Measuring Interdependence and Contagion: A Copula Approach

Samia Ben Messaoud* and Chaker Aloui**

Determining financial crises is a hard procedure to do. Financial crises are still examine an essential phenomenon known for its international influence and scope and its propagation indistinctively across developed and developing countries. There is no apparent consensus among researchers as to the adequate approach to adopt in order to test out contagion. In this paper, we develop a contagion-assessment model. We analyse the extreme dependence structure, stemming from the characteristics of the financial-asset model to which we propose to add the copula functions in order to take into consideration the dependence structure present among the various increments. Moreover, we analyse the dependence relationship existing between financial markets productivity. To this end, we consider the student-copula. This work shows nature of tail dependence which is an important dimension of contagion. Here, we propose to develop a contagion-assessment model.

Keywords: Financial Crises, Contagion, Copulas.

1. Introduction

In view of better allocating assets and managing risk, the main issue remains whether financial markets become more independent during financial crises. During the last five financial crises of the 1990s, this topic attracted much attention. The underlying premise for these events is that turmoil in one market tends to inexplicably spread to several other markets and countries as viewed in a change in fundamentals of these markets. Media and the relevant literature tend to use the term ‘contagion’ whenever this phenomenon is raised and which is qualified by a recent seminal paper as “a considerable increase of inter-markets links after a shock”. Studying financial contagion during the 1990s is done especially around the concept of “correlation breakdown” (correlations are much more conspicuous in periods of market turndown”), i.e. a significant statistical increase of correlation during the turmoil period. Among the studies which dealt with this issue, we can mention those of Bertero and Mayer (1989) and those of King and Wadhwani (1990), which attested for an increase in correlation of stock returns during the 1987 depression.

Modeling the co-movement of stock market returns is a difficult assignment. The crucial argument is that the conventional measure of interdependence, such as correlation, might not describe the difference between negative and positive returns, and also the correlation estimate is based on a linear association between financial return series under consideration while their linkages may well take nonlinear causality forms. In order to overcome this problem, we propose to apply the Copulas approach as a Solution.

In this paper, we endeavour to examine the dependence between the exchange rate returns and equity returns, by applying a relatively new method: copulas. The methodology used in this paper differs in a fundamental manner from most of the approaches used in

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the literature in interpreting dependence between the financial markets. This work also deals on the problem of interactions between financial markets. For this purpose, we use the student copula functions combined with C-GARCH models. First, copulas allow us to segregate model the dependence structure and the marginal behavior. This property gives us more choices in estimation. Second, the copula function can provide us the structure of the dependence. It used for the asymmetric dependence and tail dependence. The correlation function does not deliver the information about the symmetry property of the dependence. As a result, the copulas function is advantageous when modeling the dependence between asset returns. We wait that this paper will also ameliorate our understanding of risks associated with the extreme events.

Therefore, we have employed the model of Malevergne and Sornette (2004). Through this approach, we undertake to analyse the extreme dependence structure.

The remainder of this article is organized as follows. Section 2 provides a brief review of the existing methods. Section 3 introduces the empirical framework used to examine the extent of interdependence and contagion among the selected emerging markets. Section 4 describes the data and reports the empirical results. Concluding remarks are provided in Section 5.

2. Literature Review

Contagion studies based on change in correlation structures have been discussed by Boyer, Gibson and Loretan (1999). The authors showed that conditional heteroskedasticity-insensitive tests conducted on correlation change risk being too much biased. Computing correlation between two extreme outputs-conditioned random variables would probably lead to strong correlation during a downward market period, though observable data treatment retains a constant correlation. Forbes and Rigobon (2000) generalized and applied Boyer et al's approach (1999) to study three key crises (the 1987 depression, devaluation in Mexico and South-East Asian crisis). After adjusting for heteroskedasticity, they failed to point to a correlation breakdown in any of the three crises. The authors concluded on the absence of contagion. The phenomenon defined as contagion was but a simple temporal continuation of excessive dependence-driven volatility among international markets, which existed in stable periods.

As shown by Dungey and Zhumabekova (2000), contagion tests may be seriously affected by the extent of «crises» and “stable” periods. Nelsen (1999) defines copulas as “functions that federate or link multivariate distribution functions to one-dimensional marginal distribution functions”. Copulas contain all information on the dependence structure of a random variables-based vector. They can detect a non-linear dependence within random variables, whereas correlation is just a measure of linear dependence.

