			(0.023)		(0.019)	(0.017)	(1.41E-06)	(0.009)	(0.009)
Korea	0.0010	0.0404*				0.0416			2.65E-06	0.0728	0.9247
	(0.0003)	(0.021)				(0.019)			(6.32E-07)	(0.007)	(0.007)
Singapore	0.0006	0.04497							2.03E-06	0.1018	0.8983
	(0.0002)	(0.021)							(4.04E-07)	(0.006)	(0.005)
Taiwan	0.0005	0.0533		−0.0408					3.71E-06	0.0862	0.9063
	(0.0003)	(0.021)		(0.019)					(7.60E-07)	(0.007)	(0.008)

Note: This table reports the estimates of GARCH models for stock index returns of the economies under study. Only significant estimates are reported.

*indicates 10% significance level. The rest are significant at 1%. The intercept term in the variance model is less than 0.0001 in all cases (in scientific format). Estimation is based on log differences.

TABLE 3.4: Estimation results of GARCH models for foreign exchange rate returns.

Variable	C	AR1	AR2	AR5	AR6	AR7	DoF
Panel A:	*Mean model*						
Hong Kong	−2.88E-06	−0.1389	−0.0725	0.0395			2.5648
	(1.95E-06)	(0.004)	(0.004)	(0.009)			(0.00059)
Indonesia	1.96E-05	−0.1059	−0.0441				
	(1.17E-04)	(0.020)	(0.020)				
Korea	5.61E-05			0.0498			
	(7.60E-05)			(0.0193)			
Singapore	8.27E-05					0.0387	
	(5.43E-05)					(0.018)	
Taiwan	1.52E-05			0.0528	0.0462		
	(3.67E-05)			(0.022)	(0.019)		

Variable	Arch0	Arch1	Arch2	Arch3	Garch1	Garch2	Garch8
Panel B	*Variance model*						
Hong Kong	1.07E-08	0.2454	0.1620	0.1019			
	(6.96E-10)	(0.000)	(0.001)	(0.000)			
Indonesia	1.07E-06	0.0704	0.0830	0.0495	0.4125		0.3846
	(1.69E-07)	(0.012)	(0.011)	(0.015)	(0.062)		(0.074)
Korea	6.19E-07	0.1583			0.8417		
	(5.39E-08)	(0.007)			(0.006)		
Singapore	1.95E-08	0.0589			0.9257		
	(1.95E-08)	(0.004)			(0.004)		
Taiwan	5.69E-07	0.2742	0.0783			0.6476	
	(2.87E-08)	(0.008)	(0.004)			(0.008)	

Note: this table reports the estimation results of the GARCH models for exchange rate returns of the countries under study. Numbers in the parenthesis are standard errors. Hong Kong dollar returns series has significant Arch terms up to Arch10 and only the first three are reported in the table. All coefficients are significant at 1% level. The intercept term in both mean and variance model is less than 0.0001 (in scientific format). Estimation is based on log differences.

TABLE 3.5: Goodness-of-fit test for copula marginal models.

Copula Margins	1st moment test	2nd moment test	3rd moment test	4th moment test
Hong Kong stock index	0.9947	0.9514	0.7433	0.4913
US$/HKD	0.6411	0.5285	0.1064	0.0004
Indonesia stock index	0.6799	0.7554	0.6757	0.5831
US$/IDR	0.1359	0.3205	0.4833	0.4748
Korea stock index	0.9885	0.7242	0.2080	0.0796
US$/KRW	0.3244	0.5879	0.7983	0.8508
Singapore stock index	0.9892	0.9581	0.8784	0.7956
US$/SGD	0.9268	0.8427	0.6637	0.5296
Taiwan stock index	0.9660	0.8282	0.4094	0.1827
US$/TWD	0.1539	0.2223	0.2301	0.1128

Note: this table summarizes the goodness-of-fit test for the marginal models. The numbers in the table are p-values of the Ljung-Box test for serial correlation of the probability transforms of the standardized residuals of the GARCH models. US$ = U.S. dollar, HKD = Hong Kong dollar, IDR = Indonesian Rupiah, KRW = Korean Won, SGD = Singapore dollar, TWD = Taiwanese dollar.

TABLE 3.6a : Copula results for Hong Kong pairs: stock market

Hong Kong pairs	Parameters	SJC copula	t-copula	Clayton copula
Stock market				
Indonesia	v		4.41** (0.488)	
	λ_l	0.2825** (0.024)		0.2307** (0.011)
	λ_r	0.2052** (0.026)		
	llv	303.98	310.18	241.99
	AIC	−603.95	−618.37	−481.98
	BIC	−592.10	−612.44	−476.05
South Korea	v		6.80** (1.11)	
	λ_l	0.3701** (0.022)		0.2963** (0.010)
	λ_r	0.3354** (0.023)		
	llv	514.23	516.05	404.10
	AIC	−1024.46	−1030.09	−806.19
	BIC	−1012.60	−1024.17	−800.26
Singapore	v		5.87** (0.79)	
	λ_l	0.5063** (0.016)		0.3734** (0.009)
	λ_r	0.3792** (0.023)		
	llv	770.03	764.04	653.27
	AIC	−1536.06	−1526.08	−1304.53
	BIC	−1524.21	−1520.16	−1298.60
Taiwan	v		6.37** (0.90)	
	λ_l	0.3184** (0.023)		0.2600** (0.010)
	λ_r	0.2616** (0.026)		
	llv	380.76	390.86	307.30
	AIC	−757.52	−779.72	−612.60
	BIC	−745.66	−773.79	−606.67

Note: This table presents the three copula results for Hong Kong pairs: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC, BIC, and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are asymptotic standard errors.
**indicates significance at 1% level.

TABLE 3.6b : Copula results for Hong Kong pairs: forex market

Hong Kong pairs	Parameters	SJC copula	t-copula	Clayton copula
forex market				
Indonesia	v		90.23** (6.79)	
	λ_l	0.0065 (0.009)		0.0395** (0.010)
	λ_r	0.00		
	llv	10.37	9.83	9.17
	AIC	−16.74	−17.66	−16.33
	BIC	−4.58	−11.58	−10.25
South Korea	v		18.79** (8.68)	
	λ_l	0.0165 (0.014)		0.053 **(0.010)
	λ_r	0.0007 (0.003)		
	llv	20.30	20.08	16.82
	AIC	−36.60	−38.15	−31.63
	BIC	−24.44	−32.07	−25.56
Singapore	v		15.91** (5.21)	
	λ_l	0.0354** (0.017)		0.0767** (0.010)
	λ_r	0.0179 (0.013)		
	llv	44.32	43.69	34.16
	AIC	−86.65	−85.38	−66.32
	BIC	−72.49	−79.30	−60.24
Taiwan	v		16.61** (5.06)	
	λ_l	0.0083 (0.010)		0.0592 **(0.010)
	λ_r	0.0211 (0.014)		
	llv	30.29	32.31	19.85
	AIC	−56.58	−62.61	−37.70
	BIC	−44.42	−56.54	−31.62

Note: This table presents the three copula results for Hong Kong pairs: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC*, *BIC*, *and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are asymptotic standard errors.

**indicates significance at 1% level. forex denotes foreign exchange rate.

TABLE 3.7 : Copula results for Indonesia pairs: stock market and forex market

Indonesia pairs	Parameters	SJC copula	t-copula	Clayton copula
Stock market				
S. Korea	v		4.82** (0.55)	
	λ_l	0.2428** (0.023)		0.2018** (0.011)
	λ_r	0.1443** (0.027)		
	llv	229.08	239.20	188.18
	AIC	−454.15	−476.40	−374.36
	BIC	−442.29	−470.47	−368.43
Singapore	v		4.45** (0.51)	
	λ_l	0.3075** (0.023)		0.2409** (0.011)
	λ_r	0.1942** (0.027)		
	llv	317.73	327.51	261.67
	AIC	−631.47	−653.02	−521.35
	BIC	−619.61	−647.10	−515.42
Taiwan	v		7.18** (1.25)	
	λ_l	0.2069** (0.024)		0.1818** (0.010)
	λ_r	0.1186** (0.027)		
	llv	186.80	187.86	155.90
	AIC	−368.66	−373.71	−309.79
	BIC	−356.80	−367.79	−303.86
forex market				
	v		28.53 (24.70)	
South Korea	λ_l	0.0642** (0.020)		0.1018** (0.010)
	λ_r	0.0458** (0.019)		
	llv	74.17	73.17	58.44
	AIC	−144.34	−144.33	−114.88
	BIC	−132.18	−138.25	−108.80
Singapore	v		12.84** (3.57)	
	λ_l	0.1465** (0.022)		0.1534** (0.010)
	λ_r	0.1043** (0.023)		
	llv	163.50	161.01	130.51
	AIC	−322.99	−320.12	−259.02
	BIC	−310.83	−313.94	−252.94
Taiwan	v		22.20** (8.78)	
	λ_l	0.0582** (0.020)		0.0946** (0.010)
	λ_r	0.0365** (0.018)		
	llv	64.72	64.1900	49.9600
	AIC	−125.45	−126.38	−97.93
	BIC	−113.29	−120.30	−91.85

Note: This table presents the three copula results for Indonesia pairs: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC*, *BIC*, *and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are asymptotic standard errors.

