MODELING THE DEPENDENCE BETWEEN STOCK INDEX AND EXCHANGE RETURNS WITH COPULA-EXTREME VALUE THEORY BASED SEMIPARAMETRIC APPROACHES AND THEIR APPLICATIONS IN RISK MANAGEMENT

by

CHUN-PIN HSU

A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2009

This manuscript has been read and accepted for the Graduate Faculty in Economics in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

Peter C.Y. Chow____________________________________

________________________ ____

Date Chair of Examining Committee

Thom B. Thurston____________________________________

_________________________ ____

Date Executive Officer

Professor Peter C. Y. Chow ____

Professor Michael Grossman____

Professor Thom B. Thurston____

Supervisory Committee

THE CITY UNIVERSITY OF NEW YORK

Abstract

MODELING THE DEPENDENCE BETWEEN STOCK INDEX RETURNS AND EXCHANGE RETURNS WITH COPULA-EXTREME VALUE THEORY BASED SEMIPARAMETRIC APPROACHES AND THEIR APPLICATIONS IN RISK

by

CHUN-PIN HSU

Advisor: Professor Peter C.Y. Chow

Measuring Value-at-Risk (VaR) is an important function in financial risk management. One of the most popular methods of computing VaR is the Monte Carlo simulation, which focuses on utilizing an appropriate approach to estimate the dependence between returns of financial assets. However, the existence of fat-tailed, skewed distributions and non-linear relationships of financial asset returns makes conventional Pearson product-moment coefficient approach incongruous. To overcome this difficulty, the current research applies the extreme value theory (EVT) in order to model the tails of the return distributions and copula functions to build the joint distribution of returns. More specifically, in the copula-EVT-based methodologies, the marginal distributions of asset returns are modeled using a semiparameter approach in which the distribution center is modeled by a nonparameter empirical distribution and the distribution tails are modeled by the generalized Pareto distribution (GPD) with parameters; furthermore, three copula functions---Gaussian, Gumbel, and Clayton---are applied to model the general, upper-tail, and lower-tail dependencies.

To test the advantages of these approaches, six Asian countries were selected based on their different stock index and foreign exchange return distribution shapes, and backtestings were conducted to examine the Monte Carlo VaRs simulated from the correlation coefficients estimated by the Pearson product-moment coefficient, the Gaussian copula, the Gaussian copula-EVT, the Gumbel copula, the Gumbel copula-EVT, the Clayton copula, and the Clayton copula-EVT. The results suggest that the Clayton copula-EVT has the best performance regardless of the shapes of the return distributions.

Acknowledgment

This dissertation could not have been completed without the encouragement, guidance and efforts of my dissertation committee and my family. My deepest gratitude is to my dissertation committee, which includes Professor Peter Chow, Professor Thom Thurston, and Professor Michael Grossman.

I have indeed been blessed to have Professor Peter Chow as my advisor. He gave me the freedom to explore on my own while simultaneously providing me the guidance I needed to recover when my steps faltered. Not only was he always available for me, but he read and responded to the countless revisions of my drafts even more quickly than I could have hoped. I am forever grateful for the comments and constructive criticism he provided that helped improving the efficiency of my research—and for holding me to such a high research standard.

I am also thankful to Professor Thom Thurston, my professor of Macroeconomics and Monetary Policy, for his enthusiasm and inspiration. His numerous discussions and lectures on related topics helped me improve my knowledge in the area.

I am also grateful to Professor Michael Grossman, who taught me during the first semester of my doctoral study, for his encouragement and practical advice. His infectious enthusiasm and limitless zeal have been a major driving force throughout my graduate studies.

I also would like to acknowledge the research grant support provided by the Graduate and University Center, City University of New York.

Finally, I would like to thank my family for their love and support. Clearly, their love motivated my accomplishment of this tremendous academic goal.

Table of Contents

Lists of Tables

List of figures

1 Introduction

Due to a lower correlation with industrial markets and higher return opportunities, investment in emerging markets has gained much attention recently. In the past few decades, a wave of financial liberalization in emerging markets has attracted enormous portfolio capital flows. According to Singh and Weisse (1998), the annual average private capital flow to developing countries increased to \$107.6 billion, during the period of 1989 through 1995, whereas during the period 1983 to 1988, it only increased by \$15.1 billion. Since 2000, several Asian financial markets have released foreign investors' maximum holding volume restrictions, making the Asian financial markets even more attractive.

For U.S. investors, their overseas portfolio investments involve two transactions. The first transaction involves converting U.S. currency into the foreign local currency to invest in the foreign stock market. The second transaction occurs when the investors are ready to withdraw the foreign investments and sell the foreign shares, converting the value back to U.S. currency. In other words, their foreign portfolio investment returns comprise returns from foreign equity markets and the returns from exchange fluctuations. If the correlation between returns from foreign stock markets and the currency exchange fluctuations is positive, investors may face higher market risks, but also higher returns. This positive correlation may attract investors who are less risk averse, because when foreign stock markets are blooming, U.S. investors' foreign equity investments will bring greater rewards since the rewards are not just from equity markets but also from foreign currency appreciation. In the same manner, however, investors will suffer more if foreign stock markets are slumping, because, at the same time, foreign currency depreciates as well. In contrast, investors who are more risk averse would prefer a negative correlation. Although a negative correlation may dilute U.S. investors' losses or revenues, investors' market risk will be lower, because a negative correlation means there may be a positive return from the equity markets and a negative return from the exchange markets at the same time, or vice versa. Consequently, an appropriate approach to estimate the correlation between stock market returns and exchange rate fluctuations is important for investors to measure their market risk.

Value-at-Risk (VaR) is currently one of the most frequently used tools used to estimate market risk. VaR provides information on how the loss of a portfolio can worsen over a target horizon with a given level of confidence. This approach presents the entire potential loss of a portfolio using a simple number that investors can easily adopt as a measure of market risk. Due to its convenience, financial regulators also use VaRs as a benchmark to determine financial institutions' regulatory capital requirements against market risk[1].

A popular VaR calculation approach is the Monte Carlo method, which suggests computing VaR based on the returns from the Monte Carlo simulation. The essential point for successfully implementing the Monte Carlo approach in computing the VaR of a portfolio depends on whether the investors can appropriately estimate the joint distribution of asset returns in the portfolio. Previously, correlations of financial asset returns were estimated based on the Pearson product-moment coefficient approach, which suggests that the returns of financial assets are normally distributed and the

[1] According to the Basel Committee on Banking Supervision's regulatory (Basel I and II Accords), VaR is the preferred approach to measure market risks.

relationships between the financial assets are linear. However, recent studies imply that the foreign exchange rate and the stock indices have non-linear, time-varying correlations. The correlations are asymmetric across downside and upside markets movements, and the tails of the financial return distributions are fatter than that of a normal distribution. Therefore, the measurements of correlation, based on the normal distribution, are inappropriate and cause misleading results (Boyer et al., 1999; Longin and Solnik, 2001; Ang and Chen, 2002; Tastan, 2006; Tai, 2007; and Kolari et al., 2008).

In the past few years, researchers have suggested that copula functions can be powerful tools for modeling the correlation between the data in the characterization of nonlinearity and the asymptotic dependence (Longin and Solnik, 2001; Chen and Fan, 2006; Patton, 2006 a and b; Kole et al., 2007; and Rodriguez, 2007). Copulas involve joining the multivariate distribution functions of standard uniform random variables, and can be used to construct one-dimensional marginal distribution functions in a flexible way. Copulas have been broadly applied in the finance field in areas such as modeling joint loss distribution for risk management and modeling the correlation structure for multiple options pricing. Moreover, since the tails of return distributions are fatter than that of a nromal distribution, studies assert that the methodology derived from the extreme value theory (EVT) to model the tails of a multivariate distribution can provide a better measurement measurement in regards to tail behaviors (Da Silva and Mendes, 2003; Ho et Al., 2000; and Neftci, 2000).

Although the correlations between financial assets in Asian markets have been wildly discussed, especially the correlations during the 1997 Asian Financial Crisis (

see i.e. Granger, et. al 2000, Liu, et. al. 2007, and Broome & Morley 2004), there are several drawbacks on existing studies. First, most existing studies only examine the period to early 2000s. After early 2000s, however, most Asian emerging markets have entered post financial liberalization period by substantially released their foreign investment restrictions. Due to the large amount of foreign capital inflows, market structural has significantly changed. The results of earlier studies may be inappropriate to describe current situations. Second, Many studies only focus on cross-market correlations. However, this correlations are not thorough for US investors to measure their investment risks and make their investment allocations. For US investors, they need to convert US dollars to local currency to invest in local stock markets and convert local investment returns back to US currency. Their local investment returns could be ruined due to local currency depreciation against US currency, and their local investment loss could also be compensated by local currency appreciation. The relationship between stock returns and exchange rates has directly affected US investors returns and is needed rigorous examination. Third, previous studies are based on markets linear correlated and financial returns normality distributed assumption. Recent studies imply that foreign exchange rate and stock indices exist non-linear, time-varying correlations, the correlations are asymmetry across downside and upside market movements, and the tails of financial return distributions are fatter than that of normal distribution. Therefore, the measurements of correlation based on normal distribution may be inappropriate and may cause misleading results (See. e.g. Boyer, Gibson, & Loretan (1999), Login & Solink (2001), Ang & Chen (2002), Tastan(2006),Tai (2007), and Kolari, Moorman & Sorescu(2008))

In this study, I propose to model the correlations between stock index returns and foreign exchange returns using the copula-Extreme Value Theory(EVT)-based semiparametric approaches as demonstrated in Carmona (2004). More specifically, the copula-EVT semi-parametric approaches combine a parametric approach with the generalized Pareto distribution (GPD) in the tails and a nonparametric approach with the empirical distribution in the center of each asset return distribution, and apply copula functions to model the dependence between the two return distributions. To demostrate the advantage of the coupla-EVT methodology, seven approaches are used to estimate the correlation coefficients: the Pearson product-moment coefficient, the Gaussian copula, the Gumbel copula, the Clayton copula, the Gaussian copula-EVT, the Gumbel copula-EVT, and the Clayton copula-EVT, and back testings are adopted to test the performance of the Monte Carlo VaRs from the seven correlation estimation approaches. Di Clemente and Romano (2003) conclude that Copula-EVT methodologise better fit data than normal distribution and provides more accurate estimation. This study contributes to the literature by proposing a comprehensive examination on the dependence between daily returns of stock index and exchange rate in six Asian markets during post financial liberalization period (2000 to 2007). The six countries includes five emerging markets (India, Indonesia, Korea, Malaysia, Taiwan, and Thailand) and one developed market (Singapore). There are differences not only in the level of stock market openness but also in exchange rate policies and economic uncertainties. Singapore is developed market with long history of full financial liberalization. Among the five emerging markets, Indonesia, Korea, and Taiwan are fully opened their stock markets while Malaysia, and Thailand still apply some extends of restrictions on foreign investments. Furthermore, except for Indonesia, the other five Asian countries managed floating exchange rates regime, as what is commonly claimed by those countries and International Monetary Fund (IMF) terminology of exchange rates arrangements of its member countries[2]. By this dependence research, the results also suggest how different policies of a country would affect its correlation between exchange rate and stock returns.

Since 2000, several Asian stock markets entered the post-financial liberalization period by opening their stock markets fully. Their market structurals have considerably changed and it is worth reexamining their market situations. Most existing empirical studies of copula applications have focused on developed markets, while few have focused on Asian markets, and none have paid attention to the correlation between stock markets and currency exchange markets (i.e. McNeil and Frey, 2000; Chen and Fan, 2006; Patton, 2006 a and b; Kole et al., 2007; and Rodriguez, 2007). To the best of author's knowledge, this article is the first in the literature to focus on the correlation between stock returns and foreign exchange returns with daily data from six Asian countries in the post-financial liberalization period (2000 to 2007).