Specifically, copulas contain information on the joint behaviour of random variables within a distribution tail. This should be emphasised in any study examining contagion during financial crises. Moreover, copulas are able to detect tail behaviour without using discretion to define extreme outputs. Rodriguez (2007) conducted a study to see whether financial crises may be qualified as periods of change of inter-markets dependence structure. The author modelled dependence structure as a mixture of copulas, with parameters that change through time consistent with a regime-change markov model. The model enables copula parameters to change according to variance to identify change in dependence structure during a crisis period.
These results contribute to the ongoing debate on contagion. They show that periods of financial turmoil translate dependence. Nevertheless, and although general dependence is increasing, tail dependence models differ markedly from each other for all markets.

Other studies which focused on joint stock markets movements have been conducted by Longin and Solnik (2001), and Forbes and Rigobon (2002).

Empirical studies treating interaction and causality between stock price and exchange rate yielded mixed results (positive and negative correlation, presence or absence of causality, a one-way or two-way causality). Ning (2010) examined dependence between stock returns and exchange rate returns, using a relatively new technique known as copulas.

Ning (2010) pointed to significant tail dependence for the bond/currency pair and to important implications for risk management and assets pricing. First, tail dependence points to great losses for both international exchange and stock markets. Second, it enables investors to simultaneously measure probability of extreme losses. Finally, it should as well affect assets prices.

All these methods argue that the exchange rate effects the stock market and vice versa. Empirical studies of the interaction relationship between the exchange rate and the stock price conduct to mixed products (negative correlation, positive correlation, non existence or existence of causality).

Our methodology in this paper greatly differs from several normally used methods in the literature to examine dependence between financial markets. We use dependence and joint movements interchangeably in the remaining of this paper.

The aim of this paper is to contribute to improving our comprehension of extremes-associated risks. Accordingly, our results may lead to revising assets pricing models by reducing tail dependence.

3. Empirical Method

In this paper, our methodology consist to estimate tail dependence coefficient using semi-parametric models with a factor linking the variables marginal distribution and tail copula-estimating non-parametric models and to which we added copula functions to consider dependence structure between variables.

3.1 Estimation of Tail Dependence

Let X, Y be random variables with marginal distribution functions $F_X$ and $F_Y$. Then the coefficient of upper tail dependence $\lambda_u$ is:

$$\lambda_u = \lim_{\mu \to -\infty} \text{Pr}\{X > F^{-1}_X(\mu) \mid Y > F^{-1}_Y(\mu)\}$$

This quantifies the probability of detecting a lower Y assuming that X is itself lower. Such, the coefficient of lower tail dependence $\lambda_l$ can be defined as:
There is asymmetric tail dependence between two variables when the lower tail dependence coefficient equals the upper one, otherwise it is asymmetric. The tail dependence coefficient provides away for ordering copulas.

3.2 Copula Functions

During this last decade, copulas have become a standard tool frequently cited in the literature that examines dependence and survival models, and notably in the area of credit risk (Li, 2000, Hamilton, 2002 and Patton 2006), as well as evaluation of by-products.

3.2.1 A Mathematical Introduction of Copulas Models

A copula is a modeling tool of dependence structure between several random variables. Knowing this probabilistic tool is essential to understand the several application domains of quantitative finance like credit multiple risk measurement, structured credits products evaluation and market multiple risk measurement.

Bivariate copula $C$, function of $[0, 1]^2 \rightarrow [0, 1]$ is defined by the following characteristics:

i) $C(u, 0) = C(0, u) = 0 \cdot \forall u \in [0, 1]$  

ii) $C(u, 1) = C(1, u) = u \cdot \forall u \in [0, 1]$  

iii) $C(u_1, u_2) = P(U_1 \leq u_1, U_2 \leq u_2) \forall (u_1, u_2) \in [0, 1]^2$  

Margins of marginal distributions are uniform margins.

**Theorem:** Sklar’s Theorem

Assume $H$ a distribution function in $n$ dimensions having marginals $F_1, F_2, \ldots, F_n$.

Then, there exists an n-copula $C$ such that for $x \in [-\infty, \infty]^n$

A copula is then determined either *ex-nihilo* through definition 1.1, or through an existent bivariate law.

In this case, the Sklar’s Theorem, named after his author who introduced the concept of copula in 1959, is called upon. This theorem determines the link defined by copula $C$, determined through the joint distribution $F$, between univariate marginal distribution functions $F_1$ and $F_2$ and bivariate complete distribution $F$.