**indicates significance at 1% level. forex denotes foreign exchange.

TABLE 3.8 : Copula results for South Korea pairs: stock market and forex market

Korea pairs	Parameters	SJC copula	t-copula	Clayton copula
Stock market				
Singapore	v		5.18** (0.63)	
	λ_l	0.3696** (0.022)		0.2853** (0.010)
	λ_r	0.2774** (0.025)		
	llv	453.59	458.28	370.23
	AIC	−903.18	−914.55	−738.47
	BIC	−891.33	−908.62	−732.54
Taiwan	v		5.38** (0.66)	
	λ_l	0.3759** (0.021)		0.2863** (0.010)
	λ_r	0.2609** (0.028)		
	llv	443.40	457.92	376.20
	AIC	−882.81	−913.83	−750.40
	BIC	−870.95	−907.91	−744.47
forex market				
Singapore	v		11.48** (2.58)	
	λ_l	0.1607** (0.025)		0.1770** (0.010)
	λ_r	0.1824** (0.025)		
	llv	222.51	227.53	166.42
	AIC	−441.02	−453.05	−330.84
	BIC	−428.86	−446.97	−324.76
Taiwan	v		8.86** (1.55)	
	λ_l	0.1977** (0.025)		0.2069** (0.010)
	λ_r	0.2640** (0.023)		
	llv	325.47	328.1600	227.2200
	AIC	−646.93	−654.32	−452.44
	BIC	−634.77	−648.24	−446.36

Note: This table presents the three copula results for South Korea pairs: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC*, *BIC*, *and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are asymptotic standard errors.

**indicates significance at 1% level. forex denotes foreign exchange.

TABLE 3.9 : Copula results for Singapore-Taiwan pair: stock market and forex market

Singapore pair	Parameters	SJC copula	t-copula	Clayton copula
Stock market				
Taiwan	v		6.46** (0.97)	
	λ_l	0.3089** (0.022)		0.2512** (0.010)
	λ_r	0.2496** (0.024)		
	llv	367.78	370.68	292.81
	AIC	−731.55	−739.36	−583.62
	BIC	−719.70	−733.43	−577.69
forex market				
Taiwan	v		6.85** (0.98)	
	λ_l	0.1457** (0.025)		0.1735** (0.010)
	λ_r	0.2141** (0.024)		
	llv	238.03	241.3200	158.1300
	AIC	−472.06	−480.63	−314.27
	BIC	−459.90	−474.55	−308.19

Note: This table presents the three copula results for Singapore-Taiwan pair: SJC copula, Student t-copula, and Clayton copula. v is the estimated degree of freedom, λ_l is the left (lower) tail dependence coefficient, and λ_r is the right (upper) tail dependence coefficient. *AIC, BIC, and llv* are Akaike's information criterion, Schwarz's Bayesian information criterion, and log-likelihood value, respectively. The numbers in parentheses are asymptotic standard errors.
**indicates significance at 1% level. forex denotes foreign exchange.

TABLE 3.10: Time-varying SJC copula model results: equity pairs

	Lower tail			Upper tail				
Equity	ω	α	β	ω	α	β	*lnl*	*AIC*
Hong Kong Pairs								
Indonesia	1.9207**	−9.9997**	0.1256	0.0708**	−0.3438**	0.9891**	365.752	−719.5048
	(0.128)	(0.001)	(0.194)	(0.009)	(0.044)	(0.002)		
South Korea	2.1569	−10.0000	−0.1335	0.1396*	−0.6921*	0.9347**	544.202	−1076.404
	(7.389)	(34.417)	(3.591)	(0.080)	(0.406)	(0.053)		
Singapore	3.3566**	−9.4311**	−0.9632**	0.3352**	−1.8**	0.8957**	805.266	−1598.5327
	(0.435)	(2.125)	(0.016)	(0.148)	(0.814)	(0.060)		
Taiwan	0.1574	−0.7303	0.9684**	1.2194**	−8.5582**	−0.0726**	431.668	−851.3369
	(0.116)	(0.543)	(0.027)	(0.574)	(2.484)	(0.024)		
Indonesia Pairs								
South Korea	0.1579**	−0.736**	0.9584**	1.5847**	−9.9976**	0.4128	273.971	−535.942
	(0.048)	(0.232)	(0.017)	(0.793)	(5.089)	(0.258)		
Singapore	1.1095**	−5.6777**	0.4342	0.0547**	−0.2777**	0.9894**	365.874	−719.748
	(0.528)	(2.684)	(0.261)	(0.025)	(0.131)	(0.006)		
Taiwan	0.3491**	−1.6763**	0.9190**	0.1603	−1.2335	0.9023**	228.152	−444.305
	(0.110)	(0.562)	(0.028)	(0.379)	(2.229)	(0.124)		
S. Korea Pairs								
Singapore	1.9915**	−8.8011**	−0.2854	0.1320	−0.7210	0.9503**	479.471	−946.942
	(0.451)	(2.045)	(0.177)	(0.081)	(0.451)	(0.034)		
Taiwan	2.1845**	−9.9793**	0.1522	0.1347*	−0.7139	0.9690**	518.533	−1025.067
	(0.145)	(0.469)	(0.110)	(0.070)	(0.380)	(0.017)		
Singapore Pair								
Taiwan	0.1013**	−0.4653**	0.9792**	0.8961	−6.6101	0.1071	399.521	−787.042
	(0.017)	(0.075)	(0.004)	(0.883)	(5.836)	(0.725)		

Note: This table reports the time-varying SJC copula results for the equity pairs. ω, α, β, are the estimated parameter values and the numbers in parentheses are asymptotic standard errors. *AIC and llv* correspond to Akaike's information criterion and log-likelihood value, respectively.
** and * indicate significance at 1% and 5% level respectively.

TABLE 3.11: Time-varying SJC copula model results: currency pairs

	Lower tail			Upper tail				
Currency	ω	α	β	ω	α	β	*lnl*	*AIC*
S. Korea Pairs								
Singapore	0.3353	−10.00**	−0.7048**	0.0929**	−0.4456**	0.9823**	240.902	−469.804
	(0.842)	(3.518)	(0.149)	(0.030)	(0.160)	(0.010)		
Taiwan	0.6733	−7.852	−0.1442	1.1317	−6.5994	0.2788	349.998	−687.995
	(0.980)	(5.113)	(0.195)	(0.714)	(4.002)	(0.409)		
Singapore Pairs								
Indonesia	0.0649	−0.7427**	0.9121**	−0.0725**	0.2709**	1.0013**	177.089	−342.177
	(0.091)	(0.339)	(0.065)	(0.016)	(0.060)	(0.001)		
Taiwan	0.5471	−8.0426	−0.064	0.1827	−6.7602	−0.6259**	248.922	−485.8447
	(0.813)	(16.045)	(2.467)	(0.915)	(3.777)	(0.274)		

Note: This table reports the time-varying SJC copula results for the selected currency pairs. ω, α, β, are the estimated parameter values and the numbers in parentheses are asymptotic standard errors. *AIC and llv* correspond to Akaike's information criterion and log-likelihood value, respectively.
** and * indicate significance at 1% and 5% level respectively.