The rest of this study is organized as follows. The next chapter introduces capital market openness in Asia. Chapter 3 explains portfolio returns and their VaRs, Chapter 4 reviews literature studies on the dependence between stock index returns and exchange rate fluctuations. Chapter 5 outlines the methodological approach, Chapter 6 reveals data statictics, Chapter 7 discusses the empirical results and Chapter 8 concludes.

[2] Taiwan is not a member of IMF, but it adopted the floating rates regime with dynamic management by its central bank.

2 Capital Markets Openness in Asia

2.1 Foreign Direct Investment versus Foreign Portfolio Investment

According to Patric's theorem, the interaction of economic and financial development can be distinguished into two models: the supply leading model and the demand following model[3](Chow 2000). Regardless the causality of economic and financial development, it is no doubt that the relationship between the development of financial sector and economic growth is enormous significant. Although the Asian financial crisis in 1997 just confirmed that the relationship of financial development and economic growth is like both sides of a coin, in early 1990s, with the growth of real sectors, Asian countries had to gradually open their capital markets to supprot the development of financial sector. For developing countries, capital markets globalization can be a fast way to improve their financial development. By market openness, developing countries can rapidly grasp capital, technology, and management skills from developed countries, leading to financial development.

The capital flows of developed countries enter the developing countries through two major types: Foreign Direct Investments (FDI) and Foreign Portfolo Investments (FPI). The first type suggests that foreign institutions hold large porpotion of shares of domestic firms, and they control the operation of domestic firms. Basically, their capitals are used to build infrastructure or physical assets, such as factories,

[3]The supply leading model suggests that the development of financial sector supports the need of real sector, leading economic growth; in contrast, the demand following model asserts that the development of real sector pushed financial development.

equipments, or new firms in host countries, and there exists strong relationships between foreign institutions and their investments in host countries. Their investments in host countries usually are their subsidiaries, assembly centers, up stream companies, or downstream companies. Sometimes, this type of investments does not only transfer capitals, but transfer technology and management skills. Thus, foreign institutions in developed countries provide sufficient capitals and technologies in trade of the plenty of low cost labors in developing countries. Although foreign institutions may benefit from low costs labors, they may suffer from the problems of host countries, i.e. regulations, social instability, and proverty. Moreover, since FDI investors run the operations in domestic firms, they are considered as better informed than other investors. If they plan to shif out of the host countries and thus sell their investments, this asymmetric information may make the investments illiquid. This is because that the protential buyers may think that the sale results from bad information and unwilling to buy or only willing to pay a lower price (Goldstein and Razin (2006)). Therefore, if the host countries experience serious problems, this illiquid characteristic will make foreign institutions suffer even more.

Unlike the first type, the second type, Foreign Portfolio Investments(FPI), offers foreign institutions a relative liquid alternative. FPI means that foreign capitals enter host countries by trading securities through loacl financial markets. Basically, this type of investments only involves funds transfer. Foreign institutions hold less portion of shares, and they don't own the domestic firms or join the firms operations. Their profits from stock price fluctions. If they plan to withdraw from host countries, they can easily sell all their shares out in the local markets.

The circumstance of the Asian Financial Crisis makes this liquid choice more attractive. Also, the stock market openness even stimulate the volume of FPI.

2.2 The Progress of Stock market Liberalization

The issue of whether stock market openness benefits domestic markets has been debated since the early stage of stock market liberalization. On the one hand, stock market liberalization brings enormous foreign capital inflows, thereby improving welfare and asset value in domestic markets. On the other hand, foreign capitals are unpredictable and shift frequently. Since Asian stock markets were relatively small in the early 1990s, once the "hot money" leaves, severe price drop comes. Moreover, most governments are concerned that foreigners may acquire domestic firms. It is quite common for developing countries to protect new firms in infant industries by imposing import tariffs or by providing direct support. These firms are expected to become the major stream to stimulate economic growth. However, the target of foreign investors is to maximize their profits, not the economic growth of host countries. When foreign investors hold a greater proportion of the shares, they become strongly involved in the operation of the firms and make the firms' operations only focus on maximizing foreign investors' profits.

Due to these concerns, most Asian countries have imposed ceilings on foreign ownerships. Table 1 summarizes the official liberalization dates and limits on foreign ownerships in six emerging Asian markets[4]. As Asian stock markets developed and

[4] The limits are general guidelines. Industries may apply different limits, and some countries may require foreign investors purchase stocks through specific accounts, i.e. qualified foreign institutional investors (QFII).

domestic infant industries matured, these countries gradually released restrictions on foreign ownership. The openness of the Asian emerging markets has been one of the most important topic in the past few decades. In the late 1980s, due to an "outward-oriented" strategy to stimulate economic growth, the financial development of Asian countries was accompanied by internationalization, i.e. the opening of a domestic stock market (Chow (2000)). A wave of full financial liberalization in the Asian emerging markets caused the release of foreign ownership, attracting enormous foreign capital inflows from developed countries. Today, Asian emerging financial markets have entered in new era. Malaysia, and Thailand have raised the ceiling on foreign ownership to 50%[5]. In September 1997, the Indonesian government allowed foreign investors to purchase unlimited domestic shares, In Korea, the stock market was fully liberalized in May 1998, and full-scale liberalization in Taiwan started in December 2000[6].

In this new era, market capitalization increased dramatically. As shown in Table 2, the value of market capitalization in India increased in 2006 to 525% of the value in 2000; Indonesia, to 481%; Korea, to 358%; Malaysia, to 187%; Taiwan, to 261%; Thailand, to 399%; and Singapore, to 160%. For foreign investors, since the market structure has changed, a new approach to model dependence between the stock index returns and exchange rate changes has become important for their portfolio investment decisions.

[5] In Malaysia, foreigners can hold up to 61% of local telephone companies on a case-by-case basis, up from 49% ceiling in April 1998. (Campbell R. Harvey, Country risks analysis, http://www.duke.edu/~charvey/Country_risk/couindex.htm).

[6] Although those countries are defined as fully open, some restrictions may apply.

3 Portfolio Returns and Their Value at Risk

In the absence of capital control with low transaction costs, the returns of overseas portfolio investment can be described as:

$$R_t = \frac{i_t \times e_t}{i_{t-1\times} e_{t-1}}$$

$$\text{Therefore, } \ln(R_t) = \ln(i_t/i_{t-1}) + \ln(e_t/e_{t-1})$$

$$\text{To simplify, } r_t = r_{i,t} + r_{e,t}$$

Where R stands for the portfolio return and r is its log form. The subscripts t and t-1 are used to represent time t and time t-1. Therefore, r_t can be interpreted as the portfolio return at time t, which is defined as the log asset value differential between time t and t-1; i is the foreign stock index, and e represents currency exchange rate, which is defined as the price of one unit of foreign currency in U.S. dollars. Thus, a positive value of $\ln(e_t - e_{t-1})$ denotes foreign currency appreciation against the U.S. currency. Since the initial investment value in the stock index is exactly the same as the initial value in the exchange market, r_t can be treated as an equal weighted portfolio with the combination of $r_{i,t}$ and $r_{e,t}$. Therefore, understanding the correlation between $r_{i,t}$ and $r_{e,t}$ is very important when investors measure market risk of their portfolio investments.

One popular approach to evaluate market risk is Value-at-Risk (VaR). Given a positive value α close to 0, and over a target horizon h period (the differential period between time t and time t+h), VaR can be defined as the possible loss of the portfolio at the confidence level (1-α):

$$VaR_{\alpha}^{h} = \inf \{ r \in \mathbb{R} \mid P(R \geq r) = 1 - \alpha \}$$

Where: R is a sequence number, $r_{t,}\ r_{t-1,}\ r_{t-2,}\ ...r_{t-h}$, stands for the portfolio rate of return at time t, t-1, t-2, ...,t-h, respectively, and r is the VaR. The equation describes during h periods, the chance for the return being equal or less than r is α[7]. Empirically, 1% and 5% VaRs are commonly used. Table 3 illustrates historical 1% 1day VaR of Indonesia, Malaysia, Korea, Singapore, Taiwan, and Thailand. Among the six countries, Korea has the highest VaR at -5.6168%, and Malaysia has the lowest VaR at -2.9486%. The number means there is a 1% pobability that in Korean stock market investors may lose 5.6168% in a day, while in Malaysian stock market, the loss is 2.9486%. In other words, if the investment amount is US$ 1 million, the loss is $54,619.26 in Korean and 29,055.44 in Malaysia[8].

Although historical VaR is easy to apply, it has very limited applicability: the data range is constrained by the original data and may not be able to be extended to future periods. A more flxible approach to compute VaR is Monte Carlo VaR. By using the Monte Carlo method, VaR would be estimated with the return data simulated repeatedly from the random process, based on an appropriate joint distri-

[7] This approach is defined as unconditional VaR, or historical VaR, since the VaR are computed based on historical return distribution.

[8] These numbers are calculated by continuously compounding. i.e. in Korean Stock Market: $\$1,000,000 \times (e^{-5.6168\%} - 1)$.

bution that accurately describes bilateral correlations among all asset returns. The Monte Carlo process is defined as:

$$\frac{dv}{v} = \mu d_t + \sigma dx$$

Where: v stands for the asset value. The rate of return is $\frac{dv}{v}$, and V is defined as a sequence of v_t,$\mathrm{v}_{t-1}\mathrm{v}_{t-2}$,...$\mathrm{v}_{t-n}$, the asset value on time t, t-1, t-2,...t-n. μ is the expected asset return, σ is the volatility of the asset value, dt stands for the time differential and d_x is a random process that can be defined as $\phi\sqrt{(d_t)}$, where ϕ is drawing from its return distribution. In a two assets portfolio, the Monte Carlo process can be rewritten in matrix form with the subscript 1 and 2 to identify assets 1 and 2.

$$\frac{dv}{v} = \begin{bmatrix} \frac{dv_1}{v_1} \\ \frac{dv_2}{v_2} \end{bmatrix}, \mu d_t = \begin{bmatrix} u_1 \\ \mu_2 \end{bmatrix} d_t, \sigma dx = \Phi \begin{bmatrix} \sqrt{(d_t)} \\ \sqrt{(d_t)} \end{bmatrix}$$

in which $\Phi = \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} \\ \sigma_{1,2} & \sigma_2^2 \end{bmatrix}$. and $\sigma_{1,2} \equiv \rho_{_{1,2}} \times \sigma_1\sigma_2$. $\rho_{_{1,2}}$is the correlation coefficient of $\mathrm{V}_1$and V_2. Therefore, the accuracy of the simulation strongly depends on the accuracy of the correlation coefficient of $\mathrm{V}_1$and V_2 $(\rho_{_{1,2}})$.

4 Dependence between Stock Index Returns and Exchange Rate Fluctuations

Theoretical foundations explain the dependence between exchange rates and equity returns from a microeconomic and macroeconomic perspectives. From the microeconomic point of view, other things being equal, home currency appreciation causes exporting firms to have fewer competitive advantages, lowering their revenues and stock prices; thus, the dependence between stock returns and the foreign exchange rate fluctuations is negative[9]. On the other hand, importing firms benefit from home currency appreciation through lower costs of materials, greater revenues, and higher stock prices, which suggests a positive dependence. From the macroeconomic point of view, when the domestic interest rate rises, the demand for home currency increases, leading to appreciation. However, domestic firms suffer from increased costs of capital due to higher interest rates and decreased stock values. Therefore, the dependence between stock returns and exchange rate changes should be negative.

