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Contagion and interdependence measures: some words of caution

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Contagion and interdependence measures: some words of caution[ǂ]

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Abstract

In this paper we discuss different methods proposed in the literature to analyse the propagation mechanism of a crisis and to verify the presence of contagion. In particular, we examine the recent tests introduced by Forbes and Rigobon (2002) and by Corsetti et al. (2002) to cope with heteroskedasticity, and the DCC test introduced by Rigobon (2002a) that is also robust to endogenous and omitted variables. We consider the relationships among a set of stock market indexes (United States, Europe, Japan and Hong Kong) during the Asian financial crisis. We demonstrate that the methodologies proposed by Forbes & Rigobon (2002), and by Corsetti et al.(2002) are highly affected by the windows used and by the presence of omitted variables: we propose some analyses to strengthen the robustness of these tests. Concerning the DCC test, we show that it is unable to cope with some kinds of heteroskedasticity and loses power in a multivariate framework.

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1 Introduction

The 1990s were punctuated by a series of severe financial and currency crises: the 1992 ERM attacks, the 1994 Mexican peso collapse, the 1997 East Asian crises, the 1998 Russian collapse, the 1998 LTCM crisis, the 1999 Brazilian devaluation, and the 2000 technological crisis. One striking characteristic of several of these crises was how an initial country-specific shock was rapidly transmitted to markets of very different sizes and structures around the globe. This has prompted a surge of interest in "contagion".

This is a relevant issue from the empirical and theoretical point of view. Volatility transmission and contagion are relevant at an international level by themselves and have important consequences for monetary policy, optimal asset allocation, risk measurement, capital adequacy, and asset pricing.

Many authors have written about the propagation mechanisms of these crises. In particular, they have focused on the question whether the relationships between markets during tranquil periods are different from those during periods of crisis. Often during financial crises we observe strong co-movements in prices and in the volatility between markets. We can also observe an increase in the covariance of the returns and sometimes in their correlation.

In this paper, "contagion" – as opposed to "interdependence" – conveys the idea that international propagation mechanisms are discontinuous. There is no agreement on this definition and many other definitions have been proposed. If contagion is a structural break in the data-generating process during crisis periods, we can use tests to check the stability of parameters to find it. Unfortunately, the data often exhibit heteroskedasticity and problems of endogenous variables and omitted variable. There is no agreement on how to treat them when the three difficulties are simultaneously present. A variety of analyses use different assumptions to solve those problems and reach different conclusions on contagion.

In this paper we discuss two types of test that have been proposed in the literature to analyse the propagation mechanism of a crisis and to verify the presence of any discontinuity. The first typology of tests evaluates the correlation coefficients among markets returns (correlation analysis). In particular, we consider the test introduced by Forbes and Rigobon (2002) (henceforth F-R), which takes into consideration the bias due to the changing volatility (i.e. heteroskedasticity), and the test proposed by Corsetti et al.(2002) (henceforth C-P-S), which also deals with the endogeneity problem. The second approach, proposed by Rigobon (2002a), considers the whole variance-covariance matrix of market returns and allows for the presence of heterosckedasticity, simultaneous equations and omitted variables.

Recently in the literature many authors have addressed how changes in volatility can bias correlation coefficients. In particular, Ronn (2000) uses a restrictive assumption on the distribution of residuals in his proof of the bias and does not consider how this bias affects correlations. Boyer, Gibson and Loretan (1999) and Loretan and English (2000) propose an adjustment that, after some algebraic manipulation, is the same as the correction proposed in F-R. For this reason we concentrate only on the three tests previously mentioned.

This paper focuses on the robustness of these tests. In particular, we show that F-R and C-P-S tests are often biased because, in most of the cases (even in those empirically analysed by the previous authors), we actually do observe the presence of omitted variables. We propose a simple analysis to verify this.

Second, we show that all the tests are highly affected by the choice of window and we propose a window sensitivity analysis to avoid misdiagnosis of contagion.

Third, we demonstrate that such tests are also highly affected by the time zone, which could also induce the tests to misdiagnose contagion.

