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EMERGING EQUITY MARKETS

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Abstract

This study investigates the dependence structure of extreme realization of returns between the mature markets of Japan and the U.S. and the emerging markets of Cyprus, Greece and that of six Asia-Pacific countries, with the application of multivariate Extreme Value Theory that best suits to the problem under investigation. The evidence we obtain indicates that the left tail extreme correlations (downside risk) are not substantially different from the unconditional ones or from those obtained from a multivariate Dynamic Conditional Correlation GARCH model (DCC) with asymmetric GJR-GARCH univariates. Moreover, a clustering analysis shows that the examined countries do not belong to a distinct block on the basis of the extreme correlations we have estimated. The policy implications are that the benefits from portfolio diversification between the Cyprus stock market and the markets of Asia-Pacific countries, Greece, Japan and the U.S. are not eroded during crisis periods, in that no “correlation breakdown” has been witnessed.

Keywords

Copulas; Emerging markets; Asymmetric DCC-GARCH

JEL classification: G15; C10; F30

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1. Introduction

The most appropriate methodology to use for the estimation of the dependence structure between two markets, under extreme circumstances, converges on the choice of the most general data generating process for the tails of the distribution. In this study we use multivariate extreme value theory in order to calculate extreme correlations, for the *left tail returns* (downside risk), between Cyprus and six emerging Asia-Pacific equity markets, Japan, the U.S and Greece.

In the literature different measures of dependence for the right and left tails imply a different degree of association of financial asset returns depending on the sign of the shocks. In our paper the focus is not on testing for the validity of the multivariate normal distribution for the extreme returns but rather on the classification of the examined markets into low, medium and high risk groups on the basis of the estimated conditional extreme correlations. Therefore, we answer the question whether the contagion of financial crises is more or less the same for the investigated countries. We are also able to provide some evidence on the comparison of the extreme correlations with the conditional and unconditional ones. This line of research is of particular interest to international portfolio managers who systematically monitor correlations between various stock markets and the success of their policies is intimately linked to the stability of the estimated correlations they are based on.

In their seminal paper King and Wadhvani (1990), report that changes in the correlation coefficient of financial asset returns have been associated with the notion of contagion. This term refers to the spread of downside market shocks from one country to

another and it can be explained from the existence of real and financial linkages between the countries or the behaviour, rational and irrational, of international investors (i.e., Karolyi (2003) provides a survey on this issue). However, before we proceed with the explanations that have been offered to the correlation breakdown issue, there must be an agreement that this breakdown has really occurred.

The investigation of the stability of the correlation coefficient has proven to be an obscure issue and recent research in this area has highlighted two major problems. First, the choice of “conditioning” the correlation index on periods of high volatility is not the appropriate one if we intend to test for a correlation breakdown. Many recent studies have shown that in this case we get biased estimates of the true correlation. Forbes and Rigobon (2002) studied the correlation between Mexico and 28 other countries and showed that when the correlation is adjusted for shifts in the variances less than 5% of the cases, traditionally classified in the group exhibiting contagion, still presented significant correlation changes. Boyer et al. (1999) show how the correlation breakdown is generated, when conditioning on realizations of one variable, for the cases of a pair of bivariate normal random variables and of a bivariate GARCH(1,1) process with a constant contemporaneous correlation coefficient. Rigobon (2003) shows that the adjustment of the correlation coefficients is biased when the data on stock market returns suffers, except for heteroscedasticity, from simultaneous equations and omitted variables problems. He then applies a new methodology that allows one to test for the stability of the transmission mechanism, taking into account all three predicaments. In his study that covers 36 stock markets during the last three major financial crises (Mexico 1994, Asia 1997, Russia 1998)

in less than 10% of the cases does the transmission mechanism change. Loretan and English (2000) computed adjusted, for the effect of volatility, correlation coefficients between daily returns on the UK FTSE 100 and the German DAX stock indices and they derived no evidence of a structural change during the Mexican crisis in 1994.

A second and more critical issue is related to the suitability of the Pearson correlation index as a statistical measure of dependence when returns are not drawn from the class of elliptical distributions, a distinct member of which is the multivariate normal distribution. Embrechts et al. (2001) discuss the role of the linear correlation coefficient and other measures of dependence outside the class of elliptical distributions. It is known, for example, that the conditional correlation of a multivariate normal distribution tends to zero as the threshold used to define the tails tends to infinity. This contradicts however the widely held view that correlation across markets increases dramatically in the presence of large negative shocks.