Empirically, attempts to investigate the correlation between the stock market return and the exchange rate movements have been documented with mixed results being reported. Solnik (1987) applied the ordinary least squares (OLS) estimation to monthly and quarterly data for the period of July1973 to December 1983 for eight industrial markets. His empirical results suggest that for monthly data a weak positive relationship exists between real stock return differentials and changes in the real exchange rate. This was found to be especially true during the period of 1979

[9] Some studies define the exchange rate as the price of foreign currency against one U.S. dollar. In this case, the correlation between stock returns and the exchange rate changes were positive.

to 1983. However, for quarterly data, a negative relationship was found. Ajayi and Mougoue's (1996) employed error correction model (ECM) to examine short term and long term dynamic correlations between stock prices and the exchange rate for "The Big Eight stock markets [10]". They concluded that, in the short-run, the relationship between domestic stock prices and domestic currency was negative. However, in the long-run, stock prices increased and had a positive effect on the domestic currency value. Parto et al. (2002) studied correlations between stock returns and the exchange rate fluctuations in 16 OECD countries for the period of 1980 to 1997. They reported that the countries with higher exports were more negatively correlated with exchange rate risks, especially when the currency depreciated. At the same time, the countries with more importers were associated with a positive correlation. Moreover, several studies examined the relationship between stock returns and exchange rates at the firms' level. Doidge et al. (2006) proposed that firms with a high exposure to international sales have higher returns than firms with no international sales. In contrast, the study performed by Kolari et al. (2008) implied that firms that were highly sensitive to the foreign exchange rate risk tended to have lower returns.

After 2000, Asian emerging markets entered a post-financial liberalization period that relaxed foreign investment restrictions. Empirical data reveal that the stock market structure significantly changed, due to the large volume of foreign capital inflows. The results of earlier studies may not be appropriate to describe the current situations. Furthermore, the financial crisis of 1997[11] that approved foreign exchange

[10] The Big Eight industrial economies in 1990s were Canada, France, Germany, Italy, Japan, the Netherlands, the United Kingdom, and the U.S.

[11] In October 1997, the Hong Kong Hang Seng Index dropped 1483 points, sparking the crash in the U.S. stock market, with a 554.26 point decrease in the Dow Jones Industrial Average. In

rates and national stock indices were non-linear and time-varying with fatter tails representing financial return distributions. Studies based on purchase power parity and normal distributions on financial returns may have caused misleading results (Tai, 2007; Tastan, 2006). To cope with this difficulty, recent studies (e.g. Chen and Fan, 2006; Patton, 2006 a, and b; Kole, et al., 2007; Bartram, et al., 2007; and Rodriguez, 2007) suggested that the copula functions were powerful tools for modeling dependence.

Copulas, derived from the Latin word *copulare*, to connect or to join, were first introduced as early as 1959 by Sklar and have recently been rediscovered. Copulas join multivariate distribution functions of standard uniform random variables and can beused to construct one-dimensional marginal distribution functions. By applying copula applications, the dependence of nonlinearity variables can be examined with higher degrees of flexibility. Since the late 1990s, copulas have been broadly applied in finance field such as modeling joint loss distribution for risk management and modeling the correlation structure for multiple options pricing.

December 1997, the South Korean Won depreciated over 60% since July 1, setting off the financial turmoil in the national stock market experiencing a 50.3% freefall (Granger et al.(2000)).

5 Methodological Approach

In this section seven correlation coefficient estimation methods are introduced.

5.1 Pearson's product-moment coefficient

This is a traditional approach used to estimate the correlation coefficient between two variables. Based on the assumptions such as that $V_1$and V_2 are linear correlated, and normal distributed, this approach was defined as:

$$\rho_{1,2} = \frac{E[(V_1 - \mu_1)(V_2 - \mu_2)]}{\sigma_1 \sigma_2}$$

5.2 Copulas

Copulas join multivariate distribution functions of standard uniform random variables and can be used to construct one-dimensional marginal distribution functions. Cherubini et al. (2004) stated that "the copula methodology has become the most significant new technique to handle the co-movement between markets and risks in a flexible way". Copulas were developed based on Sklar's dependency theory, which included several underlying functions: the marginal cumulative distribution functions (CDF) and a joint CDF. If we let $U_{1,}$ $U_{2,}$ ... $U_{n,}$ be n random variables with a joint distribution function, then the joint distribution function can be presented as:

$$F_{U_1,U_2 \ldots U_n}(u_1, u_{2,} \ldots u_n) = P(U_1 \leq u_{1,} U_2 \leq u_{2,} \ldots U_n \leq u_n) \text{ for}(\ u_1, u_{2,} \ldots u_n) \in \mathbb{R}^n.$$

The marginal distribution functions of U_1, U_2, ... U_n, are

$$F_{U_1}(u_1) = P(U_1 \leq u_1)$$

$$F_{U_2}(u_2) = P(U_2 \leq u_2)$$

and

$$F_{U_n}(u_n) = P(U_n \leq u_n)$$

respectively. According to Sklar's theorem, if F_{U_1}, F_{U_2}...F_{U_n}, are continuous functions, then there exists a unique copula such that

$$F_{U_1,U_2...U_n}(u_1, u_{2,}...u_n) = C(F_{U_1}(u_1), F_{U_2}(u_2), ...F_{U_n}(u_n)). \tag{1}$$

Since most copulas are concerned with bivariate data, the above equation can be rewritten as

$$c(x, y) = P(X \leq x, Y \leq y), \text{ for } (x, y) \in [0, 1]^2$$

where X = $F_{U_1}(u_1)$ and Y =$F_{U_2}(u_2)$[12]. Studies suggest several parametric families of copulas, some of which are featured in tail dependence. On the basis of their different features, three types of copulas were used to examine the correlation correficient: Gaussian, Gumbel, and Clayton. The Gaussian copula represents data that

[12] Detailed derivation can be found in Cherubini, Luciano, and Vecchiato(2004), and Nelson (2006).

is normally distributed; The Gumbel copula shows a heavy tail on the right side; and The Clayton copula exhibits a fat tail on the left.

5.2.1 Gaussian Copula

The Gaussian copula represents normally distributed data. It is described as follows:

$$\begin{aligned} C(x,y) &= \int_{-\infty}^{\Phi^{-1}(x)} dx \int_{-\infty}^{\Phi^{-1}(y)} dy \frac{1}{2\pi\sqrt{1-\delta^2}} \exp\left\{-\frac{x^2 - 2\delta xy + y^2}{2(1-\delta^2)}\right\} \\ &= \Phi_\delta(\Phi^{-1}(x), \Phi^{-1}(y)) \end{aligned} \tag{2}$$

Where Φ denotes the distribution function of the univariate standard normal distribution and Φ_δ is the distribution function of the bivariate standard normal distribution with the correlation coefficient$-1 \leq \delta \leq 1$. Although the Gaussian copula can generate the bivariate standard normal distribution only if the margins are standard normal, the model is widely used in financial applications such as J.P.Morgan's RiskMetrics$^{\mathrm{TM}}$ system (Zivot and Wang (2006)).

5.2.2 Tail Dependence

Tail dependence can be refered as the joint probability of large moments in both markets. According to Embrechts et al. (2005), The coefficient of upper tail dependence (λ_u) of X and Y is

$$\lambda_u := \lambda_u(X,Y) = \lim_{q \to 1^-} P[Y > F_{U_2}^{\leftarrow}(q) \mid X > F_{U_1}^{\leftarrow}(q)]$$

The upper tail dependence presents the the probability that Y exceeds its q-th quantile given that X exceeds its q-th quantile and consider the limit as q goes to its infinity. If the limit $\lambda_u \in [0, 1]$ exists, then X and Y are said to show upper tail dependence. In the same manner, the coefficient of lower tail dependence (λ_l) is described as:

$$\lambda_l := \lambda_l(X, Y) = \lim_{q \to 0^+} P[Y \leq F_{U_2}^{\leftarrow}(q) \mid X \leq F_{U_1}^{\leftarrow}(q)]$$

Since both F_{U_1} and F_{U_2} are continuous density functions, the lower tail dependence can be presented as:

$$\lambda_l = \lim_{q \to 0^+} \frac{P[Y \leq F_{U_2}^{\leftarrow}(q) \mid X \leq F_{U_1}^{\leftarrow}(q)]}{P[X \leq F_{U_1}^{\leftarrow}(q)]} = \lim_{q \to 0^+} \frac{c(q, q)}{q} = \widehat{c}(0^+)$$

For upper tail dependence, it can be described as;

$$\lambda_u = \lim_{q \to 1^-} \frac{P[Y > F_{U_2}^{\leftarrow}(q) \mid X > F_{U_1}^{\leftarrow}(q)]}{P[X > F_{U_1}^{\leftarrow}(q)]} = \lim_{q \to 1^-} \frac{1 - 2q + c(q, q)}{1 - q} = 2 - \widehat{c}(1^-)$$

Embrechts et al. (2005) suggest that Gumbal copula can be the case of upper tail dependence and Clayton copula may be used for lower tail dependence.

5.2.3 Gumbel Copula

The Gumbel copula is the most common extreme value copula. It descibes upper tail dependence.

$$C(x, y) = \exp\left\{ - \left[(-\ln(x)^{\delta} + (-\ln(y)^{\delta} \right]^{\frac{1}{\delta}} \right\}, \delta \geq 1 \tag{3}$$

Where δ is the parameter used to control the strength of dependence. That is, if $\delta = 1$, then no dependence exists; if $\delta > 1$, then the Gumbal copula has upper tail dependence; and if $\delta = +\infty$, then there exists perfect dependence. The coefficient of the dependence of the upper tail equals:

$$\lambda_u = 2 - 2^{1/\delta}$$

5.2.4 Clayton Copula

The Clayton copula describes lower tail dependence. It has the following form:

$$C(x, y) = \max\left[(x^{-\delta} + y^{-\delta} - 1)^{-\frac{1}{\delta}} \right] \tag{4}$$

Where $0 \leq \delta \leq \infty$. The coefficient of the lower tail dependence is defined as:

$$\lambda_l = 2^{-1/\delta}$$

5.3 Extreme Value Theory

From 2000 to 2007, the global financial markets experienced several extraordinarily incidents, such as the September 11 tragedy in the U.S. in 2001, the severe acute respiratory syndrome (SARS) in the South East Asia in 2003, and a tsunami in Indonesia, Sri Lanka, India, and Thailand in 2005. Each of these incidents caused huge market movements in the Asian financial markets; thus, when modeling dependence, the behavior of the distribution in the tails merits more attention. Modeling dependence by empirical distributions which traditionally used for copula functions may not be sufficient as the proxies of tail behaviors. The literature suggests methodology derived from the extreme value theory (EVT) to model the tails with generalized Pareto distribution (GPD) can provide better measurements; Longin (2000) suggested a new approach that considered extreme values to calculate the VaR of a market position. He asserts that the advantages of the extreme value method include computations for high probability values, reduction of model risks, and consideration of event risks. Neftci (2000) also stressed that the extreme distribution theory performs well in capturing both the rate of occurrence and the extent of the effect of extreme events in financial markets. Da Silva and Mendes (2003) adopted EVT to examine the performance of Asian stock markets, identifying which type of extreme value asymptotic distribution better fits the historically extreme market events. Ho et al. (2000) applied this approach to value-at-risk measures (VaR) by modeling the tails of the return distributions of six Asian financial markets during volatile market conditions. They concluded that the VaR generated within this structure differed from those generated by variance-covariance and historical methods.

According to extreme value theory[13], extreme values can be statistically modeled by two different methods: the block maxima method and the peaks-over-threshold method. The first approach separates the entire data period into several sub-periods and defines extreme events as the maximum or minimum value in each sub-period. The second method models the largest (smallest) values over a high (low) threshold. The first approach wastes a great deal of data and ignores the clustering phenomenon, which is commonly found in financial data. Thus, this study adopts the second method, which focuses on incidents exceeding a specified threshold.

5.3.1 Generalized Pareto Distribution

Consider X, a sequence of independent and identically distributed (i.i.d.) random variables $x_{1,}$ $x_{2,}$ $x_{3,}$ $...x_n$, representing the profits and losses of daily returns. The excess distribution y, which X exceeds a fixed threshold u, has the following cumulative distribution function:

$$F_u(y) = P(X - u \leq y \mid X > u) = \frac{F(y+u) - F(u)}{1 - F(u)}, \text{ for } 0 \leq y \leq x_0 - u \tag{5}$$

Where x_0 is the right endpoint of F. According to Picklands-Balkema-De Haan theorem, an appropriate distribution to approximate $F_u(y)$ is the generalized Pareto distribution (GPD). The Picklands-Balkema-De Haan theorem shows that:

$$\lim_{u \to x_0} \sup_{0 \leq y \leq x_0 - u} \left| F_u(y) - G_{\xi,\beta(u)}(y) \right| = 0$$

[13] See Coles (2001) and Beirlant et al. (2004) for detailed treatments of the extreme value theory.