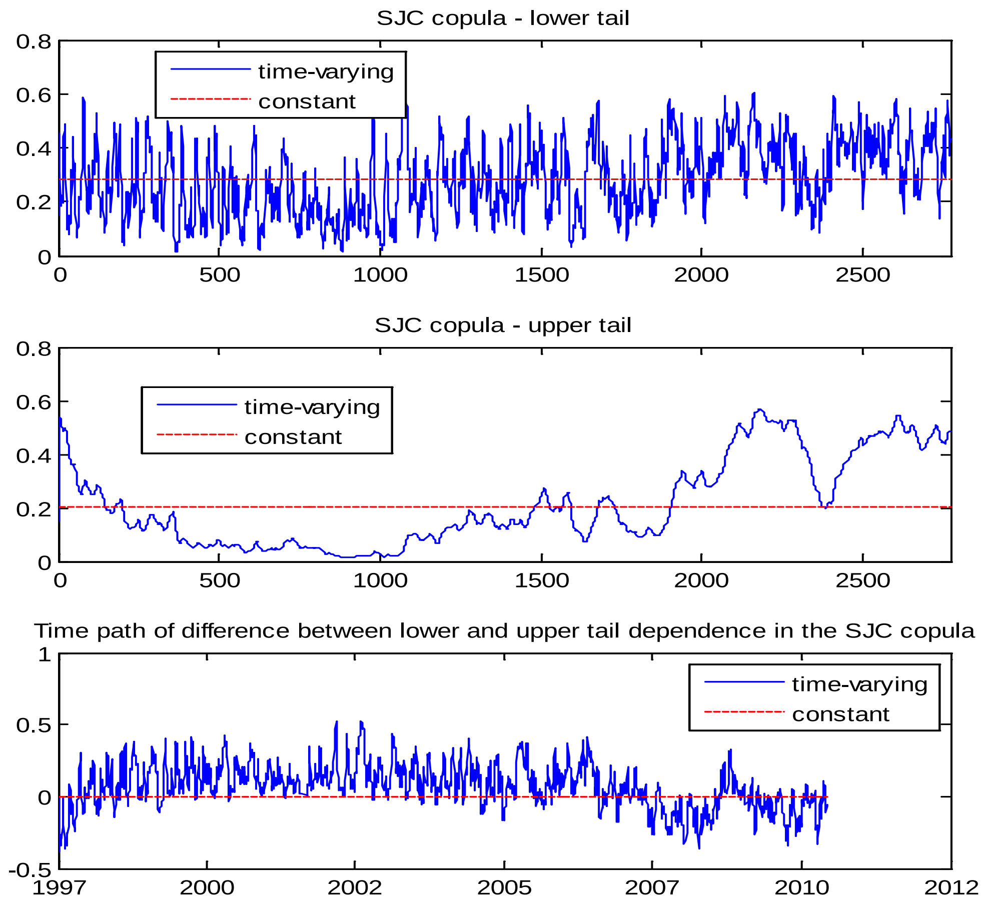

Figure 3.1

Note: Figure 3.1 depicts tail difference for Hong Kong−Indonesia equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

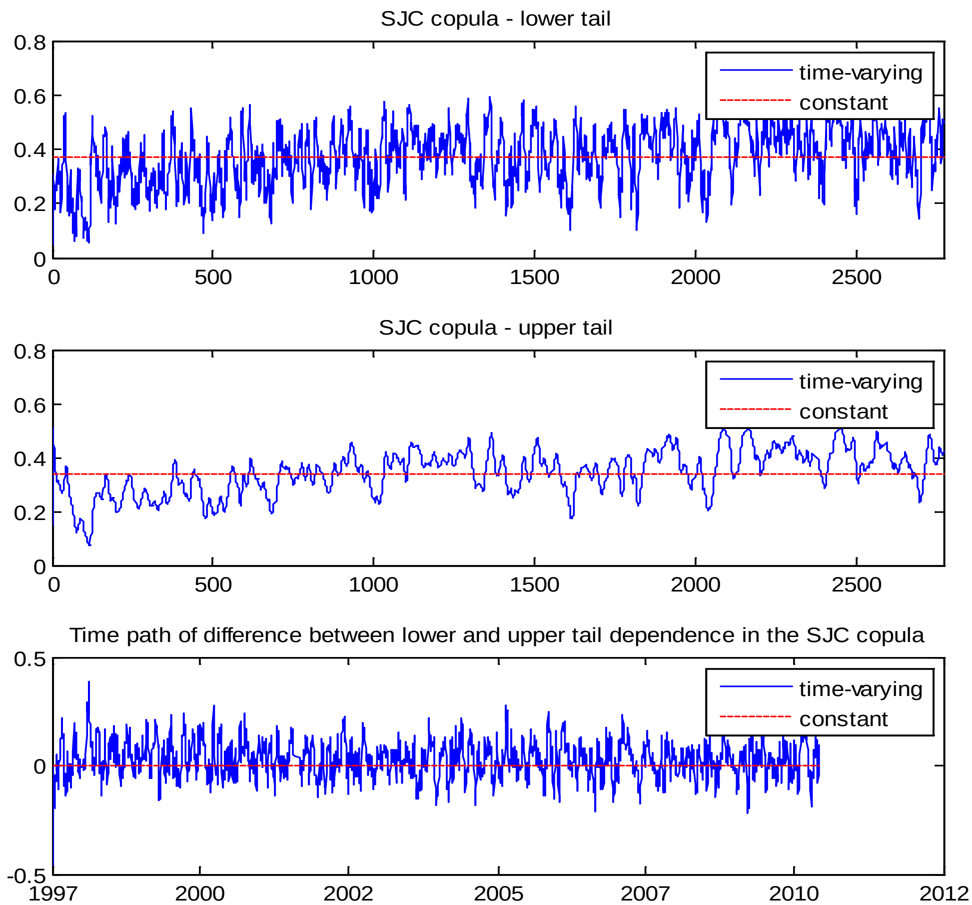

Figure 3.2

Note: Figure 3.2 depicts tail difference for Hong Kong–S. Korea equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

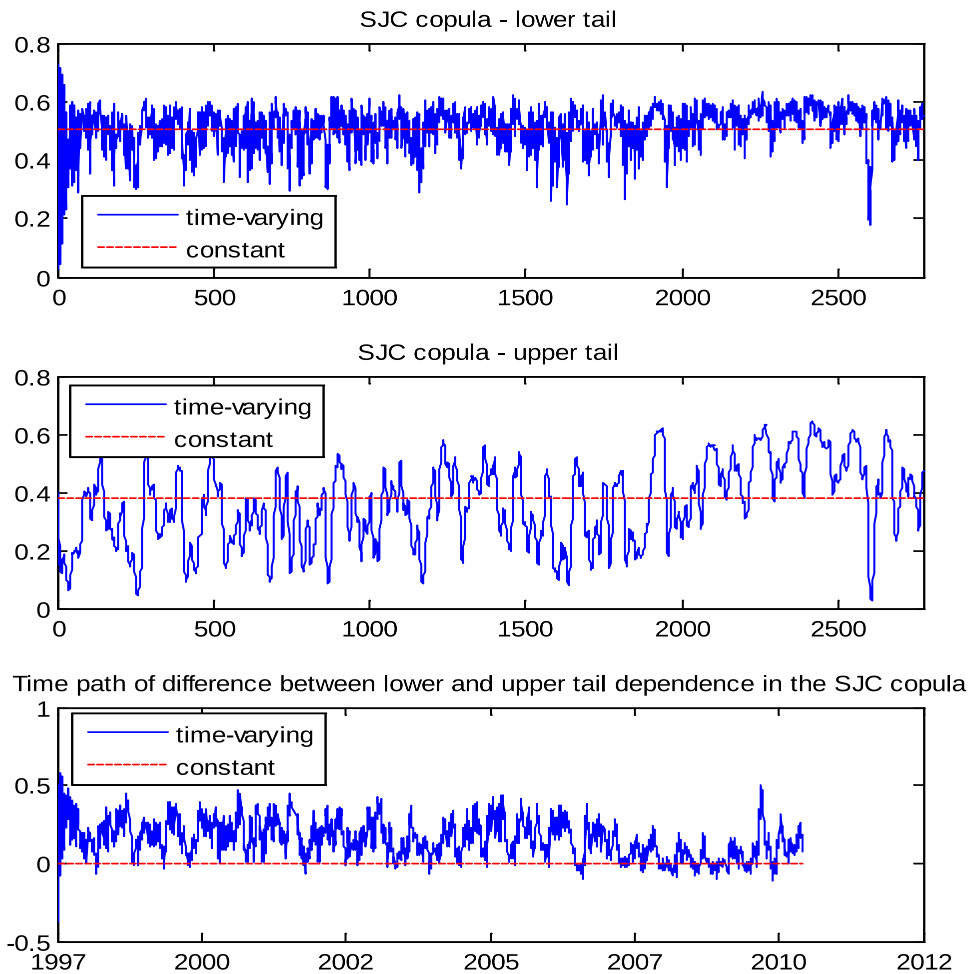

Figure 3.3

Note: Figure 3.3 depicts tail difference for Hong Kong–Singapore equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

