Contagion between markets during financial crises

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Abstract

In this work we investigate how a number of crises have affected most of the stock markets in the world. First, we apply Time Series Factors Analysis (TSFA) in order to reduce the dimensionality of the series under study and obtain a lower number of factors that can be related to regions. Then we use the dynamic conditional correlation (DCC) model to obtain the pair-wise correlations between regions. Finally, we analyse the effect of the different crisis on correlations. This approach allows us to detect contagion between markets during the most important crisis. Our results show evidence of a contagion effect between most regions.

KEYWORDS: Contagion, Multivariate Volatility, Time Series Factor Analysis and Dynamic Conditional Correlation

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1. Introduction

Over recent decades, we have seen how different financial crises, having originated in particular regions and countries, have extended geographically. As world capital markets have become increasingly integrated, information originating from one market is likely to become more important for other markets. In fact, understanding the nature of linkages between financial markets, whether intra- or international, is fundamental to establishing the limits of diversification, to security pricing, and to successfully allocating assets. If asset prices commove differently in different states of nature, portfolio diversification might be less effective than usually presumed, and investment strategies need to take this into account.

When analysing interrelations across different financial markets it is necessary to distinguish between interdependence and contagion. There is now a reasonably large body of literature that attempts to distinguish them. This literature has been reviewed by Dornbusch et al. (2000), Claessens et al. (2001), Pericoli and Sbracia (2003) and Dungey et al. (2005). Forbes and Rigobon (2002) define contagion as a significant increase in cross-market comovements, while any continued market correlation at high levels is considered to be interdependent. Therefore, the existence of contagion must involve evidence of a dynamic increment in correlations[1].

Research examining contagion and/or interdependencies among major world equity markets has provided mixed evidence about correlations among the markets. The conceptual definitions of contagion differ and the empirical analyses are only partly comparable because methodologies, time periods and financial markets vary substantially across studies. The existing literature on contagion using tests based on analysis of conditional correlation has several limitations. The use of the high frequency financial series affects the test by three types of bias: heteroskedasticity, simultaneous equations and omitted variables (Forbes and Rigobon, 2002; Rigobon, 2003; and Yoon, 2005). [2]

Forbes and Rigobon (2002) tested the increase in the correlation coefficients adjusted from only a heteroskedasticity bias, concluding that propagation of the Asian crisis resulted from the interdependence between the financial markets and not from the contagion. These authors showed

[1] Allen and Gale (2001) and Pericoli and Sbracia (2003) overview the alternative definitions of contagion that have been proposed in the literature.

[2] See Chiang et al. (2007) for a detailed explanation of the potential drawbacks and limitations of the existing contagion tests.

that their tests are biased when the data suffer from simultaneous equations and omitted variable problems. In order to correct these problems, an original methodology to test for contagion has been proposed by Chiang et al. (2007). These authors employ a multivariate GARCH model which enables them to address the heteroskedasticity problem without arbitrarily dividing the sample into two sub-periods (pre-crisis and post-crisis) and introduce lagged U.S. stock returns as an exogenous factor to solve the omitted variable problem and to account for the global common factor. By doing this, they find supportive evidence of contagion during the Asian crisis.

The core objective of this paper is to examine the dynamics of conditional correlations among nineteen international stock markets (including both developed and developing) during four important crises: the Asian crisis in 1997, the Dot.com crisis in 2000, the Subprime crisis in 2007 and the Global Financial crisis in 2008; that are decisive inputs for international asset allocation, risk dispersion and efficient hedging. Following Chiang et al. (2007), to overcome the limitations found in the existing literature, this paper employs a cross country, multivariate GARCH model, which is appropriate for measuring time-varying conditional correlations during the four important crises. Concretely, we use the dynamic conditional correlation model with an asymmetric GARCH (DCC-AGARCH) introduced by Engle (2002) which relaxes excessive parameter constraints of the earlier GARCH models.

The main contributions of this paper to the literature on financial contagion are summarized as follows. First, we examine and compare financial contagion during the above-mentioned financial crises. Unlike the previous literature on the existence of financial contagion that has mainly focused on one crisis, especially during the 1990's, we also look at the contagious effect of more recent crises. Second, we consider a large set of countries, developed and developing, and group them into regions. By doing this, we are able to analyse if the contagious effect of the financial crises is alike across markets in different geographical areas.

Empirical findings show the presence of shifts towards an increased correlation and fluctuation across most geographical areas during the four crisis periods. However, the crises periods affected more the variability than the level of correlations. These results indicate that when crises hit the market the volatility of correlation could vary greatly, reducing the benefits of international portfolio diversification when it is more desirable.

The remainder of this paper is organized as follows. Section 2 introduces the data. Section 3 analyses the methodology and evaluates the empirical findings. The paper concludes with a summary of the main results.

2. Data

The data set has been provided by Datastream and consists of daily equity index closing prices of nineteen stock market indexes across three geographical regions: North America, Europe and Asia[3]. The equity market indexes included in the study to represent the North American market are Standard and Poor's 500 (SP), Dow Jones Industrial Index (DJI), Nasdaq (NAS) and the Canadian Toronto Index SE300 (SE300); to represent the European market we use Germany (DAX), France (CAC40), Italy (MIB30), UK (FTSE) and Spain (IBEX35). Finally, we include Japan (Nikkei (NIK) and Topix (TOPX)) to represent a developed equity market from Asia and Hong Kong (Hang Seng Index HSI), Philippines (Philippines SE Composite IPSE), Korea (Korea SE Composite, KS11), Singapore (Singapore Straits Time Index STI), Taiwan (Taiwan SE Weighted Index, TWII), Indonesia (Jakarta SE Composite Index JKSE), Malaysia (Kuala Lumpur SE Index KLCI) and Thailand (BANGKOK S.E.T., SET) to represent emerging equity markets in Asia. The sample period extends from December 31, 1994 to September 30, 2009. [4]

The evolution of daily time series indexes grouped in geographical regions is plotted in Figures 1a-1d. Japan is plotted in a different graph from Southeast Asia because of the scale. In order to get a better comparison between indexes, all of them have been transformed, setting the index base of December 31, 1994 equal to 100. The dynamics of most of the time series are similar, with the exception of the group of Asian markets, where different patterns are observed at the beginning of the sample period. However, from 2002 on, all indexes show a similar pattern: significant drops in October, 1997 (Asian crisis) and in the Summer of 1998 (Russian Crisis), a continuous increase from December, 1999 associated to the Dot.com boom and a continuous decline from 2000 when the crisis of the technological firms starts. This decreasing trend finishes in 2004 when we observe a new increase in all the markets up to August, 2007. At this time, the Subprime crisis shakes the markets and, finally, at the beginning of 2008, the Global Financial crisis originates a sharp drop in all indexes. These facts show a clear interdependence among markets and suggest the existence of a contagion effect which supposes that a dramatic movement in one stock market have a powerful impact on other markets.

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[3] To adjust for time-zone difference effects we have repeated the complete analysis using stock market returns calculated as rolling-average two day returns. Results are similar to those obtained using daily returns.
[4] In case of national holidays in any country, the missing value is replaced by the last trading value.

Figure 1a. Evolution of North American stock price indexes.

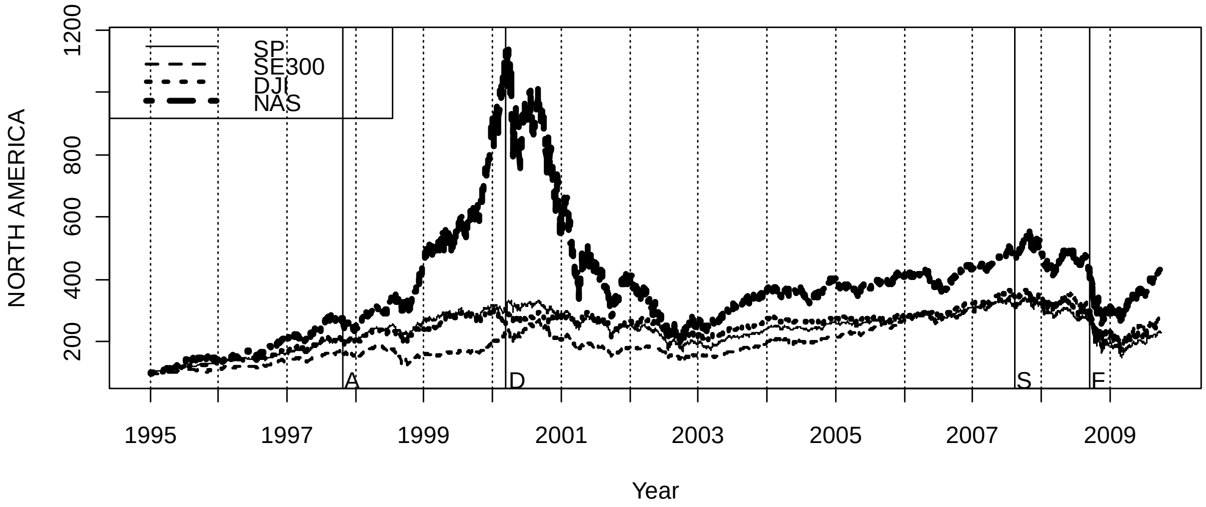


Figure 1b. Evolution of European stock price indexes.

