ISSN 1440-771X

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May 2006

Working Paper 9/06

Assessing Dependence Changes in the Asian Financial Market Returns Using Plots Based on Nonparametric Measures

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May 2006

Abstract: This paper investigates whether or not there are significant changes in the dependence between the Thai equity market and six Asian markets - namely, Singaporean, Malaysian, Hong Kong, Korean, Indonesian and Taiwanese markets - due to 1997-July financial crisis. If so, this may be an indication that the underlying bivariate joint distributions capturing the dependence between the Thai market and these six markets have changed. We employ the chi-plot proposed by Fisher and Switzer (2001) and the Kendall plot proposed by Genest and Boies (2003) to examine the dependence in these six markets for the pre- and post-1997 financial crisis periods. We find that marginal distributions of all seven markets have notably changed due to this financial crisis, and that the functional forms of the underlying joint distributions generating the dependence in the Korean, Indonesian and Taiwan markets have also changed for the post-crisis period. It appears that the same parametric copula can capture the dependence in the Singapore, Malaysia and Hong Kong markets for both pre- and post-crisis periods, and that only the tail indices of bivariate distributions between the Thai and these three markets have changed. It is interesting to observe that the same conclusions can be drawn using both chi- and Kendall plots.

Keywords: chi-plot, copula, dependence, Kendall-plot

JEL classification: C14, G14

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1 Introduction

Measuring the dependence between risky assets is the foundation of portfolio theory and other financial applications such as credit risk analysis, valuing derivatives, risk management and the like. The widely used conventional dependence measure known as Pearson correlation coefficient is designed to capture only the linear relationship between the variables. The nonparametric Spearman rank correlation measure on the other hand is somewhat robust to outliers that are often encountered in many economic and financial applications. However, this is rather a measure of functional dependence, which assumes the values 1 and -1 in case of functional (not necessarily) linear association between two random variables. Until recently, the former has been very popular in measuring the dependence between the financial series, although these series are known to follow non-elliptical distributions; see, for example, Silvapulle et al. (2006). A new model emerging for capturing and measuring various (even complex) forms of dependence is the copula. A copula measures the dependence between n ($n \geq 2$) variables. According to Sklar (1959) theorem, any n-dimensional joint distribution function may be decomposed into n marginal distributions and a copula, which completely characterize the dependence between the n variables. See Joe (1997) and Nelsen (1999) for details. Recently, it has been applied by several researchers to asset pricing models, portfolio theory, specifically for modeling the tail dependence in the foreign exchange markets, value at risk and so on. See, for example, Patton (2005), Bouyé and Salmon (2004), Ang et al. (2002), Granger et al. (2006), and the references therein. Since these financial models and their applications are highly sensitive to dependence measures, it is very important that researches pay due attention to selecting the appropriate copula.

Clearly, the attraction of the copula method comes from the fact that the underlying nature of the dependence between random variables can be characterized even when their marginal distributions are non-elliptic and each of them may have entirely different distributions. However, given that there are many families of copulas and within each family there are many members of copulas, choosing an appropriate copula to the variables under investigation is a difficult task, as the dependence can take from a simple to very complex form. This paper suggests two alternative plots, which can be used as a powerful tool for revealing complicated dependence structures, and they are directly related to the concept of copula.

The objective of this paper is to investigate the use of two plots, Chi-plot proposed by Fisher and Swartz (1985) and Kendall-plot by Genest and Boies (2003), which we believe will provide strong evidence of the nature of the underlying dependence between two time series. Specifically, we want to study if these two plots can reveal any changes in the dependence (that is, the joint distribution) due to major events such as Asian financial market crisis in July 1997. As will be seen soon, an idea based on copula is used to derive these two sets of plots. Contrary to what the global dependence measures such as Pearson and Spearman correlations and a scatter plot reveal about the dependence, these two plots can exhibit even a complex nature of dependence between the variables. As an example, we will consider the Thailand financial market crisis in July 1997. In particular, we will study whether or not the dependence between the Thai market and each of the six other financial equity markets — Hong Kong (HK), Indonesia, Korea, Malaysia, Singapore and Taiwan — has notably changed by employing the chi-plot and Kendall (K-plot).

In this paper, we argue that the chi-plot and K-plot can capture the underlying nature (even complex) of the dependence between the variables, and be used as a way of choosing an appropriate form of copula in order to model the joint distribution between the variables. Patton (2005), for example, modeled and estimated a copula in order to capture the underlying dependence between the Deutsch mark and yen. Further, Patton (2005) studied the dependence, in particular, if it has changed after the introduction of Euro. This aspect of the change in the dependence was captured by incorporating a dummy variable into the time-varying parameter governing the copula. One problem with this way of addressing this issue is that if there is indeed a change in the nature of the dependence (that is, the change in the copula with entirely different functional form), then inclusion of a dummy variable will not provide the correct measure of dependence for the post-Euro1999 period. To study the nature of such changes in the dependence due to major events, we believe that one should find strong evidence of change in dependence, by asking the following questions for the post-crisis period: (i) can the same functional form of the copula capture the dependence, with the copular parameter value significantly changed? or (ii) has the functional form of the copula (joint distribution) in itself changed? Focusing on the graphical procedures chi- and K-plots, this paper attempts to answer these questions by studying the dependence between Thai equity market and six other Asian markets before and after the collapse of the financial system (first experienced by Thailand) in July 1997. Another issue ignored by earlier empirical studies is that there can be notable changes in the marginal distributions of market returns across the two sample periods. However, many previous studies fitted a single parametric marginal distribution for the whole sample period, which can produce misleading results about the dependence in the markets. Since non-parametric plots are used in this study, the change in marginal distributions will not have any affect on the dependence measures presented in this paper. Further, this study models the margins and joint distributions for the two samples separately.

