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The Extreme-Value Dependence Between the Chinese and Other International Stock Markets

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Abstract

Extreme value theory (EVT) measures the behavior of extreme observations on a random variable. EVT in risk management, an approach to modeling and measuring risks under rare events, has taken on a prominent role in recent years. This paper contributes to the literature in two respects by analyzing an interesting international financial data set. First, we apply conditional EVT to examine the Value at Risk (VAR) and the Expected Shortfall (ES) for the Chinese and several representative international stock market indices: Hang Seng (Hong Kong), TSEC (Taiwan), Nikkei 225 (Japan), Kospi (Korea), BSE (India), STI (Singapore), S&P 500 (US), SPTSE (Canada), IPC (Mexico), CAC 40 (France), DAX 30 (Germany), FTSE100 (UK) index. We find that China has the highest VaR and ES for negative daily stock returns. Second, we examine the extreme dependence between these stock markets, and we find that the Chinese market is asymptotically independent of the other stock markets considered.

Keywords: Extreme value analysis, peaks-over-threshold, value at risk, expected shortfall, asymptotic dependence, Chinese equity market

JEL Classifications: C13, C16, C58, G15

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I. Introduction

With its rapidly growing economy and increasingly globalized financial market, China has attracted significant attention, especially in the recent period of international financial turbulence. However, there has been surprisingly little research into the risk level of the Chinese stock market, especially the extreme dependence between the Chinese and other major financial markets. This paper uses a data set which covers the recent financial crisis to study the financial situation of the Chinese stock market in relation to that of thirteen other stock markets from three continents: Asia, North American, and Europe. We contribute to the associated literature in two ways: by applying conditional extreme value theory (EVT) to estimate and compare Value at Risk (VaR) and Expected Shortfall (ES) for the Chinese and other major financial markets; and by examining the extreme dependence between the Chinese market and these other markets, to obtain some guidance on possible crisis contagion.

VaR is widely used in measuring market risk, and was first proposed by J.P. Morgan in the late 1980's. VaR itself can tell us how much we can lose over a certain time horizon given a certain probability, and is effectively a chosen quantile of the profit and loss (P&L) distribution of a given portfolio over a prescribed holding period. VaR became a key risk measure when the Basel Committee required, in 1996, that the risk capital a bank holds should be enough to cover losses on their trading portfolio over a ten-day horizon, 99 percent of the time. For internal risk control, financial firms usually use a one-day horizon and 95 percent confidence level. Although VaR has the advantages of simplicity and wide applicability as a measure of loss, VaR doesn't give us any information about the tail of the distribution in excess of VaR. This means that it cannot distinguish between two distributions with the same VaR, but different tail thicknesses. Consequently, Artzner *et al.* (1999) proposed Expected Shortfall (ES) as a coherent measure of risk. ES measure the expected loss of the excess above VaR. Therefore, the two measures together provide a more complete picture of the tail of a distribution. Many methods can be applied to estimate VaR and ES. Extreme Value Theory (EVT) has been proved by many studies to perform well in modeling the tail behavior of a P&L distribution, for example, Gençay, *et al.* (2003). Two widely used estimation techniques in EVT focus on block maxima and on excesses (or "exceedances") over a high threshold. The latter method is called Peaks over Threshold (POT), and uses the data more efficiently than the block maxima method when individual data points are available, as is the case with high frequency financial data. However, one requirement in the application of POT is that the data should be independent, and most financial series exhibit extremal clustering. Therefore, here we will apply McNeil and Frey's (2000) suggestion of combining autoregressive (AR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) filters with the POT method in order to estimate conditional VaR and ES.

The second contribution of this paper is to study the extreme dependence between the Chinese stock market and other major stock markets. One natural approach is to estimate the extreme dependence by applying bivariate EVT to two data series, as did Bekiros *et al.* (2008) and Longin and Solnik (2001), for example. However, a problem arises when the two series are *asymptotically* independent. In this case, the bivariate EVT method tends to over-estimate any dependence, because the estimation of bivariate EVT is based on the prior assumption that the two series are asymptotically dependent. Therefore it is important to first check if the two series are asymptotically independent or not. When the extreme values of a pair of series move in sympathy with one another, we term these series asymptotically dependent. Otherwise, they are asymptotically independent. However, asymptotic independence is not equivalent to pure statistical independence, as it allows a certain level of dependence between the two series for finite samples. We will apply two nonparametric measures, χ and $\bar{\chi}$ (Poon *et al.*, 2003, 2004) to describe the levels of asymptotic dependence and asymptotic independence respectively. Again, one requirement when applying these two measures is that the data should be *sampled* independently. We use a vector autoregressive model to filter for any serial correlation, and there Multivariate Garch models (Baba *et al.*, 1990; Engle and Kroner, 1995) to filter for any heteroskedasticity, then we calculate χ and $\bar{\chi}$ for the innovations to study the extreme dependence level of two series. The related empirical literature strongly suggests that any extreme dependence level is asymmetric in the two tails of the distribution. Generally, there is a greater tendency for extreme dependence in the left tail than in the right tail. So, we examine the degree of dependence for positive returns and negative returns separately for the various markets that we study.

The rest of the paper is organized as follows. Section II introduces the methodology that we adopt. Section III describes our data, and section IV presents and discusses the empirical results. The final section summarizes our main findings and conclusions.

II. Methodology

Peaks over threshold method

The Peaks over Threshold (POT) technique is an efficient method to model the behavior of extreme values above a high threshold in a distribution of data. Let $x_1, x_2, \ldots, x_n$ be a sequence of independent and identically distributed random variables with the marginal distribution F. Given the threshold u, we define the i^{th} excess (or "exceedence") as $y_i = (x_i - u)$. Then, dropping subscripts for convenience,

$$F_u(y) = \Pr(x - u \le y \mid x > u) = \frac{F(u+y) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)},\ \ y \ge 0 \quad . \qquad (1)$$

According to the asymptotics of EVT, for u large enough, $F_u(y)$ converges to the generalized Pareto distribution (GPD), whose distribution function is,

$$F_u(y) \approx G(y) = \begin{cases} 1 - \left(1 + \xi \dfrac{y}{\sigma}\right)^{-1/\xi} & \text{if } \xi \ne 0 \\ 1 - \mathrm{e}^{-y/\sigma} & \text{if } \xi = 0 \end{cases} \qquad (2)$$

defined on $\{y : y > 0 \text{ and } (1 + \xi y/\sigma) > 0\}$, where ξ is the shape parameter or tail index, and σ (> 0) is the scale parameter.