In their study Longin and Solnik (2001) addressed this issue by making use of asymptotic results from the MEVT which hold for a wide range of parametric distributions. They applied their methodology on monthly stock market returns from five mature capital markets and showed that the left tail extreme correlations are substantially larger than the right tail ones and furthermore that their asymptotic distribution is different from the multivariate normal. Poon et al. (2004) argue that traditional tests for asymptotic extremal dependence bias the results in favour of this hypothesis and they suggest an additional measure of extremal dependence for variables that are asymptotically independent. They apply the pair of dependence measures on daily data

of stock index returns of the five largest stock markets and they conclude that the asymptotic dependence between the European countries (United Kingdom, Germany and France) has increased over time but that asymptotic independence between Europe, United States and Japan best characterizes their stock markets behaviour.

In the next section we offer a brief presentation of the copula methodology that allows the extraction of the dependence structure of a set of variables independently of the marginal distributions that might refer to a wide class of models. In the third part the multivariate GARCH model is presented. The fourth part of the paper describes dependence measures that are estimated for all possible pairs of series and the results are discussed. The main evidence is that the case for the existence of correlation asymmetry does not appear to be supported empirically. Finally, the classification of the markets in risk groups shows that the examined emerging markets do not seem to belong in a distinct cluster.

2. Extreme Value Theory

2.1. Univariate models

The possibility of predicting extreme negative returns in international equity markets would result in averting vast losses in the value of portfolios. However, the conventional VaR models utilize the entire empirical return distribution in risk estimation and consequently do not focus on the tails. *Extreme Value Theory (EVT)* deals with modeling the tails of return distributions with the use of parametric methods. This approach has been extensively used in the past in hydrology, meteorology and engineering for prediction of extreme natural phenomena.

Within the EVT context, the *Peaks Over Threshold Model (POT-EVT)* has been developed. The key result in POT-EVT is that, for a wide class of distributions, losses which exceed high enough thresholds follow the *generalized Pareto distribution (GPD)*. Consider a certain high threshold u . We are interested in excesses above this threshold, that is, the amount by which observations overshoot this level. Since there are not any robust statistical methods in order to select a suitable threshold, a number of exploratory graphical methods have been developed. According to Neftci (Neftci, 2000) the threshold is $u = 1.176 \cdot \sigma$ where σ is the standard deviation of the empirical distribution. Considering that $1.176 = F^{-1}(0.1)$, extreme values will lie in above the 10th% quantile of an *F Student- t(6)*. Alternatively, the Sample Mean Excess function is defined as follows:

$$s_n(u) = \frac{\sum_{i=1}^n (Y_i - u)_{\{Y_i > u\}}}{\sum_{i=1}^n 1_{\{Y_i > u\}}} \quad (1)$$

i.e. the sum of the excesses over the threshold u divided by the number of data points which exceed the threshold u . The sample mean excess function $e_n(u)$ is an empirical estimate of the mean excess function which is defined as $e(u) = E[X - u | X > u]$. The mean excess function describes the expected overshoot of a threshold given that exceedance occurs. In plotting the sample mean excess function we choose to end the plot at the fourth order statistic and thus omit a possible three further points; these points, being the averages of at most three observations, may be erratic. The interpretation of the mean excess plot is explained in Beirlant, Teugels & Vynckier (1996), Embrechts et al. (1997) and Hogg & Klugman (1984). If the points show an upward trend, then this is a sign of

heavy tailed behaviour. Exponentially distributed data would give an approximately horizontal line and data from a short tailed distribution would show a downward trend. In particular, if the empirical plot seems to follow a reasonably straight line with positive gradient above a certain value of u , then this is an indication that the data follow a generalized Pareto distribution with positive shape parameter in the tail area above u .

Let y_0 be the finite or infinite right endpoint of the distribution F . That is to say, $F, y_0 = \sup\{y \in R : F(y) < 1\} \leq \infty$. We define the distribution function of the excesses over the high threshold u by:

$$F_u(y) = P(Y - u \leq y \mid Y > u) = \frac{F(y+u) - F(u)}{1 - F(u)} \quad (2)$$

for $0 \leq y < y_0 - u$. The theorem (Balkema & de Haan 1974, Pickands 1975) shows that under some conditions the generalized Pareto distribution is the limiting distribution for the distribution of the excesses, as the threshold tends to the right endpoint. That is, we can find a positive measurable function $\sigma(u)$ in absolute value such that

$$\lim_{u \rightarrow y_0} \sup_{0 \leq y < y_0 - u} |F_u(y) - G_{\xi, \sigma(u)}(y)| = 0$$

