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A Component Model for Dynamic Conditional Correlations: Disentangling Interdependence from Contagion

Jilber Urbina*

Abstract

We analyze whether the crisis sourced in US is spread over the world by contagion or through interdependence. Within this work, contagion is defined as a significant increase in cross-correlations after a crisis hits a country, we assumed that correlations are not constant over time and also evolve according to a GARCH(1,1)-type structure which give rise to the use of the popular DCC model introduced by Engle (2002) and extended in Colacito et al. (2011) to disentangle the short and long run component of the total correlation of the portfolio under study. We link interdependence with long-run fluctuations in correlations and contagion is associated with the short-run correlations.

JEL codes: C01, C58, G01, G15.

Keywords: contagion, financial crisis, stock markets, global transmission, market integration, Dynamic Conditional Correlations.

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1 Introduction

Assessment of the transmission mechanisms of financial crisis across countries based on correlations have been payed a lot of attention since King and Wadhwani (1990) and then reinforced by Forbes and Rigobon (2002). Correlation approach is useful since it provides a straightforward way to test for contagion (see Forbes and Rigobon, 2002), nevertheless the *"static"* correlation approach is very simplistic, it splits the sample into two subsamples (pre-crisis and post-crisis periods) and performs a test of significant increase in correlations over these two periods where the underlying correlations are fixed within periods, none dynamic is involved in the correlations.

The lack of temporal dynamics in the correlations can be overcome by using a Dynamic Conditional Correlation (DCC) model, first introduced by Engle (2002). Several attempts have been done to test for contagion by averaging the dynamic correlations belonging to each subsamples and then performing a classical t-test for mean differences, see for instance Wang and Nguyen Thi (2013), Naoui et al. (2010a), Naoui et al. (2010b) and Chiang et al. (2007) . These works rely on defining contagion as an increase in cross-market linkages after a exogenous negative shock in one country or group of countries (such definition corresponds to the World Bank's *"very restrictive"* definition), but none of them show the time varying behavior of both interdependence and contagion.

We try to shed some light on the gap, which in terms of Rigobon (2003), no satisfactory procedure has been developed to be able to answer the question whether contagion occurs or not using the correlation-based definition since the seminal contribution by King and Wadhwani (1990).

We use a component model for the DCC to capture both, interdependence and contagion via a parsimonious parameter structure and still rely on the *very restrictive definition* of contagion, but allowing the correlations to be time varying. Using the DCC-MIDAS[1] introduced by Colacito et al. (2011) we can disentangle both, the long run and short run components of the time varying correlations which can allows us to associate the former with contagion

[1]DCC-MIDAS: Dynamic Conditional Correlation - Mixed Data Sampling Model.

and the latter with interdependence.

Within this framework we identify interdependence which is in itself a contribution since it helps to better understand contagion. Forbes and Rigobon (2002) discussed the influence of heteroscedasticity over the correlations and furthermore, a correction is also proposed. Nevertheless, the test over the corrected correlation operates in a static environment such that contagion can be wrongly diagnosed, mainly because interdependence effects have not been discounted from the correlations.

As discussed in Forbes and Rigobon (2002) correlation after a negative shock can increase because of heteroscedasticity, however, as markets moves more and more together due to market integration, it is plausible to think that interdependence also varies over time and moves in the same direction of market integration, therefore, correlations also can be increased by the effect of integration and such integration is represented by interdependence which is not explicitly taken into account in previous works.

The above ideas are relevant since financial links play an important role in economic integration of an individual country into the world market (Dornbusch et al., 2000), this means that a financial crisis in one country can lead to direct financial effects to other countries. In line with Dornbusch et al. (2000) the spread of a financial crisis depends primarily on the investors' behavior and on the degree of financial market integration, they claims that in this sense, financial markets facilitate the transmission of real or common shocks but do not cause them. As these kind of links (financial and trade) give rise to market integration (interdependence) play and important role for transmitting crisis, a measure of such links over time become crucially important, this measure is provided in this context by the long-run correlation given by the MIDAS filter.

Long-run component can be seen as the measure of financial market integration which is plausible to be modeled as a slowly moving average of correlations due to the fact that such integrations are neither constant overtime nor fast-moving, it evolves slowly.

Empirical works on contagion has been focused mainly on the co-movements in asset prices rather than on "excessive" co-movements among them (Dornbusch et al., 2000). We provide such *excess* of comovements by discounting from the potential contagion the effects of interdependence, this is done by subtracting from the short-run correlation at time t, the corresponding long-run correlation. Once we have the correlation without the effects of interdependence, we can perform a test for contagion.