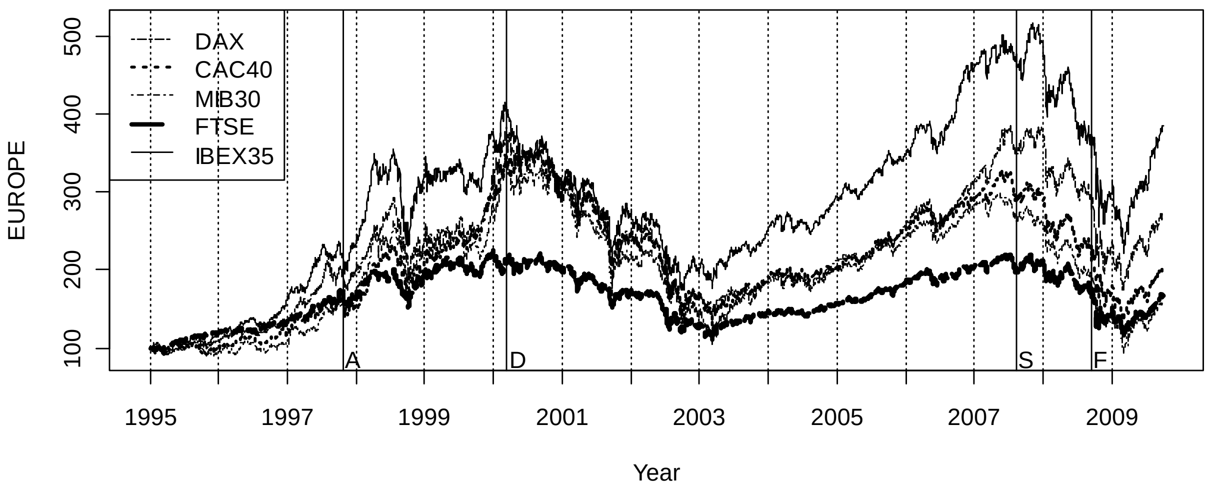


Figure 1c. Evolution of Japanese stock price indexes.

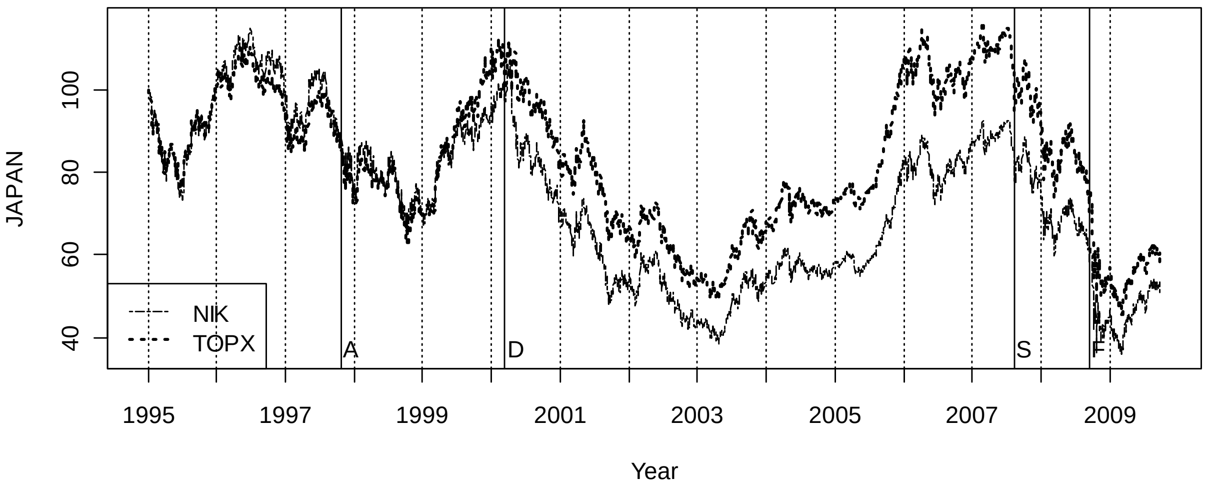
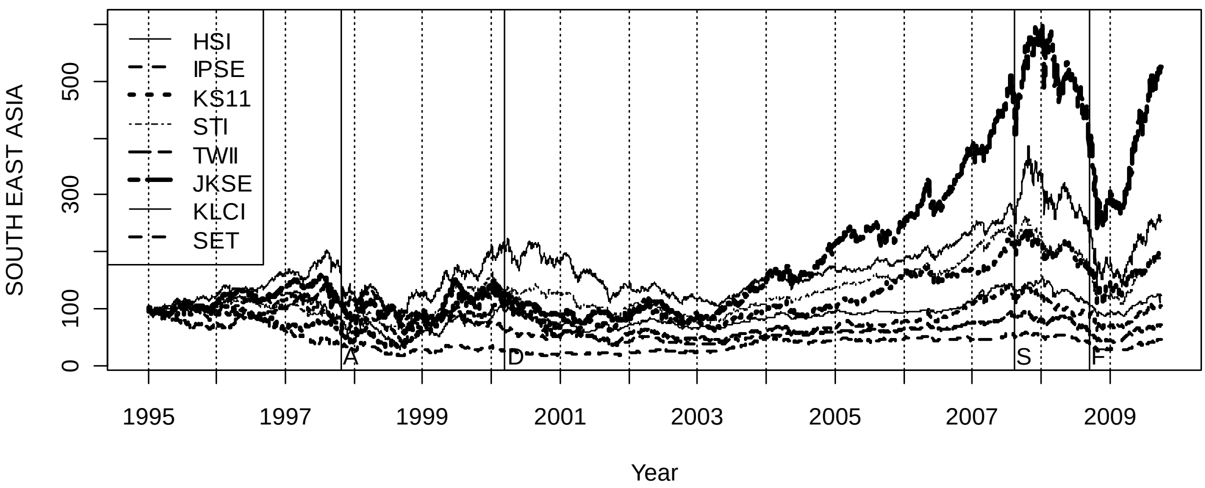


Figure 1d. Evolution of Southeast Asian stock price indexes.



Note: The vertical solid lines are placed in the start of crisis periods. A stands for Asian Crisis; D stands for Dot.com Crisis; S stands for Subprime Crisis; and F stands for Global Financial crisis

Table 1 shows descriptive statistics for the returns of the sample markets. As usual, stock returns are calculated as first differences of the natural log of stock-price indexes and expressed as percentages. The return time series exhibit the usual features of a financial time series: non-normality, skewness and high kurtosis.

Unconditional correlation coefficients, displayed in Table 2, indicate high correlations within the European, the North American, Japanese and Southeast Asian index returns. There is also high correlation across the European and North American markets and truly low correlations within the Southeast Asian index returns and across the other markets.

Table 1. Descriptive statistics for index returns.

	Mean	*St.Dev*	*Skewness*	*Kurtosis*	*Minim*	*Maxim*	*Jarque-Bera test*
SP	0.022	1.272	-0.128***	8.705***	-9.470	10.957	12129.9***
SE300	0.026	1.159	-0.729***	9.862***	-9.788	9.370	15895 ***
NIK	-0.017	1.543	-0.273***	6.226***	-12.111	13.235	6247.3***
DAX	0.026	1.552	-0.053	4.388***	-7.433	10.797	3082.6***
CAC40	0.018	1.467	-0.029	4.979***	-9.472	10.595	3966.9***
MIB30	0.012	1.465	-0.174***	5.810***	-12.239	10.765	5418.9***
FTSE	0.013	1.213	-0.132***	6.617***	-9.265	9.384	7015.5***
IBEX35	0.035	1.421	-0.164***	4.918***	-9.586	10.118	3885.7***
DJI	0.024	1.201	-0.109***	8.245***	-8.201	10.508	10880.2***
NAS	0.038	2.058	0.113***	4.424***	-11.115	17.203	3139.3***
TOPX	-0.014	1.377	-0.295***	6.909***	-10.084	12.865	7691.4***
HIS	0.025	1.772	0.116***	10.029***	-14.735	17.247	16094.8***
IPSE	0.001	1.505	0.392***	11.038***	-12.462	16.179	19582.6***
KS11	0.018	2.062	-0.146***	4.550***	-14.204	11.485	3325.6***
STI	0.017	1.363	-0.057	4.405***	-8.460	8.767	3106.8***
TWII	-0.009	1.577	-0.140***	2.537***	-9.946	8.371	1042.9***
JKSE	0.043	1.680	-0.153***	7.730***	-12.732	13.128	9572.6***
KLCI	0.006	1.528	0.430***	46.039***	-24.153	20.817	339011.1***
SET	-0.021	1.683	0.116***	6.484***	-15.155	11.223	6734.3***

Note: This table summarizes descriptive statistics of the equity index returns. Statistics include mean, standard deviation, skewness, kurtosis, minimum, maximum and Jarque–Bera normality test. *** denote statistical significance at the 1% level. The sample period includes 3834 observations.