The theorem: suppose $F$ a bivariate distribution with margins $F_1$ and $F_2$. The copula $C$ associated to $F$ is written:
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\[ C(u_1, \ldots, u_d) = C(F_1(x_1), F_2(x_2), \ldots, F_d(x_d)) \]
\[ = F(F_1^{-1}(x_1), F_2^{-1}(x_2), \ldots, F_d^{-1}(x_d)) \]
\[ = F(x_1, x_2, \ldots, x_d) \]  

(6)

C is unique when the margins \( F_1 \) and \( F_2 \) are continuous.

The density \( f \) of a bivariate law may be written also as a function of density \( c \) of the associated copula and density of margins \( f_1 \) and \( f_1' \).

\[ f(x_1, x_2) = c(F_1(x_1), F_2(x_2)) \]  

(7)

This copula is unique if the margins are continuous.

### 3.2.2 The Copula Model

#### Student Copula

Student copula is defined as follows:

\[ C(u_1, u_2; \rho, k) = T_{\rho,k}(T_k^{-1}(u_1), T_k^{-1}(u_2)) \]  

(8)

\[ t_{\rho,v}(x, y) = \int_{-\infty}^{x} \int_{-\infty}^{y} \frac{1}{2\pi \sqrt{1-\rho^2}} \left( 1 + \frac{s^2 + t^2 - 2\rho st}{\nu(1-\rho^2)} \right)^{-\frac{\nu+2}{2}} dsdt \]  

(9)

There are strong correlations for movements with similar signs. To our knowledge, there is no formula which approximates between a linear correlation coefficient and Spearman Rho for Student distributions. However, the relationship which applies for Kendall’s Tau for a Gaussian copula applies as well for a Student copula.

\[ \tau_k = \frac{2}{\pi} \arcsin \rho \]  

(10)

### 4. Data and Empirical Results

#### 4.1 Data and Stochastic Properties

We empirically examine the interaction between stock markets’ different increments. The database consists of increments of emerging market countries (Argentina, Brazil, Chile, India, Malaysia and Thailand). The study makes use of daily returns of market indices during the period from January 1st 1997 to June 15th 2010.

The following figure reports curves of chosen copula models. These curves are very informative of the copula dependence properties. For this reason, we often use curves to visualise differences between different copulas and to probably help choose the appropriate copula functions.
The following figure presents the five countries’ indices, reporting the evolution of nominal value invested at the beginning of the period in each country. The following curves indicate relative movement of prices for each increment. The initial value of each increment has been standardised into units to ease the comparison of performances with current performances.
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Figure 2: Increments' standardized daily closings

Normalized Daily Index Closings in average income country

To assess distribution and stochastic properties of returns, first we look into some descriptive statistics on the returns of the five countries reported in Table 1. The statistics prove that all returns series are negatively biased and display excessive kurtosis. This indicates that returns are not normally distributed.

Table 1: Statistics of markets daily returns

<table>
<thead>
<tr>
<th></th>
<th>Argentina</th>
<th>Brazil</th>
<th>Chile</th>
<th>India</th>
<th>Malaysia</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.035</td>
<td>0.071</td>
<td>0.036</td>
<td>0.045</td>
<td>0.007</td>
<td>-0.015</td>
</tr>
<tr>
<td>Median</td>
<td>0.036</td>
<td>0.112</td>
<td>0.014</td>
<td>0.071</td>
<td>0.000</td>
<td>-0.022</td>
</tr>
<tr>
<td>Minimum</td>
<td>-32.130</td>
<td>-16.164</td>
<td>-6.671</td>
<td>-12.128</td>
<td>-36.725</td>
<td>-17.089</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.147</td>
<td>2.302</td>
<td>1.099</td>
<td>1.653</td>
<td>1.897</td>
<td>2.197</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.132</td>
<td>-0.015</td>
<td>-0.114</td>
<td>-0.391</td>
<td>-1.302</td>
<td>0.605</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>64440.18</td>
<td>9685.504</td>
<td>2147.639</td>
<td>3204.119</td>
<td>575246.3</td>
<td>13288.38</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 2 below reports conditioned correlations for all returns series. There a positive correlation between Argentina, Brazil, Chile, India, Malaysia and Thailand. The same holds true for emerging markets, although Argentina and Brazil register higher correlation than other markets with correlation respectively of 0.508.
Table 2: Conditional correlations among markets