In order to estimate both kind of correlation, we use recently introduced DCC-MIDAS model of Colacito et al. (2011). DCC-MIDAS model is not a new model since is was introduced by Colacito et al. (2011), nevertheless the novelty of our approach is the application of this model to the context of contagion vs interdependence, where we associate contagion to short-lived events (short run correlations) and interdependence is directly linked to long-run correlations.

After adjusting the correlations by discounting the interdependence effects we perform a test for contagion leading to the conclusion that the Global Financial Crisis triggered in US was spread to other countries through interdependence. We only find evidence of contagion for one pair of countries: Brazil - Japan.

The remaining of this work is arranged as follows: in section 2 we present the model, its notation, the estimation procedure and the hypothesis test strategy. Empirical application is developed in section 3, some concluding remarks are in section 4.

2 Model Specification

2.1 Notation and Preliminaries

We begin this section by providing the meaning of the notation used throughout this work.

Let $\mathbf{r}_t = [r_{1,t}, \ldots, r_{n,t}]'$ be a vector of returns such that follows the process $\mathbf{r}_t \sim N(\mu, \mathbf{H}_t)$ with:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{Q}_t \mathbf{D}_t, \tag{1}$$

where μ is the vector of unconditional means, $\mathbf{H_t}$ is the conditional covariance matrix, $\mathbf{Q_t}$ is the conditional correlation matrix and $\mathbf{D_t}$ is a diagonal matrix with conditional standard deviations on the diagonal, with:

$$\mathbf{Q}_t = E[\xi_t \xi_t' \mid \Omega_{t-1}] \tag{2}$$

$$\xi_t = \mathbf{D}_t^{-1}(\mathbf{r}_t - \mu), \tag{3}$$

where ξ_t is a vector of standardized residuals and Ω_{t-1} is the information set available up to $t-1$. Therefore, we can write the vector of returns as $\mathbf{r}_t = \mu + \mathbf{H}_t^{1/2}\xi_t$ with $\xi_t \sim N(0, \mathbf{I_n})$

2.2 The DCC–MIDAS model

The DCC-MIDAS model is a natural extension to DCC model, they both are very similar in their formulation and the main difference between them is that DCC-MIDAS has two components: a long-run and a short-run component for correlations. The standard formulation of a DCC models is shown in (4) and the one corresponding to a DCC-MIDAS model is (5), one can tell that the difference between them is the construction of $\bar{\mathbf{R}}$. For the standard DCC model $\bar{\mathbf{R}}$ represents the matrix of unconditional correlations which is time invariant, in contrast for the DCC-MIDAS, $\overline{\mathbf{R}}$ becomes into $\bar{\mathbf{R}}_t(\omega)$, which is time varying and its behaviour is entirely determine by a slowly moving average weighting, ω. $\bar{\mathbf{R}}_t(\omega)$ is interpreted as the long-run component and its counterpart, the short-run component, is left to be represented by $\mathbf{Q_t}$:

$$\mathbf{Q_t} = (1 - a - b)\bar{\mathbf{R}} + a\xi_{t-1}\xi_{t-1}' + b\mathbf{Q_{t-1}} \tag{4}$$

$$\mathbf{Q_t} = (1 - a - b)\bar{\mathbf{R}}_\mathbf{t}(\omega) + a\xi_{t-1}\xi_{t-1}' + b\mathbf{Q_{t-1}} \tag{5}$$

where the long-run component is $\bar{\mathbf{R}}_\mathbf{t}(\omega) = \sum_{l=1}^{K} \Phi_l(\omega) \odot \mathbf{C_{t-1}}$ a slowly moving average of some correlation matrix denoted by $\mathbf{C_{t-1}}$ with typical element being $c_{i,j,t-l}$. The operator $\odot$ denotes the Hadamard product. For the short-run component to be a correlation, the following transformation is needed $\mathbf{Q_t}^* = \{\text{diag}(\mathbf{Q_t})^{-1}\mathbf{Q_t}\text{diag}(\mathbf{Q_t})^{-1}\}$ (Engle, 2002), where $q^*_{i,j,t}$ is a typical element of $\mathbf{Q_t}^*$.