Table 2. Unconditional Correlation between stock index returns.

	S.P	SE300	DJONES	NASDAK	DAX	CAC40	MIB30	FTSE	IBEX	NIKKEI	TOPIX	HSI	IPSE	KS11	STI	TWII	JKSE	KLCI	SET
S.P	1																		
SE300	0.646	1																	
DJONES	**0.956**	0.593	1																
NASDAK	**0.814**	0.564	**0.718**	1															
DAX	0.534	0.470	0.530	0.425	1														
CAC40	0.492	0.477	0.487	0.366	**0.830**	1													
MIB30	0.437	0.435	0.435	0.330	**0.745**	**0.820**	1												
FTSE	0.476	0.479	0.473	0.338	**0.769**	**0.842**	**0.747**	1											
IBEX	0.454	0.450	0.451	0.338	**0.765**	**0.836**	**0.788**	**0.764**	1										
NIKKEI	0.112	0.221	0.120	0.082	0.270	0.293	0.261	0.308	0.273	1									
TOPIX	0.103	0.223	0.111	0.069	0.251	0.282	0.252	0.297	0.264	**0.934**	1								
HSI	0.174	0.260	0.181	0.125	0.343	0.343	0.309	0.370	0.328	0.501	0.497	1							
IPSE	0.038	0.125	0.051	0.012	0.125	0.129	0.120	0.150	0.140	0.270	0.282	0.355	1						
KS11	0.128	0.164	0.125	0.106	0.228	0.226	0.203	0.246	0.219	0.387	0.387	0.412	0.250	1					
STI	0.163	0.219	0.166	0.116	0.300	0.314	0.285	0.334	0.308	0.417	0.413	0.593	0.342	0.380	1				
TWII	0.075	0.132	0.071	0.07	0.162	0.179	0.155	0.162	0.173	0.323	0.331	0.357	0.240	0.356	0.353	1			
JKSE	0.051	0.130	0.058	0.011	0.170	0.179	0.167	0.182	0.183	0.295	0.303	0.414	0.348	0.268	0.428	0.269	1		
KLCI	0.009	0.080	0.014	0.012	0.125	0.133	0.133	0.162	0.125	0.233	0.235	0.344	0.248	0.228	0.373	0.2160	0.307	1	
SET	0.106	0.173	0.110	0.073	0.204	0.214	0.201	0.225	0.213	0.275	0.282	0.410	0.303	0.318	0.429	0.246	0.372	0.325	1

Note: This table shows unconditional correlations between stock index returns over the sample period.

3. Methodology and results

This section consists of three parts. First, given the huge number of indexes under study, we use Time Series Factor Analysis to analyse common patterns in the returns time series. Next we estimate a dynamic conditional correlation model with asymmetric GARCH (DCC-AGARCH) to obtain the pair-wise correlations between factors. Finally, we analyze the effect of the crises periods on conditional correlations introducing a dummy variable for each crisis. This crisis indicator takes the value 1 during the crisis period and 0 otherwise. According to this paper's definition, there is contagion between markets when the dummy variable is significant and positive in the mean and/or variance of the pair-wise correlation coefficients. Thus, contagion exists when pair-wise correlations increase during crisis times relative to correlations during peaceful times and/or are more volatile. In each case both the employed methodology and the results are presented.

3.1. Time Series Factor Analysis (TSFA)

Understanding the dynamic structure of the markets requires the analysis of returns, volatilities and correlations and, in our case, it requires a high-dimensional statistical model. In the literature there exist different methodologies to reduce dimensionality and capture the underlying structure of the return time series. Factor Analysis is the one used most commonly, but this methodology assumes that the data have no serial correlation. This assumption is violated by daily financial data, in which case it is better to use the Dynamic Factor Analysis (DFA) introduced by Watson and Engle (1983) or Time Series Factor Analysis (TSFA) introduced by Gilbert and Meijer (2005). Both methods allow observations to be dependent over time, but Dynamic Factor Analysis (DFA) needs explicity modelling of the process dynamics in the underlying phenomena and the predictions depend on the specified dynamic factor.

Therefore, we use Time Series Factor Analysis (TSFA), which estimates a model for a time series with as few assumptions as possible about the dynamic process governing the factors. In addition to this, the observations do not need to be independent and identically distributed (i.i.d.) and the data do not need to be covariance stationary. The factors identified by the TSFA method are latent variables and, with a reduced number of factors we can explain the dynamic structure of the data.

The relationship between the observed time series y_t (M-vector of length n) and the unobserved factors ξ_t (k-vector with k << M) is explained by the model :

$$y_t = \alpha_t + B\xi_t + e_t \tag{1}$$

where α_t is the M-vector of intercept parameters, B is a Mxk matrix parameter of loadings and e_t is a random M-vector of measurement errors.

Table 3. Factors obtained by TSFA

	Factor 1	***Factor 2***	***Factor 3***	***Factor 4***	***Communality***
SP	**0.689**	-0.016	-0.008	-0.009	**0.995**
SE300	**0.382**	0.041	0.123	0.047	0.472
NIK	-0.006	**0.668**	0.010	0.009	**0.938**
DAX	0.071	-0.008	**0.570**	0.009	**0.766**
CAC40	-0.016	0.003	**0.681**	-0.018	**0.908**
MIB30	-0.024	-0.004	**0.626**	-0.011	**0.748**
FTSE	0.013	0.013	**0.593**	0.025	**0.775**
IBEX35	-0.015	-0.006	**0.635**	0.005	**0.778**
DJI	**0.658**	-0.011	0.005	-0.006	**0.918**
NAS	**0.583**	-0.011	-0.040	-0.013	0.663
TOPX	-0.007	**0.678**	-0.001	0.019	**0.931**
HIS	0.024	0.090	0.059	**0.446**	0.573
IPSE	-0.005	0.010	-0.032	**0.394**	0.251
KS11	0.033	0.109	0.015	**0.307**	0.291
STI	0.031	0.002	0.039	**0.516**	0.563
TWII	0.008	0.075	-0.004	**0.298**	0.232
JKSE	-0.015	-0.024	-0.008	**0.474**	0.350
KLCI	-0.037	-0.037	-0.003	**0.386**	0.254
SET	0.020	-0.049	0.010	**0.453**	0.349
CFI	0.431	0.727	0.930	**0.984**	
RMSEA	0.222	0.163	0.089	**0.045**	

Note: This table shows the standardized loadings CFI, RMSEA statistics for each factor and the communality of each stock market indexes return.

Following the conventional rule that the number of factors should be equal to the number of eigenvalues that are larger than one, we consider four factors. In order to reinforce the selection of four factors, we introduce two statistics for measuring models with varying number of factors (Wansbeek and Meijer (2000)), the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). The CFI is a pseudo-R^2 that compares a model to the null model[5]. Its value is always between 0 and 1. A general rule is that CFI should be greater than 0.9 for the model containing all the factors. The RMSEA is a non-negative number that measures the lack of fit per degree of freedom. Usually a RMSEA less than 0.05 for the model containing all the factors is considered a well-fitting model. Table 3 presents the values of CFI and RMSEA for a model with one, two, three or four factors, respectively. The results in the last case imply that the model fits well.

Table 3 also presents the loadings of the standardized solution for the four factors model and the communality. A larger loading (in absolute value) means a stronger relationship of the index with the factor. The communality provides information about the variance of the index which is shared with the others indexes via the common factors. The first factor represents North American indexes; the second factor represents only the two Japanese indexes; the next factor comprises the European market indexes; and finally the indexes of the Southeast Asian markets are loaded in the fourth factor.

Figures 2a-2d show the evolution of daily return time series for each factor. High volatility is observed during crisis periods, especially during the Asian crisis in the fourth factor (Southeast Asian market) and during the Global Financial crisis in all factors.

[5] In factor analysis, the usual null model is the same as the zero-factor model, i.e., the model that specifies that all observed variables are independently distributed.

Figure 2a. Evolution of Factor 1: North America.

