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NEGATIVE RETURN-VOLUME RELATIONSHIP IN ASIAN STOCK MARKETS: FIGARCH-COPULA APPROACH

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Abstract

We explore the potential dependence among different Asian stock markets, using several different statistical models. Extreme return-volume dependence in Hong Kong Seng Index, Bombay Stock Exchange, Indonesia Composite Index and Bursa Malaysia has been examined by using FIGARCH-Copula and GARCH-Copula approach. We have used Gaussian, Student-t, Frank, Clayton, Survival Clayton and Gumbel copulas. Based on Akaike information criterion (AIC), we found that using FIGARCH model for return series improves the results of copula parameter estimation. According to our finding, Hong Kong and Indian stock indices showed weak upper tail dependence between return and volume. Further, we have found that the extremely low returns for Malaysia and Indonesia stock indices are followed by high volumes, providing evidence of leverage effect. Our investigation shows that Malaysia and Indonesia stock indices are sensitive to bad news rather than good news.

Keywords: Long Memory, FIGARCH-Copula Model, Asian Stock Markets, Upper Tail Dependence, Negative Returns

1. Introduction

The return and volume relationship has been analysed from many different point of views in the literature (see for instance, past empirical studies have included the relationship between price indices and aggregate exchange volume, Granger and Morgenstern (1963), between contemporaneous absolute price change and volume, Crouch (1970), between price change and volume, Westerfield (1977), Tauchen and Pitts (1983), Rogalski (1978), and between squared price change and volume, Clark (1973)). As investors revise their reservation prices based on the arrival of new information to the market, trading volume had been used to measure disagreement among market participants by using mixture models in Epps and Epps (1976). The level of trading volume increases as the degree of disagreement among traders spreads. Their model exhibits a positive causal relation running from trading volume to absolute stock returns. Jain and Joh (1988) found strong contemporaneous relation between trading volume and returns by using hourly common stock trading volume and return on NYSE. Further, they have also found lead-lag relationship between trading volume and returns lagged up to 4 hours.

Moreover, trading volume-returns relation is higher for positive returns than for negative returns. Chen *et al.* (2001) studied the dynamic relation between trading volume, returns and volatility of stock indices of nine national markets. They found a positive dependence between trading volume and the absolute returns. They have also showed that trading volume provides some information about returns process. Gunduz and Hatemi (2005) explored the causal relationship between stock prices and volume of Hungary, Czech Republic, Russia, Poland and Turkey stock markets. Floros and Vougas (2007) had examined the relationship between trading volume and returns in Greek Stock Index Futures Market and found significant positive contemporaneous relationship between trading volume and returns in case of FTSE/ASE-20. Furthermore, the results for FTSE/ASE Mid 40 do not provide any evidence of relationship between trading volume and returns. Furthermore, literature on return-volume dependence can be found in the papers of Attari *et al.* (2012) and Kamath (2008).

There is a vivid debate in the literature about correlation between volatility and return volume. It is nowadays accepted that they tend to show relatively strong upper tail dependence (see e.g. Rossi *et al.* 2013). Ning and Wirjanto (2009) found upper tail dependence in return and volume series of East Asian stock markets. However, Chen *et al.* (2001) explain that negative return in period t raises volatility in period $\mathrm{t}+1$. Further, explanation can be seen from Wagner (2012), that when volatility increases, risk increases and returns decrease. If we combine work of Rossi *et al.* (2013) and the fact mentioned in the paper by Chen *et al.* (2001) and Wagner (2012), then one should expect positive dependence between low return and volumes. In this paper we consider negative return-volume series, in order to explore the upper tail dependence between the negative return and volume. That is the dependence between the lower tail of return and upper tail of volume. Further, we consider return-volume dependence in order to analyse the difference between dependence parameter in both cases. Ning and Wirjanto (2009) used a copula approach to examine the extreme return-volume relationship in six emerging East-Asian equity markets. They used GARCH Copula approach.

In this paper, we generalize their approach and propose the FIGARCH-Copula model. The motivation for choosing FIGARCH model is the potential presence of a long memory effect in stock index return. Kartsaklas and Karanasos (2013) provide empirical evidence on the degree of long run dependence of volatility and trading volume in the Korean Stock Exchange. Kumar (2004) have examined the long memory characteristic in Indian Stock Market by analyzing the trading volume series. Furthermore, Goudarzi (2010) has investigated the long memory issue in Indian Stock Market using Fractionally Integrated EGARCH model. Kang and Yoon (2012) examined the long memory properties in both the returns and volatility of Korean stock prices. Tan and Khan (2010) have found that the long memory property holds in both the return and volatility in Malaysian Stock Market, with and without incorporating the crisis impact. Kasman and Torun (2007) used ARFIMA-FIGARCH model and showed strong evidence of long memory in both returns and volatility for Turkish Stock Market. Navarro *et al.* (2006) identified the presence of long memory in return series of the stock markets of ASEAN-4 countries, namely, Malaysia, Philippines, Indonesia and Thailand. Our goal in this paper is to explore the extreme dependence between negative return and volume. If stock returns are well described by the multivariate normal distribution, then the linear correlation is an appropriate dependence measure. However, in our case a simple exploratory and graphical analysis of both returns and volumes distributions suggest fat tails, long memory, heteroscedasticity, clustering and other non Gaussian features. Thus linear correlation might be deceptive in our analysis. Alternative measures of dependence based on copula methods combined with FIGARCH model are considered here. Copula approach is widely used in quantitative finance literature. Here we combine copula modelling with a univariate FIGARCH model for return in order to properly calibrate a joint model for returns and volumes. The remainder of this paper is organized as follows: section two introduces the fractionally integrated GARCH model. Section three describes copula methodology. Section four reports empirical results and section five conclude with summary of our finding.

2. FIGARCH Model

To explain the conditional variance dynamics Engle (1982) proposed the auto- regressive conditional heteroscedasticity (ARCH) model that estimates the variance of returns as a simple quadratic function of the lagged values of the innovations. A useful generalization of this model is the GARCH parameterization introduced by Bollerslev (1986). Baillie *et al.* (1996) and Bollerslev and Mikkelsen (1996) introduced a new process named FIGARCH; this process generalizes the well known GARCH model and allows one to consider the persistence in the conditional variance. Breidt *et al.* (1998) proposed the long memory stochastic volatility (LMSV) model and a frequency domain based maximum likelihood estimator (FDMLE) for the parameters in this model.