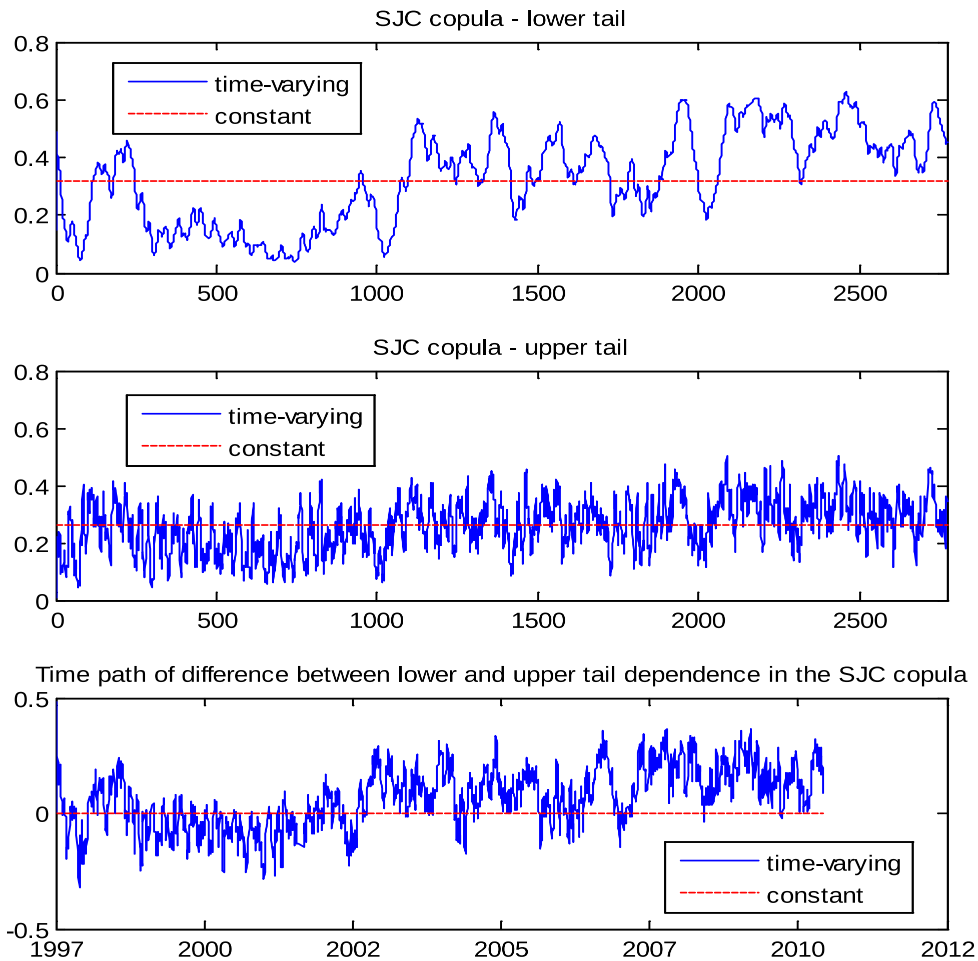

Figure 3.4

Note: Figure 3.4 depicts tail difference for Hong Kong−Taiwan equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

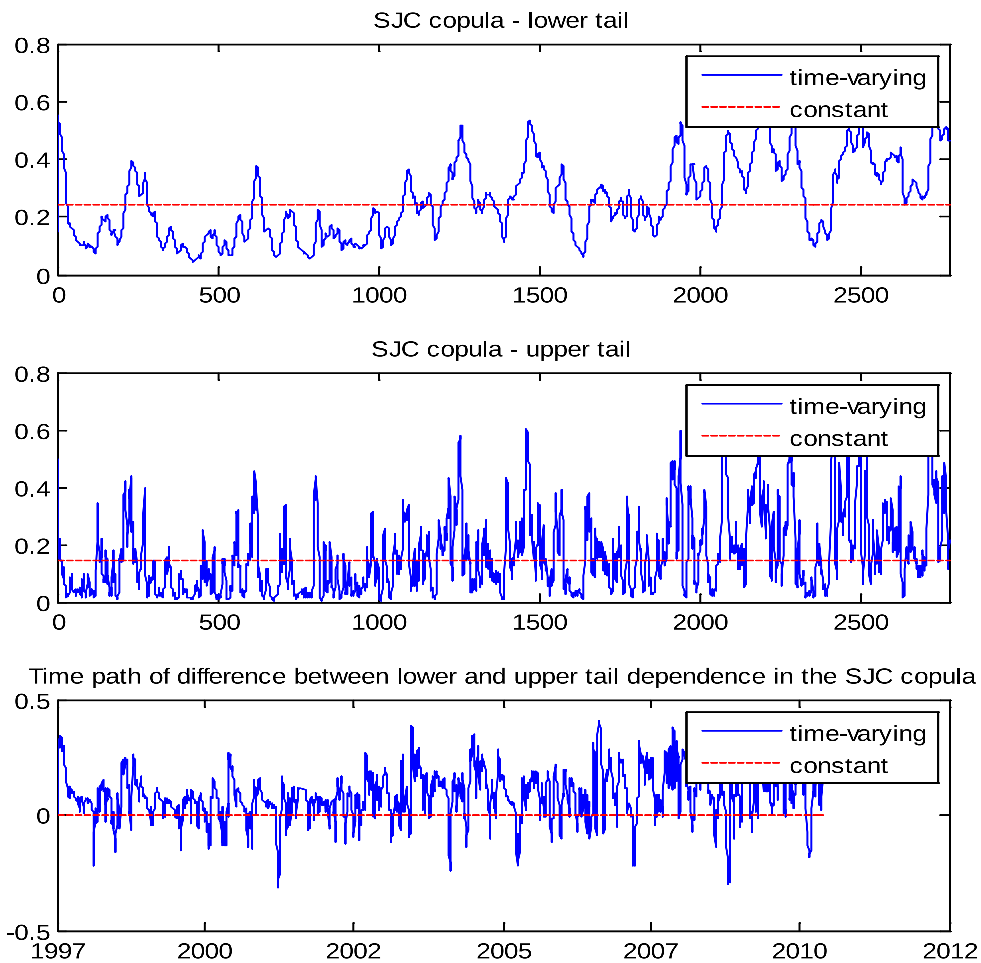

Figure 3.5

Note: Figure 3.5 depicts tail difference for Indonesia−S. Korea equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