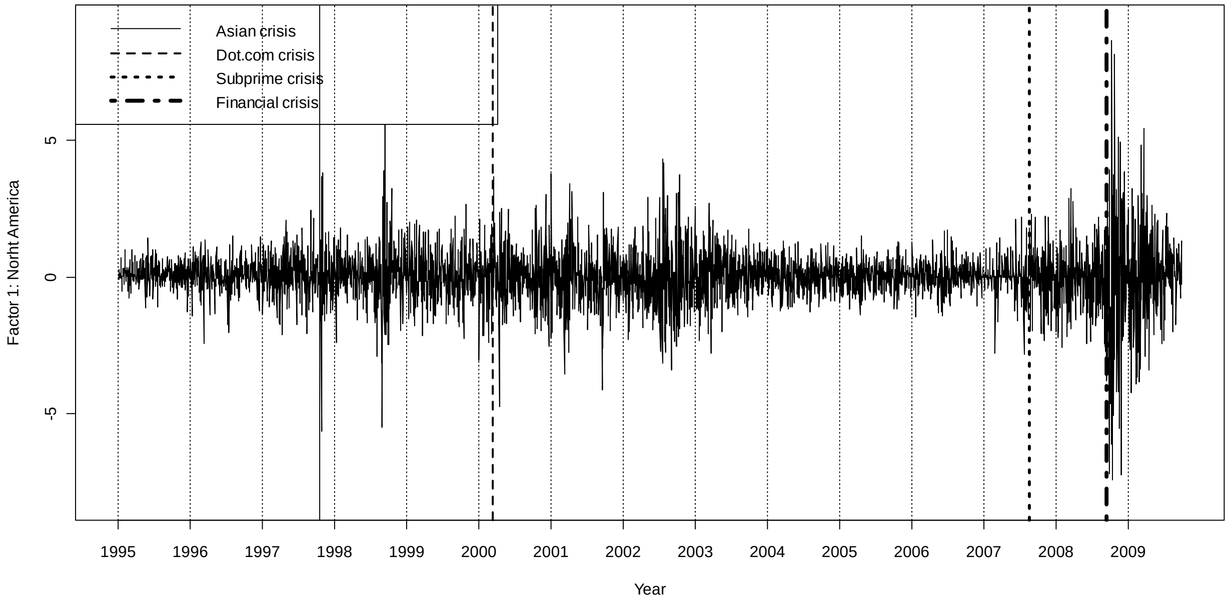


Figure 2b. Evolution of Factor 2: Japan.

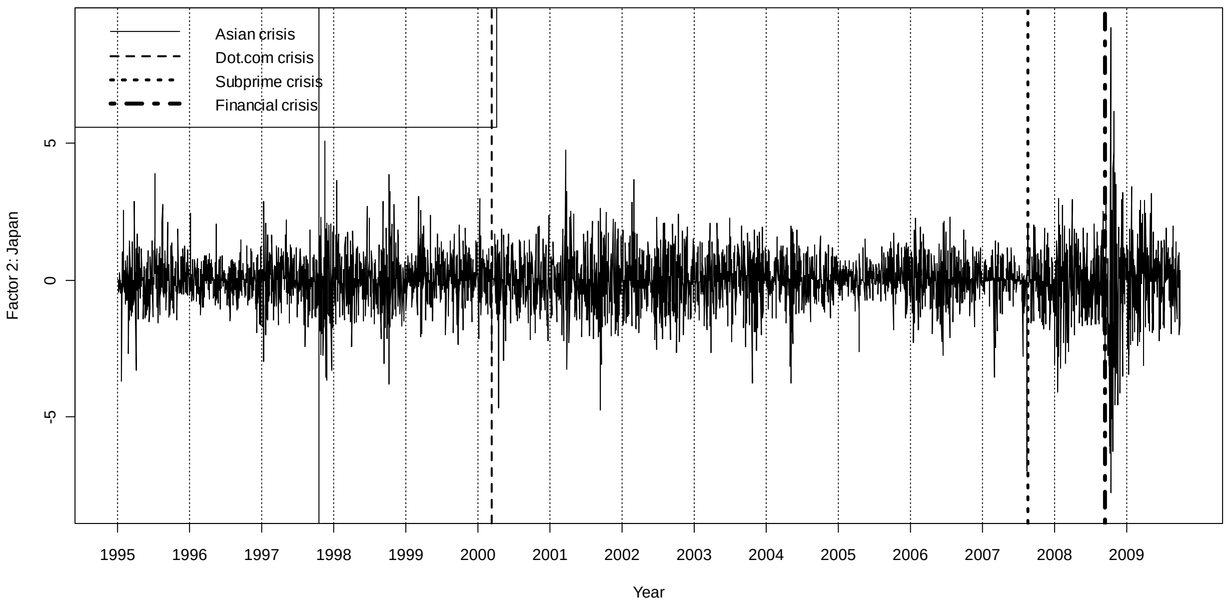


Figure 2c. Evolution of Factor 3: Europe.

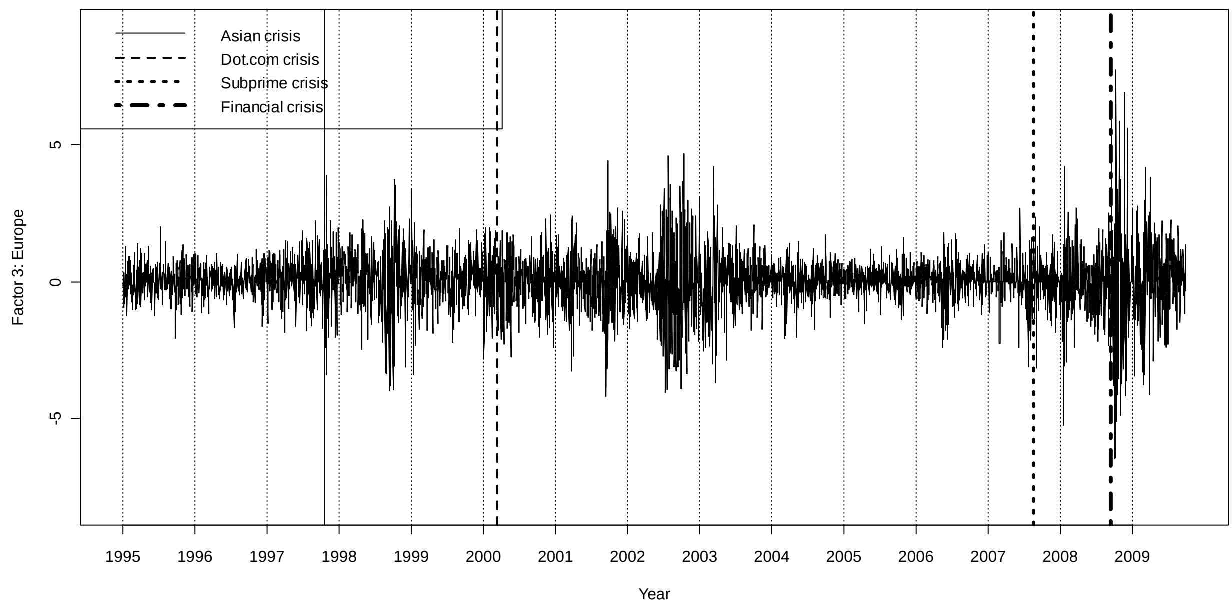
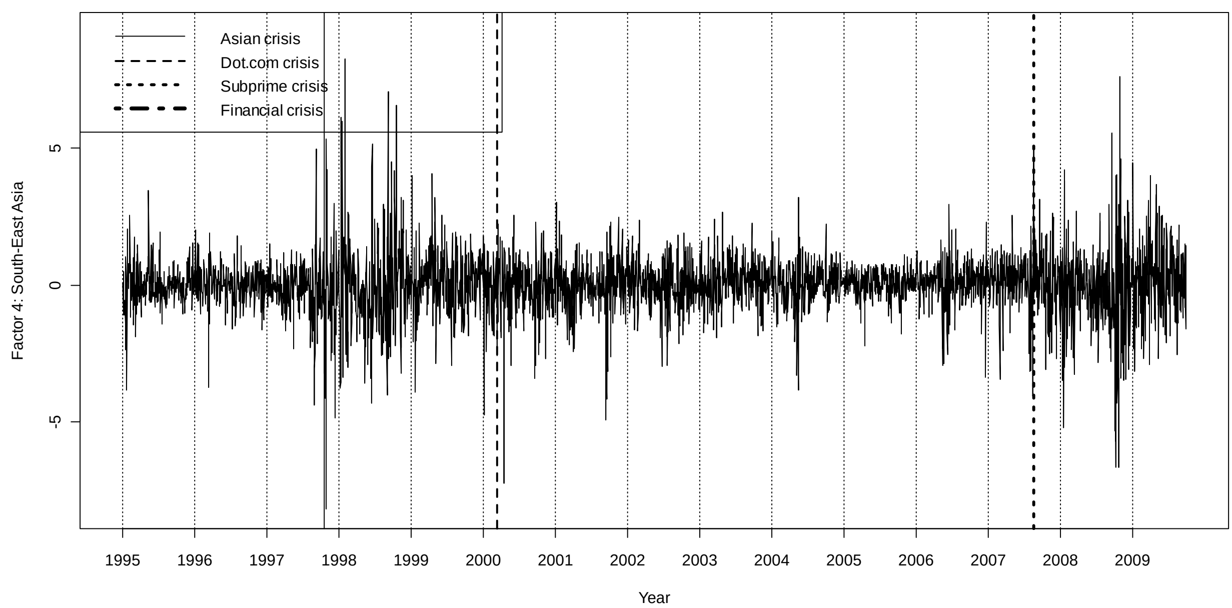


Figure 2d. Evolution of Factor 4: Southeast Asia.