The GPD is usually expressed as a three parameter distribution with d.f.:

$$G_{\xi, \sigma, \mu}(y) = \begin{cases} 1 - (1 + \xi \frac{y - \mu}{\sigma})^{-1/\xi} & \xi \neq 0 \\ 1 - e^{-\frac{y - \mu}{\sigma}} & \xi = 0 \end{cases} \quad (3)$$

where σ scale parameter ($\sigma > 0$), μ location parameter and ξ tail index. When $\xi > 0$ we have a reparametrized version of the usual Pareto distribution with shape $\alpha = 1/\xi$; if $\xi < 0$ we

have a Beta distribution; $\xi=0$ gives the exponential distribution.

According to Balkema - de Haan – Pickands theorem for selected high threshold $\mu=u$ the extreme distribution $F_u(y)$ is approximated by $G_{\xi,\sigma,u}(y)$ for determined ξ and σ . The fit to the tail of the original distribution above the high threshold is given by $F(y) = P(Y \leq y) = (1 - P(Y \leq u)) \cdot F_u(Y - u) + P(Y \leq u)$. We now know that we can estimate $F_u(Y - u)$ by for $G_{\xi,\sigma}(y - u)$ for u large. We can also estimate $P(Y \leq u) = F(u)$ from the data by $F_n(u)$, the empirical distribution function evaluated at u . This means that for $y \geq u$ we can use the tail estimate:

$$\hat{F}(y) = (1 - F(u)) G_{\xi,\sigma,u}(y) + F(u) \quad (4)$$

It can be shown that if N the number of extreme values over u and n the total sample number of empirical df F , the estimation of VaR is given as follows (Smith, 1987):

$$VaR = u + \frac{\hat{\sigma}}{\hat{\xi}} \left[\left(\frac{n}{N} (1 - p) \right)^{-\frac{1}{\hat{\xi}}} - 1 \right] \quad (5)$$

2.2. Multivariate models

Linear Correlation is used as a measure of dependence between financial instruments based on the assumption of multivariate normally distributed returns. However, linear correlation cannot capture the non-linear dependence relationships that exist between many real world risk factors.

If the variables have a jointly multivariate normal distribution that belongs to the elliptical class then the standard correlation approach to dependency is natural and unproblematic. The Normal, Student or Generalized error distributions are some

examples of the elliptical class. In addition, only in the case of the multivariate normal can uncorrelatedness always be interpreted as independence. Generally, if the joint distribution of portfolio variables is elliptical, then the following are true (Embrechts et. al., 1998):

1. *The estimation of the portfolio risk is based on the weights and the correlation matrix of the variables. No other information on dependence is necessary.*
2. *Among all portfolios with the same expected return the portfolio minimizing VaR is the Markowitz variance minimizing portfolio.*
3. *VaR is a coherent risk measure in the sense it fulfils the sub-additivity property:*

$$VaR_a(Z_1 + Z_2) \leq VaR_a(Z_1) + VaR_a(Z_2)$$

However, in the international markets the joint distribution is not univocally determined on the basis of marginals and correlation matrix. Consequently, the correlation coefficient does not provide any information on the dependence structure in the tails of the non-elliptical distributions. Additionally, given marginal distributions, all linear correlations between -1 and 1 can be attained through suitable specification of the joint distribution, only in the case of elliptical distributions. In general, the attainable correlations depend on risk factors and form a closed interval $[\rho_{min}, \rho_{max}]$ containing zero that is a subset of $[-1, 1]$. The upper boundary of the interval always represents a situation where risk variables are perfectly positively dependent, or comonotonic, whereas the lower boundary represents a situation where the factors are perfectly negatively dependent. Additionally, correlation is not invariant under transformations of the risks (e.g, $\log(X)$ and $\log(Y)$) generally do not have the same

correlation as X and Y). Finally, correlation is only defined when the variances of the risks are finite. Therefore, it is not an appropriate dependence measure for very heavy-tailed risks where variances appear infinite.

As an alternative dependence measure the rank correlation (Spearman) is used. It is invariant under (strictly) increasing transformations of the risks, it does not require that the risks be of finite variance and for arbitrary marginals a bivariate distribution can be found with any rank correlation in the interval $[-1, 1]$. But, as in the case of linear correlation, this bivariate distribution is not the unique distribution satisfying these conditions. Consequently, linear or rank correlation bear relatively narrow value.