In other words, when u is very close to the endpoint, the excess distribution is the approximation of the GPD.

$$\widehat{F_u(y)} \approx G\widehat{_{\xi,\beta(u)}(y)} \tag{6}$$

The GPD has the following analytical form:

$$G_{\xi,\beta}(x) = \{ {}^{1-\left(1+\xi\frac{x-u}{\beta}\right)^{\frac{-1}{\xi}} \text{ for } \xi\neq 0}_{1-\exp\left(\frac{-(x-u)}{\beta}\right) \text{ for } \xi=0}, \beta \geq 0 \tag{7}$$

$$x \in D(\xi, \beta) = \{ {}^{[0,\infty),\ \xi\geq 0}_{[0,\frac{-\beta}{\xi}],\xi<0}$$

Where β is the scale parameter and ξ is the shape parameter. If ξ<0, the tail is finite, and $G_{\xi,\beta}(x)$ is the Weibull type distribution such as the beta and uniform distributions. If ξ =0, then the tail declines exponentially (thin-tailed), and $G_{\xi,\beta}(x)$ is in the Gumbell family such as the normal, log normal, and exponential distributions. If ξ >0, then the tail declines slowly (fat-tailed), and $G_{\xi,\beta}(x)$ is in the Frèchet family such as the Pareto distribution. The consensus of heavy tails makes the Frèchet family the relevant case.

5.3.2 Tail Estimation

Setting x=y+u and using Equations (2) and (3), an approximation to the tails of the extreme distribution F(x) for x>u is defined as follows:

$$F(x) = (1 - F(u))G_{\xi,\beta}(x) + F(u) \tag{8}$$

The first term of Equation (4) may be estimated non-parametrically using the random proportion of the data in the tail.

$$\widehat{F(u)} = \frac{(n-k)}{n} \tag{9}$$

Where k denotes the number of observations beyond the threshold u. The choice of threshold value u is crucial, since it is an unpleasant trade-off between variance and bias. To fulfill the requirement of the Picklands-Balkema-De Haan theorem, one should choose as high as possible value of u. However, if u is too high, few exceedance data is available, leading to the high variance of estimators. In contrast, if u is too low, then the examination process will include observations not belonging to the tails, leading to biased estimators, and the Picklands-Balkema-De Haan theorem will not hold.

There is no consensus on which method is best for selecting the threshold. While Gavin (2000) suggests an arbitrary threshold level of 90%, Neftci (2000) defines the threshold as 1.645 of the unconditional variance of the data, which represents 5% of the observations if the true data is normally distributed. Longin and Solnik (2001) use the Monte Carlo simulation method to select the threshold by optimizing the trade-off between bias and variance. Frey and McNeil (2000) apply the mean-excess plot to choose the optimal threshold. This paper adopts Neftci's approach and slightly adjusts the value using the mean-excess plot approach to obtain the optimal thresholds. Combining Equations (3) and (5), F(x) can be estimated with a GPD fitted by the maximum likelihood to obtain the tail estimator.

$$\widehat{F(x)} = 1 - \frac{k}{n}\left(1 + \widehat{\xi}\frac{x-\mu}{\widehat{\beta}}\right)^{\frac{-1}{\xi}}, \text{for x>u} \tag{10}$$

Therefore, the other three correlation coefficient estimation approaches are the Gaussian copula-EVT, the Gumble copula-EVT, and the Clayton copula-EVT. They are semi-parametric approaches with an empirical distribution in the center and the GPD in the tails.

5.3.3 Parameter Estimation

Parameters were estimated by two stages. In the first stage, the scale and sharp parameters were estimated, and the marginal distributions were modeled with the GPD in the tails and the empirical distribution in the center. Then, using the marginal distributions to model the joint distribution, I applied an inference function for the margins (IFM) method, as proposed by Joe (1997) to estimate parameters.

Recall that the bivariate joint density function can be represented as:

$$f(U_1, U_2; \eta) = C\{(F_{U_1}(u_1; \theta_1), F_{U_2}(u_2; \theta_2); \theta\}; f_{U_1}(u_1; \theta_1) f_{U_2}(u_2; \theta_2).$$

Where θ_1 and θ_2 are parameters for the marginal distribution F_{U_1} and F_{U_2} respectively, θ is the parameter for the copula density and $\eta = (\theta'_1, \theta'_2, \theta')'$ are the parameters of the join density. The exact log-likelihood function is then

$$l(\eta; U_1, U_2) = \sum_{i=1}^{n} \ln c(F_{U_1}(u_1; \alpha_1), F_{U_2}(u_2; \alpha_2); \theta) + \sum_{i=1}^{n} \ln f_{U_1}(u_1; \alpha_1) + \sum_{i=1}^{n} \ln f_{U_2}(u_2; \alpha_2)$$

According to Joe (1997), these set parameters can be estimated in two steps:

First, the parameters of the marginal distributions were estimated as:

$$\widehat{\theta_1} \equiv \arg\max \sum_{i=1}^{n} \ln f_{U_1}(u_1; \theta_1)$$

$$\widehat{\theta_2} \equiv \arg\max \sum_{i=1}^{n} \ln f_{U_2}(u_2; \theta_2)$$

Then at the second step, given $\widehat{\theta_1}$ and $\widehat{\theta_2}$,the dependence parameter were estimated as:

$$\widehat{\theta_c} \equiv \arg\max \sum_{i=1}^{n} \ln c(F_{U_1}(u_1; \alpha_1), F_{U_2}(u_2; \alpha_2); \theta)$$

6 Data Statistics

The data used in this study included daily closing stock indices and daily closing prices of US foreign currency exchange rates in six countries, Indonesia, Korea, Malaysia, Singapore, Taiwan, and Thailand, as reported by Global Financial Data. The stock indices applied were the Jakarta SE Composite Index of Indonesia, the Korea Stock Exchange Stock Price Index (KOSPI), the Kuala Lumpur Stock Exchange Composite of Malaysia, the Singapore Strait Times Stock Index, the Taiwan Stock Exchange Capitalization Weighted Index, and the Stock Exchange of Thailand General Index. The sample period was from the first business day in 2000 to the last business day in 2007[14].

Table 4 summarizes the data statistics, which include the stock index returns, the currency exchange returns, and the portfolio returns. The first two columns present the mean and standard deviation. The data demonstrated high returns and high standard deviations, which is common in financial markets. The negative skew in the stock index returns for all six countries means that the distributions have long tails to the left. The Jarque-Bera (JB) test, which follows a chi-square distribution with two degrees of freedom, was used to determine normality. The null hypotheses of the stock index return, the exchange return, and the portfolio return series in all six countries were rejected, indicating that the return distributions were far from normal. The higher kurtosis also lead to a strong rejection in the JB test and confirmed that the distributions have non-normality.

[14]Since the six country has its own business days, the observations varied in each country. Indonesia had 1957 observations, Korea had 1968 observations, Malaysia had 1967 observations, Singapore had 2004 observations, Taiwan had 1997 observations, and Thailand had 1961 observations.

Figure 1 to 6 illustrate daily stock indices and foreign exchange rates, daily stock index returns and foreign exchange returns, QQ plot[15] of portfolio daily returns and daily portfolio return of the six countries respectively. Graph a provides the trend of daily stock indices and foreign exchange rates. From the graph, we can find that Malaysia held fixed exchange rate against the US dollar from 2000 to early 2005. Graph b presenting the daily stock index returns and foreign exchange returns, which indicate that extremely returns exist in all six countries. QQ plot is a scatter plot constructed by the empirical quantiles (vertical axis) against the normal quantiles (horizontal axis), which can be used to test the normality of a distribution. The results of the QQ plots in the six countries also verified that the portfolio returns of the six countries are non-normally distributed.

Table 5 presents the expected annual returns of the foreign exchange, the stock index, and the portfolio in the six countries[16]. Basically, the expected annual return of foreign exchange is lower than the expected return of stock index in the six countries. That is because most Asian countries impose currency control, and the governments are likely to keep the currency exchange rates stabilized; i.e., the Malaysia ringgit against the U.S. dollar kept around 3.799 from January 2000 to mid 2005. Although Indonesia has the highest expected return of stock index, its expected return of portfolio is only 14.9785%, because the expected return of foreign exchange of -3.439% offsets the return from the stock index. The expected portfolio returns in Korea, Malaysia, Singapore, and Thailand are higher than their expected stock index re-

[15] Q stands for quantile.

[16] The expected annual return is computed by assumeing that there are 250 business days in a yaer. Therefore, the annual expected return is $e^{mean \times 250} - 1$.

turns because the positive returns in foreign exchange make the portfolio returns even greater. In Taiwan, U.S. investors will suffer more since both negative returns in stock index and in foreign exchange made the portfolio return even worse.

7 Empirical Results

The estimations of the return distribution tails are presented in Table 6. In Taiwan and Korea, the sharp parameters of the stock index return distributions' upper tails are significantly negative, indicating the upper tails are finite. A possible explanation is that both Korean and Taiwanese stock markets impose daily price movement limitation policies[17]. When a bull market occurs, stocks are not allowed to be traded at the prices over the limit, making the stock return distribution's upper tail truncated. As for the lower tail distribution of stock index returns, Taiwan still has a truncated lower tail at 90 percent statistical significance, while in Korea, there is no significant evidence to prove the shape of the lower tail of the stock index return distribution. Thailand has significant fat tails on both upper and lower sides because the limit of daily stock price movements is 30 percent in Thailand, which gives the stock prices more space to shift. The shape of the upper tail of the stock index return distribution in Indonesia, Malaysia, and Singapore is not significant, but the lower tail of the stock index return distribution in these three countries is fat at statistically significant level.

Both upper and lower tails of the foreign exchange return distribution in Korea are truncated, implying government intervention occurs when the price of the Korean won jumps too high or drops too low. Taiwan and Thailand have significant fat tails on both upper and lower sides of the foreign exchange return distribution, while Indonesia, Malaysia, and Singapore only have significant upper fat tails, but there is

[17] Daily stock price movement is limited at 12 percent in the Korea Stock Exchange, and 7 percent in the Taiwan Stock Exchange.

not enough evidence to support that their lower tails are also fat.

Table 7 reveals the correlation coefficients estimated from the seven approaches: the Pearson correlation, the Gaussian copula, the Gaussian copula-EVT, the Gumbel copula, the Gumbel copula-EVT, the Clayton copula, and the Clayton copula-EVT. The results suggest that the stock index returns are weakly positively correlated with the foreign exchange returns. In Indonesia, Korea, Malaysia, and Singapore, the correlation coefficients estimated by Gaussian copula are close to the correlation coefficients estimated by Pearson correlation approach. This is because the Gaussian copula approach is derived based on normal distribution assumption, which is the same assumption that Pearson correlation applies. However, in Taiwan and Thailand, the correlation coefficients estimated by the Gaussian copula are quite different from the correlation coefficients estimated by thePearson correlation approach because, according to the results in the Table 6, Taiwan has significantly truncated upper and lower tails in its stock index return distribution and significantly fat upper and lower tails in its foreign exchange return distribution; therefore, the correlation between stock index return and foreign exchange return is not linear, and the correlation coefficient is quite different from that of the Pearson correlation. In Thailand, fat tails exist in upper and lower sides of both stock index return distribution and foreign exchange return distribution. In the same manner, the correlation between stock index return and foreign exchange return is not linear, and the correlation coefficient is quite different from that of the Pearson correlation.