Considering a time series $\{y_t, t \in T\}$ with conditional mean equation

$$y_t = C + r_t \tag{1}$$

$$r_t / \mathcal{F}_t = \sigma_t \varepsilon_t \tag{2}$$

where σ_t is the time varying conditional standard deviation and ε_t is an i.i.d sequence of random variables with zero mean and unit variance, and $\mathcal{F}_t$ represents the information set up at time t. The standard ARCH (p) model expresses the variance at time t as:

$$\sigma^2{}_t = \omega + \alpha(B) r^2{}_t \tag{3}$$

The standard GARCH (p, q) model expresses the variance at time t, as:

$$\sigma^2{}_t = \omega + \alpha(B) r^2{}_t + \beta(B) \sigma_t{}^2 \tag{4}$$

According to Baillie *et al.* (1996) and Bollerslev and Mikkelsen (1996), a FIGARCH (p, d, q) model for the conditional variance satisfies

$$(1 - \phi(B))(1 - B)^d r^2{}_t = \omega + [1 - \beta(B)] \upsilon^2{}_t \tag{5}$$

where $\upsilon^2{}_t = r^2{}_t - \sigma^2{}_t$ is an error component or random shock in conditional variance, $\omega > 0$ is a real constant, the fractional integration parameter $d \in [0,1]$, B is the lag operator, $\phi(B) = \alpha(B) + \beta(B)$ and $\beta(B) = \sum_{j=1}^{q} \beta_j B^j$.The fractional difference operator $(1 - B)^d$ can be expanded into a series as follows:

$$(1 - B)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j - d) B^j}{\Gamma(j + 1)\Gamma(-d)} \tag{6}$$

for $j = 1,2,3, \cdots, \infty$ .The FIGARCH(p,d,q) process has the infinite ARCH representation

$$\sigma^2{}_t = \omega(1 - \beta(B))^{-1} + \lambda(B) r^2{}_t \tag{7}$$

where the polynomial $\lambda(B)$is given by

$$\lambda(B)=\sum_{k=0}^{\infty}\lambda_k\ B^k=1-\big(1-\beta(B)\big)^{-1}\phi(B)(1-B)^d \tag{8}$$

The above expression shows how ${\sigma^2}_t$ evolves over time. The FIGARCH model has been applied to returns of stock market by Bollerslev and Mikkelsen (1996). For instance, the specific representation for the FIGARCH (1, d, 1) model in term of infinite order ARCH representation is given by:

$${\sigma^2}_t=\frac{\omega}{1-\beta_1}+\lambda_1(B){r^2}_t \tag{9}$$

where $\lambda_1(B)=\sum_{i=1}^{\infty}\lambda_{1,i}\ B^i$.

The ARCH coefficients in the lag operator polynomial $\lambda(B)$ have the recursive form

$$\lambda_{1,i}=\phi-\beta_1+d \tag{10}$$

for $i=1$ and

$$\lambda_{1,i}=\beta_1\lambda_{1,i-1}+\left[\frac{(i-1-d)}{i}-\phi_1\right]\delta_{i-1} \tag{11}$$

for $i=2,3,\cdots$ and where $\delta_i=\delta_{i-1}\frac{(i-1-d)}{i}$ being a recursive expression. For the FIGARCH (p, d, q) model, a general expression for the required parameter restrictions is not yet available, but, as Bollerslev and Mikkelsen (1996) note, the necessary restrictions for specific FIGARCH (p, d, q) models can be obtained on a case by case basis. For the FIGARCH (1, d, 1) model, these are

$$\beta_1-d\leq\phi\leq\frac{(2-d)}{3} \tag{12}$$

$$d\left[\phi-\tfrac{(1-d)}{2}\right]\leq\beta_1(\phi-\beta_1+d) \tag{13}$$

$$\phi_1=\alpha_1+\beta_1 \tag{14}$$

2.1. Statistical Inference

Parameter estimation of GARCH and FIGARCH model is commonly carried out by using the maximum likelihood method with normality assumption for ε_t. However, as mentioned by Kang *et al.* (2010) and Tang and Shieh (2006), the residuals estimated from the GARCH type model frequently exhibits lepto-kurtosis and asymmetry. To overcome these problems the Student-t distribution has been considered for the innovations process. Given the random variable $\varepsilon_t \sim t_v(0,1,v)$ the log-likelihood function is defined as follows:

$$\log(L;\Theta) = T\left\{\log\Gamma\left(\frac{\nu+1}{2}\right) - \log\Gamma\left(\nu/_2\right) - \frac{1}{2}\log[\pi(\nu-2)]\right\} - \sum_{t=1}^{T}\left[\log\sigma^2{}_t + (1+\nu)\log\left(1+\frac{\varepsilon^2{}_t}{\sigma^2{}_t(\nu-2)}\right)\right] \quad (15)$$

where $\Theta = (\omega, \alpha_1, \cdots, \alpha_p, d, \beta_1, \cdots, \beta_q)$. Matlab garchfit function has been used to estimate the parameters of the GARCH model. When fractionally integrated models are estimated, we need pre-sample values and a truncation lag of the infinite lag polynomial in conditional variances. In this study, the truncation lag is set to one thousand and the unconditional sample variance is used for all the pre-sample values as in Baillie *et al.* (1996). MFE Matlab toolbox of Sheppard (2013) has been used to estimate the parameters of the FIGARCH model. To identify the heteroscedasticity, long memory and volatility clustering nature of time series, we initially apply ARMA (1, 1)-FIGARCH (1, d, 1) to model the time series. We calculate conditional mean by using ARMA (1, 1) and conditional variance by using FIGARCH (1, d, 1) model; then the standardized residuals are calculated as follows.

$$\varepsilon_t = {}^{r_t}\!\big/\!\sqrt{\sigma_t} \quad (16)$$

3. The Copula Methodology

Copula-based models provide a great deal of flexibility in modelling multivariate distributions. This allows the researcher to specify the models for the marginal distributions separately from the dependence structure (copula) that links them to form a joint distribution. From an inferential perspective the copula representation facilitates estimation of the model in stages, reducing the computational burden.

Several surveys of copula theory and applications have appeared in the literature to date: Nelson (2006) and Joe (1997) are the most important text books on copula theory, providing detailed introductions to copulas and dependence modelling, with an emphasis on statistical foundations. Kurowicka and Joe (2011) represents an up-to-date survey on copula and vine-copula applications Cherubini *et al.* (2004) present an introduction to copulas using methods from mathematical finance, McNeil *et al.* (2005) present an overview of copula methods for risk management. Patton (2006) presents a summary of applications of copulas to financial time series. Jondeau and Rockinger (2006) proposed a GARCH-Copula approach to measure the dependence structure of stock markets. It is well known that the analysis of dependence analysis, especially of extreme events, plays a crucial role in financial applications such as portfolio selection, Value-at-Risk, and international asset allocation.