2.2.1. Dependence functions (copulas)

It is proven that every joint distribution function F can be represented as follows:

$$F(y_1^*, \dots, y_q^*) = \Pr ob[Y_1 \leq y_1^*, \dots, Y_q \leq y_q^*] = C(F_1(y_1^*), \dots, F_q(y_q^*)) \quad (6)$$

where $y_i^* = u_i + y_i$ and y_i corresponds to the extreme values of Y_i over a threshold u_i and C dependence function (Copula) of F and F_1, \dots, F_q marginals of q variables. A copula may be thought of in two equivalent ways: as a function that maps values in the unit hypercube to values in the unit interval $C: [0,1]^q \rightarrow [0,1]$ or as a multivariate distribution function with standard uniform marginal distributions (Embrechts et. al., 1998). If the marginal distributions of F are continuous then F has a unique copula, but if there are discontinuities in one or more marginals then there is more than one copula representation for F (Sklar, 1959). The copula remains invariant under (strictly) increasing transformations of the risks; the marginal distributions may change but the

copula remains the same. Additionally, in case of fat-tailed distributions where variances are not finite, they represent an ideal measure of dependence.

The possible limit nondegenerate distributions satisfying the limit condition must satisfy two properties:

1. *Its univariate marginal distributions are generalized Pareto distributions.*
2. *There exists a function called the dependence function, which satisfies the following condition: $G^u(y_1, y_2, \dots, y_q) = C(G(y_1), G(y_2), \dots, G(y_q))$*
3. *The correlation of extreme values increases in crisis periods and in high quantiles.*

Specifically for the bivariate case a model commonly used in the literature is the logistic function proposed by Gumbel (Tawn, 1988, Longin and Solnik, 2001):

$$C(s, t) = \Pr(S \leq s, T \leq t) = \exp \left[- \left\{ s^{-1/a} + t^{-1/a} \right\}^a \right], \quad 0 < a \leq 1 \quad (7)$$

In order to dissociate the correlation structure from the marginal distributions the bivariate return exceedances have been transformed to unit Fréchet margins, $S = -1/\log F_{u_1}(y_1)$, $T = -1/\log F_{u_2}(y_2)$ where $F_{u_i}(y_i)$ is the GPD of exceedance y_i . The asymptotic dependence of (S, T) is defined by:

$$d = \lim_{s \rightarrow \infty} \Pr(T > s / S > s) \quad (8)$$

where $0 \leq d \leq 1$, and the two variables are termed asymptotically dependent if $d \geq 0$ and asymptotically independent if $d = 0$. The relationship between the coefficient α , of eq. (8), and d is given by:

$$d = 2 - 2^\alpha \quad (9)$$

so when the variables are exactly independent $d = 0$ and $\alpha = 1$ while when $\alpha < 1$ the variables are asymptotically dependent to a degree depending on α . Since we have chosen the two thresholds, the bivariate distribution of return exceedances is then described by seven parameters: the two tail probabilities, the dispersion parameters and the tail indexes of each variable, and the dependence parameter of the logistic function. The parameters of the model are estimated by the maximum likelihood method. In the bivariate case, the correlation coefficient of extremes is related to the coefficient of dependence by (Tiago de Oliveira, 1973):

$$\rho = 1 - \alpha^2 \quad (10)$$

3. Multivariate GARCH models

In order to investigate the empirical implications of those two different estimation philosophies we have also chosen to estimate the correlation indices from multivariate volatility models. The first model we estimate is the one suggested by Bollerslev (1990) that handles the high dimensionality of the parameter space of the variance – covariance matrix by adopting the assumption of constant contemporaneous correlations (CCC). In the CCC-GARCH(1,1) specification the conditional variance matrix is specified as $H_t = D_t R D_t$, where H_t takes the form:

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \quad (11)$$

In this model the correlation matrix R is time invariant. For the bivariate GARCH(1,1) case the CCC model contains only 7 parameters compared to 21 encountered in the full

VECH model and the positive definiteness of the variance – covariance matrix is easily satisfied ($|\rho| < 1$). In this framework the asymmetric behavior of the conditional covariances in bull and bear markets is guaranteed by the proper parameterization of the conditional variances. In our case we apply the Glosten-Jagannathan-Runkle (1993) GJR-GARCH(1,1) model:

$$h_{ii,t}^2 = \omega + \beta Y_{t-1}^2 + \gamma h_{ii,t-1}^2 + \delta Y_{t-1}^2 I_{t-1} \quad (12)$$

where $\omega \geq 0, \beta \geq 0, \gamma \geq 0, \delta \geq 0, I_{t-1} = 1$ when $Y_{t-1} < 0$ and zero otherwise.