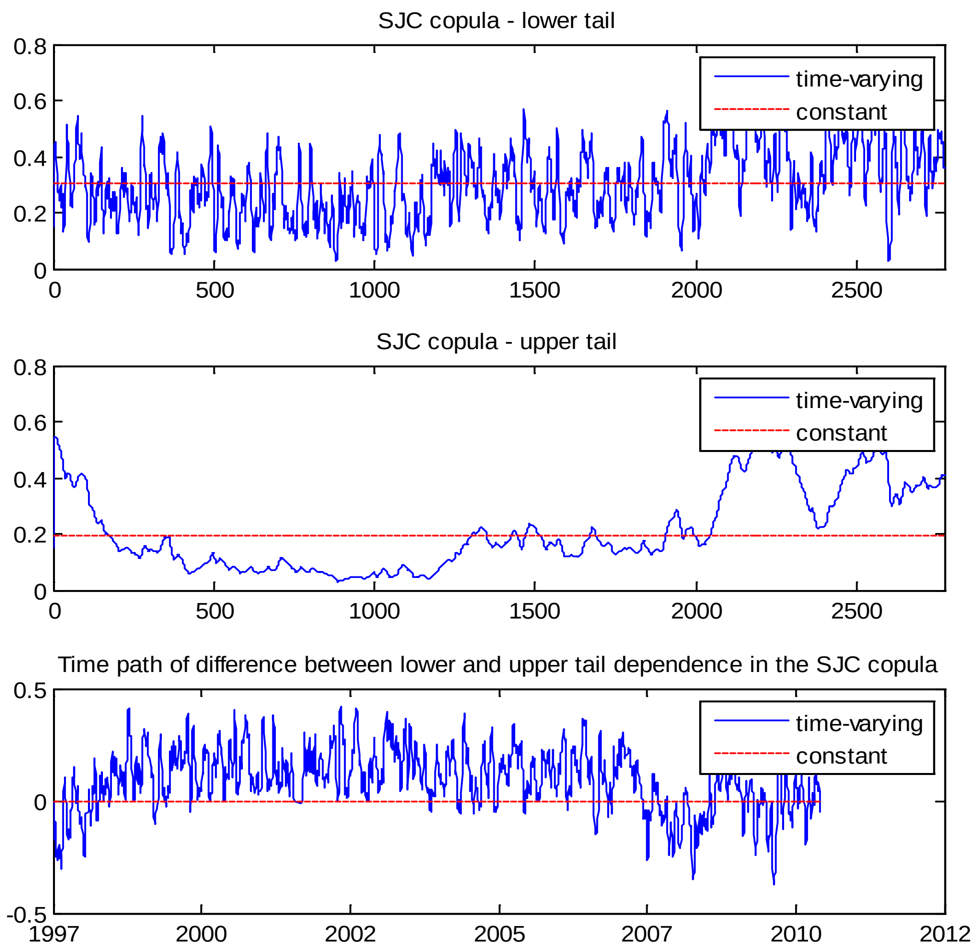

Figure 3.6

Note: Figure 3.6 depicts tail difference for Indonesia−Singapore equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

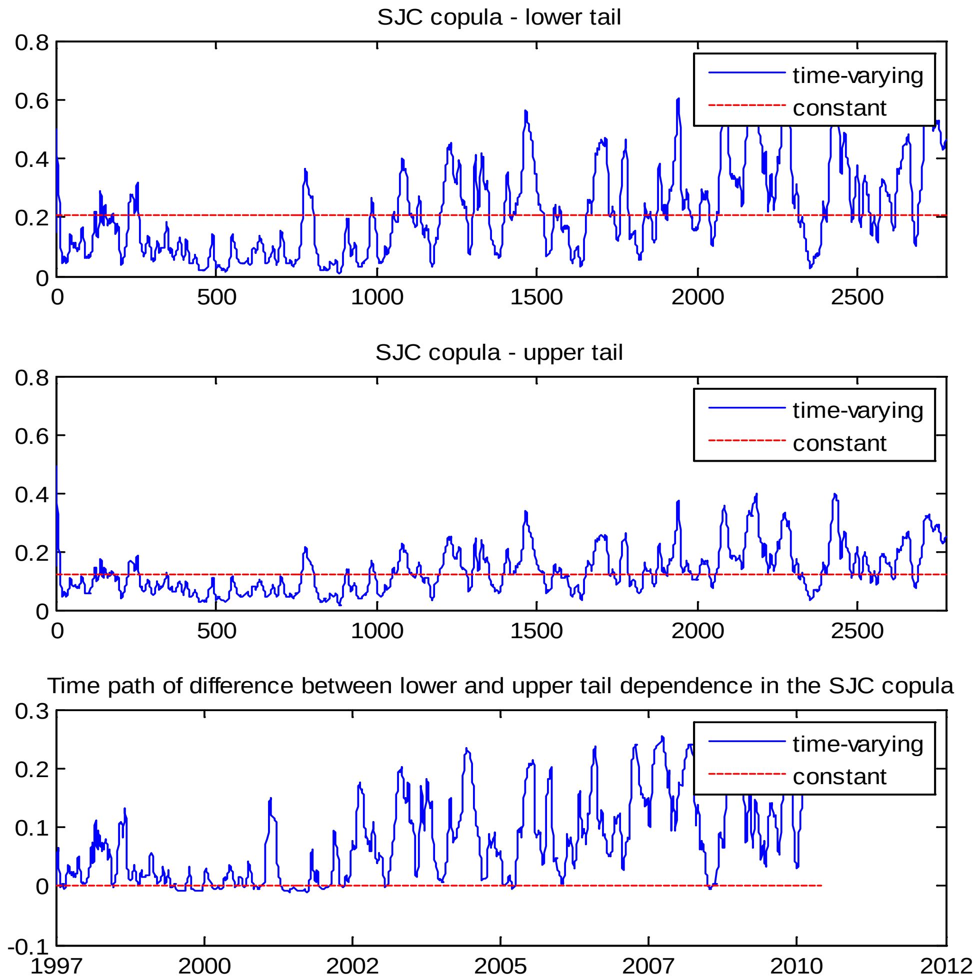

Figure 3.7

Note: Figure 3.7 depicts tail difference for Indonesia−Taiwan equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

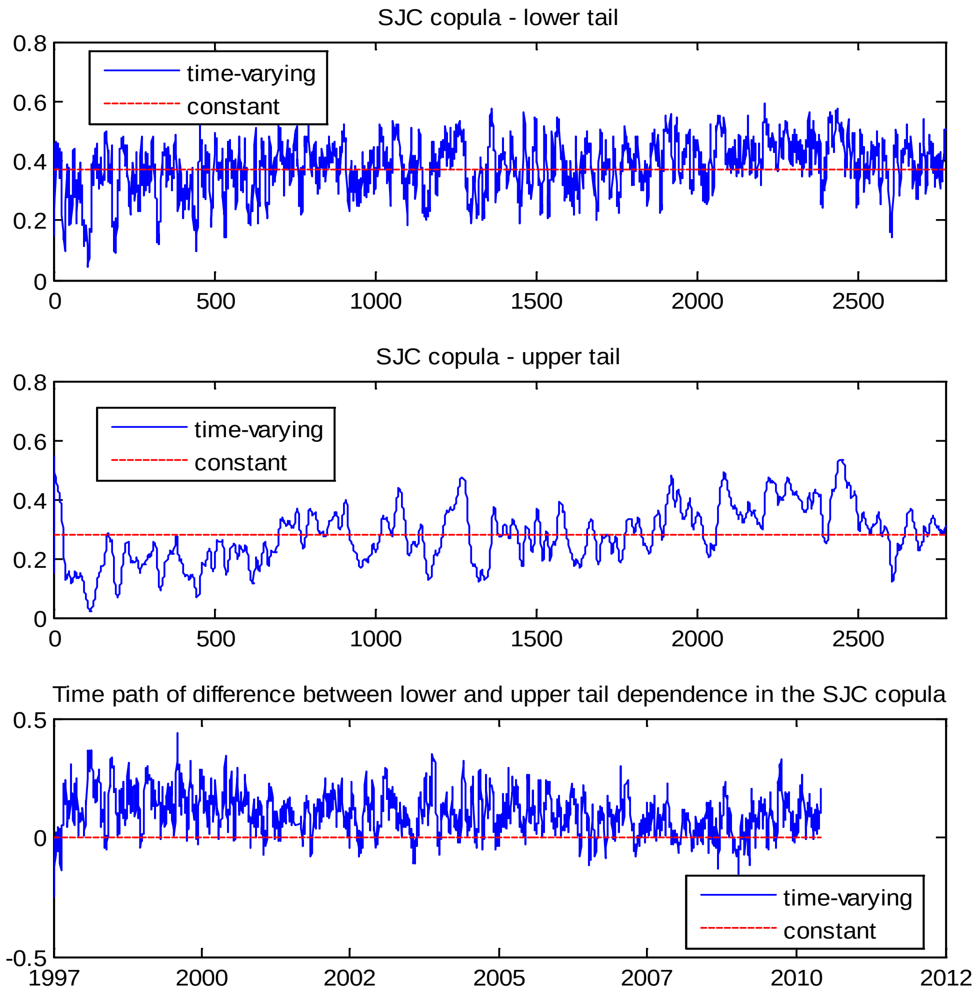

Figure 3.8

Note: Figure 3.8 depicts tail difference for S. Korea−Singapore equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