From Equation 1,

$$F(x) = \left(1 - F(u)\right) F_u(y) + F(u) \quad . \qquad (3)$$

Substituting Equation 2 into Equation 3 and simplifying, we can obtain

$$F(x) = \begin{cases} 1 - \varsigma_u \left[1 + \xi\left(\dfrac{x-u}{\sigma}\right)\right]^{-1/\xi} & \text{if } \xi \ne 0 \\ 1 - \varsigma_u \exp\left[-\dfrac{x-u}{\sigma}\right] & \text{if } \xi = 0 \end{cases} \quad . \qquad (4)$$

If $\xi < 0$, $u < x < u - \sigma/\xi$; if $\xi \ge 0$, $x \ge u$. $\varsigma_u = \Pr\{X > u\}$, which can be estimated by the sample proportion of the excesses over u; *i.e.*, (k/n).

The tail index ξ indicates the heaviness of the tail of the distribution. The larger the value of ξ, the heavier the tail is. In general, financial data have a distribution with a heavy tail, which corresponds to a positive tail index, and the summary statistics in section III support this expectation. So in the following analysis, we focus only on the case of $\xi > 0$.

The maximum likelihood estimator is generally favored to estimate the parameters of the GPD distribution. However, often the quantities in which we are interested are not the parameters themselves, but functions of the parameter, such as VaR and ES. Based on the GPD approximation of the distribution function $F(x)$, Equation 4, we can obtain (*via* "invariance") the maximum likelihood estimates of these two measures as:

$$V\hat{a}R_q = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[\left(\frac{n}{k(1-q)}\right)^{-\hat{\xi}} - 1\right] \quad , \tag{5}$$

and,

$$\hat{ES}_q = V\hat{a}R_q + E\left[x - V\hat{a}R_q \middle| x > V\hat{a}R_q\right] \quad . \tag{6}$$

The second term in Equation 6 can be obtained from the mean excess function of the GPD (when $\xi <$ 1 ; a condition that ensures the existence of the mean of the distribution), which is

$$E\left[x-u \middle| x>u\right] = \frac{\sigma}{1-\xi} \quad .$$

One well known property of the GPD is that for any valid threshold, the tail index ξ and the transformed scale parameter σ^* are invariant to changes in the threshold, where σ^* is defined as

$$\sigma^* = \sigma - \xi u \quad .$$

Hence, if we change the threshold to another valid level z, the scale parameter σ_z has the following relationship with σ:

$$\sigma_z = \sigma + \xi(z-u)$$

and

$$E\left[x-z \middle| x>z\right] = \frac{\sigma + \xi(z-u)}{1-\xi} \quad . \tag{7}$$

Therefore, we can estimate ES as

$$\hat{ES}_q = \hat{VaR}_q + \frac{\hat{\sigma} + \hat{\xi}\left(\hat{VaR}_q - u\right)}{1-\hat{\xi}} = \frac{\hat{VaR}_q}{1-\hat{\xi}} + \frac{\hat{\sigma} - \hat{\xi}u}{1-\hat{\xi}} \quad . \tag{8}$$

One remaining issue is the choice of the threshold value. Several methods can be used, the most common of which is based on plots of ξ and σ^* against the threshold *u*; and on the mean residual life plot, which plots the mean of the excesses against *u*. Considering the sampling errors, the rescaled parameters σ^* and ξ should be statistically stable, and the mean residual life should be approximately linear for all the thresholds over *u*, if *u* is a valid threshold. However, the interpretation of these plots is difficult in practice, so the choice of the threshold is somewhat subjective. In this paper, we apply the exponential regression approach proposed by Beirlant *et al*. (2000) to choose the threshold. Further details are provided by Fernandez (2003).

Application of the POT method requires independent observations on the data. The data we examine are the daily observations of the log return on a financial asset price. As noted already, financial data often exhibit dependence and extreme clustering, so we use McNeil and Frey's (2000) two-step estimation procedure based on an AR-GARCH model to filter out any serial correlation and conditional heteroskedasticity before we apply the POT methodology to estimate VaR and ES. Specifically, let r_t represent the absolute value of the log return, and assume that

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \cdots + \alpha_p r_{t-p} + \sigma_t Z_t \quad , \tag{9}$$

where $Z_t \sim i.i.d.(0,1)$, and the conditional variance σ_t^2 follows a GARCH(1,1) process:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \tag{10}$$

where $\beta_0 > 0$, $\beta_1 > 0$ and $\gamma > 0$. The condition for the strict stationarity of (9) is $\beta_1 + \gamma < 1$.

We apply a pseudo-maximum-likelihood method to estimate the model, and then generate the standardized residuals as

$$\left(z_1, z_2, \cdots, z_n\right) = \left(\frac{\hat{\varepsilon}_1}{\hat{\sigma}_1}, \frac{\hat{\varepsilon}_2}{\hat{\sigma}_2}, \cdots, \frac{\hat{\varepsilon}_n}{\hat{\sigma}_n}\right) \quad , \tag{11}$$

and $\hat{\varepsilon}_t = r_t - \hat{\alpha}_0 - \hat{\alpha}_1 r_{t-1} - \cdots - \hat{\alpha}_p r_{t-p}$.

We use the Ljung-Box test to examine the independence of the residuals. After choosing an appropriate lag number based on Akaike's information criterion (AIC) for the AR model, the Ljung-Box test does not reject the null hypothesis of independence for any of the series' standardized residuals. Then we apply the POT method to the standardized residuals in Equation 11, and recover the VaR and ES of the raw data for a one-day horizon as follows:

$$\hat{\text{VaR}}_q = \hat{\alpha}_0 + \hat{\alpha}_1 r_{t-1} + \cdots + \hat{\alpha}_p r_{t-p} + \hat{\sigma}_{t+1}\, \hat{\text{VaR}}(Z)_q \quad (12)$$

and

$$\hat{\text{ES}}_q = \hat{\alpha}_0 + \hat{\alpha}_1 r_{t-1} + \cdots + \hat{\alpha}_p r_{t-p} + \hat{\sigma}_{t+1}\, \hat{ES}(Z)_q \quad (13)$$

where $\hat{\sigma}_{t+1}^2 = \hat{\beta}_0 + \hat{\beta}_1 \hat{\varepsilon}_t^2 + \hat{\gamma}\hat{\sigma}_t^2$, and $V\hat{a}R(Z)_q$ and $\hat{ES}$ are given by Equations 5 and 8.

