Financial crises and stock market dependence

Aristeidis Samitas [a, *], Dimitris Kenourgios [b], and Nikos Paltalidis [c]

[a] Department of Business Administration, Business School, University of the Aegean, Christou Lada 6, 10561 Athens, Greece, E-mail: asamitas@econ.uoa.gr

[b] Department of Economics, University of Athens, 5 Stadiou Str., Office 213, 10562 Athens, Greece, E-mail: dkenourg@econ.uoa.gr

[c] Faculty of Finance, Cass Business School, City University London, 105 Westbourne Terrace, W2 6QT, Paddington, UK.

[*] Corresponding author. E-mail: asamitas@econ.uoa.gr

Abstract

This paper proposes a multivariate time-varying copula with Markov switching parameters to capture non-linear relationships in four emerging markets, namely Brazil, Russia, India, China (BRICs) and two developed markets, U.S. and U.K. Our results provide evidence that there is an increase in dependence among stock markets during crises periods. Also, we investigate the presence of asymmetric responses in conditional variances and correlations during crises periods, measuring risks dynamically by finding the optimal time decay of covariance information. The results show that during periods of large negative returns, equity markets volatilities share stronger linkages. Finally, using "news impact surfaces", we provide empirical evidence that crises spread through the equity markets rather than through changes in macroeconomic fundamentals.

Keywords: Financial crises, stock market dependence, BRICs, multivariate copula, AG-DCC model.

EFMA Classification Codes: 370, 630, 620, 570

1. Introduction

The global extent of recent crises and the potential damaging consequences of being affected by contagion continuously attract attention among economists and policymakers. The transmission of shocks to other countries and the cross country correlation, beyond any fundamental link incessantly attract attention for academics, fund managers and traders. Most of the recent research concentrates on understanding the causes and consequences of financial crises (see Forbes et al., 2002; Kodres et al., 2002; Bekaert et al., 2003; Kaminski et al., 2004; Barberis et al., 2005; Boyer et al., 2006).

The past decade was marked by the Asian stock market crises in 1997, the Russian default in 1998, the Internet Bubble in late 1999 and collapse in 2000 and the Brazilian stock market crash in 1997 – 1998 and 2002. According to Boyer et al. (2006), crisis is spread from one country to the other generating the "contagion phenomenon". One common feature is how an initially country – specific event seemed to transmit rapidly to markets around the globe.

This study focuses on four emerging stock markets in Brazil, Russia, India and China (BRICs) and two developed stock markets, U.S. and U.K. BRICs could become the larger force in the world economy over the next fifty years. The relative importance of the BRICs as an engine of new demand growth and spending power may shift more dramatically and quickly than expected. Higher growth in these economies could offset the impact of greying populations and slower growth in the advanced economies. The aim is to analyse five financial crises occurred during the last ten years: (i) the Asian stock market crises in 1997, (ii) the Russian default in 1998, (iii) the collapse of the internet bubble of developed markets in 2000, (iv) the Brazilian stock market crash in 1997 – 1998 and (v) the Brazilian crisis in 2002.

The purpose of this paper is: (i) to analyze the behaviour (i.e. correlation, dependency) among stock markets when at least one of them is under financial crisis. Using an extended multiparameter Copula function, we consider the time dimension in the transmission of crisis among countries. Moreover, using the asymmetric generalized dynamic conditional correlation model (AG-DCC), we identify asymmetric market frictions. As a preliminary measure, we test the lead- lag relationship by comparing sizes of autocorrelations between index returns and actual volatilities for each country; (ii) to determine whether cross-market correlation dynamics (contagion hypothesis) are driven by behavioural reasons or by changes in macroeconomic fundamentals. This is in contrast to the traditional asset pricing theory, according to which co-movement in prices reflects co-movement in fundamentals in an economy with traditional investors.

This paper proposes a new methodology to measure the dependency between stock markets during crises periods. Our approach is based on multivariate copula functions with Markov switching parameters. These functions provide an interesting tool to model a multivariate distribution when only marginal distributions are known. This approach is very useful in situations where multivariate normality does not hold. An additional interesting feature of copulas is the ease with which the associated dependency parameter can be conditioned and rendered time varying, even when complicated marginal dynamics are estimated.

Following Patton (2006a,b) and Bartram et al. (in press), we employ a GJR-GARCH-MA-t specification for the marginal distributions and the Gaussian copula for the joint distribution. The dependence parameters in the copula function are modeled as a time-varying process conditional on currently available information, allowing for time-varying, non-linear relationships and asymmetries.

Copulas offer significant advantages over other econometric techniques in analysing the comovement of financial time-series, consisting in the fact that they can model dependence beyond linear correlation and provide a high degree of flexibility. We extend the methodology proposed by Patton (2006a,b) and Bartram et al. (2006) by using a multiparameter time-varying copula with Markov switching parameters during crises periods.

Many univariate models have been proposed to specify the dynamics of returns. In a generalized autoregressive conditionally heteroskedastic (GARCH) framework correlation coefficients are assumed to be constant over the sample period. Although assuming constant correlation greatly simplifies estimation, this hypothesis is not robust to the empirical evidence. Moreover, copula functions in a GARCH framework suffer from the curse of dimensionality.

Given the focus of this research, we draw on recent advances in the modeling of conditional returns that allow second, third and fourth moments to vary over time. This paper also employs a recently developed GARCH process, the asymmetric generalized dynamic conditional correlation (AG – DCC) model (Cappiello et al., 2006). This process allows for series – specific news impact and smoothing parameters and permits conditional asymmetries in correlation dynamics.