Fourth, concerning the first approach, we show that the C-P-S test finds more episodes of contagion than the F-R test because of its set-up. This difference comes from the hypothesis that the two tests use on the theoretical correlation coefficient. In particular, the C-P-S test takes into account that the F-R test is biased under certain conditions, and, as a consequence, we should prefer this test to the F-R test. However, a proper estimation procedure of the theoretical parameters, which characterize the C-P-S test, has not yet been fixed

Fifth, concerning the DCC test we show that, even if the test is not biased in the presence of simultaneous equations and omitted variables, a rejection can be due both to a shift in the parameters or to the diffusion of the heteroskedasticity. In order to perform this analysis, we consider the stability of the propagation mechanisms among Hong Kong, Eurostoxx, Nikkei, Dow Jones and Nasdaq indexes during the Asian financial crisis. Our empirical analysis shows that the DCC finds many rejections, which, as we will see, can be generated by either: parameter instability, the form of heteroskedasticity, or both. We are therefore unable to evaluate whether the parameters have changed and thus whether there is contagion. Moreover, we show that this test has almost no power in a multivariate set up.

The outline of the paper is as follows. We start by presenting the literature in Section 2. In Section 3 we introduce the tests on correlation coefficients and the DCC test. In Section 4 we describe the results of the empirical investigation. Section 5 concludes.

2 Contagion definitions and the relative literature

The last two decades have experienced a series of financial and currency crises, many of them carrying regional or even global consequences: the 1987 Wall Street crash, the 1992 ERM collapse, the 1994 Mexican pesos crisis, the 1997 "Asian Flu", the 1998 "Russian Cold", the 1999 Brazilian devaluation, the 2000 Internet bubble burst and, finally, the more recent default crisis in Argentina of July 2001 and Enron? in the US in September 2001. Most of these crises hit emerging markets, which are more sensitive to shocks because of their underdeveloped financial markets and their large public deficits. The common feature shared by these events was that a country specific shock spreads rapidly to other markets of different sizes and structures all around the world. In some cases a rational explanation could be found in terms of macroeconomic channels linking different countries through which shocks can be transmitted to each other. On the other hand, it also seems reasonable that two or more economies display the same response (even with different intensity) to a common shock. However, it is still quite puzzling to justify the reason why a country reacts to a crisis affecting another country to which the former is not linked by any economic fundamentals. Many authors dealing with the topic of international propagation of shocks have referred to this circumstance as a contagion phenomenon even if there is still no agreement on which factors lead to identify a contagion event precisely, and it is still not clear how to define the contagion event itself.
Referring to the World Bank's classification, we can distinguish three definitions of contagion[1]:

- *Broad definition:* contagion is identified with the general process of shock transmission across countries. The latter is supposed to work both in tranquil and crisis periods, and contagion is not only associated with negative shocks but also with positive spillover effects.
- *Restrictive definition*: this is probably the most controversial definition. Contagion is the propagation of shocks between two countries (or group of countries) in excess of what should be expected by fundamentals and considering the co-movements triggered by the common shocks. If we adopt this definition of contagion, we must be aware of what constitutes the underlying fundamentals. Otherwise, we are not able to appraise effectively whether excess co-movements have occurred and then whether contagion is displayed.
- *Very restrictive definition:* this is the one adopted by F-R (2000a, 2000b). Contagion should be interpreted as the change in the transmission mechanisms that takes place during a

[1] www1.worldbank.org/economicpolicy/managing%20volatility/contagion/index.html

turmoil period. For example, the latter can be inferred by a significant increase in the cross-market correlation. As we have said, this is the definition that will be used in this paper.

Many papers have focused on the question of contagion, testing for its existence with statistical methods. Their approaches vary with regard to the definition of contagion they choose as a starting point. As we have anticipated we will use the third definition; nevertheless it is useful to mention other approaches.