Dependence estimation

As discussed above, the bivariate extreme value distribution tends to overestimate the extreme dependence between pairs of series. So, we apply two non-parametric measures to examine the extreme dependence between pairs of stock returns series. Suppose that the variables *S* and *T* are on a common scale. The events $\{S > s\}$ and $\{T > s\}$, as $s \to \infty$, correspond to equally extreme events for each variable. The first nonparametric measure of dependence, χ, is defined as

$$\chi = \lim_{s\to\infty} \Pr(T > s \mid S > s)\,, \qquad 0 \le \chi \le 1 \quad . \quad (14)$$

When $\chi > 0$, *S* and *T* are said to be asymptotically dependent, and perfectly asymptotically dependent if $\chi = 1$. When $\chi = 0$, *S* and *T* are asymptotically independent. Recall, however, that two series may show some degree of dependence for finite levels of *S*, even though they are asymptotically independent. There may be significant dependence between values of the paired series, but no co-movement in their very large values.

Coles *et al*. (1999) define a complementary measure, $\overline{\chi}$, that can be used to measure the degree of (finite) dependence when the variables are asymptotically independent, that is when $\chi = 0$. $\bar{\chi}$ is defined as

$$\bar{\chi} = \lim_{s\to\infty} \frac{2\log\left(\Pr\left(S > s\right)\right)}{\log\left(\Pr\left(T > s, S > s\right)\right)} - 1, \qquad -1 < \bar{\chi} \leq 1 \tag{15}$$

and it measures the rate at which $\Pr\left(T > s \middle| S > s\right) \to 0$. Values of $\bar{\chi} > 0$, $\bar{\chi} = 0$ and $\bar{\chi} < 0$ correspond to positive dependence, exact independence and negative dependence respectively.

The pair (χ, $\bar{\chi}$) provides all of the necessary information regarding the degree of dependence for any two series. For asymptotically dependent variables, $\bar{\chi} = 1$, and the degree of dependence is measured by χ. For asymptotically independent variables, $\chi = 0$, and the degree of dependence is measured by $\bar{\chi}$. Therefore, it is important to test if $\bar{\chi} = 1$, before we draw any conclusions based on χ. Estimates of χ and $\bar{\chi}$ can be obtained by the Hill estimator, which we now discuss.

The tail of a Fréchet-type univariate variable Z above threshold u can be modeled by

$$\Pr(Z > z) \sim L(z) z^{-1/\xi} \quad \text{for } z > u \quad , \tag{16}$$

where $L(z)$ is a slowly varying function of z. If we treat $L(z)$ as constant c and assume that the data are independent, then the MLEs of ξ (known as the Hill estimator) and c are

$$\hat{\xi} = \frac{1}{n_u} \sum_{j=1}^{n_u} \log\left(\frac{z_{(j)}}{u}\right), \tag{17}$$

$$\hat{c} = \frac{n_u}{n} u^{1/\hat{\xi}}, \tag{18}$$

where $z_{(1)}$;$\cdots$, $z_{(n_u)}$ are the n_u observations of Z above the threshold u. The asymptotic variances of $\hat{\xi}$ and $\hat{c}$ are $\frac{\xi^2}{n_u}$ and $\frac{n_u}{n^2} \frac{u^{2/\xi} \log^2(u)}{\xi^2}$, respectively.

Now we show how the calculation of χ and $\bar{\chi}$ can be used to complement the previous estimation process. First we transform the bivariate returns (X, Y), with marginal cumulative distribution functions F_X and F_Y respectively, into unit Fréchet marginals (S, T) as follows:

$$S = -\frac{1}{\log F_X(X)} \text{ and } T = -\frac{1}{\log F_Y(Y)}, \quad S > 0, T > 0 \; . \tag{19}$$

The variables (*S* , *T*) have the same dependence structure as the variables (*X*, *Y*).

Ledford and Tawn (1996, 1998) showed that under weak conditions

$$\Pr\left(S > s, T > s\right) \sim L(s) s^{-1/\eta} \quad ; \quad \text{as } s \to \infty \qquad , \tag{20}$$

where $0 < \eta \le 1$ is a constant and $L(s)$ is a slowly varying function. After transformation, *S* and *T* then have unit Fréchet marginals, and it follows that

$$\Pr\left(S > s\right) = \Pr\left(T > s\right) \sim s^{-1} \quad ; \text{ as } s \to \infty \qquad . \tag{21}$$

Based on these results and Equation 15, we have

$$\hat{\bar{\chi}} = 2\eta - 1 \; .$$

Let $Z = \min(S, T)$, then

$$\Pr\left(Z > z\right) = \Pr\left\{\min(S,T) > z\right\} = \Pr\left(S > z, T > z\right) = L(z) z^{-1/\eta} \text{ for } z > u. \tag{22}$$

So, we can use the Hill estimator to estimate $\bar{\chi}$ and its variance:

$$\hat{\bar{\chi}} = \frac{2}{n_u} \sum_{j=1}^{n_u} \log\left(\frac{z_{(j)}}{u}\right) - 1 \tag{23}$$

and $$\operatorname{var}(\hat{\bar{\chi}}) = \frac{(\hat{\bar{\chi}} + 1)^2}{n_u} .$$

When two variables are asymptotically dependent, $\hat{\bar{\chi}} = 1$, *i.e.*, $\eta = 1$, then

$$\Pr\left(S > s, T > s\right) \sim L(s) s^{-1} \quad ; \quad \text{as } s \to \infty$$

$$\chi = \underset{s \to \infty}{Lim} \Pr\left(T > s \middle| S > s\right) = \underset{s \to \infty}{Lim} \frac{\Pr\left(S > s, T > s\right)}{\Pr\left(S > s\right)} = L(s) = c \quad .$$

Therefore,

$$\hat{\chi} = \frac{n_u}{n} u \tag{24}$$

and $$\operatorname{var}(\hat{\chi}) = \frac{u n_u (n - n_u)}{n^3} .$$

In any empirical application, first we need to test if $\overline{\chi}$ is significantly less than 1; that is, if $\hat{\overline{\chi}} + 1.645\sqrt{\mathrm{var}(\hat{\overline{\chi}})} < 1$, for a 5% significance level, say. For the model in Equation 16, the choice of the optimal threshold is also achieved by using the exponential regression approach.