The assumption that the conditional correlations are constant may seem unrealistic in many empirical applications like the dependence of international equity returns. Engle (2002) extends the CCC estimator by allowing the conditional correlations to be time varying, that is the conditional variance is $H_t = D_t R_t D_t$. The dynamic conditional estimator (DCC) is obtained in two stages. In the first stage univariate GJR-GARCH(1,1) models are estimated for each return series. The standardized residuals from the first stage, $n_{i,t} = (\varepsilon_{i,t} / \sqrt{h_{ii,t}})$, are used in the second stage in the estimation of the correlation parameters. The correlation structure R is also the correlation of the original data and is given by $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, where Q^* is a diagonal matrix whose elements are the square root of the diagonal elements of the covariance matrix Q that is specified by a GARCH process as below:

$$Q_t = S(1 - \lambda - \mu) + \lambda(n_{t-1}' n_{t-1}) + \mu Q_{t-1} \quad (13)$$

where the sum of λ and μ measures the long -run persistence. Q is calculated as a weighted average of S , the unconditional covariance of the standardized residuals, a

lagged function of the standardized residuals and the past realization of the conditional variance (Engle, 2002).

4. Empirical results

The presented results have been based on data from 10 countries downloaded from Datastream. The period covered is 29/3/96 – 31/12/04 and the analysis has been broken down in 2 sub-periods 29/3/96 - 5/3/01 and 27/1/00 - 31/12/04 in order to juxtapose the differences between upward and downward trends in Cyprus Stock Exchange. Specifically, the indices used are: *Cyprus: Cyprus General Index*, *Japan: Nikkei 255 Stock Average*, *USA: S&P 500 Composite*, *Hong Kong: Hang Seng Price Index*, *Taiwan: Stock Exchange Weighted Price Index*, *Malaysia: KLCI Composite Price Index*, *Indonesia: Jakarta Stock Exchange Composite Price Index*, *Singapore: Straits Times (New) Price Index*, *Thailand: SET 100 Basic Industries Index*, *Greece: Athens Composite Index*.

The Cyprus pound had been pegged to ecu and from January 1999 to euro with fluctuation margins $\pm 2.25\%$. From January 1st, 2001, wider bands of $\pm 15\%$ were introduced. This exchange rate policy meant that the Cyprus pound was effectively floating against the US dollar. The Cyprus Stock exchange started operating on 3/29/1996 and its performance can be divided into three periods. The first period, until 6/30/1999, was characterized by low volatility, low volumes and persistence of the General index around the initial level of 100. The second period, up to 10/31/2000, had all the features of a bubble that burst after 1.5 years. During the ensuing period the General index returned to its initial levels but with a higher volatility than the first period (Nerouppos *et. al.* 2002).

The *EVT-POT method* is applied on the exceedances of the return series for high enough thresholds. In order to estimate the threshold we followed Neftçi (2000), therefore the threshold is $u = 1.176 \cdot \sigma$ where σ is the standard deviation of the empirical distribution. The choice of the optimal threshold for EVT is a delicate issue since it is confronted with a bias-variance tradeoff. If we choose too low a threshold we might get biased estimates because the limit theorems do not apply any more, while high thresholds generate estimates with high standard errors due to the limited number of observations. For threshold estimation we follow Neftçi, S. (2000), according to whom a Student-t (6) distribution, is being assumed. The selected values are shown in Table 1. Apparently, Cyprus threshold corresponds to the average of the developing countries, whereas mature markets of US and Japan exhibit a lower threshold. Additionally, in period I the threshold values are higher due the increased volatility of all the examined countries. In order to investigate the sensitivity of the results, we have calculated more threshold values that correspond to various confidence levels of the empirical return distribution of CSE and ASE. The results are depicted in Figure 1. In the Cyprus case, the left tail index is decreasing when the threshold increases in period I, whereas it remains relatively stable for period II. The opposite occurs for Greece.