According to the first definition, a part of the empirical literature focuses on the estimation of the transmission mechanisms which characterise the relationship among countries and are responsible for the transmission of volatility. For this purpose, many authors estimate an econometric model and measure the explanatory power of a certain link by looking at the size of the estimated parameters: in this way they evaluate the channels of contagion. The methodologies used to implement this analysis are the following: estimates through logit-probit regressions or simple OLS regressions and identification through Principal Components.

We must also recall other methods that do not depend on the third definition of contagion: volatility analysis assuming an ARCH-GARCH generating process (Chou et al. (1994), Ramchard and Susmel (1998), Kim, Sentana and Wadhwani (1994)) and techniques looking at changes in the cross-market co-integrating vector[2] (Longin and Solnik (1995)). Relatively innovative approaches are those that apply the switching regime models using regime probabilities (filtered or smoothed) to monitor the volatility transmission process (Hassler (1995), Ang and Bekaert (1999)) and those that work with factor regression models and limited dependent models under heteroskedasticity. In those papers, contagion is defined as simple volatility spill-over.

Rigobon (2001) argues, and we agree with him, that the third definition is more neutral because it leaves out the problem of identifying the transmission mechanism and also the fundamentals (those are required if one uses the second definition). However his position need not necessarily be accepted[3].

The variety of empirical methods developed for the analysis of contagion has the aim of testing the stability of parameters in the sphere of a chosen econometric model. Evidence of parameter shifts is a signal of a change in the transmission mechanism , so according to the third definition there has been contagion. If, on the contrary, the parameters are constant, we should move to an interdependence case. Several methodologies have been used to statistically search for contagion in

[2] However, as F-R point out, cointegration methods are less useful as valid tests for contagion because they consider long time horizons and therefore they can miss the changes in the relationship between markets that occur in the short run.

[3] Many authors define contagion in this way, see for example King and Wadhwani (1990), Bonfiglioli and Favero (2000), Loretan and English (2000), Giavazzi and Favero (2001), Baele (2002), Bekaert Harvey and Ng (2002).

this way and others have still to be applied. Rigobon (2001) offers a good survey of these procedures, which are mainly based on OLS estimates (including GLS and FGLS), Principal Components, Probit models (Baig and Goldfajin (1999), Eichengreen, Rose and Wyplosz (1997) and Kaminsky and Reinhart (1998)) and correlation coefficient analysis (King and Wadhwani (1990), Lee and Kim (1993), Calvo and Reihart (1996), Edwards (1998), Baig and Goldfajn (1998)). It is worthwhile noting that the results found by this kind of analysis could be supportive of one of the two branches of the theoretical literature about the international transmission of shocks. Indeed, evidence of contagion would support so-called *crisis-contingent* theories which argue that propagation mechanisms change during a crisis, thus giving rise to new channels of transmission: irrational behaviour through investors in the form of multiple equilibriums in traders' expectations and imperfect recall of past crises; endogenous liquidity restrictions; and political contagion. On the contrary, if the tests lead to a rejection of the hypothesis of contagion in favour of interdependence, the *non-crisis contingent* theories appear sounder because they assume that there is no innovation in the shock propagation channels. Volatility carriers present both in the crisis and in the stable periods are, for example: trade linkages, policy coordination, learning processes and finally common shocks (global or regional), which simultaneously affect asset prices in more than one country.

However, the methodologies listed above carry some imperfections because the data often suffer from heteroskedasticity, endogeneity and omitted variable problems. Some authors have tried to solve these problems in a similar way, although they have reached different conclusions in terms of contagion. F-R develop a correlation analysis adjusting correlation coefficients only for heteroskedasticity under the assumption of no omitted variables or simultaneous equations problems. Their results clearly support the thesis of strong interdependence but no contagion during the crises examined.

Contrary to F-R, C-P-S built up a model in which the specific shock of the country under crisis does not necessary act as a global shock because this could bias the analysis in favour of interdependence instead of contagion. The authors therefore introduce more sophisticated assumptions about the ratio between the variance of the country-specific shock and the variance of the global factors weighted by factor loadings. This improvement to the analysis leads to less frequent rejection of the hypothesis of contagion in favour of interdependence, and then the intuition turns out to be right. However, both the tests, as we will show, are still highly affected by (i) the windows used, (ii) the presence of omitted variables, and (iii) the time zone.