If we denote the typical element of $\mathbf{Q_t}$ as $q_{i,j,t}$ and if the typical element of matrix $\mathbf{\bar{R}_t}$ is denoted by $\bar{\rho}_{i,j,t}$, then we can write the full formulation of the DCC-MIDAS as follows:

$$\begin{aligned}
q_{i,j,t} &= (1-a-b)\bar{\rho}_{i,j,t} + a\xi_{i,t-1}\xi_{j,t-1} + bq_{i,j,t-1} \\
q^*_{i,j,t} &= \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \\
\bar{\rho}_{i,j,t} &= \sum_{l=1}^{K} \varphi(\omega)c_{i,j,t-l} \\
c_{i,j,t-l} &= \frac{\sum_{k=t-l-N}^{t-l} \xi_{i,k}\xi_{j,k}}{\sqrt{\sum_{k=t-l-N}^{t-l} \xi_{i,k}^2}\sqrt{\sum_{k=t-l-N}^{t-l} \xi_{j,k}^2}} \\
\varphi(\omega) &= \frac{\left(1-\frac{1}{K}\right)^{\omega-1}}{\sum\limits_{j=1}^{K}\left(1-\frac{j}{K}\right)^{\omega-1}}
\end{aligned} \tag{6}$$

According to the formulation of system (6), the value of N is needed for estimating the weighted correlation $c_{i,j,t-l}$ which only accounts for the last N past observations in its calculation, then over these correlations, a long run correlation is estimated as a weighting average of all the K past values giving weights $\varphi(\omega)$.

Under this formulation $q^*_{i,j,t}$ is the *short run* correlation between assets i and j, whereas $\bar{\rho}_{i,j,t}$ is a slowly moving *long run* correlation. Furthermore, $\varphi(\omega)$ are the so called Beta weights which governs the movements of the long run component, this weighting scheme allows us to extract the slowly moving secular component around which the short-run component evolves. Lag lengths are denoted by N and span lengths of historical correlations are left to be represented by K, we consider N and K are constant for all assets.

Rewriting the first equation of system (6) as:

$$q_{i,j,t} - \bar{\rho}_{i,j,t} = a(\xi_{i,t-1}\xi_{j,t-1} - \bar{\rho}_{i,j,t}) + b(q_{i,j,t-1} - \bar{\rho}_{i,j,t}), \tag{7}$$

conveys de idea of short run fluctuations around a time-varying long run relationship.

2.3 Estimation procedure

The estimation procedure is fully described in Colacito et al. (2011), here we briefly point out the main aspects. In order to estimate the parameters of the DCC-MIDAS model we follow the two step procedure of Engle (2002). Let ψ[2] be the collection of parameters of the univariate GARCH model and let Ξ be the vector of DCC parameter (a, b, ω), the quasi-maximum likelihood (QL) takes the following form:

$$\begin{aligned} QL(\psi, \Xi) &= QL_1(\psi) + QL_2(\psi, \Xi) \\ &= -\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \mathbf{r}_t' D_t^2 \mathbf{r}_t) - \sum_{t=1}^{T}(\log|R_t| + \xi_t' R_t^{-1}\xi_t + \xi_t'\xi_t). \end{aligned} \tag{8}$$

The separation of $QL(\psi, \Xi)$ into $QL_1(\psi)$ and $QL_2(\psi, \Xi)$ indicates that we can first estimate the parameters of the univariate GARCH-type processes contained in ψ by maximizing $QL_1(\psi)$ to obtain $\hat{\psi}$, then we can plug $\hat{\psi}$ in $QL_2(\psi, \Xi)$ so that it becomes into $QL_2(\hat{\psi}, \Xi)$ where standardized residuals $\hat{\xi} = \hat{D}_t^{-1}(\mathbf{r}_t - \hat{\mu})$ are used in the second stage.

System (6) requires setting two extra parameters: N the MIDAS lag length and K, the span lengths of historical correlations, both are chosen from the parameter space by maximum likelihood profiling. The profiling procedure of the likelihood function is performed over the maximization of $QL_2(\psi, \Xi)$, once we get the "optimal" N and K we reestimate the entire model using the complete likelihood defined by

$$\log \mathcal{L} = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \xi_t'\xi_t + \log|R_t| + \xi_t' R_t^{-1}\xi_t), \tag{9}$$

maximizing it in one step to obtain the relevant standard errors of the estimated coefficients to perform individual hypothesis tests.

[2]This ψ could be a standard GARCH, or an EGARCH or even a Beta-t-EGARCH

2.4 Testing procedure

In this section we present the strategies to test for contagion based on the dynamic correlations estimated under the DCC-MIDAS scheme.