A background of the graphical procedures used in this paper follows: graphical procedures relating to formal statistical tests of dependence have a rather long history, mainly because a graphical representation can sometimes provide a way of constructing the test statistics. This role as a computational aid has long since been incorporated into computers, and graphs are now being used as a powerful tool for revealing patterns. For example, autocorrelation function for serial dependence, Q-Q plot for normality, scatter plot for randomness, and so on. The graphs can be a very rich source of information about the nature of the dependence. As argued before, this is in contrast with formal tests, which can only provide a single piece of information about a single form of dependence. The capabilities of the basic scatter plot are well known in this respect and, as a plot of the raw data (or its rank transform), it is and will always be used as a primary data analytic tool.

When we examine a scatter plot to detect a pattern indicating the nature of dependence, what we observe, under the null hypothesis of independence, is a random scatter of data points. Unfortunately, as Fisher and Switzer (2001) argued, randomness is somewhat a difficult characteristic for the human eye to judge. The chi-plot proposed by Fisher and Switzer (1985) was designed to address this issue. As will be seen soon, it provides a graph that has characteristic patterns depending on whether two variables (i) are independence, (b) have some degree of monotone relationship or (iii) have more complex dependence structure. Further, chi-plot depends on the data series only through the values of their ranks. Fisher and Switzer (1985, 2001) have illustrated some of the wide variety of forms of dependence a single chi-plot can highlight by using simulated and real data series.

The other measure of dependence used in this study is the Kendall-plot or K-plot proposed by Genest and Boies (2003). This measure adopts the concept of probability plot (used to test for normality) to the detection of dependence between two variables. Genest and Boies (2003) argued that since this procedure is embedded in the probability integral transformation, it retains the key invariance property of the chi-plot with respect to monotone transformation of marginal distributions. They further argued that K-plots are easier to interpret than chi-plots, because the curvature that K-plots exhibit in cases of dependence is very much related to the copula characterizing the underlying dependence structure.

This paper is planned as follows: next section defines the chi-plot and K-plots, and briefly discusses their key properties. Section 3 describes the data series used in this study and their descriptive statistics. Section 4 reports and analyses chi-plots and K-plots of the bivariate distributions of the Thai market and other six market returns. Some concluding remarks are made in the final section.

2 Methodological Issues

In this section, we will discuss the concepts used in deriving both chi-plot proposed by Fisher and Switzer (1985) and K-plot by Genest and Boies (2003), and outline their properties, particularly under the null hypothesis of independence and the alternative hypothesis of dependence.

2.1 Chi-Plot

Fisher and Switzer (1985) developed a plotting tool known as chi-plot or χ-plot, which transforms T pairs (X_i, Y_i) series into n pairs $(\lambda_{n_i}, \chi_{n_i})$ by providing an alternative to the scatter plot of (X, Y). To describe this method, let $(X_1, Y_1), \cdots, (X_n, Y_n)$ of size $n \geq 2$, be a random sample from a bivariate cumulative distribution H, which is assumed to be a continuous function of a pair of variables (X, Y). Further, let F and G be the marginal distributions of X and Y, respectively. For each bivariate data cut-point (X_i, Y_i), define:

$$H_i = H(X_i, Y_i) = \sum_{j \neq i} I(X_j \leq X_i, Y_j \leq Y_i)/(n-1), \tag{1}$$

$$F_i = F(X_i) = \sum_{j \neq i} I(X_j \leq X_i)/(n-1), \tag{2}$$

and

$$G_i = G(Y_i) = \sum_{j \neq i} I(Y_j \leq Y_i)/(n-1), \tag{3}$$

where the indicator function $I(E)$ is defined as 1 if an event E occurs and 0 otherwise. The aim is to assess whether or not the variables X and Y are independent or exhibits some form of dependence. If X and Y are indeed independent, then it is expected that $H_i = F_i G_i$ with sampling variability at each of the sample cut-points. Therefore, under the null hypothesis of independence, the standardized test statistic,

$$\chi_{n_i} = \frac{H_i - F_i G_i}{F_i(1-F_i)G_i(1-G_i)}, \tag{4}$$

for $i = 1, 2, \cdots, n$, asymptotically follow a normal distribution with mean zero and variance $1/n$, for a given cut point (X_i, Y_i). Clearly, χ_{n_i} is a correlation coefficient between dichotomized X and Y, and therefore, all values of χ_{n_i} are expected to lie in the interval [-1,1].

Further, define $S_i = \text{sign}\{(F_i - 1/2)(G_i - 1/2)\}$ and compute

$$\lambda_{n_i} = 4S_i \max\{(F_i - 1/2)^2, (G_i - 1/2)^2\}. \tag{5}$$

λ_{n_i} is the real valued functions of the marginal frequencies, $\lambda_{n_i} \in [-1, 1]$ and $|\lambda_{n_i}|$ may be viewed as a measure of the distance from the sample point (X_i, Y_i) to the bivariate median $(\tilde{X}, \tilde{Y})$ of the distribution H. An undesirable property of λ_{n_i} is its discontinuity at $F = 1/2$ and $G = 1/2$. One might want to use $|\lambda_{n_i}|$ instead, and the recommended alternatives are the following:

(i) $|\lambda_{n_i}| = 4(F_i - 1/2)(G_i - 1/2)$, related to Spearman rank correlation.

(ii) $|\lambda_{n_i}| = 4(|F_i - 1/2| - |G_i - 1/2| - 1/2)^2$, also uniformly distributed under the null hypothesis of independence.

However, the sign of λ_{n_i} values do carry valuable information about the dependence, and therefore, we intend to use the raw values of the λ function with signs.

Fisher and Switzer (1985) further argued that the sampling behavior of the chi-plot is unreliable for the sample points at the edge of the distribution, and thus, the asymptotic normal theory breaks down. To overcome this problem, it is highly recommended that the extreme sample points for which $|\lambda_{n_i}| \geq 4(1/(n-1) - 1/2)^2$ should be discarded, and this way of censoring criterion seems to typically eliminate only a very small number of points.