Moreover, this paper investigates asymmetries in conditional covariances and correlations using "news impact surfaces" based on Kroner and Ng (1998). This test applied also to Scruggs and Glabadanidis (2003), uses a more flexible class of multivariate conditional variance models, without the assumption of constant correlation coefficients and with explicit asymmetry in conditional variances and covariances.

This paper contributes to the existing literature in the following ways: First, we extend previous work proposing a new multivariate copula model with Markov switching parameters to identify structural breaks, when the dependency parameters depend on the position of past realizations and the degree of dependence among countries during a financial turmoil. Second, we examine whether market co-movements are asymmetric during the five extreme market downturns applying the recently developed AG-DCC approach. Third, there is no other research studying stock market crises in BRICs (Brazil, Russia, India, China) in accordance with the most developed stock markets, to the best of our knowledge.

The structure of the paper is organized as follows: Section 2 briefly presents the literature review. Section 3 presents the data and analyzes methodological issues. The empirical results are reported in Section 4. The final section contains the concluding remarks.

2. Literature Review

Most financial decisions are based on the risk / return trade – off. Hence, a central issue in asset allocation and risk management is whether financial markets become more interdependent during financial crises. This issue has acquired great importance among academics and practitioners in the last decade where five major crises were obtained. Common to all these events was the fact that the turmoil originated in one market extended to a wide range of markets and countries in a way that was hard to explain on the basis of changes in fundamentals.

Generally, contagion refers to the spread of financial disturbances from one country to others. The study of financial contagion, defined in Forbes and Rigobon (2002) as “a significant increase in cross-market linkages after a shock to one country (or group of countries)”, was conducted mostly around the notion of “correlation breakdown": a statistically significant increase in correlation during the crash period. Bertero and Mayer (1989) and King and Wadhwani (1990), find evidence of an increase in the correlation of stock returns at the time of the 1987 crash. Also, Calvo and Reinhart (1996) report correlation shifts during the Mexican crisis, while Baig and Goldfajn (1999) find significant increases in correlation for several East Asian markets and currencies during the East Asian crisis.

The studies of contagion based on structural shifts in correlation were challenged by Boyer, Gibson and Loretan (1999), who pointed to biases in tests of changes in correlation that do not take into account conditional heteroskedasticity. Boyer et al. (1999) argued that the estimated correlation coefficient between the realized extreme values of two random variables will likely suggest structural change, even if the true data generation process has constant correlation. Forbes and Rigobon (2002) generalized the approach of Boyer et al. (1999) and applied it to the study of three major crises (the 1987 crash, the Mexican devaluation, and the East Asian crisis). They were unable to find evidence of correlation breakdown in any of these crises after adjusting for heteroskedasticity and concluded that the phenomenon that has been labelled as "contagion" is nonexistent. This study complements the related literature because it studies financial contagion using a methodology that goes beyond the simple analysis of correlation breakdowns, applying multivariate copula function with Markov switching parameters.

Copulas have recently become increasingly popular in various finance applications, such as modeling default correlations for credit risk management (Li, 2000), modeling portfolio allocation (Hennessy and Lapan, 2002), pricing foreign exchange rate quanto options (Bennett and Kennedy, 2004), pricing multivariate contingent claims (Rosenberg, 2003), and modeling time-varying dependence (Patton, 2006a,b and Bartram et al., in press). Copulas provide a tool to construct flexible multivariate distributions exhibiting rich patterns of tail behaviour, ranging from tail independence to tail dependence, and different kinds of asymmetry. Fitting copulas with different tail behaviour makes it possible to test whether times of increased dependence can be also characterized by changes in one or both tails of the distribution. In order to capture shifts in the dependence structure, the copula that describes it must be time varying. Patton (2006a,b) and Bartram et al. (in press) pioneered the study of time-varying copulas. They introduced the concept of conditional copula, and applied it to the study of asymmetries in the dependence structure of a set of exchange rates and stock indices respectively. Our model complements the literature since it extends previous work by applying a multivariate copula function with Markov switching parameters in a GJR-GARCH-MA-*t* specification.

Evidence that equity returns have a dependence structure that is not consistent with multivariate normality has recently been presented by Lognin and Solnik (2001). They provided a method based on extreme value theory to test formally whether conditional correlations deviate from what would be expected under the assumption of multivariate normality. They found that correlation generally increases in periods of high-volatility of the U.S. market. Also, they found that correlation is essentially affected in bear markets when it increases significantly. Recent contributions by Kroner and Ng (1998), Engle and Sheppard (2001) and Engle (2002) have developed GARCH models with time-varying covariances or correlations.

As an alternative approach, Rachmand and Susmel (1998) and Ang and Bekaert (2002) have estimated a multivariate Markov-switching model and tested the hypothesis of a constant international conditional correlation between stock markets.

They investigated that (i) correlation is generally higher in the high-volatility regime than in the low-volatility regime; (ii) equity returns appear to be more correlated during downturns than during upturns. In addition, Boyer et al. (2006) used both regime switching model and extreme value theory to gauge the cross-market transmission mechanism of financial crises for numerous of accessible and inaccessible stock indices. They identified that there is greater co-movement during high volatility periods, suggesting that crises spread through the asset holdings of international investors rather than through changes in fundamentals. Markov switching models have been limited to analyze the case of bivariate normality. Consequently, they have missed a potentially important dimension of the contagion phenomenon such as nonlinear dependence.