Tables 4a-4d show the descriptive statistics for the four factors.[6] Panel A and Panel B present the statistics during the pre-crisis and post-crisis periods, respectively. For each crisis, with the exception of the Asian crisis, the pre-crisis period starts one month after having finished the previous crisis and finishes on the day before the crisis initiates[7]. The post-crisis period starts on the day the crisis starts and finishes one day before the next crisis starts. The pre-crisis period for the Asian crisis starts on 02/01/1995. We have assumed that crisis duration is of one month; it starts the day of the crisis and finishes one month later, as has been suggested in Forbes and Rigobon (2002).

Comparing the statistics for the four factors during the pre-crisis and post-crisis periods, we observe that the mean is not significantly different in both periods with the exceptions of the Asian crisis (Table 4a), in which the mean for the North America factor is higher during the pre-crisis period than during the post-crisis period and the Dot.com crisis (Table 4b), in which the mean of the European factor is lower in the pre-crisis period. In general, variances are higher in the post-crisis period with the exception of the Southeast Asian factor volatility during the Dot.com crisis. It is important to point out that all the factors present high kurtosis during the pre- and post-crisis periods, with the exceptions of North American and Japanese factors before the Global Financial crisis; in general, skewness is more significant after the crisis than before it. All of this causes us to believe that we cannot assume the hypothesis of normality for theses factors.

Table 4a . Descriptive statistics of factors during the Asian crises (01/02/1995 – 03/09/2000)

	Mean	Variance	Skewness	Kurtosis
Panel A: Pre- crisis period	*01/02/1995 – 10/21/1997*			
Factor 1: North America	0.81**	0.338	-0.250**	1.958***
Factor 2: Japan	-0.013	0.621	0.092	2.486***
Factor 3: Europe	0.060**	0.371	-0.055	0.542**
Factor 4: Southeast Asia	-0.026	0.609	-0.227**	5.952***
Panel B: Post-crisis period	*10/22/1997 – 03/09/2000*			
Factor 1: North America	0.048	1.043	-0.191*	4.665***
Factor 2: Japan	0.019	1.047	0.152	2.240***
Factor 3: Europe	0.079*	1.138	-0.388***	1:664**
Factor 4: Southeast Asia	0.025	2.465	0.459***	4.214***

Note: Asian crisis started at 10/22//1997. The sample period includes 1348 observations. The observations for the pre-crisis and post-crisis period are 729 and 619 respectively. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

[6] Data in the tables are indicated as MM/DD/YYYY.

[7] Although the Global Financial crisis began in 2007 with the mortgage and banking crisis, the collapse started in the middle of September 2008 with the bankruptcy of Lehman and the bailout of AIG.

Table 4b. Descriptive statistics of factors during the Dot.com crises (11/22/1997 – 08/14/2007)

	Mean	Variance	Skewness	Kurtosis
Panel A: Pre- crisis period	*11/22/1997 – 03/09/2000*			
Factor 1: North America	0.052	0.952	-0.074	3.814***
Factor 2: Japan	0.027	0.947	0.081	1.705***
Factor 3: Europe	-0.087**	1.086	-0.434***	1.623***
Factor 4: Southeast Asia	0.049	2.294	0.697***	3.648***
Panel B: Post-crisis period	*03/10/2000 – 08/14/2007*			
Factor 1: North America	0.001	0.729	0.094	3.127***
Factor 2: Japan	-0.004	0.778	-0.284***	2.152***
Factor 3: Europe	-0.003	0.903	-0.095*	2.987***
Factor 4: Southeast Asia	0.030	0.673	-0.949***	6.010***

Note: Dot.com crisis started at 03/10/2000. The sample period includes 2528 observations. The observations for the pre-crisis and post-crisis period are 597 and 1931 respectively. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

Table 4c. Descriptive statistics of factors during the Subprime crisis (04/10/2000 – 09/14/2008)

	Mean	Variance	Skewness	Kurtosis
Panel A: Pre- crisis period	*04/10/2000 – 08/14/2007*			
Factor 1: North America	-0.002	0.721	0.055	3.104***
Factor 2: Japan	-0.005	0.787	-0.276***	2.168***
Factor 3: Europe	-0.002	0.899	-0.089	3.058***
Factor 4: Southeast Asia	0.031	0.665	-0.965***	6.206***
Panel B: Post-crisis period	*08/15/2007 – 09/14/2008*			
Factor 1: North America	-0.040	1.034	-0.005	0.481*
Factor 2: Japan	-0.081	1.471	-0.792***	3.424***
Factor 3: Europe	-0.060	1.118	-0.254*	2.699***
Factor 4: Southeast Asia	-0.074	1.760	-0.160	1.896***

Note: Subprime crisis started at 08/15/2007. The sample period includes 2191 observations. The observations for the pre-crisis and post-crisis period are 1910 and 281 respectively. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

Table 4d. Descriptive statistics of factors during the Global Financial crisis (09/15/2007 – 09/30/2009)

	Mean	Variance	Skewness	Kurtosis
Panel A: Pre- crisis period	*09/15/2007 – 09/14/2008*			
Factor 1: North America	-0.054	1.042	0.008	0.457
Factor 2: Japan	0.074	1.345	-0.203	0.307
Factor 3: Europe	-0.066	1.113	-0.218	2.754***
Factor 4: Southeast Asia	-0.096	1.617	-0.229	1.518***
Panel B: Post-crisis period	*09/15/2008 – 09/30/2009*			
Factor 1: North America	-0.0490	4.621	-0.096	2.489***
Factor 2: Japan	-0.060	3.434	-0.181	4.250***
Factor 3: Europe	-0.027	3.532	0.107	2.862***
Factor 4: Southeast Asia	0.056	3.376	-0.306**	2.412***

Notes: Global Financial crisis started at 09/15/2008. The sample period includes 533 observations.. The observations for the pre-crisis and post-crisis period are 260 and 273 respectively. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

3.2. Modelling dynamics in the correlations

To estimate dynamic conditional correlations we use the DCC-AGARCH model proposed by Engle (2002). The DCC model is a two-stage estimator of conditional variances and correlations. In the first stage, a univariate GARCH model is estimated; the univariate variance estimates are subsequently introduced as inputs in the second stage of the estimation process.

Prior to the estimation of the dynamic conditional correlations of the factors, we examine the mean specification of the underlying series. Following Chiang et al. (2007) we include in the mean equation an AR(1) term to account for possible autocorrelation plus two one-day lagged factor. The idea of including the lagged factors is for checking if these factors have a dynamic effect in the determination of $factor_i$. Concretely, the mean equation for each factor is:

$$factor_{i,t} = \gamma_0 + \gamma_1 factor_{i,t-1} + \gamma_2 factor_{j,t-1} + \gamma_3 factor_{z,t-1} + \varepsilon_{i,t} \quad (2)$$

where t=1,…,n, i=1,…4, and j and z refer to the other factors included in the model, the difference between them and also the difference of $factor_i$; $\varepsilon_t=(\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, \varepsilon_{4,t})'$ and $\varepsilon_t|F_{t-1}\sim N(0,H_t)$.

F_t={ $factor_{i,1}$, …, $factor_{i,t-1}$ } is the set of the observations of $factor_i$, up to time t-1, and H_t is the conditional variance matrix.

The DCC-GARCH model decomposes the conditional variance matrix into Ht=$D_tR_tD_t$, where R_t is the (nxn) time-varying correlations matrix and D_t is a (nxn) diagonal matrix of time-varying standard deviations $\sqrt{h_{ii,t}}$ obtained from the asymmetric univariate GARCH model:

$$h_{ii,t} = c_i + a_i \varepsilon^2_{i,t-1} + b_i h_{ii,t-1} + d_i \eta^2_{i,t-1} \tag{3}$$

where the variable $\eta_{i,t} = \max[0, -\varepsilon_{i,t}]$ is the Glosten et al. (1993) dummy series collecting the asymmetric volatility effect. [8]

In the second stage, the vector of the standardized residuals is employed to develop the DCC correlation specification:

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1} \tag{4}$$

and

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{5}$$

where $\overline{Q} = E[u_t u_t^{'}]$ is the unconditional covariance of the standardized residuals. $Q_t = (q_{ij,t})$ is the time-varying covariance matrix of the standardized residuals.