One of the alternatives consist of testing $H_0 : a = 0$ which implies that under the null, $q_{i,j,t}$ is determined by $(1-b)\overline{\rho}_{i,j,t}(\omega) + b_{i,j,t-1}$ with $0 \leq b < 1$. If the empirical evidence do not reject the null, then interdependence can be reached as the conclusion of the test. However, if $H_0 : a = 0$ turns out to be rejected, then this constitutes contagion defined as in Corsetti et al. (2005) who consider that "*for contagion to occur, the observed pattern of comovements in asset prices must be too strong (or too weak) relative to what can be predicted conditional on a constant mechanism of international transmission*".

Corsetti et al. (2005) definition conveys the idea that contagion can be assessed through performing a test for increases or decreases in the conditional correlations, in our context this boils out to be a test over $H_0 : a = 0$ to determine whether the co-movements are too strong or too weak, this is the reason why the one-step estimation of the DCC-MIDAS is required.

Another approach to test for contagion is using directly the time-varying conditional correlations produced by the model. Considering contagion as an increase in the mean correlation after a crisis, if such increase stemmed from a model which acts like a filter discounting the economic fundamentals, then it is plausible to assume that the increase (positive excess) in correlations is due to irrational reactions of the agents in the markets. A way to measure this excess based on the daily conditional time-varying correlation from the DCC-MIDAS model is:

$$\overline{q}_{i,j}^{l*} = \frac{1}{T^l} \sum_t \left(q_{i,j,t}^* - \overline{\rho}_{i,j,t}(\omega) \right) \mathbb{1} \left(t \in precrisis \right) \tag{10}$$

$$\overline{q}_{i,j}^{h*} = \frac{1}{T^h} \sum_t \left(q_{i,j,t}^* - \overline{\rho}_{i,j,t}(\omega) \right) \mathbb{1} \left(t \in crisis \right) \tag{11}$$

where $\mathbb{1}(\cdot)$ is an indicator function that takes value 1 when condition in () is met and 0 otherwise. $T^l = \mathbb{1} \sum_t (t \in precrisis)$ is the sample size corresponding to the stable period, while $T^h = \mathbb{1} \sum_t (t \in crisis)$ is the sample size in the turmoil period.

The proposed test of contagion interprets an increase in mean excess of correlations as evidence of contagion because it represents additional comovements in asset returns during the crisis period not present in the precrisis period. As contagion represents the additional comovements in asset returns over that predicted by changes in the market fundamentals, the identification of contagion requires the extraction of market fundamentals from the returns series (Fry et al., 2010). Within the DCC-MIDAS approach here proposed, we associate market fundamentals with the long-run correlations mainly because the MIDAS part filters the series and the result can be used as a proxy for the fundamentals, leading to identification of contagion as any excess of short-run correlation from the levels of long-run correlations. As a consequence the hypothesis test boils out to be as follows:

$$H_0 \;:\; \overline{q}^{h*}_{i,j} \leq \overline{q}^{l*}_{i,j} \tag{12}$$

$$H_1 \;:\; \overline{q}^{h*}_{i,j} > \overline{q}^{l*}_{i,j} \tag{13}$$

which is a traditional mean difference based on the standard t-test as that of Naoui et al. (2010b). For that we use:

$$\widehat{\overline{q}^{l*}_{i,j}} = \frac{1}{T^l}\sum_t \left(\widehat{q^*_{i,j,t}} - \overline{\rho}_{i,j,t}(\widehat{\omega})\right) \mathbb{1}\left(t \in precrisis\right) \tag{14}$$

$$\widehat{\overline{q}^{h*}_{i,j}} = \frac{1}{T^h}\sum_t \left(\widehat{q^*_{i,j,t}} - \overline{\rho}_{i,j,t}(\widehat{\omega})\right) \mathbb{1}\left(t \in crisis\right) \tag{15}$$

where $\widehat{q^*_{i,j,t}}$ and $\widehat{\omega}$ are obtained from the MLE of the DCC-MIDAS model.

Another alternative to test for contagion is using Corsetti et al. (2005) definition and to test whether contagion occurs by setting a threshold (τ). Testing whether deviation of the short-run correlation from the long-run correlation is bigger (smaller) than τ is in line with the idea that the comovements should be too strong (or too weak) for contagion to exist. In this case, the hypothesis test can be written as follows

$$H_0 \;:\; \left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right| \leq \tau \tag{16}$$

$$H_1 \;:\; \left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right| > \tau \tag{17}$$

where H_0 implies interdependence and H_1 contagion. Usually τ is proportional to the standard deviation of $\left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right|$.