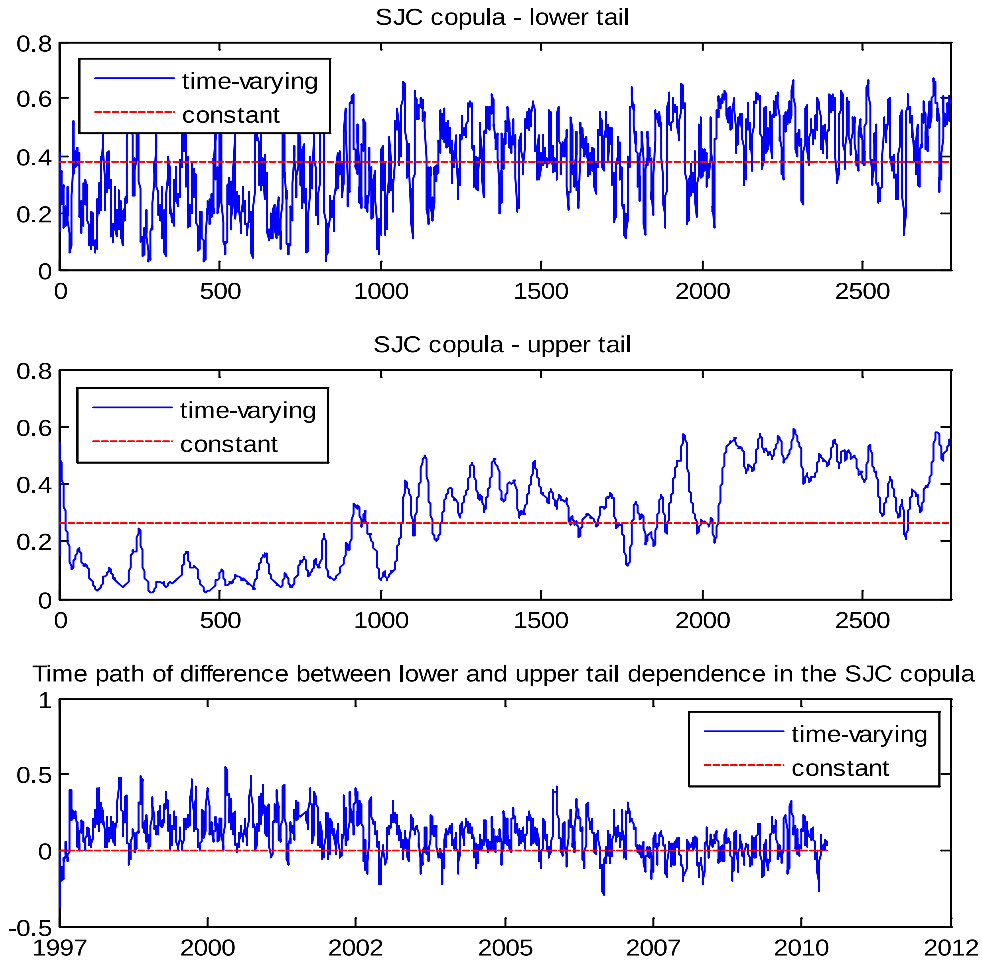

Figure 3.9

Note: Figure 3.9 depicts tail difference for S. Korea−Taiwan equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

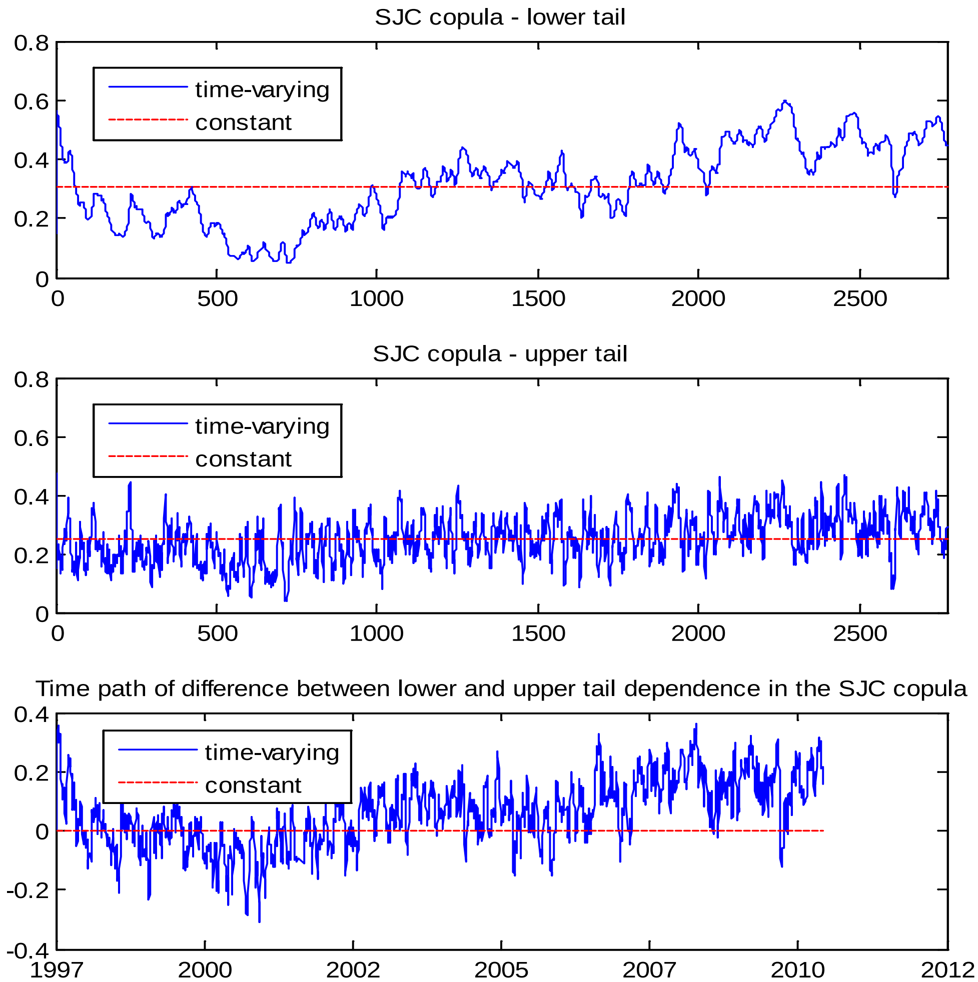

Figure 3.10

Note: Figure 3.10 depicts tail difference for Singapore−Taiwan equity pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