In Eq. (4), α and β are scalar parameters, $u_t = D_t^{-1}\varepsilon_t$ is the standardized residual matrix and Q_t is the covariance matrix of ε_t. The parameters α and β capture the effects of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlations. The empirical estimation of Eq. (4) proceeds in two steps as suggested by Engle (2002). Initially, in matrix $\overline{Q}$, which denotes correlations between standardized residuals, u_t, is estimated. In this first step, the long-run correlations are estimated from the unconditional sample correlations.

[8] Asymmetric volatility refers to the empirical evidence according to which a negative shock increases volatility more than a positive shock of the same size. In the financial literature, two explanations of the asymmetries in equity markets have been put forward: The *leverage* effect and the volatility *feedback* effect. Which of the two effects is the main determinant of asymmetric volatility remains an open question.

Subsequently, in the second step, $\overline{Q}$ is replaced by the sample analogue $T^{-1}\sum_{t=1}^{T} u_t u_t^{'}$ and the parameters α and β corresponding to the dynamic correlation are estimated.

In the case of the DCC(1,1), α and β are positive and $\alpha + \beta < 1$, ensuring that Q_t is positive and mean-reverting. This implies that after a shock occurs, the correlation between the underlying assets will return to the long-run unconditional level.

The correlation estimators of Eq. (5) are of the form:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}, \quad i, j = 1, 2, ..., n, \text{ and } i \neq j \tag{6}$$

In its full formation, the time-varying correlation coefficient can be written for a bivariate case as:

$$\rho_{ij,t} = \frac{(1-\alpha-\beta)\overline{q}_{ij} + \alpha u_{i,t-1} u_{j,t-1} + \beta q_{ij,t-1}}{\sqrt{\left[(1-\alpha-\beta)\overline{q}_{ii} + \alpha u_{i,t-1}^{2} + \beta q_{ii,t-1}\right]}\sqrt{\left[(1-\alpha-\beta)\overline{q}_{jj} + \alpha u_{j,t-1}^{2} + \beta q_{jj,t-1}\right]}} \tag{7}$$

The DCC model is estimated by maximization of the following log-likelihood function:

$$L = -\frac{1}{2}\sum_{T=1}^{T}(n\log(2\pi)) + 2\log\left|D_t\right| + \log\left|R_t\right| + u_t^{'} R_t^{-1} u_t \tag{8}$$

The results of applying the DCC-AGARCH model to the four factors are reported in Table 5. We introduce the one-day lagged North American factor as an explicative variable of the evolution of the other factors because it is well known that this factor acts as a global factor (see Chiang et al. 2007). Given the increasing importance of the European markets[9], we also introduce lagged

[9] According to the consultancy Mercer Oliver Wyman, in terms of the geographical composition of the global financial stock, Europe is catching up. Its financial stock increased by 9.9% over the past ten years, a growth rate, which exceeds that of the USA and the world (8.6% and 8.4% respectively). The depth of Europe’s financial stock has also increased considerably, from 84% of GDP in 1980 to 306% in 2003.

European stock returns as well as lagged U.S. stock returns as an exogenous factor to account for the global common factor.[10] The AR(1) term in the mean equation is significantly positive for the Southeast Asian factor and significantly negative for the European and Japanese factor. As pointed out by Chiang et al. (2007), this finding is in agreement with the evidence in the literature, in that the AR(1) is positive in emerging markets due to price friction or partial adjustment and it is negative as the presence of positive feedback trading in advanced markets. However, the AR(1) term is not significant for the North American factor, indicating that relevant market information is rapidly reflected in stock price changes.

Results also show that both the North American and European effects are highly significant for the other factors. The estimated coefficient for the North American and European effect on the other factors is always significant, indicating that a movement in these markets has an influence on the other markets but that the effect of North America is much higher than the effect of Europe. The coefficients a and b associated with the conditional variance equations are significant for all factors, which is consistent with time-varying volatility. On the basis of the estimated parameter d (which is always significantly negative), the four factors exhibit asymmetry in conditional volatility, i.e., negative news increases volatility more than positive news.

The estimated parameters α and β in the DCC model capture the effects of lagged standardized shocks and lagged dynamic conditional correlations on current dynamic conditional correlations, respectively. The statistical significance of these coefficients in both systems indicates the presence of dynamic (time-varying) factor correlations. Both estimated coefficients, α and β, are found to be positive as well as $\alpha + \beta < 1$, in both systems of equations, supporting the presence of dynamic correlations over time.

[10] Estimations are also conducted taking into account only the North American effect. Results are similar to those including both the North-American and the European effect.

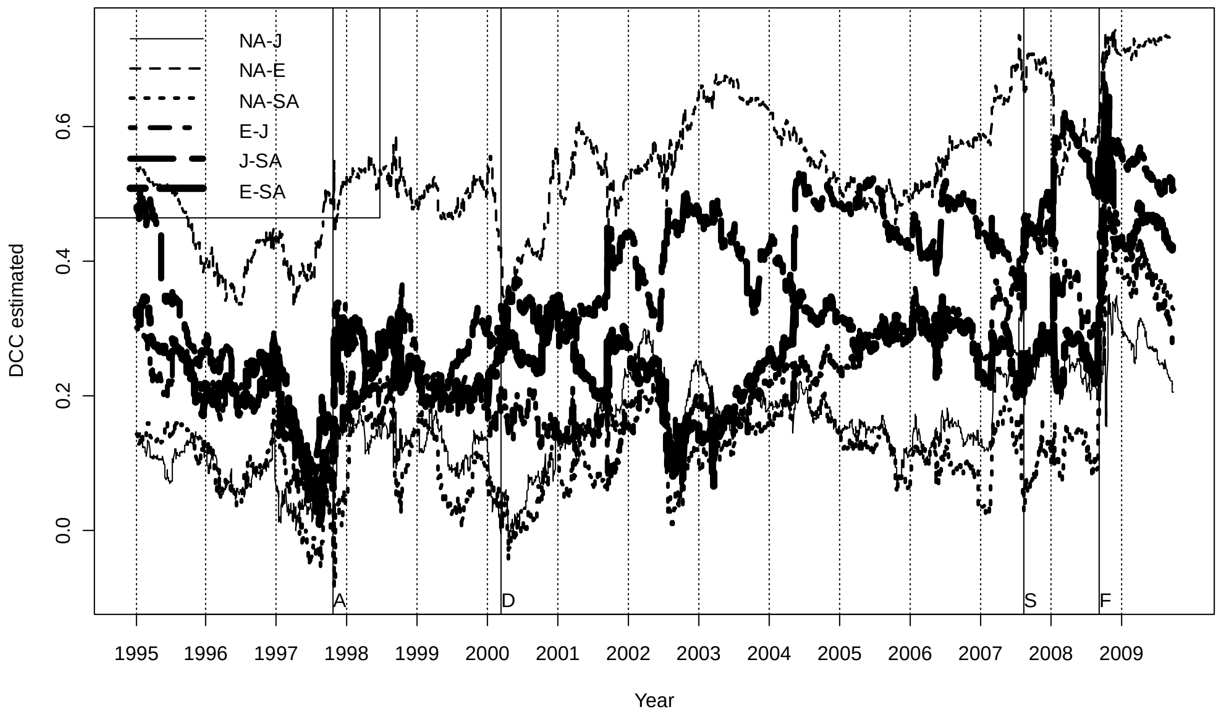
Table 5. Estimation results from the DCC with Asymmetric GARCH(1,1)

	Mean equation				Variance equation		
	γ_0	γ_1	γ_2	γ_3	c	a	b
Factor 1: North America	0.017* (1.86)	-0.021 (-1.26)		0.053*** (3.66)	0.010*** (9.32)	0.139*** (14.37)	0.922*** (165.03)
Factor 2: Japan	-0.021* (-1.82)	-0.052*** (-3.65)	0.318*** (19.80)	0.182*** (11.14)	0.015*** (6.77)	0.106*** (10.75)	0.9165*** (139.46)
Factor 3: Europe	0.017* (1.73)	-0.178*** (-11.49)	0.365*** (23.52)		0.009*** (8.23)	0.114*** (12.12)	0.921*** (135.35)
Factor 4: Southeast Asia	0.008 (0.70)	0.076*** (5.62)	0.393*** (23.56)	0.0852*** (5.22)	0.019*** (15.48)	0.130*** (24.30)	0.880*** (187.97)
	Conditional correlation equation						
	α		β				
	0.007*** (9.09)		0.991*** (919.39)				

Note: The t-statistics are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.
Mean equation: $fact_t = \gamma_0 + \gamma_1 fact_{t-1} + \gamma_2 fact\_Zone_{1,t-1} + \gamma_3 fact\_Zone_{2,t-1} + \varepsilon_t$, where $\varepsilon_t|F_{t-1} \sim N(0,H_t)$ and $Zone_1$ and $Zone_2$ refers to the North American and European effect, respectively.
Variance equation: $h_{ii,t} = c_i + a_i \varepsilon^2_{ii,t-1} + b_i h_{ii,t-1} + d_i \eta^2_{i,t-1}$, i=1,…,4,
Conditional correlation equation: $Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}$ and $R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$

Figure 3 depicts the dynamic of conditional factor correlations. As shown by the figure, there is clear evidence of shifts on almost all pair-wise correlations when the crises periods take place. The highest increases in correlations are after the Asian and the Global Financial crisis. However, the Global Financial crisis produces a shift on all the pair-wise correlations whereas the Asian crisis seems not to affect so much the pair-wise correlation between North America and Europe. Finally, note that the correlation between North America and Europe exhibit the highest conditional correlation during the sample period. In the next section we examine the effect of the crises periods on conditional correlations introducing dummy variables to detect the possible existence of contagion across regions.