In order to obtain independent data, we use a vector autoregressive (VAR) model for the mean, and a multivariate GARCH (MGARCH) model for the innovation, to filter out any serial correlation and conditional heteroskedasticity before we examine the dependence between any two variables. To estimate the dependence level we proceed as follows:

(i) Apply VAR and MGARCH models to the raw data set (*X*, *Y*), and obtain the standardized residuals, $\hat{v} = (\hat{v}_X, \hat{v}_Y)$.

(ii) Estimate the empirical distribution of $\hat{v}_X$ and $\hat{v}_Y$: $F_{v_X}(v_X)$ and $F_{v_Y}(v_Y)$.

(iii) Transform the variables into Fréchet-distributed variates, $S = -1/\log F_{v_X}(v_X)$, and $T = -1/\log F_{v_Y}(v_Y)$.

(iv) Apply (χ, $\overline{\chi}$) to (*S*, *T*) to check for extreme dependence.

III. Empirical Results

Data

Our data are the logarithmic daily returns for the following equity indices: SSE (China), Hang Seng (Hong Kong), TSEC (Taiwan), Nikkei 225 (Japan), Kospi (Korea), SENSEX30 (India), STI (Singapore), S&P500 (US), GSPTSE (Canada), IPC (Mexico), CAC40 (France), DAX (Germany) and FTSE100 (UK). These indices are the most representative ones for the Asian, European and North American continents, which in turn include China's major trading regions and countries. Our data cover the period 4 January 2000 to 16 April 2010. For the univariate analysis, we delete all of the zero returns. For the extremal dependence analysis, we retain the data when pairs of indices are both non-zero.

Table 1 shows the descriptive statistics for our data. These are similar across markets, and in each case the mean return is essentially zero, as expected. Of the various markets, that for Korea is the most volatile. All of the returns' distributions are negatively skewed except for Mexico, France and Germany, and all have kurtosis measures that are much greater than three. The excess kurtosis could be caused by clustering of extremes or by clusters of volatility. Not surprisingly, the Jarque-Bera test indicates that none of the returns series are normally distributed. The Ljung-Box Q-statistic is applied to test for the serial independence of each index up to order of sixteen lags. We strongly reject this hypothesis for all cases except for Korea. Therefore, we apply AR-GARCH for the univariate series, and VAR-MGARCH for the pairs of indices to filter the series to further analysis.

Table 1. Summary statistics for all stock markets' daily returns

	Min.	Max.	Mean	Stdev.	Skewness	Kurtosis	JB	LB
Asia								
China	-0.0926	0.0940	0.0003	0.0173	-0.0877	6.8997	0.0000	0.0109
Hong Kong	-0.1358	0.1341	0.0001	0.0170	-0.0407	10.4946	0.0000	0.0411
Taiwan	-0.0994	0.0652	0.0000	0.0164	-0.2115	5.2495	0.0000	0.0033
Korea	-0.1280	0.1128	0.0002	0.0186	-0.5174	7.5604	0.0000	0.1630
Japan	-0.1211	0.1323	-0.0002	0.0163	-0.2993	9.2488	0.0000	0.0076
India	-0.1181	0.1599	0.0005	0.0177	-0.1992	8.8110	0.0000	0.0001
Singapore	-0.0922	0.0753	0.0001	0.0134	-0.4080	8.4561	0.0000	0.0080
North America								
US	-0.0947	0.1096	-0.0001	0.0139	-0.1149	10.7135	0.0000	0.0000
Canada	-0.0979	0.0937	0.0001	0.0131	-0.6955	11.4431	0.0000	0.0003
Mexico	-0.0827	0.1044	0.0006	0.0153	0.0568	6.9575	0.0000	0.0000
Europe								
France	-0.0947	0.1059	-0.0001	0.0157	0.0189	7.9518	0.0000	0.0000
Germany	-0.0743	0.1080	0.0000	0.0166	0.0664	7.1371	0.0000	0.0033
UK	-0.0926	0.0938	-0.0001	0.0133	-0.1128	9.1614	0.0000	0.0000

Notes: JB is the Jarque-Bera statistic for testing the hypothesis of normality. LB is the Ljung-Box Q-statistic for the independence hypothesis up to a lag-order of 16 (days).

Univariate Analysis

Next, we apply the conditional POT method introduced in section II to estimate VaR and ES for the logarithmic returns of each index. Applying the Ljung-Box Q-statistics, the filtered residuals from the AR process are i.i.d., at least at the 20% significance level. Given the asymmetry of the data, we examine the risk levels separately for positive and negative returns, for each stock index.

Based on the estimates of VaR and ES, at the 5% and 1% levels, we can compare the risk levels among the various indices. Table 2 shows that VaR and ES of the stock indices in Asian countries are generally higher than in Canada, the US, Germany and the UK, for both tails of the returns distributions. Except for Singapore, France and Hong Kong, the VaRs for positive returns are all smaller than for negative returns. Similar results hold for ES except for India, France, Germany and Hong Kong. For negative returns, the VaR and ES of the Chinese stock index are higher than those of all other indices we considered. In the case of positive returns, the risk for the Chinese market is also higher than most of the other markets, exceptions being Hong Kong and India. This may reflect the relative immaturity of the Chinese stock market. On the other hand, the UK market exhibits the smallest VaR and ES. This suggests that more developed markets may be more stable than developing or undeveloped markets. These results are robust to the choice of threshold.

We also calculate the risk measures over two non-overlapping sub-periods: January 2000 to December 2005; and January 2006 to mid-April 2010, with the recent global financial turmoil occurring in the second sub-period. More specifically, the Chinese stock market experienced a dramatic boom during 2006 and the first part of 2007, with the SSE peaking at around 6,000 points. This was then followed by a "meltdown" in the second half of 2007, with the SSE losing approximately 75% of its peak value, with a subsequent slow recovery, so that the SSE stood at about 3,000 points by the end of our overall sample. From Table 3, we see that except China, the US, Mexico, Taiwan and France, the VaRs of the stock indices are higher for negative returns than for positive returns before the financial turmoil, at least at the 1% significance level. In the second sub-period, most countries or regions had similar experiences, except Hong Kong, Singapore, Mexico and France. The behavior of the Chinese, Hong Kong, Taiwan, US and UK markets changed significantly across these two sub-periods. The experiences of the stock markets in Singapore, Mexico and France were quite different from those in other countries in both periods, which had a larger risk level for the positive returns than negative returns. As expected, most of the countries and regions in this study saw the risk in their stock markets increasing during the period of financial turmoil, with respect to both negative and positive returns. However, (positive and negative) VaR in the Korean and Japanese stock markets fell during the period of turbulence. China and Taiwan are two interesting cases here: their VaR increased during the period of financial turmoil only with respect to negative returns. For positive daily returns, the risk actually decreased.