The maximum likelihood estimates of the tail index, ξ , with their corresponding standard errors, and the scale parameters are also presented in Table 1. The bigger the tail index the more fat-tailed is the distribution of the extreme values over the threshold (downside risk). It is evident from the standard error of the left tail index in Table 1 that the empirical distribution of the CSE returns is exponential in the tails (the same applies

to Normal), whereas in case of the other emerging markets the tails fit to the Pareto distribution function (df) and therefore exhibit higher risk. The above results apply for both periods. In Table 2 we present the VaR estimations in 99% confidence level, based on the eq. (5) and the point estimates of Table 1. The evidence suggests that CSE presents high probability for the one-day-ahead risk prediction. The highest loss on a 99% confidence interval is 5% and 4.6% for the 2 corresponding sub-periods. These estimations are similar to the other emerging markets specifically for period I. In Table 3 we present the correlation coefficients from the MEVT. The parameters of the model are estimated by the maximum likelihood method developed by Ledford and Tawn (1996). The basic assumptions of this method are that returns are assumed to be independent and that return observations below thresholds are treated as censored data. This implies that the likelihood contributions of those observations are calculated by using as inputs the threshold values and not the actual observations. Substantial differences between the two periods are not observed although slightly higher estimates have been obtained in the second period. The left tail extreme correlation estimates are always higher than the unconditional ones.

Table 3 also presents the estimated value of the correlation coefficients for the DCC-GARCH(1,1) model. In this framework the asymmetric behaviour of the conditional covariances in the left tails is guaranteed by the proper parameterization of the conditional variances. In our case we have applied the asymmetric Glosten–Jagannathan–Runkle (1993) model, and therefore the GARCH model we employ is signified by DCC-GJR(1,1). In the case of the DCC-GJR(1,1) model we report both the *average* correlation

estimate over the entire estimation period (in parenthesis) and the last estimate. The average values of the estimated correlation coefficients are close to the unconditional ones and lower from the MEVT estimates. This evidence supports the argument that tail dependency exists even if we allow for volatility clustering. Furthermore, the proximity of the correlation estimates from the MEVT with the conditional and unconditional ones (although somewhat different not actually high in value), weakens the argument that there has been a contagion effect among the examine markets during the most recent crises. Since from a completely statistical perspective one would expect a larger correlation index during periods of high volatility, contagion is not simply an increased correlation coefficient during a crisis period (Bekaert and Harvey, 2003).

In order to classify the various pairs of capital markets into different groups on the basis of the estimated dependence measures, we apply a clustering analysis that assigns each estimate to the cluster having the nearest mean. *K*-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume *k* clusters) fixed a priori. The main idea is to define *k* centroids, one for each cluster. Group membership is determined by calculating the centroid for each group (*the multidimensional version of the mean*) and assigning each observation to the group with the closest centroid, (MacQueen, 1967). The evidence appears in Table 4. The main result is that the classification of the estimated correlations into low, medium and high dependence groups is very similar between the MEVT, the average DCC-GJR and the unconditional correlations, perhaps with the exceptions of the

low classifications in case of the unconditional estimate in PI for Cyprus-USA and the extreme estimate in PI for Cyprus-Singapore. Finally, we examine whether there is any validity to the argument that the emerging capital markets belong to a distinct cluster of markets where the other two could be the U.S. and Japan. If this argument was correct then we would expect to find that the correlation indices between the emerging markets would be always classified to the high correlation cluster. A simple inspection of Table 4 shows that this is not the case. Cyprus market exhibits varying degrees of extreme correlation with the other emerging and mature markets of Japan and U.S. and therefore investors can benefit from diversifying their portfolios even in periods characterized as being “extreme.” Overall, the evidence indicates that extreme correlations are not substantially different from the unconditional ones or from those obtained from multivariate GARCH models, thus they should be attributed to the increased volatility in turbulent periods.

5. Conclusions

In the present study, following the results of many recent empirical papers on contagion in international equity markets, we have concluded that the degree of co-movement of the returns did not change significantly over the most recent crises that occurred in 1990s. We estimate the degree of dependence of extreme realization of returns between Cyprus, six Asia-Pacific equity markets, Greece and the mature markets of the U.S and Japan. Methodologically, we applied the multivariate extreme value theory. The main advantage of this approach is that it generates dependence measures

even if the multivariate Gaussian distribution does not apply, as the case is for the tails of high frequency stock index returns. The evidence we obtain indicates that extreme correlations are not substantially different from the unconditional ones or from those obtained from multivariate GARCH models. This evidence corroborates the conclusion that correlation breakdown is not prevailing during crisis periods as we used to believe initially. Moreover, we apply a clustering analysis that shows that the examined countries do not belong to a distinct block of countries on the basis of the extreme correlations we have estimated. The evidence of this study hinges on two conditions; the first is related to the choice of the threshold. A sensitivity analysis has shown that our results are robust to the chosen thresholds, albeit the application of optimally chosen thresholds will substantiate the results we have reached. The second condition is related to the choice of the tail dependence measure we use which has been criticized that biases the results in favor of the presence of asymptotic dependence. Combined evidence from alternative measures will provide more unequivocal conclusions. The policy implications are that that “extreme” correlations should be attributed to the increased volatility in turbulent periods and the benefits from portfolio diversification with assets from the examined stock markets are not eroded during crisis periods.