What does this chi-plot in fact capture? In a way, χ_{n_i} measures the failure of the bivariate distribution function to factorize into a product of marginal distribution functions at the sample argument (X_i, Y_i), while λ_{n_i} measures the distance from (X_i, Y_i) to the centre of the data series, bivariate median $(\tilde{X}, \tilde{Y})$. It is clear that the χ transform provides an indication of (X, Y) association separately for each data point, and the λ transform positions that point with respect to the X and Y marginal distributions. The proposed data transforms are invariant under monotonic rescaling of the X and Y measurements. And the χ-plot is scaled so that all points fall in the rectangle $[-1, 1] \times [-1, 1]$. Positive and negative departure from independence appear as corresponding deviations from the horizontal line $\chi = 0$, with calculated allowances for scatter due to sampling variability. Increasing the sample size n tends to decrease the amount of scatter in the χ-plot. Fisher and Switzer (1985) argued that the chi-plot is uniquely determined by the copula of the joint distribution. Further, since χ_{n_i} is in a way a test statistic, the confidence intervals can be computed.

Fisher and Switzer (1985) studied the properties of Chi-plot using artificial and real data examples and showed that if X and Y are indeed independent, then 95 per cent of the χ_{n_i} values lie within the confidence interval. By definition, a positive χ_{n_i} means that both X_i and Y_i are large or small relative to their respective medians simultaneously. On the other hand, a negative χ_{n_i} corresponds to both variables being on opposite sides of their respective medians. By studying both scatter and chi-plots, they demonstrated that chi-plots can exhibit a variety of patterns of dependence between the variables, which is largely concealed by usual scatter plots.

2.2 Properties of Chi-Plot

(i) To preserve the normality property of the chi-plot, omit the extreme values of λ as discussed before.

(ii) In order to examine the behavior of the chi-plot under sampling from a bivariate normal distribution with correlation, ρ, consider the transformation: $\tilde{\chi} = \sin(\pi\chi/2)$. Under the null hypothesis of independence, $\tilde{\chi} \sim N(0, \pi n^{1/2}/2)$. Moreover, $\tilde{\chi} \to \rho$ as $\lambda \to 0$. That is, at the cut-point near the bivariate median.

(iii) The values of both χ_{n_i} and λ_{n_i} depend on the data only through the rank X_i among $X_1, \cdots, X_n$, and the rank Y_i among $Y_1, \cdots, Y_n$, so that chi-plot is robust to the effect of cross outliers.

(iv) The chi-plot can be adapted to time series context.

(v) As pointed out by Fisher and Switzer (1985), it can be seen that the numerators of χ_{n_i} $(i = 1, \cdots, n)$ are connected to standard nonparametric tests of independence based on Spearman's empirical rank-order correlation coefficient ρ_n, and Kendall's sample measure of concordance, τ_n. Further, the following relationship can be established:

$$\sum_{i=1}^{n}(H_i - F_iG_i) = \frac{n}{12}\left(3\tau_n - \frac{n+1}{n-1}\rho_n\right).$$

Therefore, under independence and for large n, it is expected that $\tau_n = \rho_n/3$.

Providing simulated and real data examples of chi-plots, Fisher and Switzer (1985) and Genest and Boies (2003) argued that the patterns of dependence between two variables exhibited by chi-plots might be used to identify the underlying copula, although the exact connection at this stage is far from obvious. However, Pearson correlation r will capture the dependence in the correlated bivariate normal data, and the corresponding chi-plot will yield a smile-like pattern. Since there are various copula families available and some of which are much studied in the literature, interpretation of the richness of patterns revealed by the chi-plot is difficult at this stage. In the future research, carrying out a comprehensive simulation experiment to generate bivariate random variables form various copulas that are popular in economic and financial applications and to study the corresponding chi-plots would be very useful to applied researchers in this area. Such a study, we believe, will provide applied researchers with information on the connection between the dependence captured by copulas and the patters exhibited by chi-plots.

2.3 Kendall-Plot

To define the K-plot, recall the random sample $(X_1, Y_1), \cdots, (X_n, Y_n)$ from a continuous bivariate cumulative distribution function H with margins F and G. Now, suppose that we take a probability integral transformation of the component (X_i, Y_i) to $(U_i, V_i) = (F(X_i), G(Y_i))$, for $i = 1, \cdots, n$, in order to make them uniform on the interval [0,1]. Typically, marginal distributions $F(X)$ and $G(Y)$ are unknown, and a simple way to control their influence is to plot the pairs $(\hat{F}_n(X_i), \hat{G}_n(Y_i))$, for $i = 1, \cdots, n$, where $\hat{F}_n$ and $\hat{G}_n$ are the empirical distributions of X_i and Y_i, respectively. It will be seen in the following section that plotting (U_i, V_i) is equivalent to plotting the pairs of the rank of X_i/n and the rank of Y_i/n. Because ranks are maximally invariant under monotone transformation of the marginal distributions, and the transformed data may be regarded as observations from the unique underlying copula, given as:

$$C(u, v) = H\left\{F^{-1}(u), G^{-1}(v)\right\}, \text{ for } 0 \leq u, v \leq 1,$$

which is associated with H. Because $H = F \times G$ occurs if and only if $C(u, v) = uv$ on its entire domain, no loss of information ensues from the rank transformation. However, the scatter plot of (U_i, V_i) is of limited use in assessing the null hypothesis of independence, because as argued before randomness is a difficult characteristic for the human eyes to judge. The Chi-plot, which is discussed in section 2.2, satisfies the need for graphical method in which independence manifests itself in a more characteristic fashion than in scatter plots.

Genest and Boies (2003) proposed an alternative rank based procedure, which adopts the familiar concept of probability plot, known as Q-Q plot, to the detection of dependence. A lack of linearity of the standard Q-Q plot is an indication of non-normality of the distribution of a random variable, whereas the amount of curvature in the proposed graph is characteristic of the degree of dependence in the data. This method, the properties of which will be discussed in some detail in section 3, is rooted in the probability integral transformation, and closely related to Kendall's τ-statistic, and as such it is referred to as Kendall plot or K-plot. The proponents of these chi-plot and K-plot argued that these techniques can be adapted to time series context. As such we shall study these plots to measure the dependence between Thailand equity market returns and six other Asian stock returns for the periods of pre- and post- financial crisis, these markets experienced in July 1997.