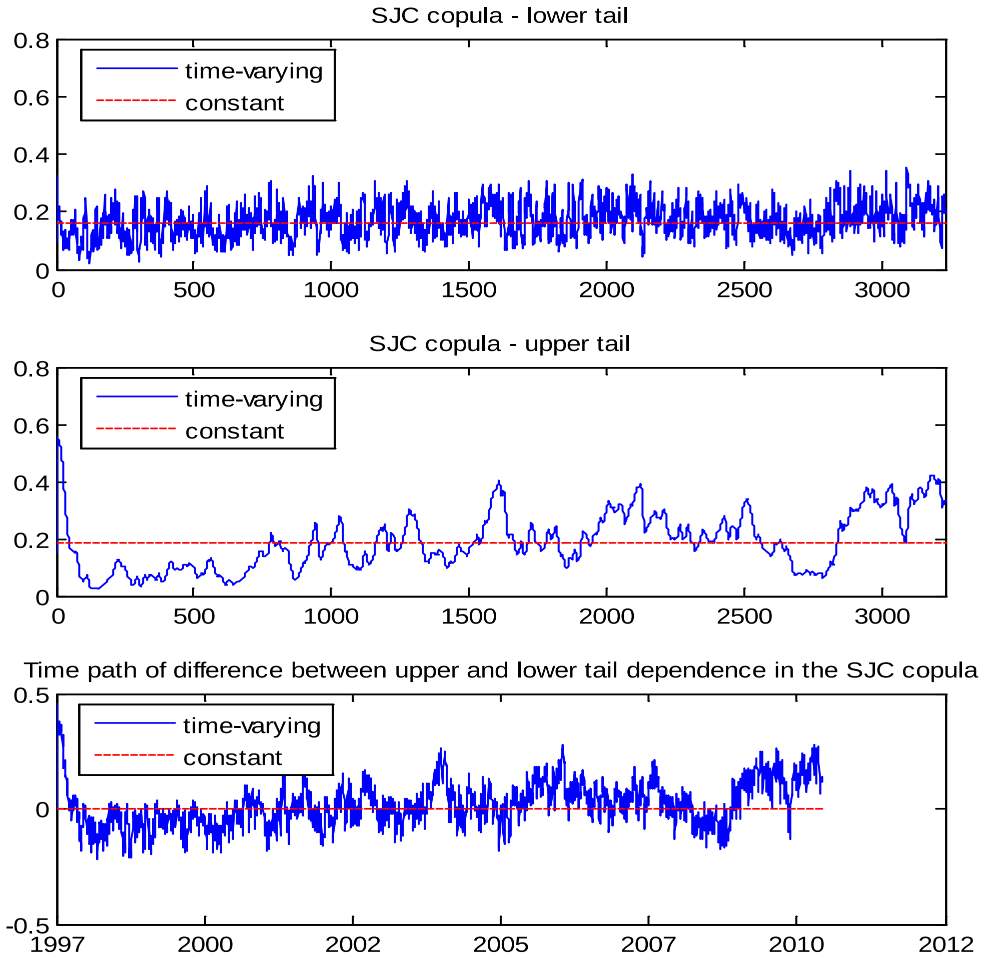

Figure 3.11

Note: Figure 3.11 depicts tail difference for Singapore−S. Korea currency pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between upper and lower tail dependence coefficients. The difference is calculated as $\lambda_r - \lambda_l$.

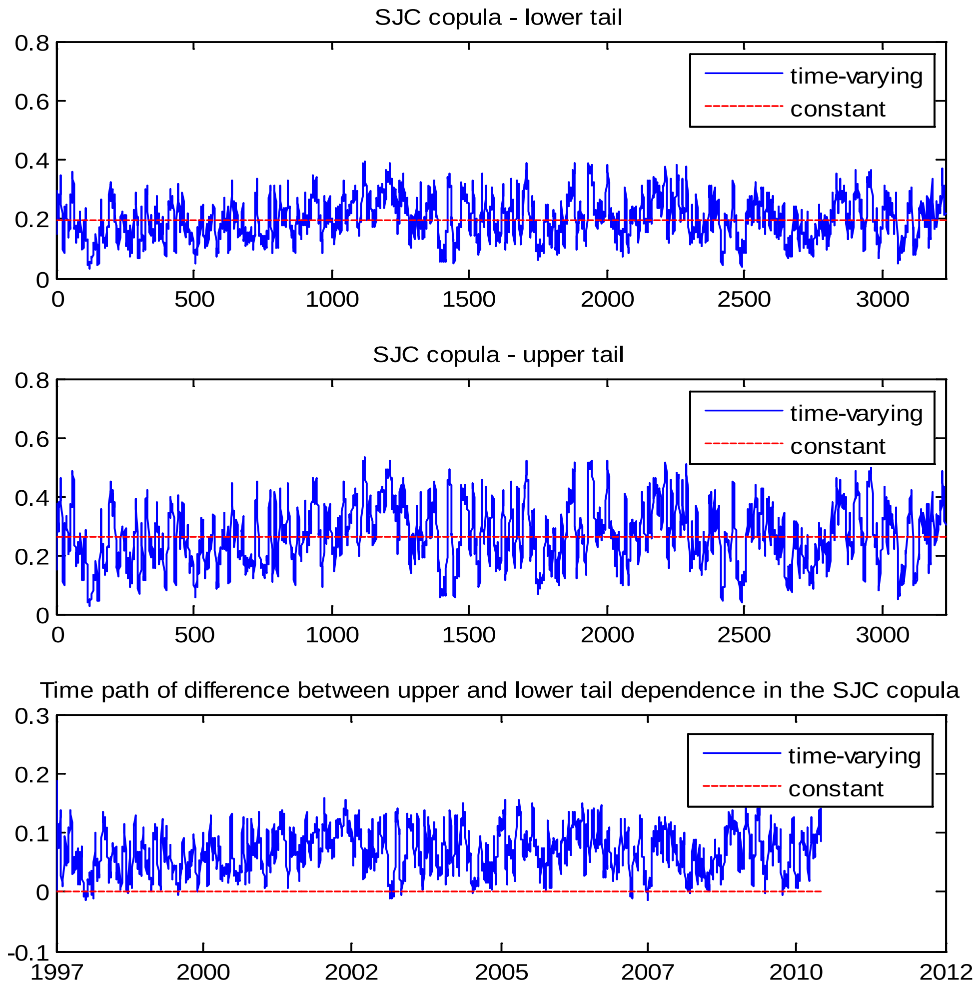

Figure 3.12

Note: Figure 3.12 depicts tail difference for S. Korea−Taiwan currency pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between upper and lower tail dependence coefficients. The difference is calculated as $\lambda_r - \lambda_l$.

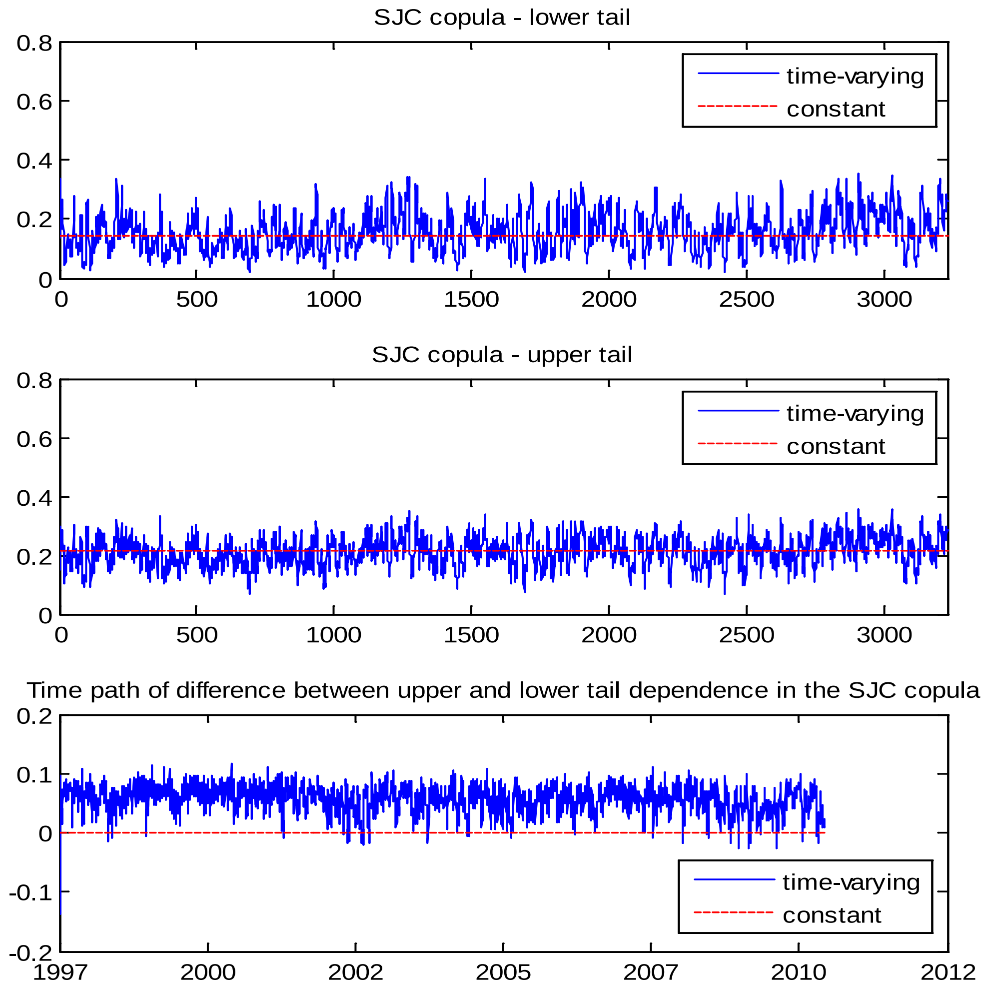

Figure 3.13

Note: Figure 3.13 depicts tail difference for Singapore−Taiwan currency pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between upper and lower tail dependence coefficients. The difference is calculated as $\lambda_r - \lambda_l$.