3 Empirical application

One of the tests of contagion presented in the previous section is now applied to identify potential contagious linkages from the US stock market to other stock markets during the subprime mortgage crisis. Our analyzed period goes from January 1, 2004 to December 31, 2012. Stock indexes and countries chosen for the analysis are in **??**.

First, we estimate the short and long run correlation of asset returns. As we pointed out before, we address the problem of selecting MIDAS lags by following Colacito et al. (2011) and Engle et al. (2006), we compare different DCC-MIDAS models with different time spans via profiling of the likelihood function.[3]

In Table 1 we report the coefficients of the DCC-MIDAS and also the resulting estimates of a DCC. Our estimation is somehow restrictive because we only consider one parameter (ω) to account for the long run dynamics. For the short run dynamics we use DCC of order (1,1), which means only one a and one b.

Results in Table 1 show that DCC-MIDAS parameters are very close to the DCC parameters as is recurrent feature in Engle et al. (2006), the superiority of DCC-MIDAS over DCC is the capability of disentangling the short run from the long run correlation which permits analyzing the behavior of them simultaneously.

Time varying correlations based on the DCC-MIDAS scheme are plotted on Figure 1, Figure 2 and Figure 3, the black lines in each plot represents the short run correlation meanwhile the long run correlation is shown in red, the dashed line splits the entire sample into two subsamples: precrisis period and crisis period as it is conventionally done in the contagion literature based on correlation. A visual analysis of these figures suggests no relevant changes in the linkages between countries neither in the general short run correlation behavior nor in the long run, from this fact we can derive the cautious "conclusion" that the economies exhibits strong linkages in all states of the world, this situation can be interpreted as interdependence, nevertheless, in order to formally draw any conclusion about the absence of contagion during the analyzed period, we perform a statistical hypothesis testing.

[3] See details of the procedure in Engle et al. (2006).

Table 1: DCC MIDAS and DCC results.

		a	b	ω
DCC-MIDAS	Estimates	0.1086	0.6789	2.3654
	t-stat	11.6943	17.8802	3.3204
	P-value	0.0000	0.0000	0.0009
DCC	Estimates	0.1192	0.6775	-
	t-stat	4.0027	7.4565	-
	P-value	0.0001	0.0000	-

Note: The top panel reports the estimates of the DCC-MIDAS while the bottom panel shows the DCC estimates. We set $K = N = 528$ as suggested by the likelihood profiling.

Table 2 consists of all the possible combinations of pairwise correlations for the analyzed sample, since we have 6 countries (stock markets) then we can compute 15 $\bar{q}^{l}_{i,j,t}$ and $\bar{q}^{h}_{i,j,t}$ and perform the test specified in subsection 2.4. Hypothesis test suggests no contagion for all pair of countries except for Brazil and Japan where the p-value confirm the rejection of the null even at 1% significance level.

The results of the test confirm that transmission of the crisis was due to real linkages, this conclusion stems from the failure in rejecting the hypothesis of interdependence.

Table 2: Contagion test results.

	Precrisis	Crisis	P-value	Result
sp500-ftse100	0.0225	−0.0060	1.0000	N
sp500-eurostoxx50	0.0142	−0.0116	1.0000	N
sp500-bovespa	0.0014	−0.0089	0.9755	N
sp500-nikkei225	0.0264	0.0093	0.9861	N
sp500-spasx200	0.0369	−0.0200	1.0000	N
ftse100-eurostoxx50	−0.0020	0.0004	0.1795	N
ftse100-bovespa	0.0106	−0.0028	0.9969	N
ftse100-nikkei225	0.0068	−0.0042	0.9327	N
ftse100-spasx200	0.0141	−0.0104	1.0000	N
eurostoxx50-bovespa	0.0050	0.0004	0.8019	N
eurostoxx50-nikkei225	0.0033	−0.0058	0.8656	N
eurostoxx50-spasx200	0.0095	−0.0288	1.0000	N
bovespa-nikkei225	0.0051	0.0278	0.0010	C
bovespa-spasx200	0.0122	−0.0101	0.9999	N
nikkei225-spasx200	0.0052	−0.0180	0.9999	N

footnotesizeNote: column 1 indicates the pairs of countries for which correlation is computed, columns 2 and 3 have the mean of those correlations, column 4 holds the p values associated to the test and the last column contains an N when No-contagion and it has a C when there is empirical evidence of contagion.