In most of existing work on modeling the dependence structure of multivariate financial time series via the copula approach, parametric copulas are used to model the contemporaneous dependence between univariate time series or between innovations of univariate parametric time series models. Commonly used parametric copulas include the normal Gaussian copula, the Student's *t* copula, Frank copula and Gumbel copula. Due to the "curse of dimensionality" problem, fully nonparametric copula modeling, although theoretically feasible, is practically difficult to implement when the number of series being modeled is greater than three.

Thus, many researchers investigated asymmetric effects in conditional covariances (see for example, Koutmos and Booth, 1995, Christiansen, 2000) for individual stocks, equity portfolios, and stock market indices using different approaches. Engle (2002) developed a model capable of allowing for conditional asymmetries in both volatilities and correlations. Cappiello et al. (2006) extended the original model along two dimensions: on the one hand, they allowed for series-specific news impact and smoothing parameters and on the other hand, permitted conditional asymmetries in correlations. The main idea was to separate the modeling of the variances from that of the correlations. Cappiello et al. (2006) identified that equity returns show strong evidence of asymmetries in conditional volatility, while little is found for bond returns. Also, they found that during periods of financial turmoil, equity market volatilities show important linkages, and conditional equity correlations among regional groups increase dramatically.

Many studies also focus on the impact of macroeconomic news announcements on conditional volatility. Kroner and Ng (1998) demonstrated the differences between several multivariate GARCH models. They found that large firm returns can affect the volatility of small firm returns, but small firm returns do not have much effect on large firm returns. Scruggs and Glabadanidis (2003) identified that stock market variance increases much more in response to negative return shocks than to positive return shocks of equal magnitude. In the empirical research, Karolyi and Stulz (1996) and Connolly and Wang (2003) showed that macroeconomic announcements and other public information do not affect co-movements of Japanese and American stock markets. Forbes (2002) provided evidence that international trade linkages allow country-specific crises to spread to stock markets elsewhere in the world.

However, these trade linkages only partially explain the reaction of stock markets to crises that originate in other countries. Moreover, correlations among market returns computed by Ang and Chen (2002) are especially large during market downturns, suggesting that contagion may be "asymmetric" and stronger during market downturns. As Bae et al. (2003) have pointed out: "The concerns (about contagion) are generally founded on the presumption that there is something different about extremely bad events that leads to irrational outcomes, excess volatility, and even panics. In the context of stock returns, this means that if panic grips investors as stock returns fall and leads them to ignore economic fundamentals, one would expect large negative returns to be contagious in a way that small negative returns are not."

3. Data and Methodology

3.1 Data

We study four emerging markets, Brazil, Russia, India and China and two developed markets, U.S. and U.K. We use the following stock indices: Bovespa Index (Brazil), RTS Index (Russia), BSE Sensex Index (India) Shanghai A Index (China), S&P 500 (U.S.) and FTSE 100 (U.K.). We construct daily log returns (in U.S. dollar terms) and actual volatilities. The sample period is from January, 2, 1995 till October, 31, 2006 and excludes holidays. We split our data as follows: (i) Asian crisis: 1997; (ii) Brazilian crisis: 1997, 1998; (iii) Russian crisis: 1998; (iv) Internet collapse in developed markets: 2000; (v) Brazilian crisis: 2002. Then, we compare the difference in returns, actual and asymmetric volatilities and correlations, between stable and crisis periods.

3.2 Conditional Copula

Copula functions permit flexible modeling by enabling the construction of multivariate densities that are consistent with the univariate marginal densities. Hence, they allow separation of the marginal distributions from the dependence structure that is entirely represented by the copula function. This separation enables researchers to construct multivariate distribution functions, starting from given marginal distributions that avoid the common assumption of normality for either marginal distributions or their joint distribution function.

Copulas have certain properties that are very useful in the study of dependence. First, copulas are invariant to strictly increasing transformations of the random variables. Second and most important in the study of financial contagion, asymptotic tail dependence is also a property of the copula.

A switching copula can capture increases in tail dependence, reflecting for example, that the probability of markets crashing together is higher in periods of financial turmoil, while a model based on multivariate normality imposes tail independence.

In this paper, we employ multiparameter conditional copula to represent the dependence between two index returns, conditional upon the historical information provided by previous pairs of index returns (parameter 1) and actual volatilities (parameter 2). When we test for dependence, we employ the copula function with the return and volatility from one country against the other. We estimate firstly the univariate distributions and then the joining distributions. The parameters of the conditional copula depend upon the conditioning information. Important conditional theory and modifications of our model has been developed in Patton (2006a,b) and Bartram et al. (in press).

Let X_t and Y_t be random variables that represent two returns for period *t* and let their conditional cumulative distribution functions (c.d.f.s) be $F_t(x_t\,|\Phi_{t-1})$ and $G_t(y_t\,|\Phi_{t-1})$ respectively, with Φ_{t-1} denoting all previous returns, i.e. $\{x_{t-1},y_{t-1},i>0\}$. Moreover, let M_t and N_t be random variables that represent two volatilities for period *t* and their c.d.f.s are $F_t^*(m_t\,|\Lambda_{t-1})$ and $G_t^*(n_t\,|\Lambda_{t-1})$ respectively, with $\Lambda_{t-1,}$ denoting all previous volatilities, i.e. $\{m_{t-i,}n_{t-i,}i>0\}$. Define two further random variables by $U_t = F_t\,(X_t\,|\Phi_{t-1})$ and $V_t = G_t\,(Y_t\,|\Phi_{t-1})$, whose marginal distributions are uniform on the interval from zero to one. Then the conditional copula density function, denoted by