For the tail dependence, the figures in the Gumbel copula or the Gumbel copula-EVT mean that when one asset has a higher positive rate of return on a day, the probability that the other asset will also yield a higher positive rate of return on the same day, i.e. In Indonesia, the correlation coefficient of the Gumbel copula is 20.72 percent, which means when the stock index yields a higher rate of return on a specific day, there is a 20.72 percent probability that the foreign exchange will also yield a higher rate of return on the same day. By the same fashion, the figures in the Clayton copula or the Clayton copula-EVT present the lower tail dependence. Therefore, if the stock market is slumped on a specific day in Indonesia, the probability for the Indonesia rupiah to plunge on the same day is 18.42 percent. By comparing the correlation coefficients among the Gaussian copula, the Gumbel copula, and the Clayton copula, the correlation coefficients of the Gumbel copula and the Clayton copula are smaller that of the Gaussian copula, indicating that the tail dependence is weaker. Moreover, in general, the correlation coefficients of the Gumbel copulas, the upper tail dependence, are higher than that of the Clayton copulas, the lower tail dependence, implying that the government stepped in especially when bear markets occurred. Among the six countries, the values of correlation coefficients in Indonesia are the largest. A possible explanation for this circumstance is that Indonesia does not impose foreign exchange control and the limit of the stock price movement is 30 percent, providing more freedom for both stock index and foreign exchange rate movements.

7.1 Backtesting

To examine the advantage of the copula-EVT methodologies in estimating the correlation coefficients, Backtestings were conducted to test the Monte Carol VaRs generated by the correlation coefficients of the seven approaches. Assume at time t, $\widehat{VaR_{\alpha}^{h}}$ can be computed from a historical series, $r_{t,}\ r_{t-1,}\ r_{t-2,}\ ...r_{t-h}$. At time t+1, a violation is said to occur if $r_{t+1} < \widehat{VaR_{\alpha}^{h}}$[18]. According to McNeil and Frey (2000), if the indicator variances are defined as $I_{t+1} = I_{r_{t+1} < \widehat{VaR_{\alpha}^{h}}}$, the process $(\mathrm{I}_t)_{t\in\mathbb{R}}$, is binomially distributed with violation probability α. In this paper, α is set at 1 percent,and h is 250, since there are roughly 250 business days in a year.

The backtesting results of the Monte Carlo VaRs are reported in table 8. Due to different return distribution shapes among the six countries, the backtesting results vary among the seven methodologies. By comparing the p values, in general, the copula-EVT approaches can provide better performance than others. The Pearson correlation approach reaches 99 percent significance in Singapore, and 95 percent significance in Malaysia. That is because these two countries do not include significant fat tails on their stock index return distribution or foreign exchange return distribution. When applying the Pearson product-moment coefficient approach in the country that has significant fat tails on its return distributions, i.e., Thailand, this approach will not be able to provide an accurate estimate. Basically, the copula-EVT approaches have better performance in the six countries. In Indonesia, except for the Pearson correlation, the Gaussian copula, the Gaussian copula-EVT, the Gumbel copula, the Gumbel copula-EVT, the Clayton copula, and the Clayton copula-EVT approaches can provide accurate estimates of performance at a 99 percent significant level. The estimates provided by the Gumbel copula-EVT and the Clayton copula-EVT have better performance than other approaches in Korea, Malaysia, Singapore,

[18]In some VaR documents, this inequality is presented as $r_{t+h+1} > \widehat{VaR_{\alpha}^{h}}$ by assumeing $r_{t+h+1}$is loss function and both r_{t+h+1} and $\widehat{VaR_{\alpha}^{h}}$ are in absolute value.

and Taiwan. In Thailand, only the Clayton copula and the Clayton copula-EVT can provide more accurate estimates. To sum up, the Clayton copula-EVT approach has the best performance, which reaches 95 percent significance in Korea and 99 percent significance in Indonesia, Malaysia, Singapore, Taiwan, and Thailand.

8 Conclusion

This study examines the dependence between stock index returns and foreign exchange returns from 2000 to 2007 for Indonesia, Korea, Malaysia, Singapore, Taiwan, and Thailand. Conventionally, correlation is estimated by the Pearson product-moment coefficient, which assumes that the relationship between two assets is linear. However, the existence of fat-tailed, skewed distributions of returns and a non-linear relationship between financial assets makes the conventional approach incongruous. To cope with this difficulty, this research applies copula-EVT based semiparametric approaches to model the distributions of stock index returns and foreign exchange returns, and the correlation between the two return distributions. In particular, the marginal distributions are modeled by a semiparameter approach in which the distribution center is modeled by a nonparameter empirical distribution, and the distribution tails are modeled by the generalized Pareto distribution (GPD) with parameters, and copula functions are used to build flexible models of the joint distribution of the two asset return distributions.

The Pearson product-moment coefficient, the Gaussian copula, the Gaussian copula-EVT, the Gumbel copula, the Gumbel copula-EVT, the Clayton copula, and the Clayton copula-EVT approaches are adopted to estimate the correlation coefficients between the stock index return distributions and the foreign exchange return distributions. To examine the advantage of the copula-EVT semi-parameter approaches when applying VaR computing, backtestings are applied to test the Monte Carlo VaRs generated with the correlation coefficients from the above seven methodologies. To verify if the copula-EVT approaches could perform well even with data that don't have strong fat tails of their distributions, Indonesia, Korea, Malaysia, Singapore, Taiwan, and Thailand are selected based on their different shapes of return distributions. In Thailand, both stock index return distribution and foreign exchange return distribution have upper and lower fat tails, while in Taiwan, the upper and lower tails of the stock index return distribution are truncated, and the upper and lower tails of the foreign exchange return distribution are fat. Indonesia, Malaysia, and Singapore have fat lower tails of their stock index return distributions and fat upper tails of their foreign exchange return distributions. The upper tail of the stock index return distribution and both upper and lower tails of the foreign exchange return distribution in Korea are truncated.

The estimation results of the correlation coefficient suggest that although the six countries all have positive correlations between returns from stock index and currency exchange, the extent of these correlations is weak. Among the six countries, Singapore has the lowest correlation between its stock index return and foreign exchange return, while Indonesia has the highest correlation level. In comparison to the results of upper tail dependence, the dependence in the lower tail is relatively small. The results imply that developed markets have a long history of foreign capital inflows, which do not easily shift out; therefore, stock market movements may not cause exchange rate movements and vice versa. Moreover, in emerging markets, it is quite common to see government intervention, especially when the market is on a downside; thus, the results of lower tail dependence are smaller than those of upper tail dependence. Furthermore, except for Indonesia, the other five Asian countries managed floating exchange rates regime, as what is commonly claimed by those countries and International Monetary Fund (IMF) terminology of exchange rates arrangements of its member countries[19]. This exchange rate policy may contribute to the weak correlations.

The backtesting results of the Monte Carlo VaRs reveal that the copula-EVT approaches can provide better performance. Although the Pearson product-moment coefficient approach has acceptable performance in a country that doesn't have significant fat tail or truncated tails on its return distributions, i.e., Singapore, in a country with significant fat tails on both its stock index return and foreign exchange return distributions, such as Thailand, the Pearson product-moment coefficient approach cannot provide an accurate estimate. In general, the copula-EVT approaches perform better than the copula approaches. Among the seven correlation estimation approaches, the Clayton copula-EVT approach has the best performance; it reaches the highest significant level in all six countries no matter the shapes of their return distributions.

[19] Taiwan is not a member of IMF, but it adopted the floating rates regime with dynamic management by its central bank.

Table 1: Stock market liberalization in the Six Asian Emerging Markets

Country	**Liberalization Date**	**Limit of foreign ownership**	As of January 01, 2001
India	November 1992	24%	49%
Indonesia	September 1989	49%	No limits
Korea	January 1992	20%	No limits
Malaysia	December 1988	limits vary	49%
Taiwan	January 1991	10%	No limits
Thailand	September 1987	limits vary	50%

Source: Campbell R. Harvey, Country risks analysis, http://www.duke.edu/~charvey/Country_risk/couindex.htm

Table 2: Market Capitalization (Currency in Millions)

Country	2000	2001	2002	2003	2004	2005	2006
Indonesia:							
In rupian	259,620,958	239,258,731	268,422,777	460,365,963	679,949,067	801,252,702	1,249,074,451
In U.S. dollars	26,834	23,006	29,991	54,659	73,251	81,428	138,886
Growth rate	100%	92%	103%	177%	262%	309%	481%
Korea:							
In won (1/1000)	217,057	289,030	296,084	392,737	443,737	725,972	776,725
In U.S. dollars	171,587	220,046	249,639	329,616	428,649	718,180	835,188
Growth rate	100%	133%	136%	181%	204%	334%	358%
Malaysia:							
In ringgit	444,352	456,028	470,715	639,830	722,040	684,980	830,335
In U.S. dollars	116,935	120,007	123,837	168,376	190,011	181,236	235,356
Growth rate	100%	103%	106%	144%	163%	154%	187%
Taiwan:							
In New Taiwan dollars	8,191,165	10,238,812	9,091,463	12,867,827	13,989,100	16,946,321	21,388,555
In U.S. dollars	247,602	292,621	261,474	379,023	441,436	515,980	654,858
Growth rate	100%	125%	111%	157%	171%	207%	261%
Thailand:							
In baht	1,279,224	1,607,737	1,990,035	4,803,548	4,533,597	5,119,428	5,100,514
In U.S. dollars	29,489	36,349	46,172	119,051	115,400	123,539	139,564
Growth rate	100%	126%	156%	376%	354%	400	399%
Singapore:							
In Singapore dollars	265,001	216,665	176,746	247,815	280,047	346,361	423,927
In U.S. dollars	152,827	117,338	101,900	229,328	277,004	316,658	276,329
Growth rate	100%	82%	67%	94%	106%	131%	160%

Source: Global Stock Markets Facebook, Standard & Poor's 2007

Table 3: Historical One Day VaR

Country	1% VaR	Expected loss
Indonesia:	-5.2148%	-50,811.17
Korea:	-5.6168%	-54,619.26
Malaysia:	-2.9486%	-29,055.44
Singapore:	-3.4052%	-33,478.75
Taiwan:	-4.5969%	-44,928.02
Thailand:	-4.2011%	-41,140.64

Source: Author's Calculation

Table 4: Data Summary and Statistics

Country		Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Indonesia:	Foreign Exchange:	-0.00014	0.007771	1.039	24.79	***39068.85
	Stock Index:	0.0006982	0.01378	-0.7058	7.615	***1899.39
	Portfolio	0.0005583	0.01772	-0.6056	9.035	***3089.41
Korea:	Foreign Exchange:	0.00009226	0.004613	-0.4036	5.475	***555.59
	Stock Index:	0.0002962	0.01816	-0.5519	6.966	**1389.63
	Portfolio	0.0003885	0.01976	-0.5209	6.295	***979.04
Malaysia:	Foreign Exchange:	0.00007094	0.001428	2.093	19.79	***23116.07
	Stock Index:	0.00027953	0.009237	-0.5709	8.961	***3019.51
	Portfolio	0.0003504	0.009598	-53.09	8.409	***2490.30
Singapore:	Foreign Exchange:	0.00006787	0.00267	0.05554	5.927	***716.60
	Stock Index::	0.0001438	0.01155	-0.5157	7.668	***1908.35
	Portfolio	0.0002117	0.01208	-0.4713	6.784	***1269.55
Taiwan:	Foreign Exchange:	-0.00002261	0.003397	0.4196	95.08	***705855.05
	Stock Index:	-0.00002099	0.01553	-0.1011	4.945	***318.37
	Portfolio	-0.00004359	0.01638	-0.1276	4.733	***255.514
Thailand:	Foreign Exchange:	0.0001121	0.00599	0.8475	137.7	***1481785.00
	Stock Index::	0.000277	0.0145	-0.7406	13.53	***9340.70
	Portfolio	0.0003891	0.01606	-0.435	10.67	***4864.47

*0.90 statistical significance, **0.95 statistical significance, ***0.99 statistical significance