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Table 1 : Extreme-value Parameters

Parameter	ξ (Left Tail Index)		σ (scale parameter)		Threshold	
	29/3/96 - 5/3/01	27/1/00 - 31/12/04	29/3/96 - 5/3/01	27/1/00 - 31/12/04	29/3/96 - 5/3/01	27/1/00 - 31/12/04
<i>Japan</i>	0.069 (0.046)	-0.037 (0.047)	0.009 (0.001)	0.009 (0.001)	0.016	0.017
<i>USA</i>	0.245 (0.063)	0.055 (0.052)	0.006 (0.002)	0.007 (0.001)	0.012	0.012
<i>Hong Kong</i>	0.325 (0.078)	0.128 (0.062)	0.011 (0.001)	0.011 (0.001)	0.022	0.019
<i>Taiwan</i>	-0.172 (0.047)	0.009 (0.063)	0.019 (0.001)	0.013 (0.001)	0.025	0.021
<i>Malaysia</i>	0.265 (0.075)	0.206 (0.073)	0.012 (0.001)	0.011 (0.001)	0.020	0.018
<i>Indonesia</i>	0.275 (0.095)	0.183 (0.074)	0.012 (0.002)	0.011 (0.002)	0.021	0.018
<i>Singapore</i>	0.355 (0.084)	0.189 (0.068)	0.008 (0.001)	0.008 (0.001)	0.017	0.015
<i>Thailand</i>	0.116 (0.071)	0.151 (0.069)	0.016 (0.001)	0.013 (0.001)	0.026	0.025
<i>Cyprus</i>	0.116 (0.106)	0.126 (0.100)	0.014 (0.002)	0.010 (0.001)	0.022	0.019
<i>Greece</i>	-0.073 (0.107)	0.250 (0.121)	0.016 (0.002)	0.007 (0.001)	0.023	0.017

Notation:

Total In-sample Period observations: 2286 (29/3/96 - 31/12/04)

Cyprus: Cyprus General Index

Japan: Nikkei 255 Stock Average

USA: S&P 500 Composite

Hong Kong: Hang Seng Price Index

Taiwan: Stock Exchange Weighted Price Index

Malaysia: KLCI Composite Price Index

Indonesia: Jakarta Stock Exchange Composite Price Index

Singapore: Straits Times (New) Price Index

Thailand: SET 100 Basic Industries Index

Greece: Athens Composite Index

Table 2: EVT-POT VaR (99%) Estimates (*in absolute value*)

Parameter	VaR (99%)	
<i>In-sample Period</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>
<i>Japan</i>	3.9%	3.9%
<i>USA</i>	3.1%	3.2%
<i>Hong Kong</i>	5.6%	3.7%
<i>Taiwan</i>	4.6%	4.7%
<i>Malaysia</i>	5.5%	2.8%
<i>Indonesia</i>	5.9%	3.8%
<i>Singapore</i>	4.4%	3.3%
<i>Thailand</i>	7.4%	4.8%
<i>Cyprus</i>	5.0%	4.6%
<i>Greece</i>	5.7%	3.9%

Notation as in Table 1

Table 3: Cyprus Correlations' Estimation

Bivariate Model	MEVT		MGARCH DCC-GJR		UNCONDITIONAL	
	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>
<i>Cyprus – USA</i>	0.146	0.249	0.039 (0.043)	0.150 (0.148)	-0.022	0.088
<i>Cyprus – Hong Kong</i>	0.093	0.275	0.197 (-0.028)	-0.001 (0.091)	0.033	0.158
<i>Cyprus – Taiwan</i>	0.210	0.227	-0.152 (-0.135)	-0.104 (0.072)	-0.007	0.082
<i>Cyprus – Malaysia</i>	0.035	0.211	-0.051 (-0.029)	-0.091 (0.042)	-0.009	0.072
<i>Cyprus – Indonesia</i>	0.050	0.132	0.051 (0.002)	0.006 (-0.007)	0.010	0.009
<i>Cyprus – Singapore</i>	0.066	0.256	-0.040 (0.019)	-0.212 (0.090)	0.019	0.141
<i>Cyprus – Thailand</i>	0.034	0.178	0.010 (0.024)	0.059 (0.046)	0.024	0.070
<i>Cyprus – Japan</i>	0.112	0.212	0.238 (0.013)	0.122 (0.102)	0.044	0.106
<i>Cyprus – Greece</i>	0.109	0.203	0.122 (0.090)	0.087 (0.132)	0.107	0.150