Since the idea based on Q-Q plot was used to develop K-plot, we recall the definition of Q-Q plot. Let $\{X_1, \cdots, X_n\}$ be a univariate random sample. In order to assess if it comes from normal distribution, standard practice is to draw a Q-Q plot, which is in fact a plot of $(Z_{(i:n)}, X_{(i)})$, for $i = 1, \cdots, n$, where $X_{(i)}$ denotes the ith ordered statistic of the sample, and $Z_{(i:n)} = E(Z_{(i)})$ with $Z_{(i)}$ being the ith ordered statistic of standard normal random variables $\{Z_1, \cdots, Z_n\}$.

Based on this idea, Genest and Boies (2003) proposed K-plot, which is a visual tool for assessing dependence in a bivariate random sample $\{(X_i, Y_i) : i = 1, \cdots, n\}$, is defined as follows:

(i) Order H_i defined in (1) as $H_{(1)} \leq \cdots, \leq H_{(n)}$.

(ii) Plot the pair $(W_{(i:n)}, H_{(i)})$, for $i = 1, \cdots, n$, where $W_{(i:n)}$ is the expectation of the ith ordered statistic of a random sample of size T drawn from the distribution K_0, which is the distribution under the null of independence of (X, Y). The resulting graph is known as Kendall-plot or K-plot. The form of the bivariate distribution K_0 is given as follows:

$$K(\omega) = K_0(\omega) = Pr\{UV \leq \omega\} = \omega - \log(\omega), \tag{6}$$

for $0 \leq \omega \leq 1$, where U and V are independent uniform random variables on the interval $[0, 1]$. $W_{(i:n)}$ is given by

$$W_{(i:n)} = n \begin{pmatrix} n-1 \\ i-1 \end{pmatrix} \int_0^1 w \{K_0(w)\}^{i-1} \{1 - K_0(w)\}^{n-i} dK_0(w). \tag{7}$$

See Genest and Rivest (1993) for details.

3 Properties of the Joint Distribution K and the K-Plot

In this section, we discuss the properties of the bivariate distribution K and the K-plot. They are very useful to be discussed here as they have bearing on the interpretation of the K-plot.

3.1 Properties of K

(i) K is the cumulative function of the random variable $W = H(X, Y)$ given in (6) can be obtained from the bivariate probability integral transformation of the random pair (X, Y) with cumulative distribution function H. According to (6), $K(w)$ represents the probability of the event $\{H(X, Y) \leq w\}$, and therefore, the distribution puts no mass outside the interval $[0, 1]$.

(ii) The cumulative distribution K depends only on the copula associated with H, and therefore, is not influenced by the margins F and G of H. Further, if $H(x, y) = C\{F(x), G(y)\}$ and $I(E)$ is an indicator function defined as before, then

$$\begin{aligned} k(w) &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(\{H(x,y) \leq w\}\, dH(x,y) \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I\left(C\left\{F(x), G(y)\right\} \leq w\right) dC\left\{F(x), G(y)\right\} \\ &= \int_{0}^{1}\int_{0}^{1} I\left\{C(u,v) \leq w\right\} dC(u,v) = Pr\left\{C(U,V) \leq w\right\}, \end{aligned}$$

where C is the copula and the cumulative distribution function of (U, V).

(iii) The cumulative distribution function of $H(X, Y)$, K is a univariate summary of the dependence embodied in the copula C. Using this property, Capéraà, Fougères and Genest (1997), suggested that a stochastic ordering could be defined as follows: a random pair (X, Y) with distribution H is less dependent than another pair (X_*, Y_*) with H_*, denoted as $(X, Y) \prec_K (X_*, Y_*)$, if and only if $K(w) \geq K_*(w)$ for all $0 \leq w \leq 1$, where K and K_* are the cumulative distribution functions of the random variables $H(X, Y)$ and $H_*(X_*, Y_*)$, respectively.

(iv) For a given random pair (X, Y) with distribution H, the population Kendall's τ

is defined as follows:

$$\tau(X,Y) = 4E\{X,Y\} - 1 = 3 - 4\int_0^1 K(w)dw. \tag{8}$$

The sample estimate of Kendall's coefficient of concordance is defined as:

$$\tau_n = 4\tilde{H} - 1,$$

with $\tilde{H} = (H_1 + \cdots + H_n)/n$.

(v) The random pair (X,Y) is said to be co-monotonic whenever $\tau(X,Y) = \pm 1$, which is equivalent to saying that Y is almost surely a monotonic increasing or decreasing function of X. If $\tau = 1$, then $Y = G^{-1}\{F(X)\}$ with probability 1 and hence $K(w) = w$, which can be seen from (7). If $\tau = -1$, then $Y = G^{-1}\{1 - F(X)\}$ almost everywhere and hence $K = 1$ on its domain, which can also seen from (7). That is, it is the distribution of a point mass at the origin.

3.2 Properties of K-plot

The empirical function $K_n(w) \to K(w)$ as $n \to \infty$ in probability for all and hence it is also true that in probability for all $0 \le w \le 1$. Because K_n and inverse are bounded, this convergence property naturally extends to their expectations. These attractive properties of the K-functions in turn led the K-plot to posses the following desirable properties:

(i) Let [np] denote the smallest integer greater than or equal to np for $n \ge 2$ and $0 \le p \le 1$. Then, under the null hypothesis of independence:

$$H_{([np])} = K_n^{-1}(p) \to K^{-1}(p),$$

and

$$\lim_{n\to\infty} E(H_{([np])}) = \lim_{n\to\infty} W_{[np]:n} = K^{-1}(p).$$

(ii) The pairs $(W_{i:n}, H_{(i)})$ tends to concentrate along the curve $p \longmapsto (K_0^{-1}(p), K^{-1}(p))$ asymptotically; that is, for large values of n. This means that the points on the K-plot will look like plot of $w \longmapsto K^{-1}\{K_0(w)\}$.

(iii) Under the null hypothesis of independence, the K-plot tends to be linear when $K = K_0$.