Table 5: Expected Annual return

Country		Expected Annual Return
Indonesia:	Foreign Exchange:	-3.439%
	Stock Index:	19.071%
	Portfolio	14.9785%
Korea:	Foreign Exchange:	2.3333%
	Stock Index:	7.6861%
	Portfolio	10.1998%
Malaysia:	Foreign Exchange:	1.7893%
	Stock Index:	7.2382%
	Portfolio	9.1551%
Singapore:	Foreign Exchange:	1.7112%
	Stock Index:	3.6604%
	Portfolio	5.4351%
Taiwan:	Foreign Exchange:	-0.564%
	Stock Index:	-0.523%
	Portfolio	-1.084%
Thailand:	Foreign Exchange:	2.8421%
	Stock Index:	7.1704%
	Portfolio	10.2163%

Source: author's calculation

Table 6: Estimation Results of Distribution Tails

Country		Indonesia	Korea	Malaysia	Singapore	Taiwan	Thailand
Stock Index Returns:							
	ξ	0.0131	-0.2299	0.0468	-0.0027	-0.2788	0.2087
	(t-Sta)	(0.1169)	**(-1.9414)	(0.4955)	(-0.0228)	***(-2.6621)	**(1.8101)
Upper tail	β	0.0074	0.0147	0.0058	0.0075	0.0135	0.0063
	(t-sta)	***(6.3511)	***(5.8178)	***(7.8426)	***(6.1583)	***(7.1298)	***(6.7876)
	llv	308.1	210.4	573.8	315.4	379.7	431.9
	ξ	0.2505	0.2359	0.3383	0.1482	-0.1439	0.2787
	(t-Sta)	**(1.8354)	(1.6891)	**(2.2113)	*(1.3776)	*(-1.3596)	***(2.6082)
Lower tail	β	0.0085	0.0104	0.0059	0.0078	0.0125	0.0085
	(t-sta)	***(5.9346)	***(5.7843)	***(5.6042)	***(6.8733)	**(6.7104)	***(5.8577)
	llv	338	303.1	398.3	366	313.5	292.72
Foreign Exchange Returns:							
	ξ	0.2897	-0.1761	0.2465	0.2259	0.4383	0.5542
	(t-Sta)	***(2.5664)	**(-2.3007)	*(1.6092)	**(1.9080)	***(3.8363)	***(3.6700)
Upper tail	β	0.0050	0.0034	0.00135	0.0012	0.0018	0.0027
	(t-sta)	**(7.1975)	***(8.9451)	***(5.5971)	***(6.8782)	***(7.1390)	***(5.7995)
	llv	480.8	696.5	598.7	525	602.9	435.3
	ξ	0.0136	-0.2156	0.0149	0.1086	0.6394	0.4149
	(t-Sta)	(0.1107)	**(-1.7427)	(0.1101)	(1.0154)	***(3.7947)	***(3.1819)
Lower tail	β	0.0076	0.0047	0.0020	0.0015	0.0116	0.0033
	(t-sta)	**(6.2212)	***(5.8190)	***(5.7423)	***(6.8173)	***(5.3800)	***(6.3579)
	llv	360	306.1	432.7	509.1	463.3	460.7

*0.90 statistical significance, **0.95 statistical significance, ***0.99 statistical significance

Table 7: Estimation Results of Correlation Coefficients

Country		Indonesia	Korea	Malaysia	Singapore	Taiwan	Thailand
Pearson		0.2974	0.2361	0.1802	0.0852	0.1493	0.0666
Gaussian	δ	0.2857	0.2392	0.1659	0.0925	0.2334	0.1629
	(t-Sta)	***(14.2341)	***(11.5053)	***(7.6204)	***(4.1687)	***(11.2645)	***(7.4596)
	llv	82.29	57.24	27.08	8.503	55.26	26.02
Gaussian-EVT	δ	0.2850	0.2738	0.1429	0.0913	0.2298	0.1600
	(t-Sta)	***(14.2684)	**(11.4877)	***(6.9313)	***(4.1354)	***(11.1347)	**(7.3665)
	llv	82.89	57.22	22.91	8.374	54.27	25.45
Gumbel	δ	1.1873	1.1537	1.0814	1.0504	1.1430	1.1030
	λu	0.2072	0.1764	0.1017	0.0655	0.1661	0.1254
	(t-Sta)	***(60.3273)	***(62.2950)	***(65.8997)	***(70.6829)	***(62.0077)	***(64.6103)
	llv	66.48	47.98	16.51	7.094	38.74	24.32
Gumbel -EVT	δ	1.1852	1.1524	1.0781	1.0497	1.1403	1.1016
	λu	0.2053	0.1752	0.0980	0.0646	0.1635	0.1239
	(t-Sta)	***(60.5464)	**(62.4653)	***(67.3352)	***(71.2186)	***(62.2600)	**(64.8894)
	llv	65.5	47.49	15.98	7.033	37.78	24.02
Clayton	δ	0.4098	0.3090	0.1818	0.1086	0.2685	0.1758
	λ_l	0.1842	0.1061	0.0221	0.0017	0.0757	0.0194
	(t-Sta)	***(11.9434)	***(9.5011)	***(6.2297)	***(4.0050)	***(8.4661)	***(5.7942)
	llv	97.96	59.33	24.13	9.631	45.56	20.58
Clayton-EVT	δ	0.4030	0.3028	0.1274	0.1060	0.2589	0.1708
	λ_l	0.1791	0.1013	0.0043	0.0014	0.0688	0.0173
	(t-Sta)	***(11.8683)	**(9.4039)	***(5.1229)	***(3.9630)	***(8.2757)	***(5.6856)
	llv	97.9	58.5	15.83	9.456	43.77	19.36

*0.90 statistical significance, **0.95 statistical significance, ***0.99 statistical significance

Table 8: Backtesting Results (P-Values)

Country	Indonesia	Korea	Malaysia	Singapore	Taiwan	Thailand
Pearson	*0.0730	*0.0764	**0.0437	***0.0012	*0.0542	0.2874
Gaussian Copula	***0.0005	0.7508	**0.0238	0.0954	0.3352	0.9767
Gaussian Capula-EVT	***0.0001	0.7508	**0.0123	0.0565	0.1487	0.4116
Gumbel Copula	***0.0005	0.5755	0.0759	**0.0170	0.1487	0.2874
Gumbel Copula-EVT	***0.0000	**0.0124	**0.0123	***0.0008	**0.0161	0.1212
Clayron Copula	***0.0001	*0.0764	0.1254	***0.0003	0.0376	*0.0730
Clayton Copula-EVT	***0.0000	**0.0124	***0.0028	***0.0000	***0.0001	***0.0057

*0.90 statistical significance, **0.95 statistical significance, ***0.99 statistical significance