Table 2. VaR and ES estimates for the market returns (full sample period)

	Negative Tail						Positive Tail				
	VaR			ES			VaR			ES	
	5%	1%		5%	1%		5%	1%		5%	1%
Asia											
China	0.0326 (0.001)	0.0449 (0.002)		0.0403 (0.002)	0.0532 (0.004)		0.0278 (0.001)	0.0427 (0.003)		0.0377 (0.003)	0.0572 (0.001)
Hong Kong	0.0254 (0.001)	0.038 (0.003)		0.0338 (0.003)	0.0498 (0.006)		0.0314 (0.001)	0.0430 (0.002)		0.0390 (0.002)	0.0528 (0.005)
Taiwan	0.0319 (0.001)	0.0438 (0.002)		0.0396 (0.002)	0.054 (0.005)		0.0243 (0.001)	0.0329 (0.001)		0.0297 (0.001)	0.0387 (0.003)
Japan	0.0272 (0.001)	0.0386 (0.002)		0.0346 (0.002)	0.0483 (0.005)		0.0225 (0.001)	0.0314 (0.002)		0.0284 (0.002)	0.0394 (0.004)
Korea	0.0281 (0.001)	0.0428 (0.003)		0.0381 (0.004)	0.0582 (0.009)		0.0235 (0.001)	0.0339 (0.002)		0.0300 (0.002)	0.0410 (0.003)
India	0.0290 (0.001)	0.0384 (0.001)		0.0347 (0.001)	0.0429 (0.002)		0.0282 (0.001)	0.0406 (0.002)		0.0362 (0.002)	0.0512 (0.005)
Singapore	0.0224 (0.001)	0.0326 (0.002)		0.0293 (0.002)	0.0426 (0.005)		0.0232 (0.001)	0.0317 (0.001)		0.0285 (0.001)	0.0367 (0.002)
North America											
US	0.0203 (0.001)	0.0278 (0.001)		0.0251 (0.001)	0.0335 (0.003)		0.0196 (0.001)	0.0255 (0.001)		0.0232 (0.001)	0.0276 (0.001)
Canada	0.0196 (0.001)	0.0297 (0.002)		0.0264 (0.002)	0.0396 (0.005)		0.0173 (0.001)	0.0249 (0.001)		0.0221 (0.001)	0.0302 (0.002)
Mexico	0.0263 (0.001)	0.0372 (0.002)		0.0330 (0.002)	0.0433 (0.003)		0.0236 (0.001)	0.0334 (0.001)		0.0297 (0.001)	0.0393 (0.003)
Europe											
France	0.0226 (0.001)	0.0324 (0.002)		0.0290 (0.002)	0.0408 (0.004)		0.0270 (0.001)	0.0367 (0.002)		0.0331 (0.001)	0.0433 (0.003)
Germany	0.0220 (0.001)	0.0305 (0.002)		0.0274 (0.001)	0.0373 (0.003)		0.0217 (0.001)	0.0308 (0.002)		0.0277 (0.002)	0.0390 (0.004)
UK	0.0196 (0.001)	0.0254 (0.001)		0.0231 (0.001)	0.0274 (0.001)		0.0161 (0.000)	0.0211 (0.001)		0.0192 (0.001)	0.024 (0.001)

Note: Asymptotic standard errors appear in parentheses.

Table 3. VaR estimates for the market returns

	Period 1: 05/01/2000 – 30/12/2005				Period 2: 04/01/2006 – 16/04/2010			
	Negative Tail		Positive Tail		Negative Tail		Positive Tail	
	5%	1%	5%	1%	5%	1%	5%	1%
Asia								
China	0.0267	0.0383	0.0312	0.0425	0.0417	0.0528	0.0302	0.0468
	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.007)
Hong Kong	0.0242	0.0361	0.0185	0.0239	0.0269	0.0355	0.0359	0.0491
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.004)
Taiwan	0.0233	0.0346	0.0280	0.0374	0.0318	0.0388	0.0175	0.0223
	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Japan	0.0319	0.0453	0.0283	0.0357	0.0278	0.0365	0.0223	0.0344
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.005)
Korea	0.0322	0.0489	0.0282	0.0371	0.0259	0.0343	0.0218	0.0313
	(0.002)	(0.006)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)
India	0.0333	0.0464	0.0269	0.0399	0.0317	0.0427	0.0296	0.0394
	(0.002)	(0.004)	(0.001)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)
Singapore	0.0171	0.0252	0.0180	0.0252	0.0249	0.0362	0.0302	0.0395
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
North America								
US	0.0154	0.0209	0.0157	0.0206	0.0210	0.0281	0.0195	0.0259
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Canada	0.0197	0.0318	0.0153	0.0205	0.0206	0.0261	0.0175	0.0279
	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)
Mexico	0.0244	0.0340	0.0256	0.0324	0.0276	0.0377	0.0285	0.0418
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)
Europe								
France	0.0176	0.0256	0.0197	0.0260	0.0231	0.0333	0.0247	0.0305
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)
Germany	0.0200	0.0252	0.0163	0.0222	0.0241	0.0365	0.0230	0.0330
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.005)	(0.001)	(0.003)
UK	0.0140	0.0190	0.0142	0.0188	0.0203	0.0298	0.0152	0.0188
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)

Note: Asymptotic standard errors appear in parentheses.