A copula model is a way of constructing the joint distribution of a random vector $X = (X_1, \cdots, X_m)$. It is possible to show that there always exists an m-variate function ***C***: $[0, 1]^m \to [0, 1]$, such that

$$\boldsymbol{F}(x_1, \cdots, x_m) = C(F_1(x_1), \cdots, F_m(x_m)) \quad (17)$$

The copula function C is a cumulative distribution function (CDF) with uniform margins on [0, 1]: it binds together the univariate cumulative distribution functions F_1, F_2, and F_m to produce the m-variate CDF ***F***. The three main properties are

i.) $C(x_1, x_2, \cdots x_m)$ is increasing in component x_i

ii.) $C(1, \cdots, 1, x_i, 1, \cdots, 1) = x_i \; for\ all\ \; i = 1, \cdots, m, x_i \in [0,1]$

iii.) For all $(a_1, \cdots, a_m), (b_1, \cdots, bm) \in [0,1]^m \; with\ a_i \le b_i$ one has

$$\sum_{i_1=1}^{2} \cdots \sum_{i_m}^{2} (-1)^{i_1+\cdots+\mathcal{B}_m} C(x_{1i_1}, \cdots, x_{mi_m}) \geq 0$$

where $x_{j1} = a_j \; and \; x_{j2} = b_j \; \forall \, j \; \in \{1, \cdots, m\}$

For any continuous multivariate distribution the copula representation is unique. If the marginal $F_1, \cdots, F_m$ are not all continuous it can be shown that the joint CDF still have a copula representation although this representation is not unique. In the continuous case one can take derivatives of both side of Equation (17), we get the density representation of ***F***:

$$\begin{aligned} f(x_1, x_2, \cdots, x_m) &= \frac{\partial^m F(x_1, \cdots, x_m)}{\partial x_1, \cdots, \partial x_m} \\ &= \frac{\partial^m C(F_1(x_1), \cdots, F_m(x_m))}{\partial F_1(x_1) \cdots \partial F_m(x_m)} \times f_1(x_1) \times \cdots \times f_m(x_m) \\ &= c(F_1(x_1), \cdots, F_m(x_m)) \times \prod_{i=1}^{m} f_i(x_i) \end{aligned} \quad (18)$$

where $c(u_1, \cdots, u_m)$ is the density of copula C, and $f_i(x_i)$ is the density of i-th margin. The joint use of GARCH and Copula models separates the temporal dependence, absorbed by the univariate GARCH structure, and the co-dependence among different variables, which is captured by the copula model.

3.1. Tail Dependence and Some Bivariate Copulas

In this paper, we use the copula approach to measure the tail dependence between the return and volume of East-Asian stock markets, so we keep focus on the two-dimensional case only. We can use the tail dependence coefficient to measure the concordance between the extreme events of different random variables. It is expressed in terms of a conditional probability that the asset X will incur a large loss (or gain), given that the asset Y also experiences a large loss (or gain). We consider two random variables X and Y, with joint continuous CDF ***F***, copula C and margins F_X; F_Y; the lower tail dependence and the upper tail dependence are defined as follows:

$$\lambda_L = \lim_{u \to 0^+} \Pr(F_X(x) < u) \,|F_Y(y) < u) = \lim_{u \to 0^+} \frac{C(u, u)}{u} \quad (19)$$

$$\lambda_U = \lim_{u \to 1^-} \Pr(F_X(x) > u) \,|F_Y(y) > u) = \lim_{u \to 1^-} \frac{1 - 2u + C(u, u)}{1 - u} \quad (20)$$

Intuitively, if λ_L and λ_U exist and fall in (0, 1], X and Y show lower or upper tail dependence. On the other hand, if λ_L and λ_U are equal to 0, one can say that the two variables are independent in the tails, so extreme events seem to occur independently. We can describe different tail dependence behaviour by choosing the appropriate copula model

3.1.1. Gaussian Copula and Student T-copula

These are symmetric and elliptical copulas. In the bivariate case the Gaussian copula is defined by the following expression:

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

$$= \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left\{-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right\} dsdt \qquad (21)$$

where $\Phi_\rho$the bivariate normal cumulative distribution function with linear correlation coefficient is $\rho \in [0,1]$, Φ is the standard normal cumulative distribution function and Φ^{-1} is its inverse function. We can see that the bivariate Gaussian copula density is symmetrical, so it has weak capability to capture asymmetrical dependence. It implies that if we go far into the tail, the extreme events tend to be independent, even though we choose a very high correlation. The t-copula is corresponding to a Student t distribution. It is defined by:

$$C_{\nu,\rho}^{t} = t_{\nu,\rho}(t_\nu^{-1}(u), t_\nu^{-1}(v))$$

$$= \frac{\Gamma(\frac{\nu}{2}+1)}{\Gamma(\frac{\nu}{2})\pi\sqrt{1-\rho^2}} \int_{-\infty}^{t_\nu^{-1}(u)} \int_{-\infty}^{t_\nu^{-1}(v)} 1 + \frac{-(s^2+2\rho st+t^2)}{2(1-\rho^2)} dsdt \qquad (22)$$

where $t_{\nu,\rho}$ is the CDF of a two-dimensional t distribution with ν degree of freedom and correlation ρ. The t-copula also has symmetric shape, upper and lower tail dependence is identical, and it is determined by ν and ρ. When ν gets large, then t-copula decays to a Gaussian copula. The expression of λ_L and λ_U follows:

$$\lambda_L = \lambda_U = 2T_{\nu+1}\left(\frac{\sqrt{(\nu+1)(1-\rho)}}{\sqrt{\rho+1}}\right) \qquad (23)$$

where $T_{\nu+1}$ is the CDF of the scalar Student t distribution with $\nu+1$ degrees of freedom (Demarta and McNeil, 2005).

3.1.2. Archimedean Copulas

Archimedean copulas are defined through their generator functions. Generally, if a function $\varphi: [0,1] \to [0,\infty]$ with the continuous derivative is decreasing and convex, it can be considered as a generator function of Archimedean copula. By definition an-dimensional Archimedean copula has the following expression: $C(u_1, u_2, \cdots, u_n) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2) + \cdots + \varphi(u_n))$, different generator function creates different Archimedean copula. More details about generator function can be found in Joe (1997) and Nelson (2006). In our case the copula function is defined by:

$$C(u,v) = \varphi^{-1}(\varphi(u) + \varphi(v)) \quad if\ \varphi(u) + \varphi(v) \le \varphi(0) \qquad (24)$$

where $\varphi(u)$ is a C^2 function with $\varphi(1) = 0$, $\varphi^{'} < 0, \varphi^{''} > 0$.

Examples of Archimedean copulas include the following:

- **Clayton Copula**

The Clayton copula has the following form:

$$C(u,v;\rho) = max[(u^{-\rho} - v^{-\rho} - 1,0)]^{-1/\rho} \qquad \rho \in (-1,+\infty) \setminus \{0\} \qquad (25)$$

Where is the dependence parameter$\lambda_L = 2^{-1/\rho}, \lambda_U = 0$. When $\rho \to 0$ the margins tend to be independent, oppositely when $\rho \to \infty$, the margins tend to be strongly dependent. Clayton copula is asymmetric and it shows stronger low tail dependence. It can be proved that the components of a Gaussian copula are asymptotically independent.