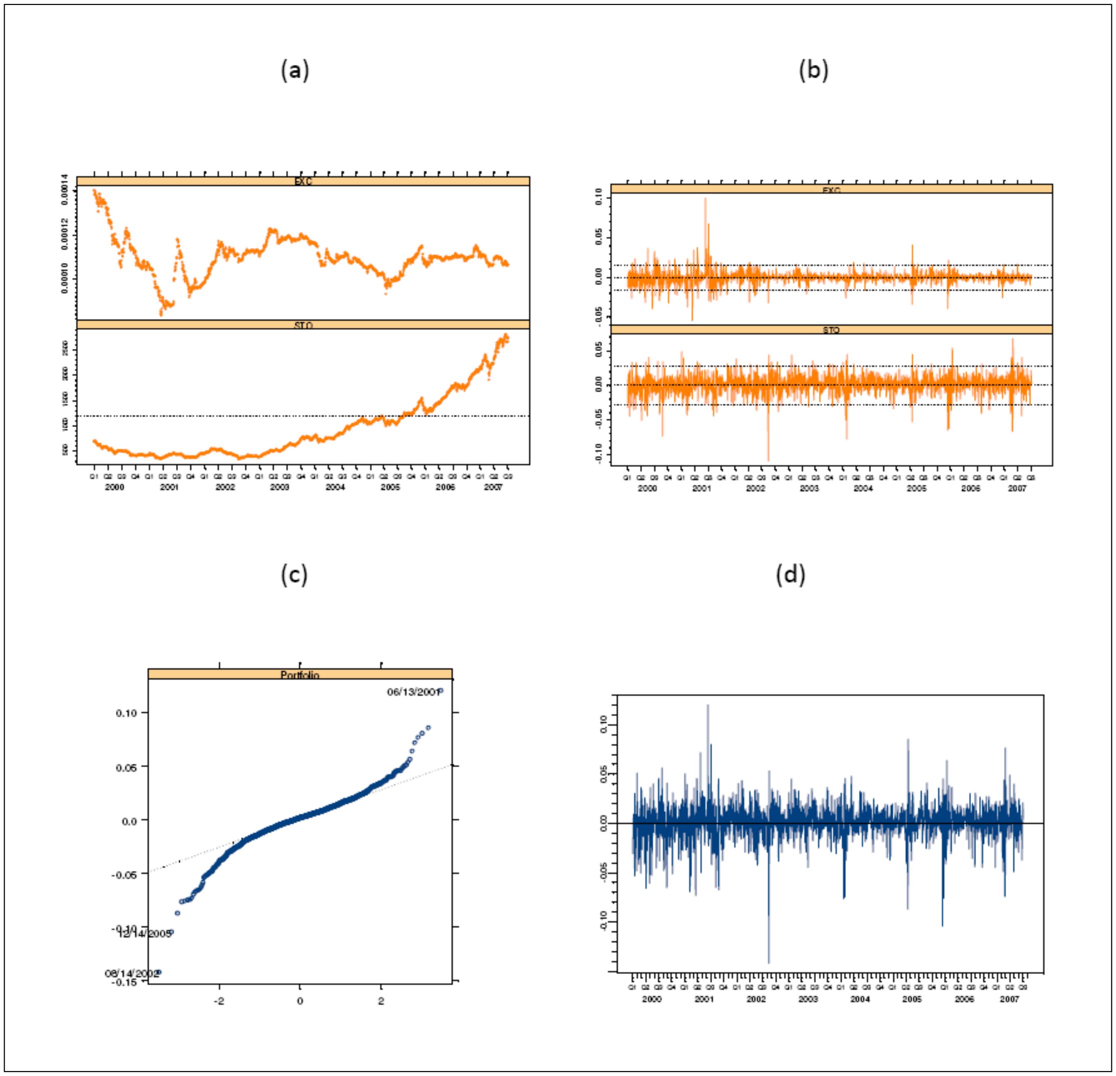

Figure 1: Indonesia: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

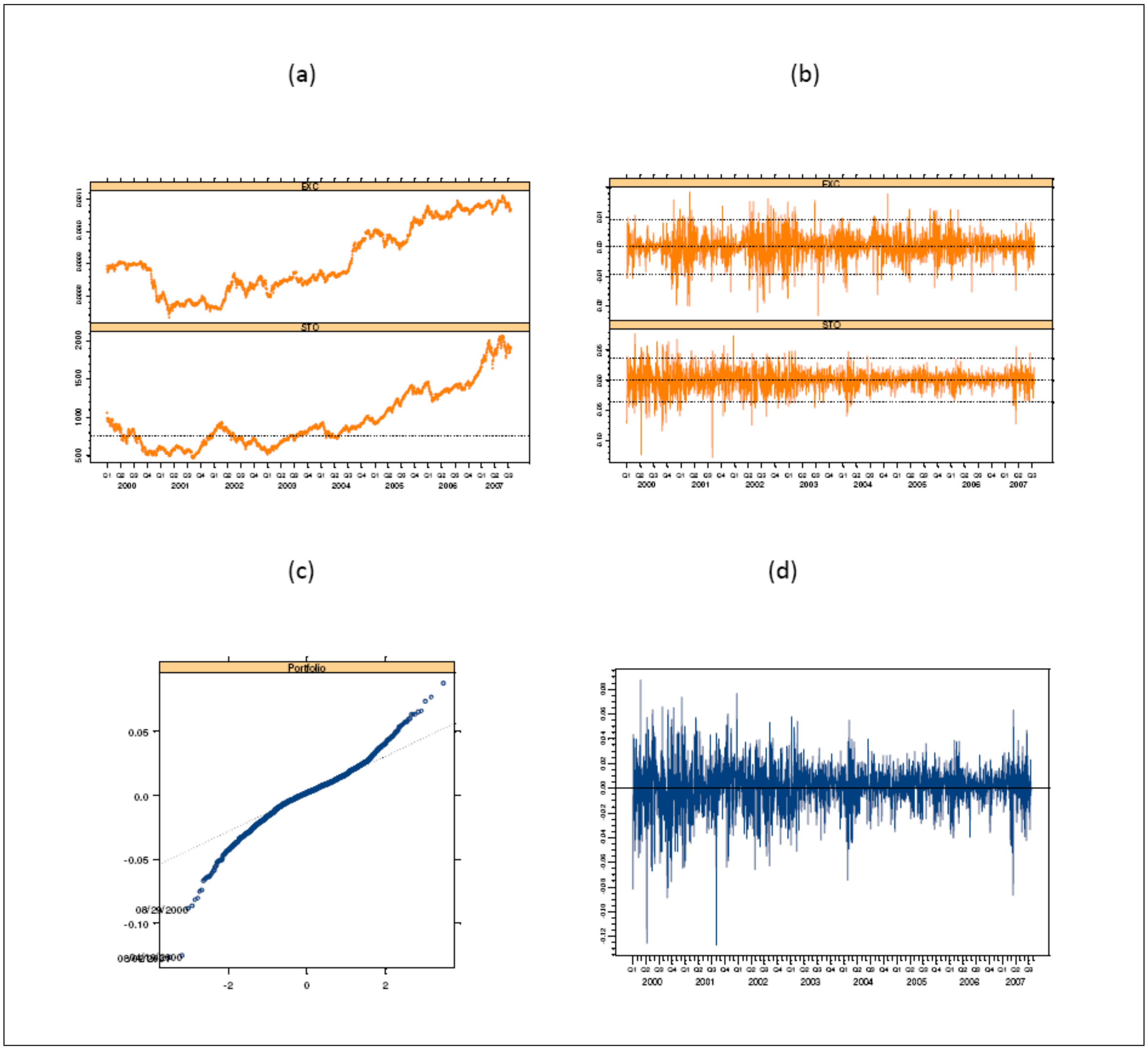

Figure 2: Korea: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

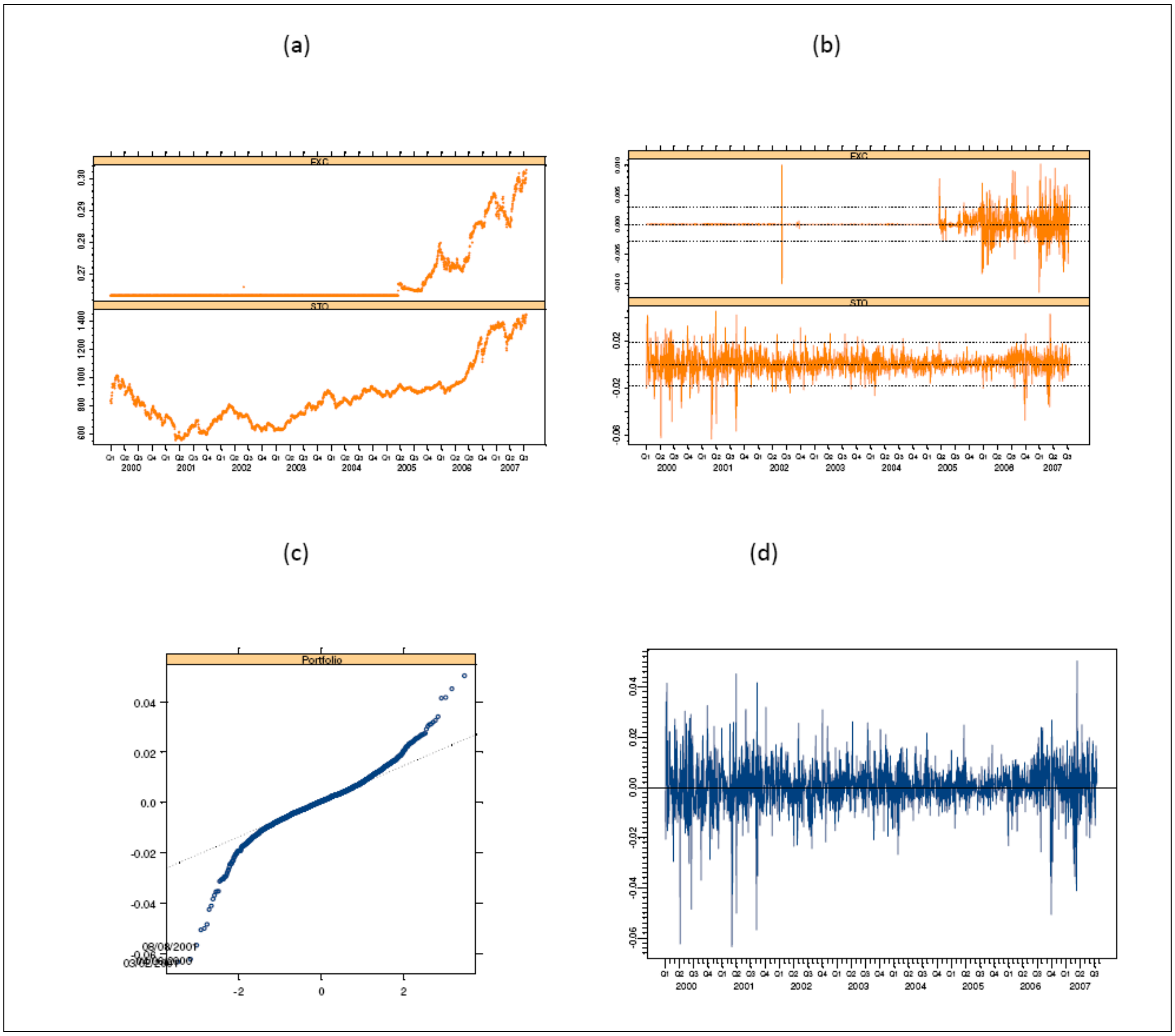

Figure 3: Malaysia: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

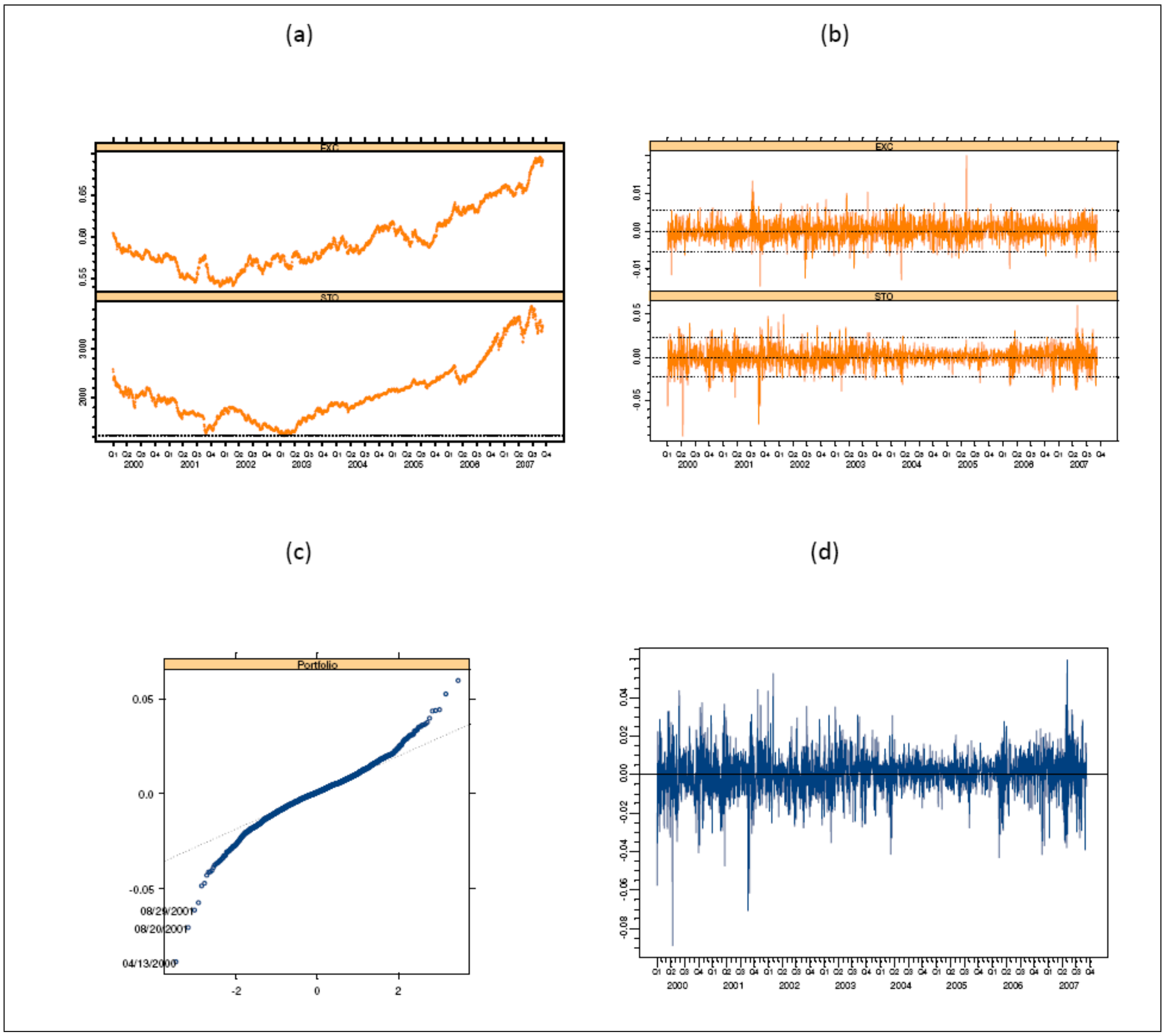

Figure 4: Singapore: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

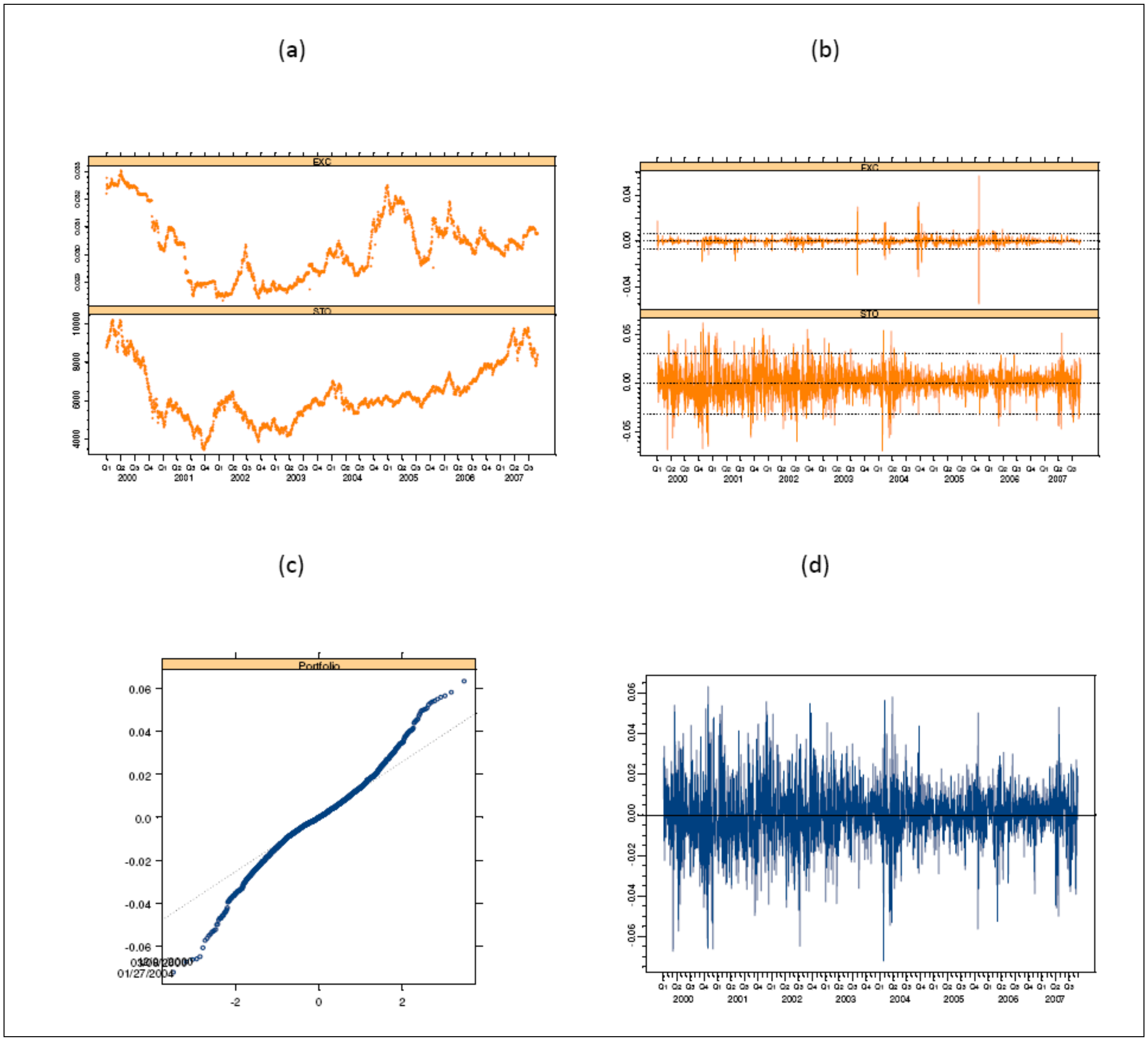

Figure 5: Taiwan: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

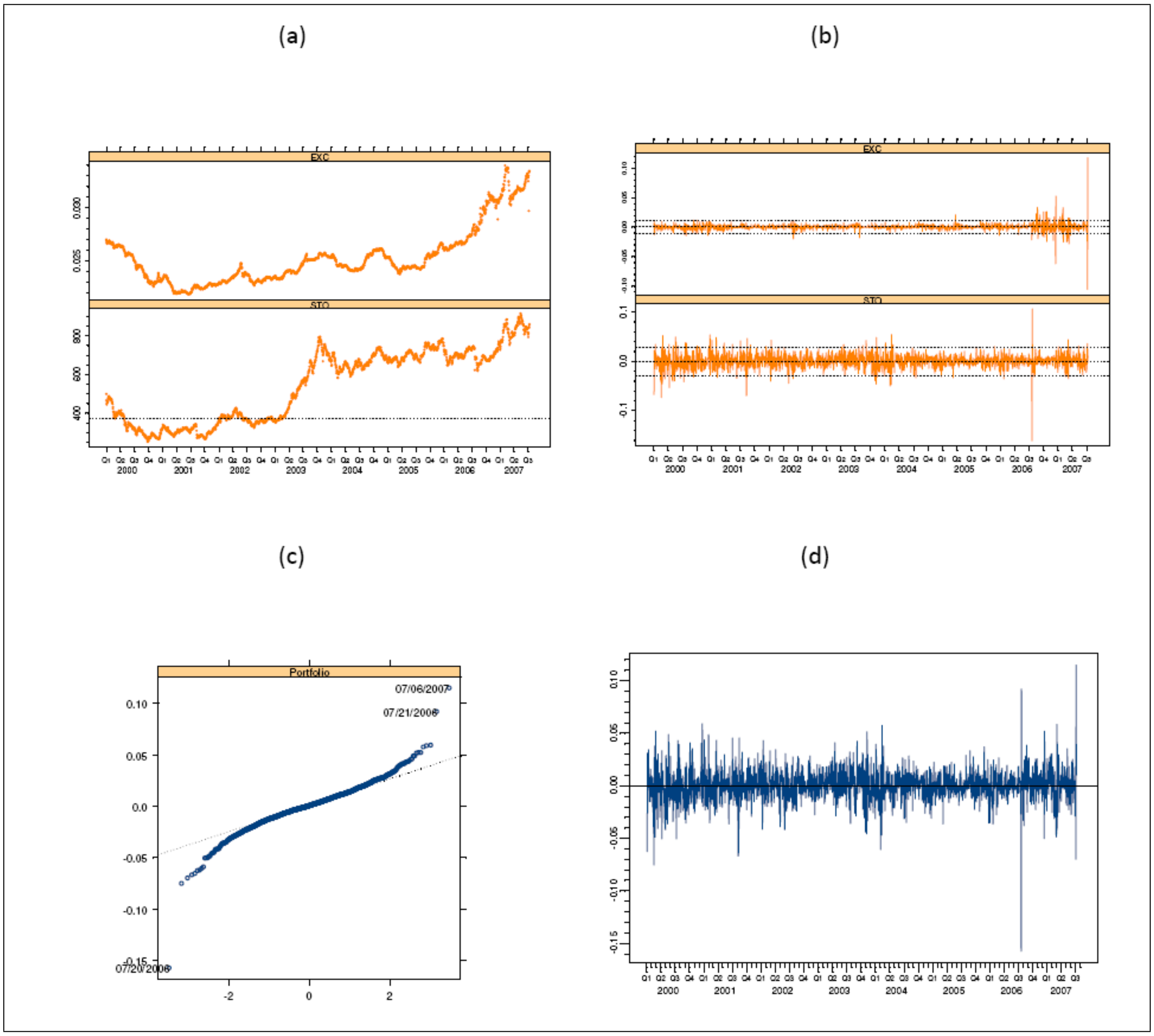

Figure 6: Thailand: (a) Daily stock indices and foreign exchange rates; (b) Daily stock index returns and foreign exchange returns; (c) QQ plot of portfolio daily returns; (d) Daily portfolio return.

References

[1] Agbeyegbe, T., 2002, The tail behavior of stock index return on the Jamaican Stock Exchange. Working Paper, Hunter College, City University of New York.

[2] Ajayi, R., and Mougoue, M., 1996, On the dynamic relationship between stock prices and exchange rates, Journal of Financial Research XIX, 193-207.

[3] Ang, A., and Chen, J., 2002, Asymmetric correlations of equity portfolios, Journal of Financial Economics 63, 443–494.

[4] Bartram, S. M., Taylor, S. J., and Wang, Y. H., 2007, The euro and european financial market dependence, Journal of Banking & Finance 31(5), 1461-1481.

[5] Beirlant, J., Goegebeur, Y., Segers, J., and Teugels, J., 2004, Statistics of Extremes:Theory and applications, Wiley, West Sussex, England.

[6] Boyer, B. H., Gibson, M. S. and Loretan, M., 1999, Pitfalls in tests for changes in correlations, Federal Reserve Board, IFS Discussion Paper No. 597R.

[7] Carmona, R., 2004, Statistical Analysis of Financial Data in S-Plus, Springer, New York.

[8] Chang, C., Chiou, W. P., and Lee, A. C., 2008, Do investors still benefit from international diversification with investment constraints, Quarterly Review of Economics and Finance, Forthcoming.

[9] Chen, X., and Fan, Y., 2006, Estimation of copula -based semiparametric time series models. Journal of Econometrics 130, 307-335.

[10] Cherubini, U., Luciano, E., and Vecchiato, W., 2004, Copula Methods in Finance, Wiley, Hoboken NJ.

[11] Chow, P., 2000, Weathering the storm : Taiwan, its neighbors, and the Asian financial crisis, Brookings Institution Press, Washington DC.

[12] Coles, S., 2001, An introduction to statistical modeling of extreme values, Springer, UK.

[13] Da Silva, A., and Mendes, B., 2003, Value-at-risk and extreme returns in Asian stock markets. International Journal of Business 8(1), 17-40.

[14] Di Clemente, A. C., and Romano, C., 2003, Measuring portfolio value-at-risk by a copula-evt based approach, University of Rome.

[15] Doidge, C., Griffin, J., and Williamson, R., 2006, Measuring the economic importance of exchange rate exposure, Journal of Empirical finance 13, 550-576.

[16] Embrechts, P., Lindskog, F., and McNeil, A., 2003, Modelling dependence with copulas and applications to risk management, Handbook of Heavy Tailed Distributions in Finance, Elsevier/North-Holland, Amsterdam.