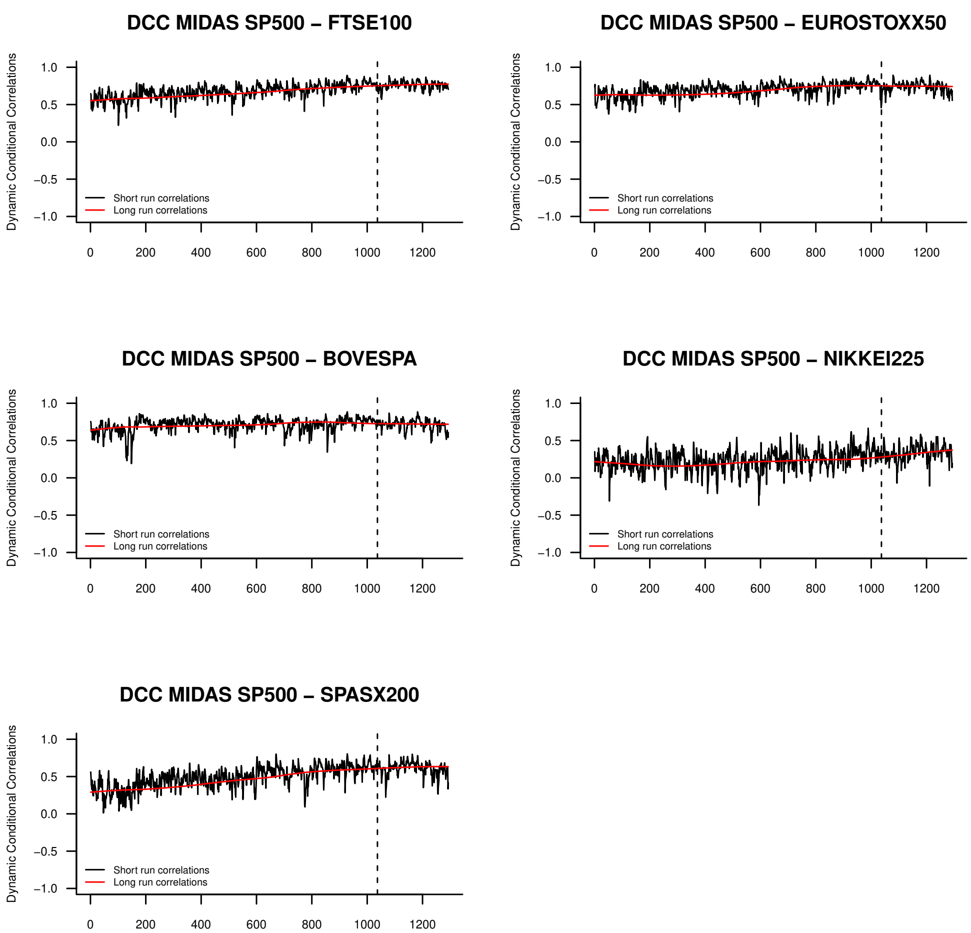

Figure 1: Long and short correlations for returns.