$c_t(u_t,v_t\,|\Phi_{t-1})$, is defined by the time-varying, bivariate density function of U_t and V_t. Also, the conditional bivariate density functions of X_t , Y_t, and M_t, N_t are given by the product of their copula density and their two marginal conditional densities, respectively denoted by f_t and g_t.:

$$H_t(x_t,y_t\,|\Phi_{t-1}) = c_t(F_t(x_t\,|\Phi_{t-1}), G_t(y_t\,|\Phi_{t-1})\,|\Phi_{t-1})f_t(x_t\,|\Phi_{t-1})g_t(y_t\,|\Phi_{t-1}) \tag{1}$$

The conditional densities of equity index returns are leptokurtotic and have variances that are asymmetric functions of previous returns. Therefore, we obtain our marginal distributions by fitting appropriate ARCH models that have conditional Gaussian distributions.

Introducing regime switches in variance, u_t is modeled as:

$u_t = \sqrt{g_{st}} * \bar{u}_t$ and $\bar{u}_t$ follows a GJR-GARCH-MA t specification process.

The level of the variance can occasionally change, depending on the values of g_{st}, where g_{st} is a scaling parameter that changes in time as a function of a latent variable s_t. This latent variable is assumed to take values 1,2,…,K and to be described as a Markov Chain:

$$P=\begin{pmatrix} p_{11} & p_{12}\ldots.p_{k1} \\ p_{12} & p_{22}\ldots p_{k2} \\ \ldots & \ldots \quad \ldots \\ p_{1k} & p_{2k}\ldots p_{kk} \end{pmatrix},$$

where $p_{ij}= p(s_t=i|s_{t-1}=j)$. s_t is regarded as the regime that the process is in at date t. Hence, variable s_t can be in any K states at time t and q is the number of lags in the conditional variance. Therefore, the variable u_t is multiplied by $\sqrt{g_1}$ in state 1, $\sqrt{g_2}$ in state 2, and so on. Hamilton (1989) describes how to estimate the parameters in through the maximization of a likelihood function and also how to do inference about the state in which the process has been at date t. Inferences based on information up to time t are called "filtered probabilities", while inferences based on information from the full sample are called "smoothed probabilities."

The model selected to investigate the presence of different volatility regimes in the markets considered in this paper follows a (2, 1) process. Although the selection of the number of states and lags has been based on practical reasons of avoiding overparameterization and cumbersome computation in the multivariate case, specification tests on the copulas suggest that the GJR-GARCH-MA-t −switching (2, 1) performs well in describing the structure of the marginals.

3.2.1 Estimation of parameters

In the first stage, the parameters of the marginal distributions parameters are estimated from univariate time series as:

$$\hat{\theta}_{\chi} \equiv \arg\max \sum_{t=1}^{n} \log f_t(x_t \mid \Phi_{t-1,} \theta_x)$$

$$\hat{\theta}_{y} \equiv \arg\max \sum_{t=1}^{n} \log g_t(y_t \mid \Phi_{t-1,} \theta_y) \tag{2}$$

The second stage then estimates the dependence parameters as:

$$\hat{\theta}_{c} = \arg\max \sum_{t=1}^{n} \log c_t(u_{t,} v_t \mid \Phi_{t-1,} \theta_{c,} \hat{\theta}_{x,} \hat{\theta}_{y}) \tag{3}$$

According to Patton (2006a), the two stage ML estimates

$$\hat{\theta} = \left[\hat{\theta}_{\chi}; \hat{\theta}_{y}; \hat{\theta}_{c} \right] \tag{4}$$

are asymptotically as efficient as one-stage ML estimates. The variance-covariance of $\hat{\theta}$ has to be obtained from numerical derivatives.

3.2.2 Specifying the dependence parameter

Patton (2006a) proposes that dependence between markets is explained by the previous dependence and the historical average difference of cumulative probabilities for the markets. Follow Patton (2006a), we suppose that p_t depends on the previous dependence p_{t-1} to capture persistence, and historical absolute differences, $|u_{t-1} - v_{t-1}|$, i>0, to capture variation in the dependence process. We estimate the following dependence process:

$$(1-\beta_1 L)(1-\beta_2 L)\rho_t = \omega + \gamma\, |u_{t-1} - v_{t-1}| \quad (5)$$

where L is the lag operator, β_1 and β_2 are conditional correlation parameters with cumulative probabilities, γ are large negative returns and ω is the white noise innovation term. The intuition for the use of $|u_{t-1} - v_{t-1}|$ is the smaller (larger) the difference between the realized cumulative probabilities, the higher (lower) is the dependence. So, equation (5) describes an AR (2) model when extra assumptions are made, namely that a linear function of the previous absolute difference, $|u_{t-1} - v_{t-1}|$, provides a white noise innovation term. We model the dependence structure as a mixture of copulas, with parameters changing over time according to a Markov switching model.