<table>
<thead>
<tr>
<th>Argentina</th>
<th>Brazil</th>
<th>Chile</th>
<th>India</th>
<th>Malaysia</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>1.000</td>
<td>0.505</td>
<td>0.389</td>
<td>0.081</td>
<td>0.089</td>
</tr>
<tr>
<td>Brazil</td>
<td>0.505</td>
<td>1.000</td>
<td>0.508</td>
<td>0.141</td>
<td>0.084</td>
</tr>
<tr>
<td>Chile</td>
<td>0.389</td>
<td>0.508</td>
<td>1.000</td>
<td>0.139</td>
<td>0.128</td>
</tr>
<tr>
<td>India</td>
<td>0.081</td>
<td>0.141</td>
<td>0.139</td>
<td>1.000</td>
<td>0.156</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.089</td>
<td>0.084</td>
<td>0.128</td>
<td>0.156</td>
<td>1.000</td>
</tr>
<tr>
<td>Thailand</td>
<td>0.116</td>
<td>0.136</td>
<td>0.193</td>
<td>0.190</td>
<td>0.351</td>
</tr>
</tbody>
</table>

As a first stage, we adopted the maximum likelihood technique and GARCH model to model returns. Akaike (AIC), Bayesian information criterion (BIC) and the logarithmic likelihood function are employed to compare between the various specifications pertaining to the GARCH models when applied to returns series. As for these statistics, we considered a GARCH-M. For all returns series, the parameter is close to 0.9. These results indicate that volatility is highly persistent. The estimated coefficients for power limits are significant at the 5% level with the exception of Chile returns which indicate presence of volatility’s asymmetric response to shocks. The ARCH-M model shows that the expected limits for India, Malaysia and Thailand are negative.

Table 3: GARCH-M estimation parameters for all returns series

<table>
<thead>
<tr>
<th>Argentina</th>
<th>Brazil</th>
<th>Chile</th>
<th>India</th>
<th>Malaysia</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>0.069</td>
<td>0.082**</td>
<td>0.046*</td>
<td>0.207</td>
<td>0.047**</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.011)</td>
<td>(0.039)</td>
<td>(0.042)**</td>
<td>(0.047)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.008</td>
<td>0.021***</td>
<td>0.0437*</td>
<td>-0.026</td>
<td>0.0143</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.012)</td>
<td>(0.032)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.300 ***</td>
<td>0.194***</td>
<td>0.105***</td>
<td>0.190</td>
<td>0.090***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.023)</td>
<td>(0.017)</td>
<td>(0.037)**</td>
<td>(0.011)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.250***</td>
<td>0.226***</td>
<td>0.235***</td>
<td>0.354</td>
<td>0.216***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.018)</td>
<td>(0.015)**</td>
<td>(0.009)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.957***</td>
<td>0.954***</td>
<td>0.930***</td>
<td>0.915</td>
<td>0.973***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.011)</td>
<td>(0.007)**</td>
<td>(0.002)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.328***</td>
<td>-0.110***</td>
<td>-0.234***</td>
<td>-0.426 ***</td>
<td>-0.165***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.004)</td>
</tr>
</tbody>
</table>

Significance at the 1% levels. ** Significance at the 5% levels. *** Significance at the 10% levels.

4.2 Probability Distribution by Fragments

We display returns distribution of each increment using the copula approach. By using simultaneously Malevergne and Sornette’s semi-parametric model, we provide a statistical description of daily returns probability distribution of whatever capital increments. We suppose that this description is reported in the form of semi-parametric fragmented distribution where asymptotic behaviour in each tail is characterized by a Pareto general distribution.

Finally, a copula will be used to produce random figures to run simulations. Average return of each increment is managed by a risk-free rhythm and incorporated into the drift limit of the stochastic differential equation. The following figure extracts average of each increment. We employed extreme value theory to describe each return series distribution of capital increments.
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Figure 3: Logarithmic centred returns

a) Logarithmic centred returns: Brazil

b) Logarithmic centred returns: Chile
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c) Logarithmic centred returns: Malaysia

![Graph of Daily Logarithmic Centered Returns: Malaysia]

-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3

Date
Return


d) Logarithmic centred returns: India

![Graph of Daily Logarithmic Centered Returns: India]

-0.15
-0.1
-0.05
0
0.05
0.1
0.15

Date
Return


e) Logarithmic centred returns: Thailand

![Graph of Daily Logarithmic Centered Returns: Thailand]

-0.2
-0.15
-0.1
-0.05
0
0.05
0.1
0.15
0.2

Date
Return

Given the standardized residuals, we estimate cumulative distribution function of each increment with a Gaussian nucleus. This would enable smoothing estimation of cumulative distribution function.