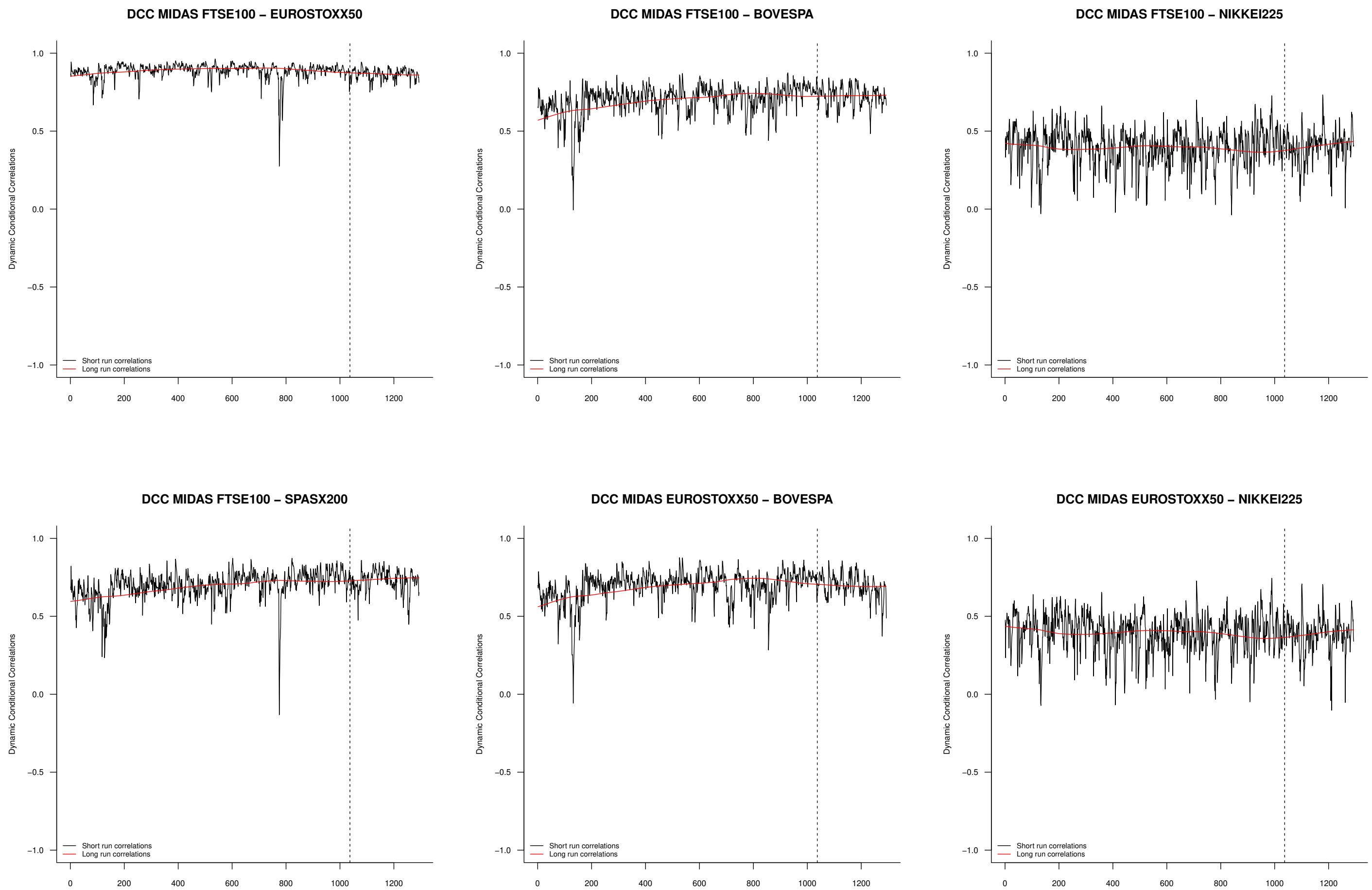

Figure 2: Long and short correlations for returns.