We let $R_{i,t}$ and $h_{i,t}$ denote the return from equity index I and its conditional variance for period t. Also, $L_{i,t}$ and $\lambda_{i,t}$ denote the actual volatility from equity index I and its conditional variance for period t. The ARCH model for the returns from index I is defined by:

$$R_{i,t} = \mu_i + \varepsilon_{i,t} + \Theta_i \varepsilon_{i,t-1},$$

$$h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \alpha_{i,1} \varepsilon^2_{i,t-1} + \alpha_{i,2}\, s_{i,t-1}\, \varepsilon^2_{i,t-1}, \tag{6}$$

$$\varepsilon_{i,t}\,|\Phi_{t-1} \sim t_{vi}\,(0,h_{i,t}),$$

and for the volatility:

$$L_{i,t} = \mu_i + \varepsilon_{i,t} + \Theta_i \varepsilon_{i,t-1},$$

$$\lambda_{i,t} = \omega_i + \beta_i \lambda_{i,t-1} + \alpha_{i,1} \varepsilon^2_{i,t-1} + \alpha_{i,2}\, s_{i,t-1}\, \varepsilon^2_{i,t-1}, \tag{7}$$

$$\varepsilon_{i,t}\,|\Phi_{t-1} \sim t_{vi}\,(0,\lambda_{i,t}),$$

with $s_{i,t-1} = 1$ when $\varepsilon_{i,t-1}$ is negative and otherwise $s_{i,t-1} = 0$. In the first stage of parameters estimation, all of the parameters, including the degrees of freedom v_i, are estimated separately for each equity index by maximizing the log-likelihood for each time series of index returns.

Our approach is different since we use all historical information about the absolute differences, rather than arbitrarily truncating the historical information. Also, instead of a logistic transformation function, we use a constraint in the estimation procedure to keep the dependence process within zero plus one. The use of a logistic transformation function would unhelpfully restrict the volatility of the dependence term when it is near its limiting values.

3.3 AG-DCC Model

Volatilities and correlations measured from historical data may miss changes in risk. Hence, Cappiello et al. (2006) investigate properties of international equity returns generalizing the DCC-GARCH model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation.

Following Cappiello et al. (2006), we let r_t be a k*1 vector of asset returns, which is assumed to be conditionally normal with mean zero and covariance matrix H_t:

$r_t \mid \mathcal{F}_{t-1} \sim N(0,H_t)$ (8)

where $\mathcal{F}_{t-1}$ is the time t-1 information set. All DCC class models use the fact that H_t can be decomposed as follows:

$H_t = D_t P_t D_t$ (9)

where, D_t is the k*k diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the ith diagonal and P_t is the time-varying correlation matrix.

As the DCC model is designed to allow for three-stage estimation of the conditional covariance matrix, any univariate GARCH process that is covariance stationary and assumes normally distributed errors (irrespective of the true error distribution) can be used to model the variances (Engle and Sheppard, 2001). In the first stage, univariate volatility models are fit for each of the assets, and estimates of hit are obtained. In the second stage, asset returns, transformed by their estimated standard deviations, are used to estimate the intercept parameters of the conditional correlation. Finally, the third stage conditions on the correlation intercept parameters to estimate the coefficients governing the dynamics of correlation. In the original DCC estimator, the correlation evolves according to a process with identical news impact and smoothing parameters for all pairs of variables. Cappiello et al. (2006) propose the asymmetric generalized DCC (AG-DCC) estimator to better capture the heterogeneity present in the data. The efficiency of the three-stage estimation process has been studied asymptotically in Engle and Sheppard (2005) and in simulations in Engle and Sheppard (2001).

Once the univariate volatility models are estimated, the standardised residuals, $\varepsilon_{i,t} = r_{i,t} / \sqrt{h_{i,t}}$, are used to estimate the correlation parameters. The evolution of the correlation in the standard DCC model (Engle, 2002) is given by

$$Q_t = (1-a-b)\bar{P} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \qquad (10)$$

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (11)$$

where $\bar{P} = E[\varepsilon_t \varepsilon'_t]$ and α and b are scalars such that α+b<1. $Q_t^* = \left[q_{iit}^*\right] = \left[\sqrt{q_{iit}}\right]$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position. As long as Q_t is positive definite, Q_t^* is a matrix which guarantees $P_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is a correlation matrix with ones on the diagonal and every other element≤1 in absolute value. The model described by equations (10) and (11), however, does not allow for asset-specific news and smoothing parameters or asymmetries.

Cappiello et al. (2006) modify the correlation evolution equation as:

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B \qquad (12)$$

where A, B and G are k*k parameter matrices, $n_t = I\left[\varepsilon_t < 0\right] \circ \varepsilon_t$($I\left[\bullet\right]$is a k*1 indicator function which takes on value 1 if the argument is true and 0 otherwise, while "∘" indicates the Hadamard product) and $\bar{N} = E\left[n_t n'_t\right]$. Equation (12) is the AG-DCC model.

3.4 News Impact Surfaces

Kroner and Ng (1998) introduced news impact surfaces for multivariate GARCH models, which are analogous to news impact curves for univariate processes. For the model considered in this paper, the news impact surface for correlation will be asymmetric, having (potentially) greater response to joint bad news than to joint good news. The news impact surface for correlation is given by:

$$f(\varepsilon_i,\varepsilon_j) \approx \tilde{c}_{ij} + (\alpha_i\alpha_j + g_i g_j)\varepsilon_i\varepsilon_j, \text{ for } \varepsilon_i\varepsilon_j < 0 \qquad (13)$$

$$f(\varepsilon_i,\varepsilon_j) \approx \tilde{c}_{ij} + \alpha_i\alpha_j\, \varepsilon_i\varepsilon_j, \qquad \text{otherwise}$$

where ε_i and ε_j are standardized residuals. The news impact surface for covariance will be the news impact surface for correlations multiplied by the appropriate portion of the news impact curve for the univariate models. Considering the wide range of univariate specifications for the conditional variances, the covariance impact surfaces can be very different for the univariate volatilities, producing asymmetries in covariance in all directions from the origin.