Table 4. ES estimates for the market returns

	Period 1: 05/01/2000 – 30/12/2005				Period 2: 04/01/2006 – 16/04/2010			
	Negative Tail		Positive Tail		Negative Tail		Positive Tail	
	5%	1%	5%	1%	5%	1%	5%	1%
Asia								
China	0.0342 (0.003)	0.0481 (0.009)	0.0380 (0.002)	0.0478 (0.004)	0.0485 (0.003)	0.0584 (0.006)	0.0415 (0.006)	0.0645 (0.018)
Hong Kong	0.0322 (0.003)	0.0477 (0.010)	0.0219 (0.001)	0.0275 (0.003)	0.0322 (0.002)	0.0402 (0.004)	0.0441 (0.003)	0.0577 (0.007)
Taiwan	0.0308 (0.003)	0.0454 (0.009)	0.0338 (0.002)	0.0433 (0.005)	0.0361 (0.002)	0.0422 (0.003)	0.0205 (0.001)	0.0250 (0.002)
Japan	0.0406 (0.003)	0.0566 (0.009)	0.0330 (0.002)	0.0413 (0.004)	0.0332 (0.002)	0.0417 (0.005)	0.0304 (0.004)	0.0463 (0.012)
Korea	0.0433 (0.005)	0.0652 (0.014)	0.0337 (0.002)	0.0422 (0.004)	0.0310 (0.002)	0.0391 (0.005)	0.0278 (0.003)	0.0384 (0.007)
India	0.0414 (0.003)	0.0542 (0.006)	0.0355 (0.003)	0.0523 (0.010)	0.0385 (0.003)	0.0489 (0.006)	0.0358 (0.002)	0.0465 (0.006)
Singapore	0.0224 (0.002)	0.0326 (0.006)	0.0225 (0.002)	0.0299 (0.004)	0.0323 (0.004)	0.0465 (0.010)	0.0358 (0.002)	0.0465 (0.006)
North America								
US	0.0188 (0.001)	0.0245 (0.003)	0.0187 (0.001)	0.0231 (0.001)	0.0255 (0.002)	0.0329 (0.004)	0.0234 (0.001)	0.0296 (0.004)
Canada	0.0281 (0.004)	0.0459 (0.012)	0.0185 (0.001)	0.0233 (0.002)	0.0239 (0.001)	0.0289 (0.004)	0.0246 (0.004)	0.0395 (0.012)
Mexico	0.0304 (0.002)	0.0398 (0.004)	0.0297 (0.001)	0.0347 (0.002)	0.0339 (0.003)	0.0439 (0.006)	0.0372 (0.004)	0.0536 (0.012)
Europe								
France	0.0227 (0.002)	0.0318 (0.005)	0.0235 (0.001)	0.0289 (0.002)	0.0298 (0.003)	0.0421 (0.009)	0.0283 (0.002)	0.0344 (0.004)
Germany	0.0232 (0.001)	0.0283 (0.003)	0.0200 (0.001)	0.0264 (0.003)	0.0323 (0.004)	0.0478 (0.011)	0.0295 (0.003)	0.0412 (0.007)
UK	0.0175 (0.001)	0.0224 (0.003)	0.0171 (0.001)	0.0216 (0.003)	0.0264 (0.003)	0.0371 (0.010)	0.0174 (0.001)	0.0205 (0.002)

Note: Asymptotic standard errors appear in parentheses.

The results for expected shortfall in Table 4 are similar to those in Table 3. When we compare ES before and during the financial turmoil in different countries, we find that the majority of countries experienced higher ES for positive returns during the financial turmoil. Japan and Korea again experienced decreasing ES in both tails of the returns distribution after the onset of the financial turmoil. However, China, Hong Kong, Singapore, the US and Mexico saw their ES in the stock market rise in both tails. Overall, although there is no strong indication that the risk associated with negative returns is consistently higher than that for positive returns, we see that risk levels for negative returns increased (as expected) in our second sub-period for most countries and regions.

Dependence Analysis

Next, we examine the tail dependence of pairs of stock indices – in particular, pairs involving China and each of the other countries under consideration. Tables 5 and 6 report the tail dependence estimates $\bar{\chi}$ and their standard errors over different periods. In all of the cases, the estimates of $\bar{\chi}$ and their standard errors indicate that the pairs of stock index returns are asymptotically independent, so χ is not reported in any case. These tables report the dependence results for the unfiltered stock returns, and the filtered stock returns derived from three types of MGARCH models: constant conditional correlation (CCC) MGARCH, dynamic conditional correlation (DCC) MGARCH, and the Glosten *et al*. (1993) (GJR) MGARCH model, which includes the dynamic and asymmetric cases. We also checked the independence of the filtered residuals based on the Ljung-Box Q-statistics, and found that the dependence condition can be satisfied for all of the indices at the 20% significance level.

Table 5 reports the tail dependence between the Chinese and other stock markets for positive and negative returns over the whole period, with filtered and unfiltered data sets. In all cases, the tail dependence is positive and the Chinese market is asymptotically independent of all of the other stock markets under consideration. So, although there is significant dependence between the Chinese and other stock markets, this dependence doesn't apply for extremely large returns values. Given the size of the US stock market, and the fact that it is the last one to close each trading day, it is reasonable to assume that this market has a major influence on other markets (*e.g*., the Chinese market) the next trading day. So, we examine the extremal dependence between the Chinese stock index and another form of the US stock index – an "adjusted index" obtained by moving the closing price back by one day. We then find that the extremal dependence between the Chinese and US stock markets is less using the original index than with the adjusted index, implying that the US stock market in the previous day has a larger effect on the Chinese stock market than in the same calendar day for unfiltered data. For MGJR and DCC filtered residuals, the dependence level increases for the adjusted index in the left tail, but decreases n the right tail. For CCC filtered residuals, this pattern is reversed. The larger US effect from the previous day significantly decreases once we filter for serial correlation and conditional heteroskedasticity.

Comparing the unfiltered results with the filtered ones, we find that except for a few cases, the extremal dependence of the Chinese stock market with those of the other countries and regions decreases for the filtered cases, and the results are generally consistent among the different MGARCH models (using different filters). Comparing the dependence level between the left and right tails, there is no strong reason to believe that joint crashes between China and other stock markets are more likely to happen than are simultaneous booms. This finding is not consistent with others in the literature, such as Poon *et al*. (2003), Martens and Poon (2001) and Longin and Solnik (2000), who found the dependence level in the left tail tends to be larger than in the right tail for most other countries.