- **Frank Copula**

The Frank copula is defined by:

$$C(u,v;\rho) = -\frac{1}{\rho}\log\left\{\frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}-1\right\} \tag{26}$$

$$\rho \in (-\infty,0) \cup (0,+\infty)$$

Just like Gaussian copula, Frank copula is symmetric in both tails and it is not sensitive to the relationship between the extreme negative values or between the extreme positive values. There is strong dependence in the centre of the distribution. This means that Frank copula fails to capture tail dependence behaviour and it suggests that it is suited to use when the tail dependence is relatively weak.

- **Gumbel Copula**

The Gumbel copula is an asymmetric extreme value copula, which takes the following expression:

$$C(u,v;\rho) = \exp\left[\left(-\left(-\log u\right)^{\rho} + (\log v)^{\rho}\right)^{1/\rho}\right], \qquad \rho \in [1,\infty) \tag{27}$$

where ρ is a dependence parameter that describes different dependence behaviour, $\lambda_L = 0, \lambda_U = 2 - 2^{1/\rho}$. When $\rho \to \infty$ the margins show totally dependence, while ρ = 1 corresponds to independence case. Unlike the Clayton copula, Gumbel copula deals with upper tail dependence. If two margins perform simultaneous extreme upper tail values, the Gumbel copula should be an appropriate considerable choice.

3.2. Copula Parameters Estimation

Most of the methods for copula parameter estimation are related to Maximum Likelihood procedures. The standard ML method which estimates both marginal parameters and copula parameters simultaneously is also named one step method. Mashal and Naldi (2001) noted that this method is computational costly, and when the data sets are not sufficiently large, the ML estimators seem to be ineffective. The inference function for margins method (IMF) is based on the work of Joe and Xu (1996). The estimation procedure is split in two steps; first one estimates the parameters of the marginal distributions. In the second step one tries to estimates of the copula parameters, conditionally on the values of estimates obtained at the first step. This approach offers computational convenience, although it may be sensitive to the choice of marginal distributions form. A poor estimator of the copula parameter might be a consequence of an inappropriate marginal distribution. There is also an alternative, two steps method, named Canonical Maximum Likelihood (CML). Unlike IMF method, in the 'CML' approach the transformation is done by using empirical CDF function to obtain uniform margins, which are used in copula parameters estimation.

Given two time series $\{X\}_{t=1}^{T}$ and $\{X\}_{t=1}^{T}$, let Ω be the parameter space, $a_x \in \Omega, a_y \in \Omega$ denote marginal parameters for X and Y, while $\theta \in \Omega$ denotes copula parameters. From Equation (18), the log maximum likelihood function can be obtained as:

$$(a_x, a_y, \theta; X, Y) = \sum_{t=1}^{T} lnc\big(F_X(x_t; \alpha_x), F_Y\big(y_t; \alpha_y\big); \theta\big)$$

$$+\sum_{t=1}^{T}(lnf_X(x_t; \alpha_x) + lnf_y(y_t; \alpha_y)) \tag{28}$$

Here we sketch the necessary inferential steps.

- **Step 1**

Estimating parameters of the marginal distributions, a_x and a_y.

$$\hat{\alpha}_x = arg\max_{\alpha_x} \sum_{t=1}^{T} lnf_X(x_t, \alpha_x) \tag{29}$$

$$\hat{\alpha}_y = arg\max_{\alpha_y} \sum_{t=1}^{T} lnf_Y(y_t, \alpha_y) \tag{30}$$

- **Step 2**

Estimating the copula parameters by using the estimator $\hat{\alpha}_x$ and $\hat{\alpha}_y$ obtained in step 1.

$$\hat{\theta} = \operatorname{argmax}_{\theta} \sum_{t=1}^{T} lnc(F_X(x_t; \hat{\alpha}_x), F_Y\big(y_t; \hat{\alpha}_y\big); \theta) \tag{31}$$

The copula parameters were estimated by employing the maximum likelihood method described in Equation (31). For the IMF estimation, a MATLAB copula toolbox written by Patton (2008) has been used.

4. Empirical Studies and Analysis

4.1. Primary Data Analysis

In empirical studies, we choose daily prices and corresponding trading volume series of four indices, Hong Kong Seng Index (HKSE), India (BSE), Indonesia Composite Index (JKSE) and Bursa Malaysia KLCI (FTSE). HKSE ranges from July 9, 2001 to August 2, 2013, BSE data ranges from July 14, 2003 to July 19, 2013, JKSE ranges from October 19, 2000 to August 2, 2013 and FTSE ranges from April 28, 1998 to July 19, 2013. Data have been obtained from the Yahoo Finance Website. Figure 1 illustrates the relative price movements of each index. We take the daily log returns defined as $R_t = 100 \times \log\left({}^{p_t}/_{p_{t-1}}\right)$ which can be seen in Figure 2.