Notation as in Table 1

Table 4: Clustering Analysis

Bivariate Model	MEVT		MGARCH DCC-GJR		UNCONDITIONAL	
	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>
<i>Cyprus – USA</i>	2	3	3	3	1	2
<i>Cyprus – Hong Kong</i>	2	3	2	3	2	3
<i>Cyprus – Taiwan</i>	3	2	1	2	1	2
<i>Cyprus – Malaysia</i>	1	2	2	2	1	2
<i>Cyprus – Indonesia</i>	1	1	2	1	2	1
<i>Cyprus – Singapore</i>	1	3	2	3	2	3
<i>Cyprus – Thailand</i>	1	2	2	2	2	2
<i>Cyprus – Japan</i>	2	2	2	3	2	2
<i>Cyprus – Greece</i>	2	2	3	3	3	3

K-Means Centers

K-Groups	MEVT		MGARCH DCC-GJR		UNCONDITIONAL	
	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>	<i>29/3/96 - 5/3/01</i>	<i>27/1/00 - 31/12/04</i>
<i>G₁ : Low Correlation</i>	0.046	0.132	-0.135	-0.007	-0.013	0.009
<i>G₂ : Medium Correlation</i>	0.115	0.206	0.000	0.053	0.026	0.084
<i>G₃ : High Correlation</i>	0.210	0.260	0.066	0.113	0.107	0.149

Notation: 1,2,3 refer to the classification to Low, Medium and High Correlation

Figure 1: Threshold Simulation (Period I)

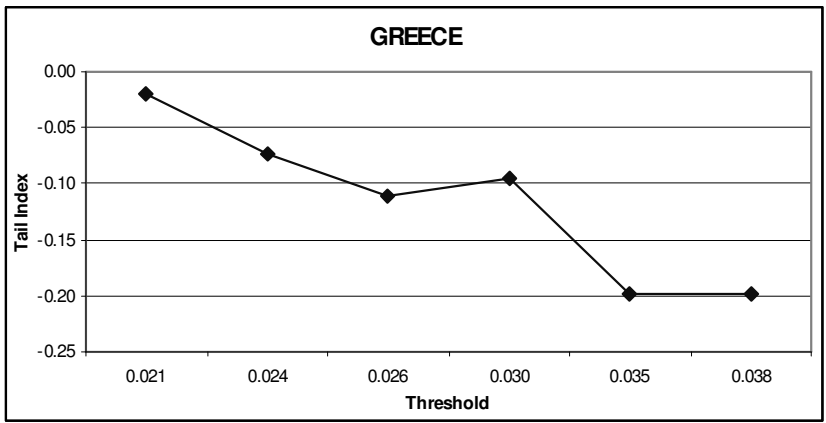
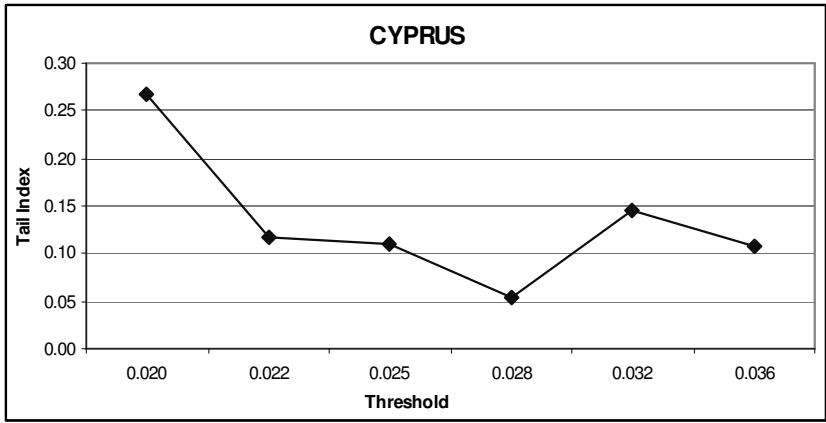


Figure 1: Threshold Simulation (*Period II*)