Figure 3. Dynamics of conditional factor correlations



Note: The vertical solid lines are placed in the start of crisis periods. A stands for Asian Crisis; D stands for Dot.com Crisis; S stands for Subprime Crisis; and F stands for Global Financial crisis.
NA-J means the pair-wise dynamical conditional correlation estimated for North America-Japan factors, NA-E for North America-Europe factors, NA-SA for North America-Southeast Asia factors, E-J for Europe-Japan factors, J-SA for Japan-Southeast Asian factors and E-SA for Europe- Southeast Asian factors

3.3. The effect of crises on the dynamics of conditional correlations

To asses the effect of the crises periods on the dynamics of conditional correlations, we introduce a set of dummy variables, one for each crisis. The applied equations system is described as:

$$\rho_{ij,t} = \mu + \sum_{p=1}^{P} \phi_p \rho_{ij.t-p} + \alpha_k Crisis_{k,t} + e_{ij,t} \tag{9}$$

$$h_{ij,t} = \varpi_0 + \varpi_1 \varepsilon_{ij,t-1}^2 + \beta_1 h_{ij,t-1} + \delta_k Crisis_{k,t} \tag{10}$$

Crisis variables are defined as dummy variables, indicators that take the value 1 during the crisis period and 0 otherwise. $Crisis_k$ for k=1,…,4 is a dummy variable for the Asian crisis (10/22/1997 – 11/21/1997), the Dot.com crisis (3/10/2000 – 04/09/2000), the Subprime crisis (8/15/2007 –

9/14/2007) and the Global Financial crisis (9/15/2008 – 10/14/2008), respectively. A significant estimated coefficient for the dummy variable will be interpreted as a structural change in the mean and/or variance that produces a shift in the mean and/or variance of the conditional correlation. The order *p*, in equation (9), has been chosen by means of the AIC criterion. This analysis will enable us to detect if conditional correlations are different and/or more volatile before, during or after the crises.

Table 6 shows the tests for detecting changes in correlations after the North American and European effects are introduced. We observe that the goodness of fit is quite correct as indicated by the values of the Ljung-Box Q(20) and $Q^2(20)$. The coefficients associated with the GARCH(1,1) model are all significant, indicating that it is necessary to correct the dynamic correlations by heteroskedasticity. When we look at the coefficients related to the crisis variables, we can conclude the following results. If we look at the Asian crisis (Panel A, $Crisis_1$), we observe that the crisis increased the correlation on the one hand between North America/Japan and on the other hand between Europe/Japan. Therefore, the Asian crisis only increased the level of the correlation between the developed country of Asia in our sample, i.e., Japan, and Europe and North America. When we examine the variance equation, it is found that the Asian crisis produced volatile changes in all the pair-wise correlations since the coefficient associated to the dummy variable is always significant. Thus, we find evidence of contagion across all regions during the Asian crisis.

When we introduce the dummy variable for the Dot.com crisis (Panel B, $Crisis_2$), we observe again that the crisis had an effect on all the pair-wise correlations but the effect was different depending on the geographical region. The Dot.com crisis diminished the correlation between North America/Europe but, at the same time, increased the volatility of all the pair-wise correlations. Looking at the results of the Subprime crisis (Panel C, $Crisis_3$), we observe that this crisis significantly increased the level of the correlation between North America/Europe but diminished its volatility. This crisis period also increased the volatility of all of the pair-wise correlations with the exception of North America/Southeast Asia and Japan/Southeast Asia. Therefore, the Subprime crisis ($Crisis_3$) had no effect, neither on the level nor on the volatility of the correlation between North America/Southeast Asia and Japan/Southeast Asia. Finally, the Global Financial crisis (Panel D, $Crisis_4$), increased the level of correlation between North America/Europe and North America/Southeast Asia. This crisis also increased the volatility of the pair-wise correlations of North America/Japan, North America/Southeast Asia and

Europe/Southeast Asia. All in all, the Global Financial crisis had no effect on the correlation between Japan/Europe and Japan/Southeast Asia.

These results highlight five important points concerning contagion during the different crises. First, the effects of the Asian and the Dot.com crises were widespread, with no immunity for any geographical region. Second, there exists contagion between more geographical zones during the Global Financial crisis than during the Subprime crisis. Third, during the Global Financial crisis, there is contagion between Japan/North America but not between Japan and the rest of the geographical regions. Fourth, the effect of the US collapse does not increase its correlation with Southeast Asian markets until September 2008. The Subprime crisis did not pose any direct threat to these markets; however the spillover from the global financial turmoil has affected them. Fifth, during the Subprime and Financial crises, the correlation between Japan/Southeast Asia does not increase. This result suggests that, due to the size and world economic importance of North-American and European markets, the potential influence of these markets on the emerging Southeast Asian markets should not be ignored. Additionally, this outcome could be explained by Asia's exceptional integration into the global economy. Much of Asia relies heavily on technologically sophisticated manufacturing exports, products for which demand has collapsed. At the same time, Asia's financial ties with the rest of the world have deepened over the past decade, exposing the region to the forces of global deleveraging.

Summarizing the empirical findings, all the crises had an effect on most pair-wise correlations of the factors, either through their level or their volatility. However, the different crises considered are found to increase more the volatility than the level of conditional equity correlation series among factors. This is clearly an important point in that the construction of an efficient portfolio relies on correlations and our results show that correlations are more volatile during financial turmoil.

Table 6.Test for detecting changes in the dynamic correlations across the markets due to the different crisis, adjusted by autocorrelation coefficient and conditional heteroscedasticity.

Panel A. Asian crisis						
	North America/Japan	North America/Europe	North America/ Southeast Asia	Europe/Japan	Japan/Southeas t Asia	Europe/Southe ast Asia
Mean Equation						
Constant	5.25e-04** (2.40)	1.91e-04 (0.43)	8.82e-04*** (5.94)	9.69e-04*** (3.75)	5.82e-04** (2.13)	4.37e-04 (1.54)
ρ_{t-1}	0.996*** (850.13)	0.999*** (1244.96)	0.995*** (964.01)	0.996*** (1016.13)	0.998*** (1348.42)	0.997*** (931.48)
$Crisis_{1,t}$	6.25e-03** (2.49)	-1.62e-03 (-0.74)	-4.67e-03 (-1.42)	0.008*** (2.73)	0.001 (0.448)	0.009* (1.822)
Variance Equation						
Constant	1.81e-06*** (20.65)	1.40e-06*** (23.95)	6.75e-06*** (31.57)	3.98e-06*** (23.97)	4.30e-06*** (38.68)	2.49e-06*** (31.83)
ε_{t-1}^2	0.095*** (35.41)	0.153*** (25.76)	0.256*** (30.18)	0.144*** (25.93)	0.221*** (30.63)	0.171*** (37.50)
h_{t-1}	0.884*** (341.05)	0.837*** (159.15)	0.703*** (111.99)	0.796*** (117.27)	0.765*** (166.93)	0.813*** (220.92)
$Crisis_{1,t}$	1.75e-05 (1.58)	4.01e-05*** (3.00)	1.30e-04*** (2.87)	4.43e-05** (2.08)	4.51e-05** (2.23)	1.11e-04*** (3.20)
Q(20)	24.077	32.413**	17.933	10.762	18.211	28.471*
$Q^2(20)$	220.257**	5.107	2.125	11.444	2.829	10.835