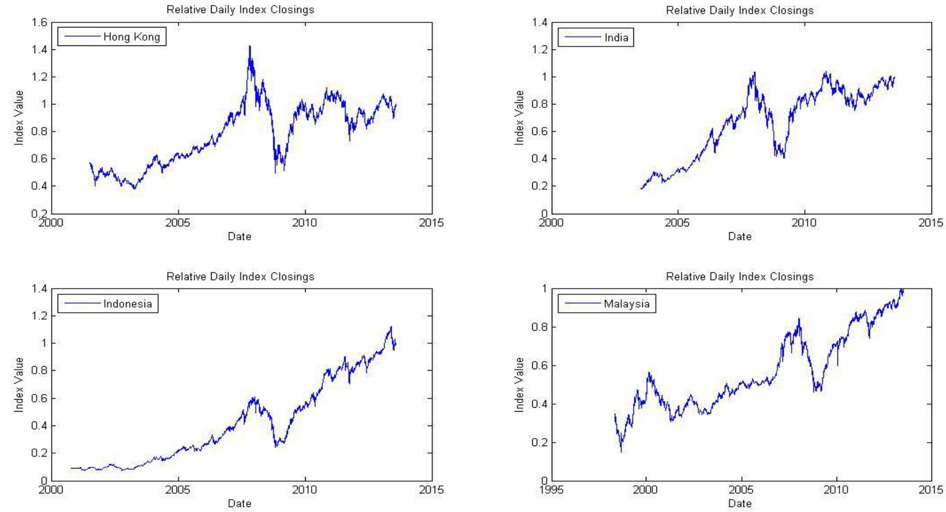

Figure 1. Daily closing prices of each index

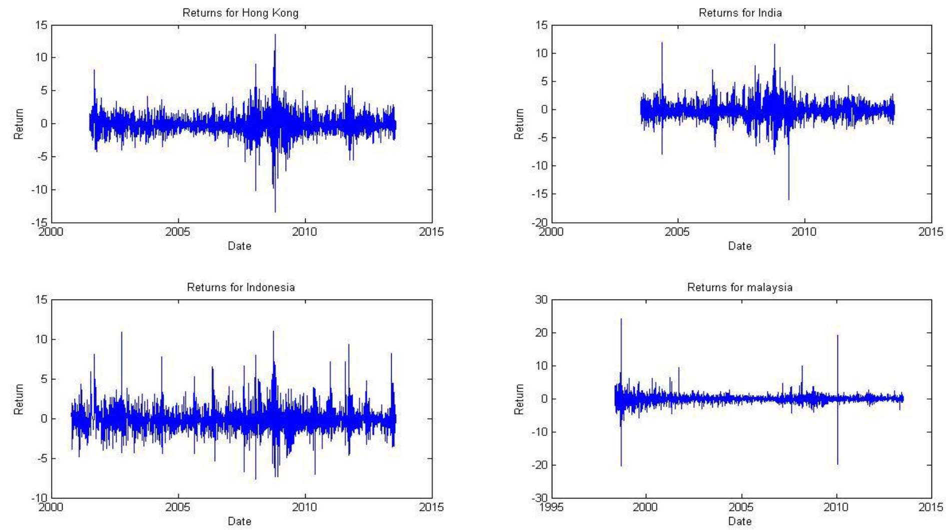

Figure 2. Logarithm Return of each index series

We have deleted all holidays from the data. The preliminary descriptive statistics of the data are presented in Table 1. Hodrick and Prescott (1997) filter have been used to remove the trend from the log-volume series. As shown in Table 1, the kurtosis of each index is greater than 3 and the skewness is not zero, which both suggest that presence of fat tails and leptokurtosis.

Table 1. Descriptive statistics of the sample data

Descriptive Statistics	**Hong Kong**	**Indonesia**	**India**	**Malaysia**
observation	2967	2480	2845	3729
mean	0.0188	0.0681	0.0842	0.0285
std	1.5732	1.6394	1.5341	1.3536
max	13.5820	11.8092	10.95	24.15
min	-13.40	-15.99	-7.6234	-20.25
skewnss	-0.0145	0.0695	0.7950	0.4513
kurtosis	11.65	10.81	9.39	79.05
Jarque-Bera	9257	6309	5141	8985
Q(20)	36.11*	44.55*	62.14*	115.88*
ARCH-LM	896.8*	298.9*	334.9*	1541*
Adjusted Volume				
mean	0.0000	0.0000	0.0000	0.0000
std	0.3217	0.3038	0.5505	0.4377
skewnss	0.2754	-0.4885	-0.1973	0.0125
kurtosis	4.3232	20.50	14.47	4.6440
Jarque-Bera	253.94	3177	1562	413.28
Q(20)	1968*	1098*	1193*	5288*
ARCH-LM	122.28*	36.55	187.43	1513*

Notes: Table 1 shows Jarque-Bera is 2 statistics for the test of normality. Q (20) is the Ljung-Box statistic for serial correlation in the return and adjusted volumes computed with 20 lags. ARCH-LM is the Engel's LM test for heteroscedasticity, conducted using 20 lags.
* A rejection of the null hypothesis at 5% level.

The order for the ARMA part has been chosen, after careful inspection of ACF and PACF of both return and de-trended volume series. Parameter estimation for negative return and volume are reported in Table 2. One motivation for using ARMA-GARCH type model is the inspection of ACF of return and volume and ACF of squared return in Figure 3. After performing ARCH test over the series of residuals we proceed with the selection of order of GARCH model. Here we have applied FIGARCH and GARCH type models for return and de-trended volume series respectively. One purpose of this study is to show that FIGARCH model is robust for stock index returns. Therefore, long memory should also be considered in the volatilities of indices return, when the dependence between them is estimated. Further, residuals and squared residuals series do not possess significant autocorrelation for both return and volume series as it can be seen in Figures 4 and 5.

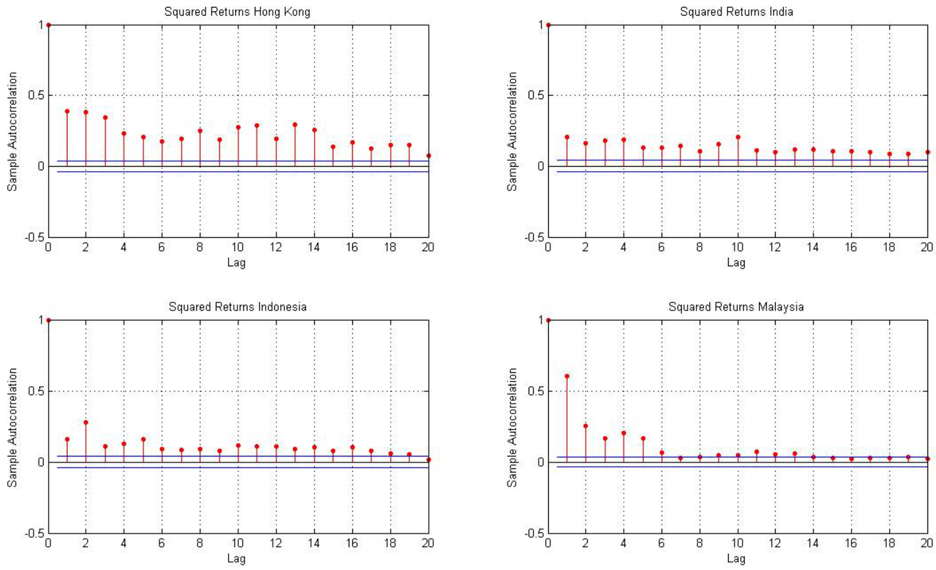

Figure 3. Autocorrelation of squared returns

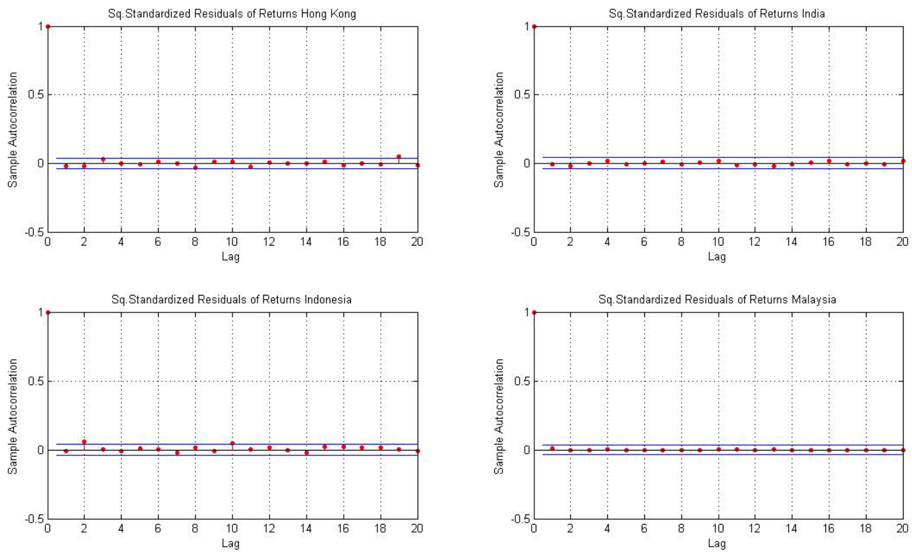

Figure 4. ACF of squared standardized residuals of returns

The test shows that residuals are approximately i.i.d series, therefore copula approach can be applied to the residuals after getting student t CDF from the residuals. We use FIGARCH and GARCH model to fit the marginal distribution of each return and each volume series. Estimated parameters for each type of model are given in Table 2.