4. Empirical results

4.1 Identifying dependence with Copula function

Modeling dependence by conditional copula densities requires appropriate specifications for the marginal densities. Table 1 shows descriptive statistics. We observe leptokurtosis and variances with asymmetric functions. We use diagnostic test of Berkowitz (2001) to evaluate the goodness-of-fit of our marginal return densities, specified by the GJR-GARCH-MA-t model. The residual series pass the goodness-of-fit test at the 10% level for all 6 country indices.

Table 2 shows the estimates of the copula dependence model for our sample. The time varying dependence model is estimated for each country index. Across all countries and indices, correlation parameter β_1 is always larger than 0.5, implying high dependence persistence. The other autoregressive parameter, β_2 is smaller than β_1 and it is rarely significant different from zero. Conditional correlations with cumulative probabilities appear to be higher during crisis periods. As expected the parameter γ is always negative; it is also highly significant, indicating that the latest absolute difference of returns is consistently a relevant measure when modeling market dependence.

Table 3 shows results for the multivariate copula with switching regime parameters for all five crises periods. At least two regimes exist (s_{11} and s_{22}). The maximum value of the restricted likelihood (LF) shows that a crisis in one market affects the movement to the other markets. Also, all variances (v) are significantly different from 1, implying strong significance at the 5% level.

Figure 1 shows the regimes listed in Table 3. The higher is during the 1997 – 1998 Brazilian crisis (i.e. 0.868) implying that Brazilian crisis affected strongly the movements of other markets.

The findings for changes of dependence between stable and crises periods suggest that all crises drive higher market dependence. Similarly, while different economies follow different economic/business cycles, there are obvious linkages among stock markets during crises periods.

4.2 Dependence with AG-DCC model

The first stage of the DCC model building consists of fitting univariate GARCH specifications to each of the return series and selecting the best one according to the Bayesian information criterion. Table 4 summarises information about the distribution of the unconditional correlations between indices. Overall, indices are in the higher correlated level during the Internet collapse period where crisis begun from the developed markets. However, in all crises periods we observe that markets share co-movement even in cases where correlation is slightly higher than 0.5.

In Table 5, we show nonparametrically the presence of asymmetries in conditional second moments. Our results indicate that covariances are higher during a negative shock than in stable periods, supporting the findings in Cappiello et al. (2006). In both Tables 4 and 5, correlations and covariances increase during crisis, implying that dependence is higher during large negative returns.

Table 6 reports results for testing whether we should adopt the symmetric or the asymmetric model. Asymmetry is introduced in the form of threshold effects in the specifications and by recentering the news impact curves in the remaining two where the AGARCH parameterization is adopted. The $g^2{}_i$ term in the asymmetric model is always higher than zero (i.e. $g^2{}_i>0$), implying that there are asymmetric movements. Also, the asymmetric $b^2{}_i$ is always higher than the symmetric $b^2{}_i$ providing further evidence to support the use of the asymmetric model in the study.

4.3 News Impact Surface

In Table 5, the conditional partial covariance is higher following a negative shock in the markets. Consequently, shared negative shocks have strong impact on correlations (see Table 4) and covariances. This provides strong evidence for the news impact surface methodology. Figure 2 plots the news impact surfaces for BRIC and developed equity correlation. The correlation news impact surface is highly asymmetric, showing a larger response to shocks in large negative returns (i.e., it is more responsive to joint bad news). When we analyze the correlation news impact surface, the symmetry becomes even more striking, with a huge increase for joint negative shocks, even though macroeconomic fundamentals are very different among countries in our sample. This implies that crises spread through the equity markets rather than through changes in macroeconomic fundamentals. Also, Figure 2 shows that Chinese stock market tends to follow an independent movement after joining crisis with other markets.

In Figure 3, we compare the two methodologies followed in the paper. Although both models provide support to the contagion hypothesis, they report different level of dependence for the financial markets.

An increase in cross-market correlations or comovements around crises, however, may not necessarily indicate contagion due to econometric problems with heteroskedasticity, omitted variables and endogeneity. More specifically, heteroskedasticity in asset price movements (which is likely because volatility tends to increase during crises) can cause estimated cross- market correlations to increase after a crisis, even though there is no increase in the underlying correlations. Similarly, changes in omitted variables (such as economic fundamentals, risk perception, and preferences) can cause an increase in asset price correlations, even when contagion is not present. It is also difficult to control for any endogeneity or feedback effects when estimating the effect of a crisis in one country on another. In order to adjust for these problems, we employed asymmetric models with several restrictions. Our results provide evidence of cross-market comovements in the second moments of asset prices during crises periods.

A possible explanation for the increase in contagion during recent crises is that investors retrenched from many emerging markets after the series of crises in the late 1990s, causing significant changes in the countries' international financial structures. In particular, commercial banks substantially reduced their volume of short-term loans to emerging markets, eliminating their risks for possible future crises. Portfolio investors also substantially reduced their exposure to emerging markets, although this exposure has increased again over the past two years. This created a "domino effect", where investors tried to protect their investments creating the "contagion phenomenon" in global markets.

5. Concluding Remarks

The financial crises of the late 1990s prompted extensive empirical research on contagion. Some of this empirical research focuses on examining comovements in asset prices around the time of crises. In this paper, we propose a general time-varying copula dependence model in order to study market linkages. Subsequently, we use this model to investigate the impact of crises periods from one country to the other. In particular, we investigate whether there are significant changes in the time-varying dependence structure of markets within crises periods. We find that dependence increases significantly for both BRIC and developed markets during crises periods.