Again, a possible explanation lies in the immaturity of the stock market, and the limitation of the investment channels, in China. Basically in China, there are only two ways for private individuals to invest their money: stocks and real estate. The amount required to invest in real estate is relatively large, making it inaccessible for most people. So when people have excess cash, they generally deposit it in savings accounts or buy stocks. However, any Chinese stockholders have limited knowledge of the stocks in which they invest, so they can be quite irrational. In particular, they tend to exaggerate positive information. Therefore, in the Chinese market, we may not be able to observe the anticipated risk asymmetry between positive and negative returns. Further, comparing the various results based on the filtered data, we find that when markets decline, the Canadian stock market seems to have a larger influence on the Chinese stock market than do the markets for the other countries and regions (especially France). When markets are booming, the Chinese stock market seems to move closely with the Hong Kong, Japanese, German and Mexican markets, and less closely with the markets in Taiwan, Singapore and Korea.

One possible explanation for the markets of France, Singapore, Korea and Taiwan having less extremal influence on the Chinese stock market than do some other financial markets is that they are small compared with those of the other countries in this study. Two large Asian financial markets - Hong Kong and Japan - seem to have greater importance than others in generating large fluctuations in the Chinese market, especially during strong upswings. Closer and closer trading ties between

Canada and China have put Canada at the top of influential countries for the Chinese stock market when markets are down, but interestingly this relationship is less apparent when markets are booming.

Table 5. Asymptotic dependence estimates for Chinese and other stock indices

	Unfiltered Data				MGJR filtered residuals			
	Negative Tail		Positive Tail		Negative Tail		Positive Tail	
	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.
China-Hong Kong	0.5561	0.1339	0.6761	0.0934	0.3755	0.0942	0.4304	0.0969
China-Taiwan	0.3295	0.1180	0.2162	0.0897	0.3736	0.0957	0.2150	0.0844
China-Korea	0.5132	0.1016	0.4696	0.0913	0.3604	0.0977	0.2533	0.1075
China-Japan	0.5079	0.1153	0.4600	0.0982	0.3392	0.1055	0.4674	0.1109
China-India	0.5669	0.1001	0.5357	0.0936	0.3855	0.1053	0.3695	0.0849
China-Singapore	0.5411	0.1056	0.4802	0.0902	0.4761	0.0951	0.3074	0.0809
China-US	0.1421	0.1142	0.3881	0.0907	0.3465	0.0916	0.3955	0.0912
China-US(adjusted)	0.4024	0.1149	0.4748	0.0881	0.3626	0.1002	0.3031	0.0926
China-Canada	0.6422	0.0978	0.3415	0.0824	0.6275	0.1042	0.2472	0.0927
China-Mexico	0.4548	0.1037	0.4335	0.0905	0.3856	0.1113	0.3865	0.0832
China-France	0.3778	0.0972	0.2745	0.0871	0.2185	0.1015	0.3349	0.0979
China-Germany	0.2902	0.1083	0.3340	0.0802	0.2292	0.1141	0.4384	0.0968
China-UK	0.4854	0.1056	0.2374	0.0960	0.4131	0.1244	0.3748	0.1058
	DCC filtered residuals				**CCC filtered residuals**			
	Negative Tail		**Positive Tail**		**Negative Tail**		**Positive Tail**	
	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.	$\bar{\chi}$	a.s.e.
China-Hong Kong	0.3783	0.0915	0.5218	0.0961	0.3566	0.0967	0.5381	0.1008
China-Taiwan	0.2850	0.0974	0.1910	0.0908	0.3075	0.0918	0.2316	0.0817
China-Korea	0.2873	0.0990	0.2526	0.1066	0.2451	0.1000	0.2363	0.1060
China-Japan	0.3780	0.0927	0.4880	0.0926	0.3876	0.0944	0.4272	0.0947
China-India	0.2489	0.1052	0.2932	0.0853	0.2845	0.1028	0.2905	0.0842
China-Singapore	0.2377	0.0900	0.1714	0.0845	0.2483	0.0880	0.1958	0.0948
China-US	0.0457	0.1084	0.2619	0.0873	0.2119	0.1093	0.2060	0.0950
China-US(adjusted)	0.2798	0.0867	0.1630	0.0940	0.2075	0.0961	0.3018	0.0872
China-Canada	0.3945	0.0991	0.2879	0.0831	0.3477	0.1062	0.2769	0.0809
China-Mexico	0.1956	0.1033	0.3411	0.0821	0.4553	0.1032	0.3372	0.0842
China-France	0.2331	0.1090	0.3022	0.0886	0.1623	0.1040	0.2882	0.0893
China-Germany	0.2750	0.1159	0.3510	0.0897	0.2690	0.1275	0.3570	0.0939
China-UK	0.3451	0.1166	0.1709	0.0990	0.2810	0.1174	0.1864	0.0982

Note: “a.s.e” denotes asymptotic standard error.

Table 6. Asymptotic dependence estimates for Chinese and other stock indices over two sub-periods

Subperiod 1: 5 January 2000 – 30 December 2005

	MGJR Filtered residuals				**DCC Filtered residuals**			
	Negative Tail		**Positive Tail**		**Negative Tail**		**Positive Tail**	
	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.
China-Hong Kong	0.2522	0.1183	0.4899	0.1174	0.1932	0.1170	0.3581	0.1215
China-Taiwan	0.2735	0.1121	0.0632	0.1058	0.1915	0.1152	0.0952	0.1426
China-Korea	0.3566	0.1185	0.2098	0.1241	0.3301	0.1194	0.2946	0.1365
China-Japan	0.3879	0.1177	0.4605	0.1333	0.3154	0.1108	0.3960	0.1375
China-India	0.3034	0.1254	0.2994	0.1015	0.3610	0.1242	0.3095	0.1080
China-Singapore	0.2670	0.1382	0.1289	0.1164	0.1037	0.1250	0.1594	0.1086
China-US	0.1089	0.1653	0.1507	0.1139	0.0427	0.1138	0.1551	0.1112
China-US(adjusted)	0.1505	0.2256	0.2777	0.1386	0.2663	0.1133	0.1013	0.1272
China-Canada	0.1236	0.1272	0.2037	0.1148	0.0094	0.1272	0.1504	0.1064
China-Mexico	0.2634	0.1289	0.2306	0.1173	0.1961	0.1184	0.2495	0.1118
China-France	0.1723	0.1311	0.1121	0.1065	0.1482	0.1224	0.2302	0.1152
China-Germany	0.3442	0.1365	0.2269	0.1203	0.1834	0.1284	0.2492	0.1186
China-UK	0.4390	0.1292	0.1475	0.1237	0.4415	0.1289	0.1915	0.1152