Table 2. Parameter estimation of GARCH and FIGARCH model

	GARCH for Volume				FIGARCH for Negative Returns			
Parameters	Hong Kong	India	Indonesia	Malaysia	Hong Kong	India	Indonesia	Malaysia
Mean Equation								
M	-0.0023 (0.0049)	-0.0053 (0.0041)	0.0056 (0.0050)	0.000039 (0.0045)	0.0770** (0.0378)	0.1560*** (0.0389)	0.1466*** (0.0290)	0.0222** (0.0091)
ϕ_1	0.4268*** (0.0194)	0.3883*** (0.0205)	0.4540*** (0.0190)	0.6682*** (0.0121)	-0.5103 (0.3150)	-0.2306 (0.1467)	0.0591 (0.1111)	0.4160*** (0.0519)
Variance Equation								
Ω	0.0681*** (0.0169)	0.0385*** (0.0047)	0.0217*** (0.0033)	-0.0174*** (0.0068)	0.1261*** (0.0014)	0.1534*** (0.0024)	0.3485*** (0.0107)	0.0999*** (0.0004)
α_1	0.1005*** (0.0277)	0.1940*** (0.0450)	0.3315*** (0.0506)	0.2805*** (0.0396)	0.0012 —	0.1368*** (0.0027)	0.0000 —	0.0002 —
D	— —	— —	— —	— —	0.8637*** (0.0014)	0.6692*** (0.0066)	0.4739*** (0.0253)	0.4619*** (0.0043)
Β	0.0000 (0.2253)	0.2011** (0.0792)	0.6406*** (0.0300)	0.9927*** (0.0029)	0.8649*** (0.0007)	0.7181*** (0.0031)	0.3289*** (0.0250)	0.2358*** (0.0048)
γ_1	— —	— —	— —	0.0529** (0.0268)	— —	— —	— —	— —
Ν	9.3698*** (1.0901)	4.2837*** (0.2716)	3.3039*** (0.1716)	7.0208*** (0.7216)	7.8579*** (1.2096)	10.4999 (6.8571)	4.8739*** (0.2674)	4.7815*** (0.1470)

Notes: Table 2 reports the estimated parameters for FIGARCH and GARCH models for returns and volumes respectively, together with standard errors (in parentheses).
* indicates significance at 10% level.
** indicates significance at 5% level.
*** indicates significance at 1% level.

4.2. Marginal Distribution Models

ARMA(1,1)-FIGARCH(1,1) models were estimated for all negative return[1] series by selecting lag order for mean equation by the inspection of ACF and PACF, maintaining the conditional variance equation as FIGARCH(1,1) model. Further, AR (p)-GARCH (1, 1)-t models have been applied to volume series except Malaysia. AR-EGARCH (1, 2)-t[2] model was estimated for Malaysia volume series. MATLAB function 'garchfit' has been used to estimate the parameters of the GARCH model and MFE MATLAB toolbox of Sheppard (2013) has been used to estimate the parameters of the FIGARCH model. Parameters estimates can be seen in Table 2. We can see clear evidence of long memory in return series. In Table 2 most of the coefficients in the conditional variance equation are significant. Engle's ARCH test has been applied to the square of the standardized residuals. The test fails to reject the null hypothesis of no ARCH effect[3].

[1] ARMA (1, 1)-FIGARCH (1, 1) models were estimated for all return series as well and similar kind of estimates have been obtained except for intercept parameter. Estimated MA (1) parameter for negative return has not been mentioned due to space restriction.
[2] AR(1) and AR(2) parameters have also been estimated for volume series
[3] Results of the test will be provided upon request

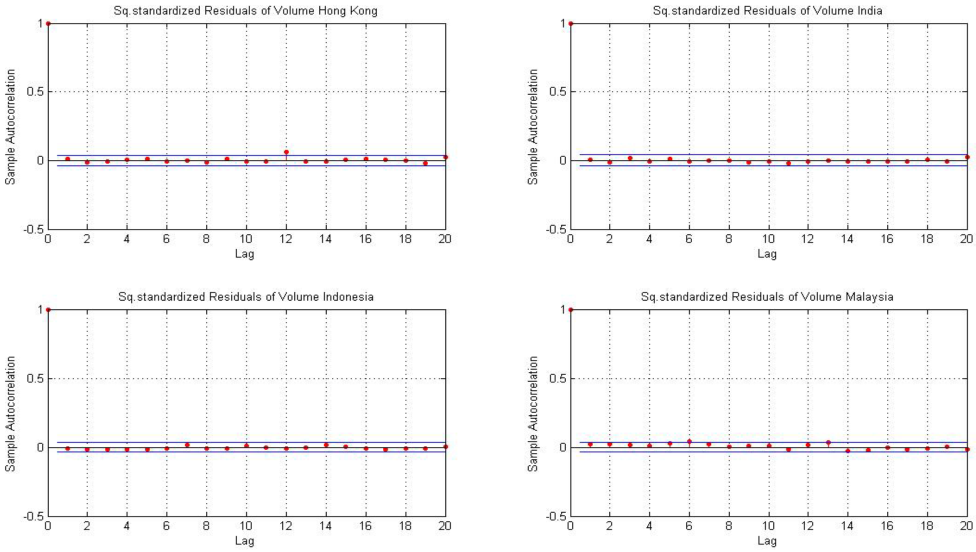

Figure 5. ACF of squared standardized residuals of volumes

4.3. Copula Parameter Estimation

We are interested in the dependence structure between the stock returns and trading volume in four Asian stock markets, our main goal being to explore the extreme dependence between return and volumes. We employed six copulas in our analysis, the first three, namely, Gaussian, Student-t, and Frank copula, are symmetric and they have been used to analyse the dependence structure between each pair of return and volume. The other three have been used to analyse the dependence between return and volume, as reported in literature (Karpoff, 1987; Gervais *et al.* 2001). The asymmetric copulas are able to capture potential difference between lower and upper tail. The parameter estimates for each copula have been reported in Table 3. Based on Akaike information criterion (AIC), we notice that FIGARCH-Copula model improves the results. We also found that FIGARCH-Copula approach performs better in most cases (16 out of 21) and produce relatively smaller values of AIC. As one can see from Table 2, the long memory parameters are significant for all return series. Malaysia stock index exhibits small negative relationship between return and trading volume and the parameter estimates of Gaussian , Student-t and Frank copula vary from -0.0957 to -0.8723.Only for Indonesia the parameters of Student-t and Frank copulas suggest a negative relationship.