Moreover, using the AG-DCC model, we investigate asymmetries in conditional variances and correlation dynamics for all countries during crises periods. We find that conditional volatilities of equity indices returns show widespread evidence of asymmetry. The AG-DCC results provide further evidence for higher joint dependence during sock market crises. When bad news hits stock markets, equity correlation among BRICs and developed markets increases dramatically. This finding has important implications for international investors, as the diversification sought by investing in multiple markets is likely to be lowest when it is most desirable.

Finally, we used the news impact surface to investigate that crises are spread through equity markets rather than through changes in macroeconomic fundamentals. Our results imply that a crisis in one market may induce investors to sell their holdings in other markets in order to maintain certain proportions of a country's stock index in their portfolios. This implication is supported in Boyer at al. (2006).

Similarly, an increase in risk aversion (which could be caused by a crisis in one country) can lead investors to sell assets in which they are overweight in order to track their benchmarks.

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Table 1. Descriptive Statistics

	Mean	St. Deviation	Skewness	Kurtosis
Brazil	0.093	2.85	-0.624	7.24
Russia	0.096	2.97	-0.747	6.39
India	0.081	2.80	-0.603	16.33
China	0.062	2.86	-1.215	19.27
U.S.	0.046	1.69	-0.880	6.83
U.K.	0.054	1.71	-1.114	12.79

Table 2. Estimates of correlation using multi-parameter Copula with Markov switching regimes

Country Period	with	ω	β1	β2	γ	LLF(c)
Brazil 1997-1998	Russia	0.0468	0.783 (0.639)	0.702 (0.612)	-0.0371	385.19
	India	0.0392	0.794 (0.608)	0.715 (0.572)	-0.0316	347.11
	China	0.0386	0.785 (0.539)	0.710 (0.518)	-0.0349	321.17
	U.S.	0.0472	0.813 (0.697)	0.802 (0.625)	-0.0303	390.06
	U.K.	0.0419	0.791 (0.630)	0.784 (0.592)	-0.0455	418.77
Russia 1998	Brazil	0.0374	0.723 (0.639)	0.680 (0.612)	-0.0347	385.99
	India	0.0348	0.631 (0.544)	0.607 (0.493)	-0.0388	401.42
	China	0.0365	0.627 (0.537)	0.601 (0.491)	-0.0479	314.60
	U.S.	0.0421	0.728 (0.642)	0.716 (0.583)	-0.0597	396.12
	U.K.	0.0480	0.683 (0.611)	0.628 (0.587)	-0.0521	402.71
India 1997	Brazil	0.0368	0.623 (0.608)	0.597 (0.572)	-0.0738	631.43
	Russia	0.0372	0.629 (0.544)	0.615 (0.493)	-0.0583	431.00
	China	0.0829	0.782 (0.679)	0.751 (0.615)	-0.0694	579.42
	U.S.	0.0548	0.587 (0.511)	0.560 (0.476)	-0.0428	468.93
	U.K.	0.0620	0.564 (0.503)	0.540 (0.428)	-0.0676	350.04
China 1997	Brazil	0.0576	0.643 (0.539)	0.619 (0.518)	-0.0686	578.93
	Russia	0.0627	0.628 (0.537)	0.620 (0.491)	-0.0517	476.31
	U.S.	0.0579	0.527 (0.409)	0.516 (0.370)	-0.0438	495.47
	U.K.	0.0730	0.530 (0.428)	0.518 (0.388)	-0.0691	416.30
U.S.-U.K. 2000	Brazil	0.0942	0.874 (0.697)	0.826 (0.625)	-0.0807	682.22
	Russia	0.0752	0.839 (0.642)	0.810 (0.583)	-0.0641	529.03
	India	0.0740	0.816 (0.511)	0.793 (0.476)	-0.0431	368.89
	China	0.0781	0.827 (0.409)	0.798 (0.370)	-0.0588	402.36
Brazil 2002	Russia	0.0376	0.721	0.689	-0.0582	361.47
	India	0.0437	0.708	0.682	-0.0544	421.73
	China	0.0482	0.693	0.658	-0.0371	366.19
	U.S.	0.0475	0.724	0.700	-0.0466	385.42
	U.K.	0.0439	0.711	0.695	-0.0427	437.88

Note: In parenthesis results for stable periods. LLF(c) is the maximum of the copula component of the log-likelihood function.

Table 3. Results for multivariate copula with switching regime parameters

	Brazil	Russia	India	China	U.S.	U.K.	Brazil
LF	-1347.9	-1474.1	-1186.2	-1495.5	-1082.4	-1107.3	-1.265
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
v	4.377	4.806	4.129	4.900	2.065	2.131	4.279
s_{11}	0.868	0.739	0.744	0.645	0.672	0.680	0.632
s_{22}	0.733	0.712	0.686	0.619	0.620	0.627	0.608

Table 4. Unconditional correlations using AG-DCC model

Country Period	with	Crisis period	Stable Period
Brazil 1997-1998	Russia	0.648	0.584
	India	0.612	0.579
	China	0.639	0.503
	U.S.	0.682	0.674
	U.K.	0.627	0.591
Russia 1998	Brazil	0.624	0.584
	India	0.527	0.518
	China	0.536	0.483
	U.S.	0.618	0.586
	U.K.	0.614	0.571
India 1997	Brazil	0.589	0.579
	Russia	0.539	0.518
	China	0.896	0.644
	U.S.	0.630	0.581
	U.K.	0.613	0.539
China 1997	Brazil	0.582	0.503
	Russia	0.523	0.483
	U.S.	0.627	0.527
	U.K.	0.615	0.534
U.S.-U.K. 2000	Brazil	0.872	0.674
	Russia	0.754	0.586
	India	0.783	0.581
	China	0.789	0.527
Brazil 2002	Russia	0.682	0.584
	India	0.653	0.579
	China	0.671	0.503
	U.S.	0.720	0.674
	U.K.	0.691	0.591