**4.3 Correlation of the Returns of Each Index**

Linear correlation is a natural dependence measure of elliptically distributed risks. Modeling tails of a distribution with a GDP requires approximately i.i.d observations. However, most returns series indicate some degree of autocorrelation. For instance, autocorrelation function (ACF) of returns of an increment indicates some kind of a sequential correlation. Observing ACF of the two industrial returns, we may notice that for all increments there is a proof of a sequential correlation at the first lag.

**Figure 4: Autocorrelation function of residuals squared**

a) Sample ACF of squared returns: Brazil

![Sample ACF of Returns: Brazil](image)

b) Sample ACF of squared returns: Chile

![Sample ACF of Returns: Chile](image)
c) Sample ACF of squared returns: India

d) Sample ACF of squared returns: Malaysia

e) Sample ACF of squared returns: Thailand
However, squared autocorrelation of returns indicate persistence degree of variance and it implies that modeling a GARCH may significantly condition data used to estimate the tail.

Moreover, ACF of squared returns suggests that all increments indicate heteroskedasticity and it implies that modeling a GARCH may significantly condition data used to estimate the tail.

To produce a series of i.i.d observations, we adopt a first-degree auto-regressive model using conditional means to estimate returns of each capital increment and asymmetry of a GARCH model to estimate variance.

\[ \Gamma(\tau) = c + \theta r(\tau-1) + \epsilon(\tau) \quad (11) \]

\[ \sigma^2(\tau) = \kappa + \alpha \sigma^2(\tau-1) + \phi \epsilon^2(\tau-1) + \psi(\epsilon(\tau-1) < 0)\epsilon^2(\tau-1) \quad (12) \]

The first-degree auto-regressive model compensates for autocorrelation, whereas the GARCH model compensates for heteroskedasticity. Specifically, the last period assimilates asymmetry to variance by a Boolean indicator that takes 1 if the residual model is negative, otherwise it takes 0.

Furthermore, standardized residuals of each increment are modelled as a standardized t-student distribution to compensate for fat tails often associated to capital increments. Then, we extract filtered residuals and volatilities through returns of each capital increment. For the selected increment, we compare the corresponding filtered residuals models and conditional standard deviations for the returns of each incurred capital increment. The following figure shows volatility variance (heteroskedasticity) characterizing filtered residuals.

Estimation of average conditional standard deviation series could be done with an AR, MA or GARCH models. The following figures report residuals series for the GARCH increments and conditional standard deviations.
Figure 5: Filtered residual and filtered conditional standard deviation

a) Filtered residual and filtered conditional standard deviation: Brazil

![Filtered Residuals: brazil](image)

![Filtered Conditional Standard Deviations: brazil](image)

b) Filtered residual and filtered conditional standard deviation: Chile

![Filtered Residuals: chile](image)

![Filtered Conditional Standard Deviations: chile](image)
c) Filtered residual and filtered conditional standard deviation: India

Filtered Residuals: india

Filtered Conditional Standard Deviations: india

d) Filtered residual and filtered conditional standard deviation: Malaysia

Filtered Residuals: malaysia

Filtered Conditional Standard Deviations: malaysia
4.4 Upper and Lower Functions Results

In this sub-section, we present detailed results and test uncertainty. We focus the analysis on the highest (upper group) and lowest (lower group) values. All the results reported below are computed for $k/N = 0.12$ of a rate corresponding to a value rounded at 21 (information scores) for $k$ as $N = 173$. Examining the results of Malevergne and Sornette's non-parametric approach, we notice that upper and lower groups are almost assimilated. There is no difference at the lower tail. It is interesting then to see that the standard deviation is relatively small, knowing that the sample is small as well. Comparing standard deviations of the different indices, we notice that the highest tail dependence coefficient possesses a large standard deviation. However, if we examine variation coefficient, lower tail dependence coefficients have generally higher variation coefficients than higher tail dependence. In view of these two comments and of the fact that for values with near-zero average the variation coefficient is sensitive to minor changes, we may conclude that tail dependence seems to lay within the same range for low and high tail dependence coefficients.
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Table 3: λ upper tail to accommodate with the Malevergne and Sornette’s non-parametric approach by applying the Gabaix estimator and the results obtained by bootstrapping (bs) the 5000 time data with k/N = 0.2. The numbers 90, 95, and 99, correspond to a quintile granted to the λ bootstrapping distribution.