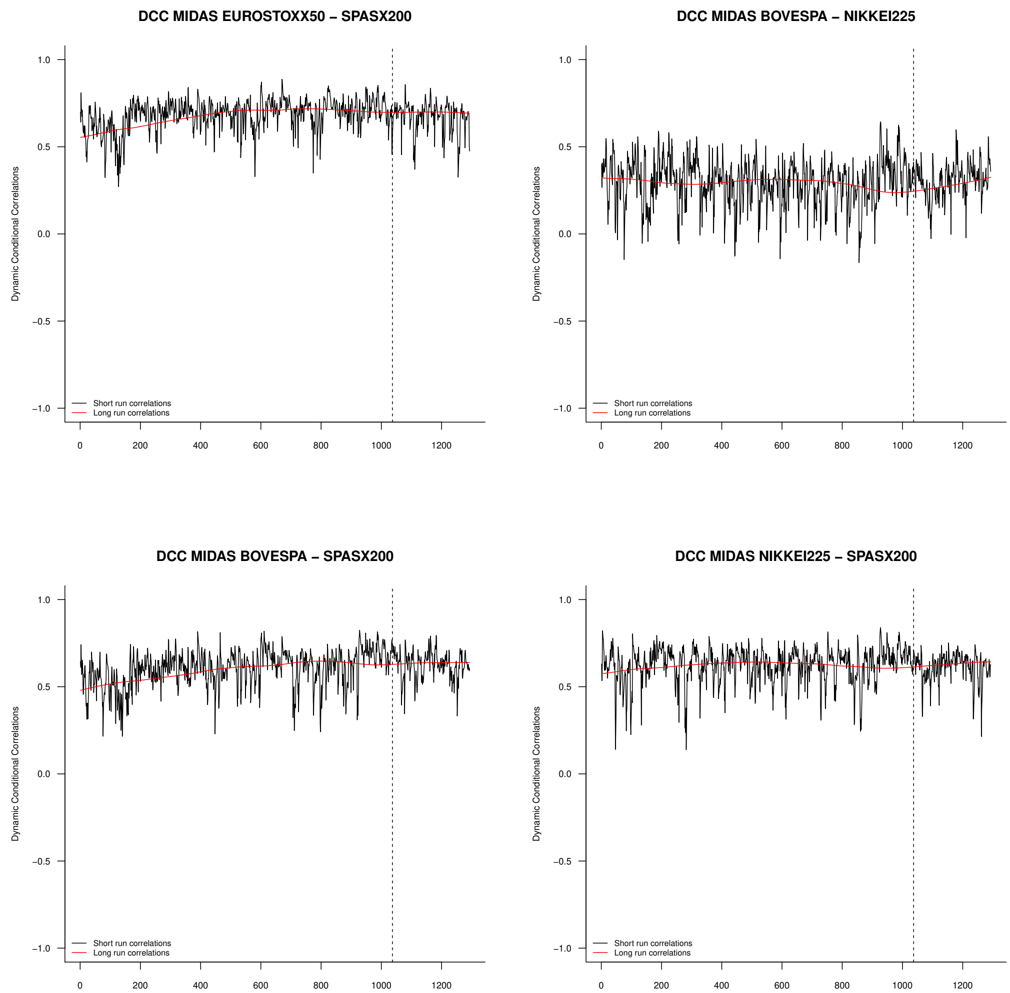

Figure 3: Long and short correlations for returns.

4 Conclusions

In this paper we analyzed whether the crisis sourced in US is spread over the world by contagion or just through real linkages known as interdependence. Within this chapter, contagion is defined as a significant increase in cross-correlations after a crisis hits a country, we assumed that correlations are not constant over time and also assuming that they evolves according to a GARCH(1,1)-type structure which give rise to the use of the popular DCC model introduced by Engle (2002) and extended in Colacito et al. (2011) to distill the short run and long run component of the total correlation of the portfolio under study.

Our results suggest that linkages between stock markets remains the same before and after the crisis, there is no evidence of significant increase in correlations, therefore interdependence is the main channel of transmission of the crisis which is plausible since stock markets are more and more integrated and the lagged values of the correlation associated to the interdependence are dominant over the influence of the short run correlations.

Evidence of contagion is only found for Brazil and Japan. It is worthy to say that the test only identifies the existence/non-existence of contagion but it is not allow to identify the directionality of such a contagion, for the case of Brazil and Japan we found the correlation strengthened after the crisis in US providing evidence of contagion but we do not know if contagion ran from Brazil to Japan or in the other way around.

References

Chiang, T. C., Jeon, B. N., and Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance*, 26(7):1206–1228.

Colacito, R., Engle, R. F., and Ghysels, E. (2011). A component model for dynamic correlations. *Journal of Econometrics*, 164(1):45–59.

Corsetti, G., Pericoli, M., and Sbracia, M. (2005). Some contagion, some interdependence?: More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24(8):1177 – 1199.

Dornbusch, R., Park, Y. C., and Claessens, S. (2000). Contagion: Understanding How It Spreads. *World Bank Research Observer*, 15(2):177–97.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Engle, R., Gysels, E., and Sohn, B. (2006). On the economic sources of stock market volatility. NYU and UNC unpublised manuscript.

Forbes, K. and Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. *The Journal of Finance*, 57(5):2223–2261.

Fry, R., Martin, V. L., and Tang, C. (2010). A new class of tests of contagion with applications. *Journal of Business & Economic Statistics*, 28(3):423–437.

King, M. A. and Wadhwani, S. (1990). Transmission of Volatility between Stock Markets. *The Review of Financial Studies*, 3(1):5–33.

Naoui, K., Khemiri, S., and Liouane, N. (2010a). Crises and Financial Contagion: The Subprime Crisis. *Journal of Business Studies Quaterly*, 2(1):15–28.

Naoui, K., Liouane, N., and Brahim, S. (2010b). A Dynamic Conditional Correlation Analysis of Financial Contagion: The Case of the Subprime Credit Crisis. *International Journal of Economics and Finance*, 2(3):85–96.

Rigobon, R. (2003). On the measurement of the international propagation of shocks: is the transmission stable? *Journal of International Economics*, 61(2):261 – 283.

Wang, K.-M. and Nguyen Thi, T.-B. (2013). Did China avoid the Asian flu? The contagion effect test with dynamic correlation coefficients. *Quantitative Finance*, 13(3):471–481.