Table 5. Conditional partial covariances

Country Period		with	Crisis period	Stable Period
Brazil	1997-1998	Russia	0.732	0.671
		India	0.697	0.620
		China	0.684	0.562
		U.S.	0.795	0.706
		U.K.	0.741	0.619
Russia	1998	Brazil	0.706	0.671
		India	0.645	0.600
		China	0.630	0.524
		U.S.	0.679	0.662
		U.K.	0.648	0.583
India	1997	Brazil	0.629	0.620
		Russia	0.658	0.600
		China	0.918	0.827
		U.S.	0.677	0.634
		U.K.	0.635	0.587
China	1997	Brazil	0.633	0.562
		Russia	0.658	0.524
		U.S.	0.629	0.577
		U.K.	0.625	0.576
U.S.-U.K.	2000	Brazil	0.905	0.706
		Russia	0.870	0.662
		India	0.842	0.634
		China	0.818	0.577
Brazil	2002	Russia	0.727	0.671
		India	0.671	0.620
		China	0.695	0.562
		U.S.	0.759	0.706
		U.K.	0.782	0.619

Table 6. DCC GARCH models

	Symmetric model		Asymmetric model		
	a^2_i	b^2_i	a^2_i	g^2_i	b^2_i
Brazil	0.0019	0.9627	0.0015	0.0012	0.9649
Russia	0.0017	0.9603	0.0012	0.0009	0.9678
India	0.0022	0.9634	0.0015	0.0011	0.9642
China	0.0016	0.9682	0.0011	0.0008	0.9695
U.S.	0.0084	0.9243	0.0057	0.0051	0.9420
U.K.	0.0079	0.9286	0.0034	0.0025	0.9461

Figure 1. Copula regimes on crises periods

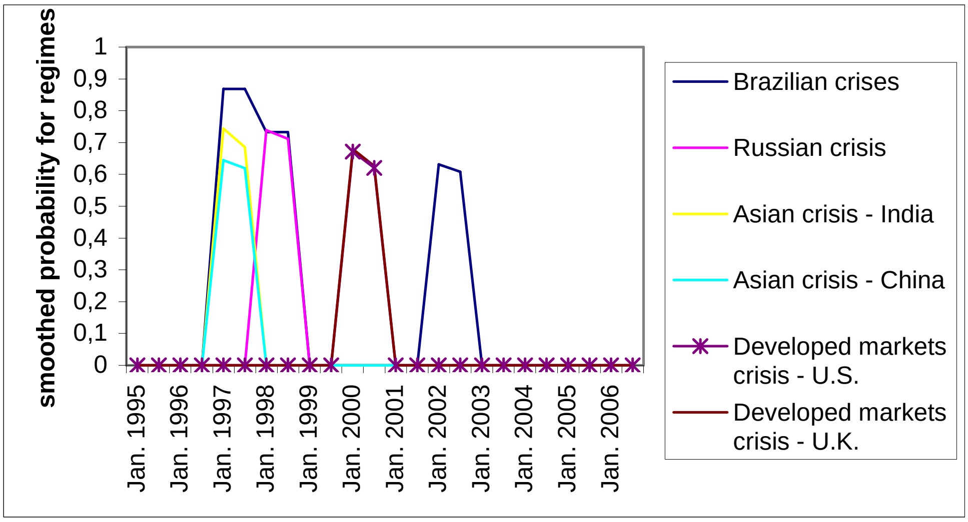

Figure 2. News Impact Curve

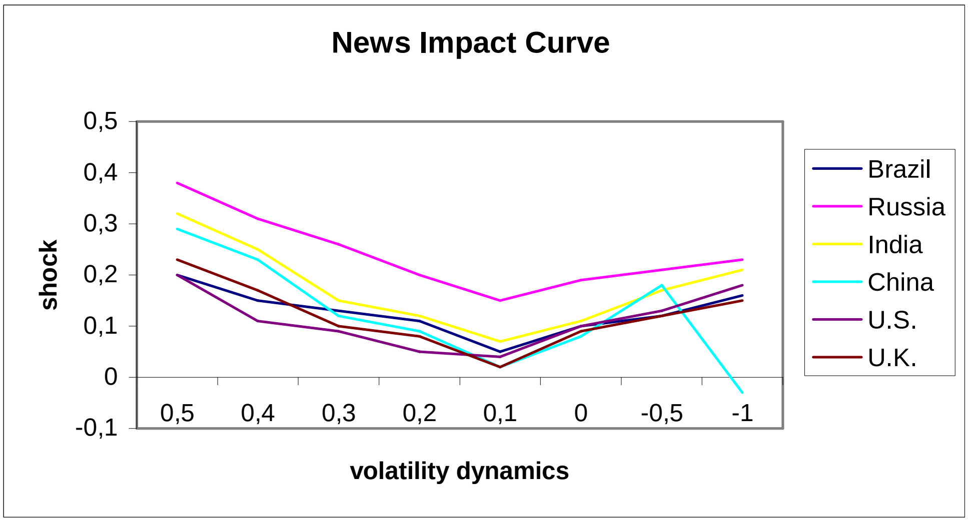

Figure 3. Comparison between Copula and AG-DCC results