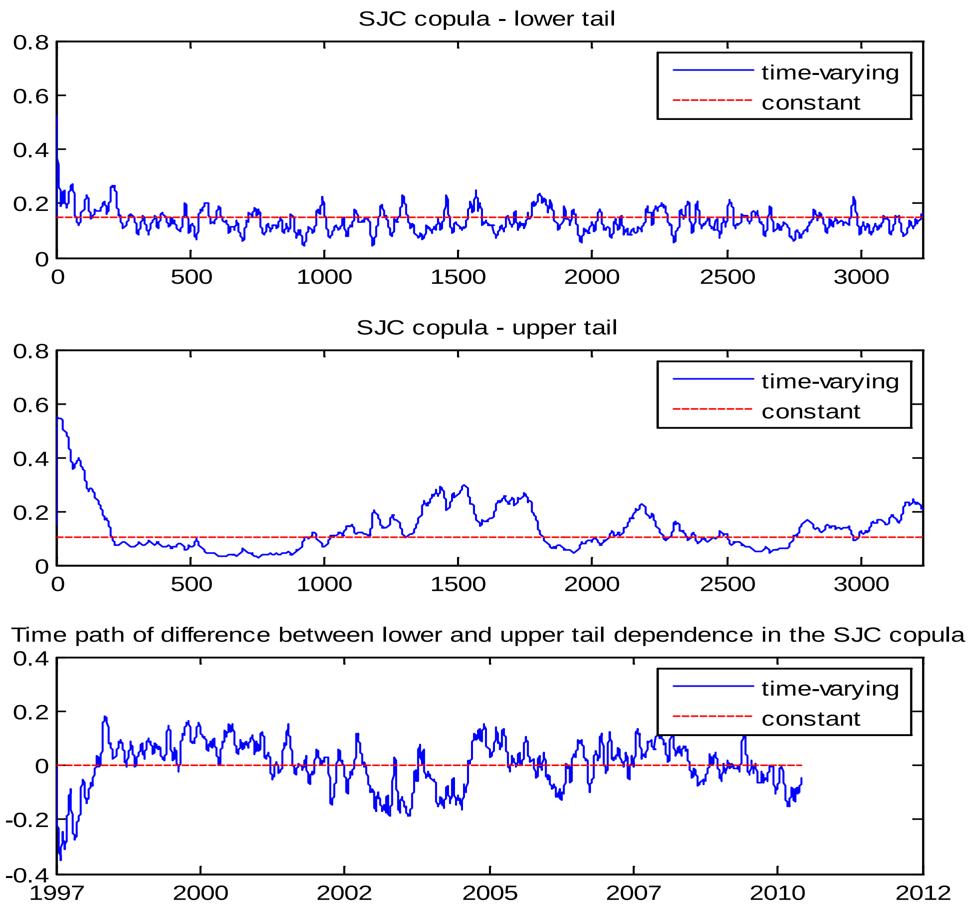

Figure 3.14

Note: Figure 3.14 depicts tail difference for Singapore−Indonesia currency pair. The top two plots show the lower and upper tail dependence coefficients. The red dashed line is the corresponding tail coefficient estimated using static SJC copula. The bottom plot shows the time path of difference between lower and upper tail dependence coefficients. The difference is calculated as $\lambda_l - \lambda_r$.

Chapter 4

Summary of Findings

In this study I propose to model the tail behavior of stock index returns and foreign exchange rate fluctuations, the cross-market extreme dependency between the stock market and foreign exchange market within each country, as well as the pairwise extreme dependencies across the stock markets and across the currency markets. More specifically, using data from several East Asian economies, I first examine the tail behavior of individual returns series (stock index returns and foreign exchange rate returns) for each country via extreme value theory, then I model the cross-market extreme dependency within each individual country using copula models, and lastly, using unconditional and conditional copulas I analyze the cross-country extreme dependence patterns in the stock index returns as well as in the foreign exchange rate returns, with a focus on tail dependencies. I summarize the empirical findings and discuss the important implications for practical finance work as follows.

In chapter one, I use extreme value theory (EVT) to analyze six East Asian financial markets (stock market and foreign exchange market): two major markets (Hong Kong and Singapore) and four emerging markets (Indonesia, South Korea, Malaysia, and Taiwan). My empirical results indicate that the generalized Pareto distribution (GPD) fits the tails of the return distributions in these markets reasonably well. I find for nearly all returns series a tail behavior compatible with the existence of the first and second moments. For some even higher moments seem to exist. In the area of risk management for emerging market investments, an accurate measure and understanding of market specific tail behavior is critical to hedging risk in these markets. By directly comparing the tail mass based on the point estimates across markets, I can draw the following conclusions: the right tails of currency returns for Indonesia and Singapore are fatter than that of the stock index returns; Hong Kong, South Korea, and Taiwan have both fatter tails in the currency returns than stock index returns; in the case of Malaysia, its stock index returns distribution has both a fatter left and right tail than the currency returns counterpart. These results indicate that the daily return distributions have different left and right tail characteristics across markets in the same country and across countries in the same geographical region. Therefore, the risk and reward are not equally likely in the financial markets of these economies. For an investor interested in international diversification the study of cross-market co-movement may also be of great importance because it will affect the portfolio returns. Therefore, a natural extension of this study will be on the co-movements between financial markets within a country, especially in the tail area. That is the aim for chapter two.

In chapter two, I apply the concept of copulas to estimate the tail dependency between stock index returns and foreign exchange rate returns for five East Asian economies: Hong Kong, Indonesia, South Korea, Singapore, and Taiwan. In particular, I use three copulas models to examine the dependence patterns, especially in the tail area, between the two returns series. Major empirical results reveal that the tail dependence coefficient is significant for the three East Asian emerging markets (asymmetric tail dependence for Indonesia and South Korea and symmetric tail dependence for Taiwan), and for the more advanced countries, namely Hong Kong and Singapore, there isn't enough evidence to prove the existence of any tail dependency. Examination of the time path of the tail dependence coefficients also confirms the aforementioned results. These findings have important finance implications in risk management and asset pricing. For global investors seeking to diversify their portfolio into emerging markets, ignoring the joint downside risk would underestimate the value-at-risk (VaR), which is a common market risk measure in risk management. Tail dependence serves as a true measure for systematic risk in times of financial crisis and global investors should be compensated for exposure to such risk during joint market downturns. For international investors seeking diversification into Indonesia and South Korea stock markets, it is more likely for them experiencing extreme double losses (one in the stock market and the other in the currency market when translating into home currency returns) than extreme double gains. Therefore hedging equity investments with currency derivatives is highly recommended. For investments made in the two advanced markets, currency hedging does not seem quite necessary.

Since the year 2000, some Asian stock markets fully opened their stock markets to foreign investors and entered the post-financial liberalization period. Most existing studies using copula methods on extreme dependence structure have focused on developed financial market, few have focused on Asian markets. The third aspect of this study will focus on the tail dependency across stock markets and across foreign exchange markets in this geographical region. In chapter three, using unconditional as well as conditional copula models, I model the extreme co-movements across the stock markets as well as across the foreign exchange markets for the same five economies as in chapter two. Co-movements between international financial markets are often studied within the context of "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. My empirical results indicate that, across stock markets, there is an obvious asymmetry between the dependencies in bear markets and bull markets, consistent with previous research results. 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. 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. Co-movements across the currency markets of the countries are quite different from stock market co-movements, as manifested from the empirical estimates. The bivariate currency pairs for South Korea, Singapore and Taiwan exhibit strongest tail dependency with greater right tail coefficients than left tail coefficients. For Indonesia currency pairs, only the extreme co-movement between US$/IDR and US$/SGD is significant, with higher probability depreciating than appreciating together against U.S. dollar. Using time-varying SJC copula model I also examine the dynamics of tail dependencies 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, suggesting that these stock markets are in the process of becoming more integrated. Again my findings have important implications in international finance, especially for those investors who seek international diversification to improve their asset allocation and overall portfolio returns. My empirical results also imply that advantages from international diversification may be offset since the equity pairs are more likely to crash together than boom together.

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