Panel B. Dot.com crisis						
	North America/Japan	North America/Europe	North America/ Southeast Asia	Europe/Japan	Japan/Southeas t Asia	Europe/Southe ast Asia
Mean Equation						
Constant	5.98e-04*** (2.80)	2.43e-04 (0.57)	7.60e-03*** (3.41)	0.001*** (4.09)	2.521-04 (0.77)	4.55e-04* (1.73)
ρ_{t-1}	0.996*** (863.87)	0.999*** (1344.25)	0.995*** (801.30)	0.995*** (1051.06)	0.999*** (1354.41)	0.997*** (998.26)
$Crisis_{2,t}$	2.46e-03 (0.56)	-6.57e-03*** (-3.63)	-3.97e-03 (-0.36)	4.80e-04 (0.19)	0.007 (0.321)	0.002 (0.56)
Variance Equation						
Constant	1.78e-06*** (24.72)	1.54e-06*** (8.78)	5.45e-06*** (11.29)	3.93e-06*** (24.39)	4.51e-06*** (34.15)	2.70e-06*** (31.72)
ε_{t-1}^2	0.094*** (36.07)	0.165*** (10.63)	0.226*** (10.83)	0.151*** (26.43)	0.233*** (31.54)	0.198*** (38.57)
h_{t-1}	0.885*** (346.86)	0.824*** (63.62)	0.737*** (45.657)	0.794*** (118.42)	0.745*** (136.10)	0.792*** (193.09)
$Crisis_{2,t}$	2.12e-05*** (4.87)	6.04e-05** (2.21)	4.13e-04** (2.42)	1.96e-05*** (2.78)	3.80e-05** (2.47)	5.81e-05*** (6.27)
Q(20)	22.933	24.457*	21.436	11.084	20.318	29.024*
$Q^2(20)$	227.961**	5.225	1.967	9.510	2.844	12.791

Panel C. Subprime crisis						
	North America/Japan	North America/Europe	North America/ Southeast Asia	Europe/Japan	Japan/Southeast Asia	Europe/Southeast Asia
Mean Equation						
Constant	5.66e-04** (2.29)	2.06e-04 (0.526)	8.88e-04*** (4.24)	0.001*** (4.32)	5.69e-04* (1.85)	4.92e-04* (1.88)
ρ_{t-1}	0.996*** (699.41)	0.999*** (1496.52)	0.995*** (837.20)	0.995*** (1039.64)	0.998*** (1360.69)	0.998*** (1019.64)
$Crisis_{3,t}$	-9.75e-03 (-1.48)	3.57e-03*** (2.71)	-1.08e-03 (-0.05)	0.004 (1.45)	0.007 (1.57)	-3.97e-04 (-0.07)
Variance Equation						
Constant	2.16e-06*** (13.24)	1.33e-06*** (8.55)	6.46e-06*** (9.06)	4.01e-06*** (24.08)	4.96e-06*** (9.37)	2.88e-06*** (31.06)
ε_{t-1}^2	0.090*** (24.49)	0.159*** (11.99)	0.269*** (9.61)	0.152*** (26.29)	0.227*** (9.83)	0.203*** (37.56)
h_{t-1}	0.876*** (480.96)	0.838*** (72.36)	0.706*** (30.98)	0.793*** (115.64)	0.746*** (43.03)	0.787*** (185.28)
$Crisis_{3,t}$	1.63e-04*** (3.28)	-5.90e-06*** (-1.65)	-6.79e-04 (-1.04)	1.34e-05* (1.70)	1.12e-05 (1.52)	2.11e-05* (1.74)
Q(20)	21.556	32.573**	17.469	12.176	17.261	29.860*
$Q^2(20)$	33.588**	4.529	2.136	8.6521	3.054	10.441

Panel D. Global Financial crisis						
	North America/Japan	North America/Europe	North America/ Southeast Asia	Europe/Japan	Japan/Southeast Asia	Europe/Southeast Asia
Mean Equation						
Constant	6.08e-04*** (2.87)	1.95e-04 (0.44)	18.85e-04*** (6.10)	0.001*** (4.29)	6.18e-04** (2.00)	5.23e-04* (1.92)
ρ_{t-1}	0.996*** (865.23)	0.999*** (1252.22)	0.995*** (980.44)	0.995*** (1043.36)	0.998*** (1354.23)	0.998*** (976.21)
$Crisis_{4,t}$	2.93e-03 (0.06)	0.008** (2.35)	0.013* (1.74)	0.006 (0.275)	0.004 (1.158)	0.016** (2.06)
Variance Equation						
Constant	1.81e-06*** (24.86)	1.49e-06*** (26.18)	7.08e-06*** (31.83)	3.95e-06*** (24.15)	4.32e-06*** (10.60)	2.73e-06*** (32.38)
ε_{t-1}^2	0.094*** (35.88)	0.162*** (30.62)	0.265*** (31.91)	0.140*** (26.12)	0.223*** (9.69)	0.182*** (39.29)
h_{t-1}	0.885*** (344.82)	0.828*** (176.50)	0.692*** (108.62)	0.800*** (120.67)	0.764*** (51.78)	0.801*** (216.36)
$Crisis_{4,t}$	3.42e-05* (1.72)	4.08e-05 (1.46)	1.883e-04* (1.94)	5.70e-05 (1.59)	2.86e-05 (1.51)	1.34e-04* (1.74)
Q(20)	22.743	30.20*	15.136	12.139	15.804	29.751*
$Q^2(20)$	221.699**	4.786	2.139	7.743	3.095	10.057

Notes: The t-statistics are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

Mean equation: $\rho_{ij,t} = \mu + \sum_{p=1}^{P} \phi_p \rho_{ij,t-p} + \alpha_k Crisis_{k,t} + e_{ij,t}$

Variance equation: $h_{ij,t} = \varpi_0 + \varpi_1 \varepsilon_{ij,t-1}^2 + \beta_1 h_{ij,t-1} + \delta_k Crisis_{k,t}$

where $Crisis_{k,t}$ are the dummy variables defined in eq. (4) and (5), indicators of the different crises. $Crisis_1$ is the dummy variable for the Asian crisis (11/22/1997 – 11/21/1997); $Crisis_2$ is the dummy variable for the Dot.com crisis (3/10/2000 – 7/04/200); $Crisis_3$ is the dummy variable for the Subprime crisis (8/17/2007 – 9/16/2007); and $Crisis_4$ is the dummy variable for the Global Financial crisis (9/15/2008 – 10/14/2008). Q(20) is the Ljung-Box statistic up to 20 days for testing the independency of the residuals and $Q^2(20)$ is the Ljung-Box statistic up to 20 days for the squared residuals in order to test the heteroskedasticity of them.

4. Conclusions

There is a common presumption that financial crises are not alike as the causes of crises are different, and the institutional and economic environments in which crises occur vary among countries. Financial crises are characterized by the sudden and simultaneous materialization of risks that in times of tranquillity were believed to be independent (Mink and Mierau, 2009), implying that the benefit from market-portfolio diversification is lower. The final goal of this paper is to determine if different crisis periods have affected most of the stock markets in the world or, in contrast, they affected some markets in certain regions. To do this we examine the time-series behavior of correlation coefficients and analyze the impact of the crisis on their movements and variability.

The data set consists of nineteen international stock markets and the sample period covers December, 1994 to September, 2009. We consider four major crises: the Asian crisis in the second half of 1997, the Dot.com crisis in 2000, the Subprime crisis in 2007 and the recent Global Financial crisis in 2008. The analysis is carried out in three steps. First, a Time Series Factor Analysis is applied to reduce dimensionality. Then, a dynamic conditional correlation model (DCC-AGARCH) is used to estimate cross country correlations. Finally, using dummy variables we test if conditional correlations increase and/or are more volatile in turmoil periods. According to this paper's definition, there is contagion between markets when the dummy variable is significant and positive in the mean and/or variance of the pair-wise correlation coefficients. Thus, contagion exists when pair-wise correlations increase during crisis times relative to correlations during peaceful times and/or are more volatile

The most important results of the paper are the following: first, after applying Time Series Factor Analysis we find that the nineteen stock indices can be grouped into four regions: North America, Japan, Europe and Southeast Asia. Second, we find that the response of most of the pair-wise correlation coefficients to the crisis periods is heterogeneous. The Asian and the Dot.com crises had a widespread impact. During these crises there was contagion across all the regions. Third, there is no contagion between North America/Southeast Asia during the Subprime crisis indicating that the reaction of developing markets to the US financial collapse was later than that of developed markets.

Fourth, neither the level nor the volatility of the correlation between Japan/Southeast Asia increase during the Subprime and the Global Financial crises, suggesting that European and North American markets move Southeast Asian markets but not Japan. Since Japan is a major investor and trading partner on many Southeast Asian countries, it would be expected that the financial markets of Japan and the Southeast Asian countries may be related. However, our results suggest that Southeast Asian markets are influenced by European and North American markets due to their size and world economic importance. Finally, we observe that after the occurrence of the different crises the variability of the pair-wise correlation coefficients increases more than their movements. These results suggest that the gain from international diversification investment in multiple markets is likely to be lowest when it is most required.

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