(iv) When the variables X and Y are co-monotonic with $\tau(X, Y) = -1$ all points on the graph fall on the horizontal axis $p \equiv 0$. Because when $\tau(X, Y) = -1$, $K^{-1} \equiv p$ on $[0, 1]$.

(v) When X and Y are co-monotonic and $\tau(X, Y) = 1$ all points fall on the curve $K_0(p)$, because $K_0(p) \equiv p$ on $[0, 1]$.

4 The Data Series and the Empirical Results

In this section, we will provide a brief description of data series, in particular, the properties of empirical marginal distributions of seven stock markets returns. Further, the results of chi-plots and K-plots are reported and analyzed.

4.1 Data Series

The data series on equity prices of seven countries - Thailand, HK, Singapore, Malaysia, Korea, Taiwan and Indonesia - for the period 1990 to 2005 are used in this study. Following the Thai market collapse in July 1997, many Asian financial markets experienced a financial meltdown. Tables 1 and 2 reveal respectively the summary statistics of marginal distributions of equity market returns for all seven markets for the pre- and post-crisis periods. There are some notable differences in the marginal distributions between the two sample periods emerge from these statistics.

The mean of the distribution is positive only for the Thai market, while it is negative for all other six markets for the pre-crisis period. Further, the mean is positive for all seven stock returns distributions in the post-crisis period. The median, on the other hand, is positive for three markets - Thailand, Malaysia and Indonesia, while it is negative for other four markets — HK, Korea, Singapore and Taiwan. Further, the median of the returns distribution is negative across all equity markets in the post-crisis period. There is no notable difference in the minimum returns earned by these markets during the pre- and post-crisis periods, while the maximum returns are very high indeed during the post-crisis period. The least maximum return was earned by Thai market in both sample periods. The maximum return of 17 per cent was earned by HK market before the crisis, while it was as high as 28 per cent earned by Taiwan in the post-crisis period.

On the skewness and kurtosis of returns distributions: the skewness of the distribution is negative for all market distributions except for the HK market before the July 1997 crisis. This skewness (in absolute value) varied from 0.06 for the Taiwan market to 0.23

for the Thai market market. The excess kurtosis of these distributions during this period ranged from 1.66 for Korean market to 5.29 for HK market. These two measures - skewness and kurtosis- have notably increased after these countries experienced the 1997-financial crisis. For the post-crisis period, distributions for all markets have positive skewness, varying from 0.44 for the Thai market to 1.73 for the HK market. The excess kurtosis - varying from 1.92 to 17.99 — has increased by four fold for Malaysian, Singaporean and Taiwanese markets, while it has increased rather significantly for the other four market distributions.

The foregoing discussion on the summary statistics representing the marginal distributions of seven equity markets returns suggest that there are notable changes in the underlying marginal distributions after the crisis in July 1997. The studies attempt to modeling marginal distributions of these equity market distributions should take these changes into account.

4.2 Empirical Results

The chi-plots for the dependence between Thai and six other markets for the pre- and post-97 crisis sample periods are exhibited in Figures 1 and 2, respectively, along with their confidence bounds. Under the null hypothesis of independence, the graphs are expected to be horizontal and randomly scattered around the χ_{T_i}=0 with most pairs lying between the confidence bounds. Examining the plots presented in Figure 1, it is clear that there is a significant dependence between the Thai and other markets, except with Taiwanese market. However, the dependence in the Taiwanese market becomes prominent only for large positive values of λ_{n_i} and χ_{n_i}. Except for Indonesian market, it is noticeable that as

$\lambda_{n_i} \to \infty$, the χ_{n_i} values are unstable, ranging from -0.05 to 0.5 in some cases. Judging from the shapes of these graphs, the strength of the dependence on Thai market can be ordered as follows: Singapore, Malaysia, HK, Indonesia, Korea and Taiwan. Now, the question is, does the plots revealed in the Figures show that there are significance changes in the dependence in these markets for post-crisis period? If so, can the same parametric form of copula (with significant change in the copula parameter) still capture the change in dependence? Or, does a copula with entirely different functional form capture this change? Inspection of Figure 2 clearly shows the striking changes in the dependence structures in the Korean and Taiwanese markets, and to lesser extent in the Indonesian market.

We find that marginal distributions of all seven markets have notably changed due to 1997-financial crisis (discussed in detail in the previous section), and that the functional forms of the underlying joint distributions generating the dependence in the Korean, Indonesian and Taiwan markets have changed significantly for the post-crisis period. Further, it appears that the same parametric copula can still capture the dependence in the Singapore, Malaysia and Hong Kong markets for both pre- and post-crisis periods, and that only the tail indices (defined by the copula parameters) of bivariate distributions between the Thai and these three markets have changed. However, what type of copulas can capture or explain these changes in the dependence remain to be studied.

The K-plots (that is, plots of $W(i:n)$ against $H(i)$) of the dependence in the six countries on Thailand for pre- and post-crisis in 1997 are exhibited in Figures 3 and 4 respectively. Recall that if two markets returns are indeed independent, then the plots will be straight lines being close to the 45-degree line shown in all graphs. An inspection of the graphs for the pre-crisis period shows that the dependence in the Taiwan and Korea is very weak, and we can say that these markets were functioning largely independent of Thailand market. There is notable dependence in Hong Kong, Malaysian and Singaporean markets. Further, there is evidence of weak dependence in the Indonesian market. An examination of K-plots presented in Figure 4 and their comparison with corresponding plots for the pre-crisis period, interesting information about the changes in the dependence in these markets emerge: the Korean and Taiwan markets that were close to being independent of Thai market, had become notably dependent in the post-crisis period; and the dependence in the Indonesian market has significantly increased. There are only some marginal changes in the shapes of the K-plots for the Hong Kong, Malaysian and Singaporean markets, and it appears that only the tails of the joint distributions of these three markets have changed.

The results of both sets of Chi-plot and K-plot are consistent. At this stage, it is difficult to say what copula family would explain the nature of the dependence observed in these plots, which requires further investigation. The overall results suggest that the margins have significantly changed due to the crisis, and that the functional form of bivariate joint distributions of the Thai market and Indonesian, Korea and Taiwanese markets have changed. However, it appears that the joint distributions of Thai with other three markets - Singapore, Hong Kong and Malaysia have not changed, and, however, the tail indices of these three joint distributions appeared to have changed.