Now we focus on the potential asymmetry in the return-volume dependence by adopting Clayton, Survival Clayton and Gumbel copulas. We can see from Table 3 that the parameters of the Clayton copula are never significant; it suggest that absence of lower tail dependence. It implies that extremely low returns are not associated with low volumes. At the same time, the parameters of the Survival Clayton copula are highly significant for all pairs except Indonesia. Further, if we check the parameters of the Gumbel copula, then all the parameters are found to be significant for all pair of return and volume except for Malaysia. The upper tail dependence coefficients for Gumbel and Survival Clayton copula are reported in Table 4, which have been extracted from the FIGARCH-Copula model.

Table 3. Copula estimates of return-volume dependence with GARCH and FIGARCH model

	Hong Kong		India		Indonesia		Malaysia	
	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH
Gaussian copula								
P	-0.0041 (0.0239)	-0.0039 (0.0242)	0.0334 (0.0300)	0.0327 (0.0310)	-0.0506 (0.0437)	-0.0542 (0.0509)	-0.0957*** (0.0261)	-0.0964*** (0.0255)
AIC	-0.0482	-0.0446	-2.7238	-2.6097	-7.2261	**-8.3383**	-34.1326	**-34.6889**
Student-t copula								
ρ	-0.0153 (0.0202)	-0.0138 (0.0205)	0.0364 (0.0302)	0.0352 (0.0307)	-0.1126*** (0.0337)	-0.1236*** (0.0346)	-0.1502*** (0.0242)	-0.1495*** (0.0240)
v	6.7681*** (1.2701)	6.3937*** (1.1314)	11.2445*** (3.7593)	9.1431*** (2.6547)	4.3172*** (0.5858)	3.7360*** (0.4126)	4.9514*** (0.6747)	5.1185*** (0.7027)
AIC	-30.5138	**-33.1406**	-14.0640	**-17.7768**	-67.9657	**-85.3632**	-97.9460	-96.3768
Frank Copula								
ρ	-0.1015 (0.1248)	-0.0884 (0.1255)	0.1538 (0.1514)	0.1569 (0.1565)	-0.6898*** (0.1632)	-0.8065*** (0.1661)	-0.8723*** (0.1211)	-0.8663*** (0.1313)
AIC	1.3948	**1.5470**	-0.9757	**-0.9815**	-10.8776	**-13.6504**	-40.4320	**-40.5348**
Clayton Copula								
ρ	0.0001 —	0.0001 —	0.0203 (0.0141)	0.0201 (0.0142)	0.0001 —	0.0001 —	0.0001 —	0.0001 —
AIC	—	—	-0.7778	-0.7069	—	—	—	—
Survival Clayton Copula								
ρ	0.1572*** (0.0268)	0.1619*** (0.0270)	0.1227*** (0.0346)	0.1305*** (0.0350)	0.0337 (0.0331)	0.0438 (0.0369)	0.0182*** (0.0244)	0.0237 (0.0242)
AIC	-43.6003	**-44.3778**	-16.3331	**-17.8246**	-0.9241	**-1.2409**	-0.5794	**-1.0065**
Gumbel Copula								
ρ	1.0585*** (0.0140)	1.0610*** (0.0142)	1.0514*** (0.0180)	1.0562*** (0.0183)	1.0171*** (0.0181)	1.0243*** (0.0206)	1.001*** (0.0132)	1.0001*** (0.0130)
AIC	-23.570	**-24.6900**	-7.5234	**-9.0032**	1.0032	0.6043	1.8184	**1.8410**

Notes:Table 3 reports the estimates of parameters of six copulas for each pair of return and volume, together with standard errors (in parentheses) and the values of Akaike Information Criteria(AIC).
*** indicates significance at 1% level.

We can see from Table 4 that AIC of Survival Clayton copula is significantly small. For Hong Kong there exists upper tail dependence for both copulas parameters, but for Gumbel it is only 7.8%, when Survival Clayton exhibits only 1.3% upper tail dependence. Similar results have been found for India, upper tail dependence exists but relatively weak in both copulas. Furthermore, for Indonesia and Malaysia there is no significant evidence that the upper tail coefficients are different from zero. Only Hong Kong and India extremely large returns are accompanied with extremely high volumes, Market booms are followed by large number of transactions. But this relation is not so strong, the probability that trading volume will be extremely high is relatively small (not more than 10%). On the other hand for Malaysia and Indonesia extremely high return and extremely high volume are independent. High returns do not strongly effects volumes in these two stock markets.

Table 4. Upper tail dependence coefficients for return and volume

	Gumbel		SC	
	λ_U^G	AIC	λ_U^{SC}	AIC
Hong Kong	0.0781	-24.6900	0.0138	-44.3778
India	0.0724	-9.0032	0.0049	-17.8246
Indonesia	0.0326	0.6043	0.0000	-1.2409
Malaysia	0.0001	1.8410	0.0000	-1.0065

Notes: Table 4 reports the upper tail dependence coefficients, calculated from the Gumbel copula $\lambda_U^G = 2 - 2^{1/\rho_G}$ and Survival Clayton Copula $\lambda_U^{SC} = 2^{-1/\rho_{SC}}$ by taking parameters from Table 3.

Considering the unusually weak negative relationship between return and volume which is captured by Gaussian, Student-t and Frank copulas (see Table 3) for Hong Kong, Malaysia and Indonesia, we also investigated each pair of negative return and volume to explore whether the extremely high volumes are associated with extremely low returns. The procedure is exactly the same as the one we employed for return-volume series, the results are reported in Table 5 and 6. Since the first three copulas have a symmetric structure and we just change the sign of returns, the absolute value of the estimated parameters of the elliptic copulas does not change; also the changes in Frank copula are negligible. Comparing the AIC, similar results have been found, the FIGARCH-Copula dominates the GARCH-Copula again (16 out of 22). Our estimates for Clayton copula are insignificant except for Indonesia. Extremely low trading volume shows independent behaviour for both extremely high return and extremely low return in these four countries. Survival Clayton and Gumbel copulas estimated parameters are highly significant for Hong Kong, Indonesia and Malaysia, while only the Survival Clayton copula parameter is significant for India. Upper tail dependence coefficients extracted from these two copulas are reported in Table 6. For Hong Kong and India upper tail dependence is relatively weak. Conversely, as we mentioned before, Indonesia and Malaysia exhibit strong tail dependence, 19% and 17% respectively.