[17] Embrechts, P., Frey,R., and McNeil, A., 2005, Quantitative Risk Management, Princeton University Press.

[18] Fok, R.C., Liu,Y. A., and Pan, M. S., 2007, Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets, International Review of Economics & Finance 16, 503-520.

[19] Frey, R. and McNeil, A., 2000, Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach, Journal of Empirical Finance 7, 271-300.

[20] Gavin J., 2000, Extreme value theory- an empirical analysis of equity risk. UBS Warburg working paper.

[21] Ho, L., Burridge, P., Cadle, J., and Theobald, M., 2000. Value-at-Risk: Applying the Extreme Value Approach to Asian Markets in the Recent Financial Turmoil, Pacific-Basin Finance Journal 8, 249-275.

[22] Joe, H., 1997, Multivariate models and dependence concepts, Chapman & Hall/CRC, New York.

[23] Joe, H., and Xu, J.J., 1996, The estimation method of inference functions for margins for multivariate models, Dept. of Statistics, University of British Columbia, Tech. Rept. 166.

[24] Kolari, J., Moorman, T., and Sorescu, S., 2008, Foreign exchange risk and the cross-section of stock returns, Journal of International Money and Finance 27, 1074-1097.

[25] Kole, E., Koedijk, K., Verbeek, M., 2007, Selecting copulas for risk management, Journal of Banking and Finance 31, 2405 -2423.

[26] Longin, F., 2000, From value at risk to stress testing: The extreme value approach, Journal of Banking and Finance 24, 1097-1130.

[27] Longin, F., and Solnik, B., 2001, Extreme correlation of international equity markets, Journal of Finance LVI, 649-676.

[28] Neftci, S., 2000, Value at risk calculations, extreme events, and tail estimation, Journal of Derivatives 7 (3), 23 - 38.

[29] Nelsen, R., 2006, An introduction to copulas, Springer-Verlag, New York.

[30] Parto, D., Wald, J., and Wu, Y., 2002, Explaining exchange rate risk in world stock markets: A panel approach, Journal of Banking & Finance 26, 1951-1972.

[31] Patton, A., 2006a, Modelling Asymmetric Exchange Rate Dependence, International Economic Review 47, 527–556.

[32] Patton, A., 2006b, Estimation of Multivariate Models for Time Series of Possibly Different Lengths, Journal of Applied Econometrics 21, 147–173.

[33] Rodriguez, J. C., 2007, Measuring financial contagion: A Copula approach, Journal of Empirical Finance 14, 401-423.

[34] Singh, A. and Weisse, B., 1998, Emerging Stock Markets, Portfolio Capital Flows and Long Term Economic Growth, Micro and Macroeconomic Perspectives, World Development 26 (4),607-622.

[35] Solnik, B., 1987, Using Financial Prices to Test Exchange Rate Models, Journal of Finance 42(1), 141-149.

[36] Susmel, P., 2001, Extreme observations and diversification in Latin American emerging equity markets, Journal of International Money and Finance 20, 971-986.

[37] Tai, C., 2007, Market integration and contagion:Evidence from Asian emerging stock and foreign exchange markets, Emerging Market Review 8, 264-283.

[38] Tastan, H., 2006, Estimating time-varying conditional correlations between stock and foreign exchange markets, Physica A 360, 445-458.

[39] Wang, J., and Zivot, E., 2006, Modeling Financial Time Series with S-Plus, Springer, New York.