5 Conclusion

This paper uses the chi-plot proposed by Fisher and Switzer (1985, 2001) and the Kendall-plot proposed by Genest and Boies (2003) to investigate whether or not there are significant changes in the dependence between Thai equity market and six Asian markets due to financial market crisis in July 1997. If indeed there are significant changes in the dependence, then it may be an indication that the bivariate joint distributions of Thai market and these six markets have changed. This paper focuses on assessing the changes in the dependence in these six markets for the pre- and post-1997 financial crisis periods; this crisis was first experienced by Thai market.

The chi-plots and Kendall-plots collectively indicate the various nature of the dependence between the Thai equity market returns and Singapore, Malaysia, Hong Kong, Korean, Indonesian and Taiwan market returns. Much can be learned from the plots for the pre- and post-1997 crisis periods. Convincing evidence is found to say that the functional forms of underlying joint distributions generating the dependence in the Korean, Indonesian and Taiwan markets have changed in the post-crisis period. Further, although there are significant changes in the dependence between Thai market and Singapore, Malaysia and Hong Kong markets, it appears that these changes occurred only in the tails of the joint distributions. In other words, the copulas with breaks in the parameter values can capture the dependence in these three markets. It is interesting to note that similar conclusions can be reached using both chi- and K-plots, and these plots can provide guidance to choose an appropriate copula to model the bivariate joint distribution (thus the dependence), and to indicate if there are any notable change in the process generating the dependence.

The overall results of the investigation carried out in this paper suggest that the margins of all seven equity markets have significantly changed due the crisis, and that the functional forms of bivariate joint distributions of Thai market and Indonesian, Korea and Taiwanese markets have changed. On the other hand, it appears that the functional forms of the joint distributions of Thai and other three markets — Singapore, Hong Kong and Malaysia have not changed. However, the tail indices of these distributions appeared to have changed. At this stage the connection between the shapes of these plots and the copulas generating them is unclear, and is an interesting and important topic for the future research.

Acknowledgements

The authors wish to thank Clive Granger for contributing significantly to the ideas presented in the paper, and comments on the empirical results. The authors extend their sincere thanks to Christian Genest for providing S-Plus code to generate K-plots and for his helpful comments. The first author wishes to thank departments of Economics at Warwick and Manchester Universities and UCSD for providing her with excellent research environment, which facilitated completion of this paper.

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Table 1: Descriptive statistics for daily returns of 7 Asian countries: 1990-97

Statistics	Countries						
	Hong Kong	Indonesia	Korea	Malaysia	Singapore	Taiwan	Thailand
No of obs	1754	1737	1743	1728	1782	1723	1782
Mean	-0.0304	-0.0306	-0.0305	-0.0309	-0.0300	-0.0312	0.0273
Median	-0.0205	0.0145	-0.0092	0.0099	-0.0043	-0.0226	0.0077
Stdev	1.7813	1.7796	1.7622	1.8033	1.7298	1.7846	1.0642
Minimum	-9.2947	-9.2947	-9.2947	-12.1320	-9.2947	-9.2947	-7.5229
Maximum	16.8790	10.0803	8.6634	9.3600	8.6634	10.0066	5.2902
Range	26.1737	19.3750	17.9581	21.4920	17.9581	19.3013	12.8131
Q_1	-0.8730	-0.8473	-0.8774	-0.8556	-0.8597	-0.8774	-0.4963
Q_3	0.8486	0.8569	0.8464	0.8486	0.8448	0.8464	0.5553
$Q_3 - Q_1$	1.7217	1.7042	1.7237	1.7042	1.7044	1.7237	1.0516
Skewness	0.2137	-0.1800	-0.1947	-0.2261	-0.2122	-0.0622	-0.2341
Kurtosis	5.2873	1.7997	1.6627	2.5027	1.7375	1.8540	2.8999

Note: "Stdev" refers to the standard deviation. Q_1 and Q_3 represent the 1st quartile and the 3rd quartile, respectively. "Kurtosis" represent excessive kurtosis.

Table 2: Descriptive statistics for daily returns of 7 Asian countries: 1997-05

Statistics	Countries						
	Hong Kong	Indonesia	Korea	Malaysia	Singapore	Taiwan	Thailand
No of obs	1864	1846	1864	1856	1900	1858	1900
Mean	0.0146	0.0148	0.0147	0.0147	0.0144	0.0147	0.0077
Median	-0.0432	-0.0393	-0.0352	-0.0327	-0.0335	-0.0393	-0.0001
Stdev	2.0493	2.0117	1.9925	2.0278	2.0007	2.0499	1.5824
Minimum	-10.0280	-10.0280	-10.0280	-10.0280	-10.0280	-12.7741	-9.6719
Maximum	27.0909	24.4966	15.4087	27.5071	27.0909	27.6360	14.8685
Range	37.1189	34.5247	25.4367	37.5351	37.1189	40.4101	24.5404
Q_1	-1.0572	-1.0801	-1.0572	-1.0693	-1.0578	-1.0561	-0.7526
Q_3	0.9621	0.9658	0.9765	1.0052	0.9765	0.9757	0.7432
$Q_3 - Q_1$	2.0193	2.0459	2.0337	2.0744	2.0343	2.0318	1.4958
Skewness	1.7313	1.2988	0.6415	1.6249	1.5948	1.4398	0.4402
Kurtosis	16.8487	10.9867	1.9177	17.1262	16.7092	17.1880	5.6582

Figure 1: Chi Plots obtained through samples of 1990-1997. Graphs (1) to (6) are for HK, Indonesia, Korea, Malaysia, Singapore and Taiwan, respectively.