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_{up,mean}^{bs} )</td>
<td>0.24</td>
<td>0.39</td>
<td>0.46</td>
<td>0.11</td>
<td>0.08</td>
<td>0.1</td>
</tr>
<tr>
<td>( \lambda_{up,90}^{bs} )</td>
<td>0.25</td>
<td>0.4</td>
<td>0.47</td>
<td>0.12</td>
<td>0.08</td>
<td>0.1</td>
</tr>
<tr>
<td>( \lambda_{up,95}^{bs} )</td>
<td>0.26</td>
<td>0.4</td>
<td>0.47</td>
<td>0.13</td>
<td>0.09</td>
<td>0.11</td>
</tr>
<tr>
<td>( \lambda_{up,99}^{bs} )</td>
<td>0.26</td>
<td>0.41</td>
<td>0.48</td>
<td>0.13</td>
<td>0.09</td>
<td>0.11</td>
</tr>
<tr>
<td>( \lambda_{up,max}^{bs} )</td>
<td>0.27</td>
<td>0.42</td>
<td>0.49</td>
<td>0.14</td>
<td>0.1</td>
<td>0.12</td>
</tr>
<tr>
<td>( \lambda_{up}^{bs} )</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 4: λ lower tail to accommodate with the Malevergne and Sornette’s non-parametric approach by applying the Gabaix estimator and the results obtained by bootstrapping (bs) the 5000 time data with k/N = 0.2. The numbers 90, 95, and 99, correspond to a quintile granted to the λ bootstrapping distribution.

<table>
<thead>
<tr>
<th></th>
<th>Argentina</th>
<th>Brazil</th>
<th>Chile</th>
<th>India</th>
<th>Malaysia</th>
<th>Thailand</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \lambda_{lo,mean}^{bs} )</td>
<td>0.13</td>
<td>0.36</td>
<td>0.3</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>( \lambda_{lo,90}^{bs} )</td>
<td>0.14</td>
<td>0.37</td>
<td>0.31</td>
<td>0.06</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>( \lambda_{lo,95}^{bs} )</td>
<td>0.15</td>
<td>0.38</td>
<td>0.32</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>( \lambda_{lo,99}^{bs} )</td>
<td>0.15</td>
<td>0.38</td>
<td>0.33</td>
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<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>( \lambda_{lo,max}^{bs} )</td>
<td>0.17</td>
<td>0.4</td>
<td>0.34</td>
<td>0.07</td>
<td>0.04</td>
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</tr>
<tr>
<td>( \lambda_{lo}^{bs} )</td>
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<td>0.01</td>
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<td>0</td>
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</tr>
</tbody>
</table>

The tables indicate that dependence between increments is normally distributed. They caution about the risks related to an appropriate use of this approach and specifically indicate that a met-elliptic student copula may be an interesting alternative in some situations.

5. Conclusion

In this paper, we posed to analyse financial contagion by means of a methodology that goes beyond a simple correlation analysis. Correlation is generally known to increase during markets turmoil and remains sensitive to asymptotic and non-linear dependence properties. Our approach enabled us to avoid any form of misspecifying contagion episodes and defining extreme results. It allows for achieving its aims by using copula approaches and Malevergne and Sornette’s semi-parametric and non-parametric methods.
Ben Messaoud & Aloui

After having used stock markets index returns, we showed dependence structures during financial turmoil. Economies of Argentina, Brazil, Chile, India, Malaysia and Thailand showed tail dependence and asymmetry during high volatility periods.

This study helped show nature of tail dependence which is an important potential dimension of contagion. If contagion is a non-linear, as suggested by this study, it may then be inappropriate to think that rejecting the correlation-breakdown hypothesis may be a proof to maintain a stable dependence structure without conducting further research.

This study proves that tail dependence structural breaks are important features of contagion. Nevertheless, it is important to caution that these changes are not imperatively detected by changes in correlations.

According the increasing interests in observing potential gains from international portfolio alteration in globalized situation, further investigations on stock market relationships is demanded. Future extensions of this paper can aims on an explicit explanation of extreme financial interdependence by country-specific fundamentals.

References