This provides evidence that in these two countries extremely high volume are likely to be associated with extreme low return. In other words, market stress or in crisis are accompanied by high trading volumes. These results are not consistent with the finding for US market, which have been reported in Balduzzi *et al.* (1996) and also opposite to what Ning and Wirjanto (2009) obtained for East-Asian markets. Their work shows that high volumes are positively dependent with high returns and they did not find evidence on upper tail dependence between negative return-volume. The past empirical research on return-volume relation has specified some characteristics, such as an asymmetric positive correlation between absolute stock returns and trading volume, as asymmetry implies that high trading volume involves in price increasing rather than decreasing. There is no theoretical explanation to this asymmetric relation yet. Jenning *et al.* (1981) and Karpoff (1988) proposed a costly short-sale constraint hypothesis as a generally considerable explanation. They argued that transactions on short positions require higher cost than on long positions, and this may generate an asymmetric relation. However, this hypothesis has been rejected by Puri *et al.* (2008). In their paper they investigated volume-return relation in LIFFE futures market, where the correlation also exhibits an unexpected asymmetric behavior. If the costly short-sale hypothesis was true, this correlation should be symmetric in futures market, since such costly short-sale restriction does not exist in future markets. It implies that the costly short-sale do not explain relatively stronger positive return-volume dependence on upper tail in stock markets appropriately.

Table 5. Copula estimates for negative return-volume dependence

	Hongkong		India		Indonesia		Malaysia	
	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH	GARCH	FIGARCH
Gaussioan copula								
ρ	0.0041 (0.0239)	0.0039 (0.0242)	-0.0334 (0.0300)	-0.0326 (0.0310)	0.0506 (0.0437)	0.0542 (0.0509)	0.0957*** (0.0260)	0.0964*** (0.0255)
AIC	-0.0482	-0.0446	-2.7238	-2.5957	-7.2262	**-8.3261**	-34.1011	**-34.8670**
Student-t copula								
ρ	0.0153 (0.0202)	0.0138 (0.0205)	-0.0364 (0.0291)	-0.0352 (0.0307)	0.1126*** (0.0337)	0.1236*** (0.0346)	0.1499*** (0.0241)	0.1495*** (0.0240)
v	6.7681*** (1.2715)	6.3937*** (1.1296)	11.2445*** (3.4241)	9.1434*** (2.6498)	4.3172*** (0.5860)	3.6872*** (0.4412)	5.0184*** (0.6918)	5.1185*** (0.7077)
AIC	-30.5138	**-33.1406**	-14.0640	**-17.7768**	-67.9657	**-86.8620**	-98.8090	-96.3768
Frank Copula								
ρ	0.1015 (0.1248)	0.0885 (0.1255)	-0.1538 (0.1514)	-0.1568 (0.1529)	0.6900*** (0.1632)	0.8065*** (0.1661)	0.8968*** (0.1210)	0.8663*** (0.1203)
AIC	1.3948	**-0.4524**	-0.9757	1.0176	-12.8771	**-15.6497**	-42.3746	**-45.5343**
Clayton Copula								
ρ	0.0001 —	0.0001 —	0.0001 —	0.0001 —	0.0931*** (0.0368)	0.1464*** (0.0382)	0.0399 (0.0275)	0.0240 (0.0268)
AIC	—	—	—	—	-3.7861	**-8.0783**	-1.1809	-0.4404
Survival Clayton Copula								
ρ	0.1762*** (0.0258)	0.1734*** (0.0259)	0.0307 (0.0293)	0.0366 (0.0300)	0.2572*** (0.0356)	0.2896*** (0.0362)	0.3015*** (0.0274)	0.3035*** (0.0270)
AIC	-47.7393	-47.4601	-1.0908	**-1.4467**	-40.0647	**-45.6977**	-114.5395	**-119.7785**
Gumbel Copula								
ρ	1.0689*** (0.0142)	1.0699*** (0.0143)	1.0044*** (0.0159)	1.0090*** (0.0163)	1.1422*** (0.0214)	1.1650*** (0.0222)	1.1518*** (0.0165)	1.1517*** (0.0163)
AIC	-29.0940	**-29.7814**	1.9254	**1.6960**	-45.5840	**-54.2021**	-102.9023	**-106.4146**

Notes: Table 5 reports the estimates of parameters of six copulas for each pair of negative return and volume, together with standard errors (in parentheses) and the values of Akaike Information Criteria (AIC). ***indicates significance at 1% level.

Our study also provides an evidence for rejecting the costly short-sale hypothesis, since we found strong dependence between the high volumes and low returns in Malaysia and Indonesia stock markets. The leverage effect can be considered as an appropriate explanation for these two emerging Asian markets. Here leverage effect is referred to an asymmetric negative correlation between stock return and the volatility. As we have already explained that the volumes are positively associated with volatility, and further extreme low return are also positively associated with volatility. In our case, the extremely negative returns are positively associated with volumes and it results in a persistent high volatility and it increases the risk of markets. Our finding suggest that, these two markets impacted seriously in crisis, when the prices falls significantly the traders perform relatively stronger sensitivity to risk and choose more transactions to avoid risk rather than holding stocks. In these two markets traders are more sensitive to bad news rather than good news.

Table 6. Upper tail dependence coefficients for negative return and volume

	Gumbel		SC	
	λ_U^G	AIC	λ_U^{SC}	AIC
Hong Kong	0.0886	-29.7814	0.0184	-47.4601
India	0.0123	1.0960	0.0000	-1.4467
Indonesia	0.1870	-54.2021	0.0913	-45.6977
Malaysia	0.1745	-106.4146	0.1112	-119.7785

Notes: Table 6 reports the upper tail dependence coefficients, calculated from the Gumbel copula $\lambda_U^G = 2 - 2^{1/\rho_G}$ and Survival Clayton Copula $\lambda_U^{SC} = 2^{-1/\rho_{SC}}$ by taking parameters from Table 5.

5. Conclusion

We have analyzed the dependence structure between return-volume and negative return and volume. Our analysis was based on modeling dependence structure via FIGARCH-Copula and GARCH-Copula models. We have used both tail independent and tail dependent copulas. Our aim was to explore upper tail dependence between Return-Volume and negative return and volume by FIGARCH-Copula and GARCH-Copula models and further to see which model is more adapt for copula parameter estimation. Based on Akaike information criterion (AIC), we found that using FIGARCH model for return series improves the results of copula parameter estimation. The weak upper tail dependence between Return and Volume has been found in Hong Kong and Indian stock indices. We have found that a large negative return for Malaysia and Indonesia stock indices is followed by high volumes, providing evidence of leverage effect.

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