Subperiod 2: 4 January 2006 – 16 April 2010

	MGJR Filtered residuals				**DCC Filtered residuals**			
	Negative Tail		**Positive Tail**		**Negative Tail**		**Positive Tail**	
	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.	$\overline{\chi}$	a.s.e.
China-Hong Kong	0.4420	0.1512	0.6030	0.1244	0.5128	0.1423	0.5042	0.1309
China-Taiwan	0.3593	0.1483	0.3256	0.1186	0.3939	0.1354	0.3012	0.1133
China-Korea	0.2419	0.1406	0.5442	0.1291	0.3837	0.1475	0.3231	0.1310
China-Japan	0.4287	0.1401	0.4615	0.1201	0.5008	0.1412	0.3893	0.1187
China-India	0.3601	0.1467	0.4000	0.1209	0.4732	0.1520	0.3303	0.1195
China-Singapore	0.4713	0.1262	0.3087	0.1072	0.3470	0.1235	0.1986	0.1113
China-US	0.2773	0.1722	0.4690	0.1304	0.2312	0.1603	0.4442	0.1229
China-US(adjusted)	0.3792	0.1648	0.3660	0.1359	0.2815	0.1602	0.3393	0.1307
China-Canada	0.5559	0.1605	0.5127	0.1265	0.5238	0.1643	0.4446	0.1267
China-Mexico	0.5799	0.1745	0.5702	0.1282	0.2996	0.1838	0.4432	0.1286
China-France	0.2687	0.1368	0.3022	0.1309	0.1646	0.1402	0.2339	0.1273
China-Germany	0.2646	0.1522	0.4435	0.1389	0.1780	0.1484	0.4339	0.1221
China-UK	0.2020	0.1480	0.4664	0.1301	0.2376	0.1559	0.5470	0.1367

Note: "a.s.e" denotes asymptotic standard error.

Based on the Ljung–Box test, we strongly reject the null hypothesis of independence for all pairs of the unfiltered data, but we cannot reject the independence hypothesis for all pairs of the filtered data at least at the 20% significance level. This suggests that the estimates based on the dependent data set may give us some misleading results about the tail dependence. So, we turn to the results based on the filtered data sets to check the stability of dependence across the two sub-periods that we examined before. The results based on the three MGARCH models are quite similar, so we just report those based on the MGJR and DCC MGARCH models to conserve space. The results in Table 6 are consistent with the findings in Table 5: in general, the markets in Hong Kong, Japan, Canada and Mexico all have closer ties with the Chinese stock market after the onset of the period of financial turmoil, than before. On the other hand, the influence of India and the three European countries studied here on the Chinese stock market was as weak, or weaker, after 2006 than before. Overall, we can see that the extremal dependence between the Chinese and most other stock markets has increased over time with respect to both positive and negative returns.

IV. Conclusions

In this paper we have applied conditional extreme value theory to estimate the Value at Risk and Expected Shortfall of thirteen stock indices. We find that the Chinese market has the highest VaR and ES for negative returns, and the third highest level of risk for positive returns. The UK market has the lowest such measures in both tails of the returns distribution. In addition, the risk level tends to increase for most indices over time. From our extremal dependence analysis, we find that fluctuations in the Chinese stock market are positively correlated with those in all other countries or regions. However, these movements are asymptotically independent of those in all other stock markets, implying that there is no dependence between *extremely* large values of these fluctuations when the Chinese and other stock markets are compared in a pair-wise manner.

References

Artzner, P., Delbaen, F., Eber, F-M. and Heath, D. (1999) Coherent measure of risk, *Mathematical Finance*, **9**, 203-28.

Baba, Y., Engle, R. F., Kraft, D. F. and Kroner, K. F. (1990) Multivariate simultaneous generalized ARCH, mimeo., Department of Economics, University of California, San Diego.

Beirlant, J., Dierckx, G., Goegebeur, Y. and Matthys, G. (2000) Tail index estimation and an exponential regression model, *Extremes*, **2**, 177-200.

Bekiros, S. D. and Dimitris, A. G. (2008) The extreme-value dependence of Asia-Pacific equity markets, *Journal of Multinational Financial Management*, **18**, 197-208.

Coles, S., Hefferman, J., and Tawn, J. (1999) Dependence measure for extreme value analyses, *Extremes*, **2**, 339-65.

Engle, R. F. and Kroner, K. F. (1995) Multivariate simultaneous generalized ARCH, *Econometric Theory*, **11**, 122–50.

Fernandez, V. (2003), Extreme value theory: value at risk and returns dependence around the world, http://www.webmanager.cl/prontus_cea/cea_2003/site/asocfile/ASOCFILE12003062516071.pdf

Gençay, R., Selçuk, F. and Ulugülyağci, A. (2003) High volatility, thick tails and extreme value theory in value-at-risk estimation, *Insurance: Mathematics and Economics*, **33**, 337-56.

Glosten, L., Jaganathan, R. and Runkle, D. (1993) On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance*, **48**, 1779-1801.

Ledford, A., and Tawn, J. A. (1996) Statistics for near independence in multivariate extreme values, *Biometrika*, **83**, 169-87.

Ledford, A., and Tawn, J. A. (1998) Concomitant tail behavior for extremes, *Advances in Applied Probability*, **30**, 197-215.

Longin, F. and Solnik, B. (2001) Extreme correlation of international equity markets, *Journal of Finance*, **56**, 649-76.

Martens, M. and Poon, S. (2001) Returns synchronization and daily correlation dynamic between international stock markets, *Journal of Banking and Finance*, **25**, 1805-27.

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

Nieto, M. and Ruiz, E. (2008) Measuring financial risk: comparison of alternative procedures to estimate VaR and ES, Statistics and Econometrics Series 26, Working Paper 08-73, Departamento de Estadística, Universidad Carlos III de Madrid.

Poon, S., Rockinger, M. and Tawn, J. A. (2003) Modelling extreme-value dependence in international stock markets, *Statistica Sinica*, **13**, 929-53.

Poon, S., Rockinger, M. and Tawn, J. A. (2004) Extreme value dependence in financial markets: diagnostics, models and financial implications, *Review of Financial Studies*, **17**, 581-610.