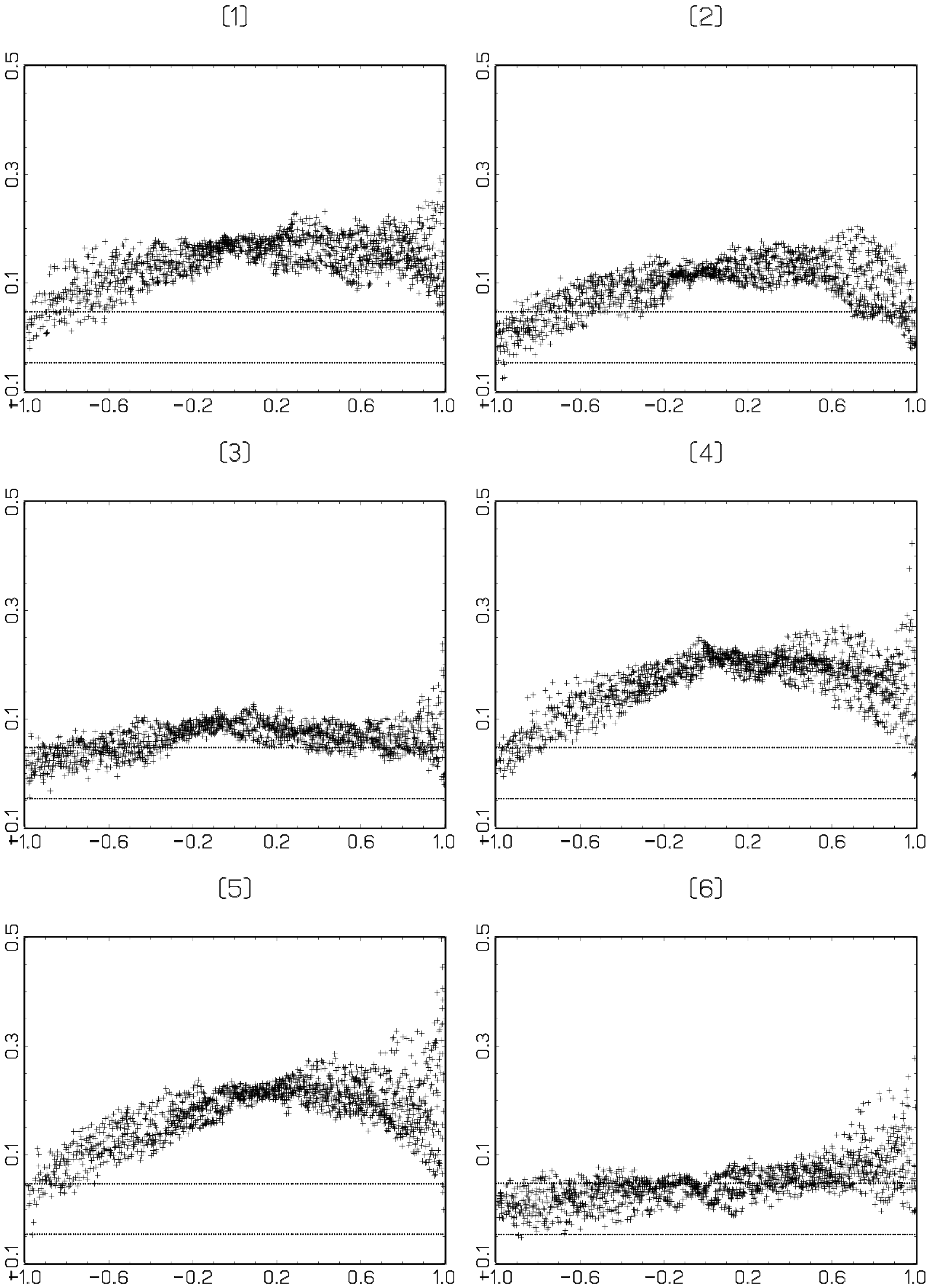

Figure 2: Chi Plots obtained through samples of 1997-2005. Graphs (1) to (6) are for HK, Indonesia, Korea, Malaysia, Singapore and Taiwan, respectively.

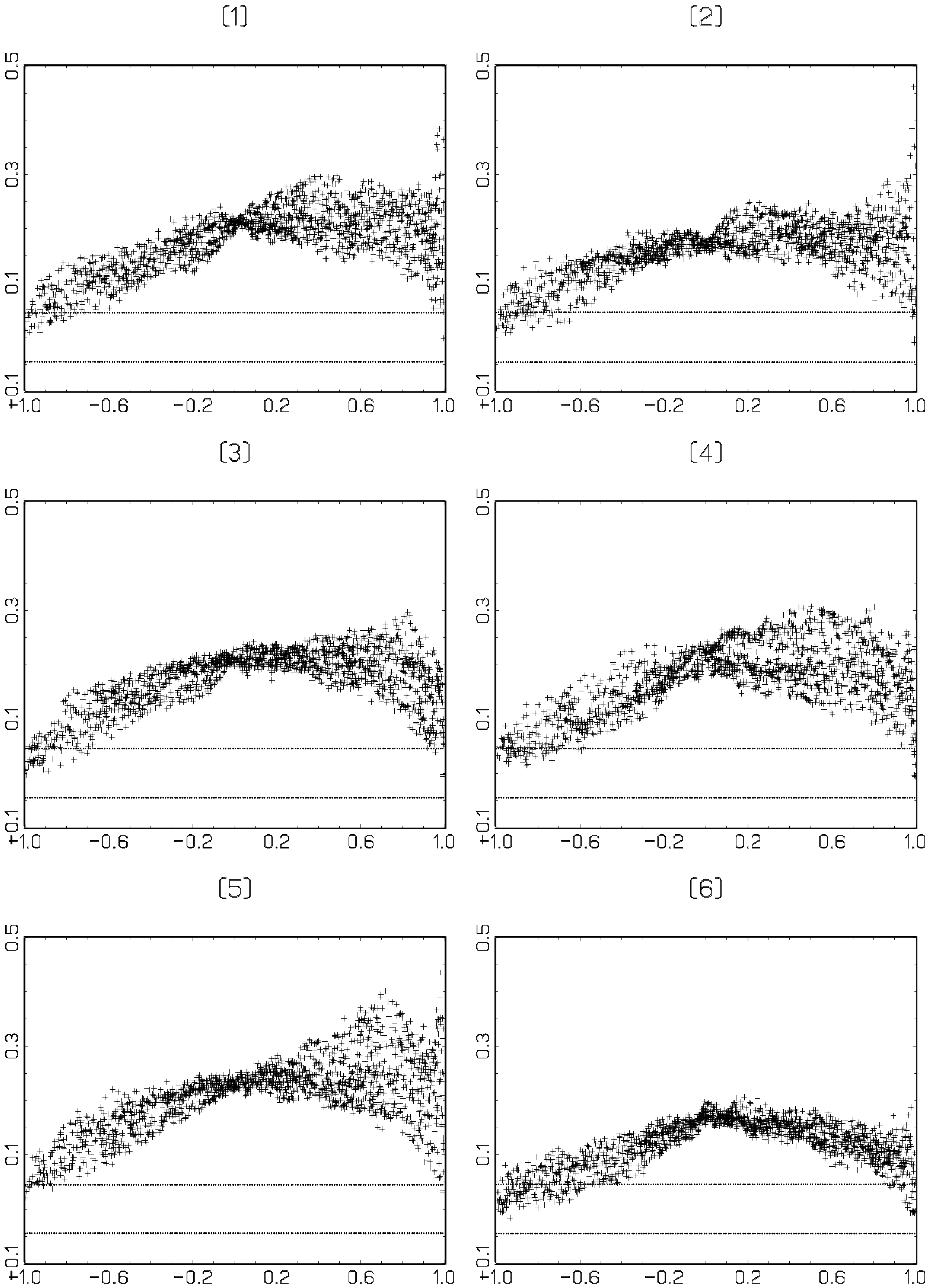

Figure 3: Kendall's Plots obtained through samples of 1990-1997. Graphs (1) to (6) are for HK, Indonesia, Korea, Malaysia, Singapore and Taiwan, respectively.

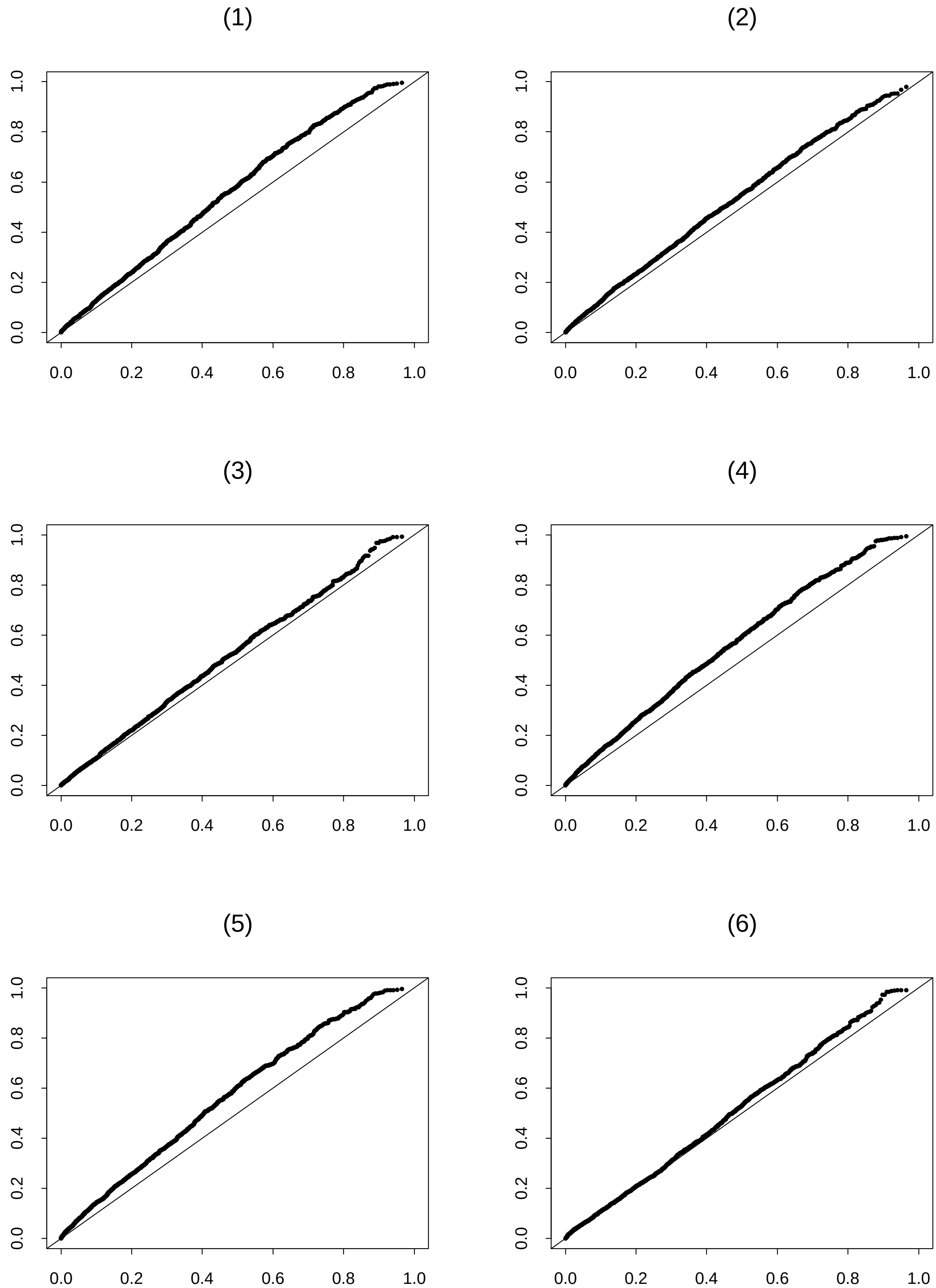

Figure 4: Kendall's Plots obtained through samples of 1997-2005. Graphs (1) to (6) are for HK, Indonesia, Korea, Malaysia, Singapore and Taiwan, respectively.