Rigobon (2002a) developed a test that is able to cope with endogeneity and omitted variable problems simultaneously. However as we shall see, the rejections of this test are difficult to interpret because fails to cope with a certain type of heteroskedasticity.

In this paper we adopt the same definition of contagion and a methodology for analysis of it as in F-R and C-P-S. Moreover, we also use the new approach proposed by Rigobon (2002a): the DCC test. More specifically, this paper defines and studies the cases of contagion characterized by a significant increase in cross-market linkages after a shock to an individual country.

Why do we concentrate on this aspect of contagion? Why is this definition of contagion important and as is its exploration? Because, as observed by F-R, the other definitions of contagion and relative approaches of analysis are unable to shed light on three main issues: international diversification, evaluation of the role and the potential effectiveness of international institutions and bail-out funds, and propagation mechanisms.

Indeed, a critical assumption of investment strategies is that most economic disturbances are country specific. As a consequence, stock in different countries should be less correlated. However, if market correlation increases after a bad shock, this would undermine much of the rationale for international diversification. There is in fact no reason to diversify if the international diversification effect is eliminated when the risk of losses is higher (Boyer (1999) and Loretan (2000)).

The evaluation of the role and the potential effectiveness of international institutions and bail-out funds are also related to the presence of contagion or interdependence. Policy-makers worry that a negative shock to one country can reduce financial flows to another country, even if the fundamentals of the second economy are strong and there are few real linkages between the two countries. If this sort of contagion exists (and could be verified), it could justify International Monetary Fund (IMF) intervention and the dedication of massive amounts of money to bailout funds. On the contrary, if the fundamentals of these two countries are closely linked, this transmission would not constitute contagion and a bailout fund might only reduce the negative initial impact, and the intervention would be less effective and harder to justify.

3. Contagion Tests

The tests used in this paper build upon those recently proposed by F-R, C-P-S and Rigobon (2002a), and we therefore keep our description of them to their bare essentials.

3.1 Forbes and Rigobon test

Assume that r_i and r_j are stochastic variables identifying stock markets returns in two different markets *i* and *j* according to the following equation[4]:

$$r_{it} = \alpha + \beta r_{jt} + \varepsilon_{it}$$
$$\mathrm{E}(\varepsilon_{it}) = 0$$
$$\mathrm{E}(\varepsilon_{it}^2) < \infty$$
$$\mathrm{E}(r_{jt}\varepsilon_{it}) = 0$$

F-R show that if we consider two stochastic variables, r_i and r_j, and the variance of one of them increases, then the correlation between them also increases. Instead of testing whether the correlation coefficient observed in the period before the crisis and the one observed during the crisis are the same[5], starting from the coefficient recorded during the tranquil period (ρ_t), F-R calculate a correlation coefficient that takes into account the increase in the variance (ρ_t^{tc}). This correlation coefficient is the one that we should observe during the crisis. So the test verifies whether the theoretical coefficient introduced by F-R (ρ_t^{tc}) and the one observed during the crisis (ρ_t^{c}) are the same.

If δ_t is the relative increase in the variance of *j*, which is the market under crisis, then the relationship that allows us to find the theoretical correlation coefficient for the crisis, given the correlation coefficient ρ_t, that can be observed during tranquil periods, is the following:

$$\rho_t^{tc} = \rho_t \sqrt{\frac{1+\delta_t}{1+\delta_t \rho_t^2}} \; .$$

[4] We will refer to this model as the "F-R model".
[5] Like King and Wadhwani (1990), Baig and Goldfajn (1999), Lee and Kim (1993), and Calvo and Reinhart (1996).

If ρ_t^c is the correlation we observe during the turmoil period (the crisis) and ρ_t^{tc} is the theoretical correlation, the null hypothesis is[6]:

$$H_0 : \rho_t^c = \rho_t^{tc} .$$

Unfortunately, the increase in the variance of the generator market *j* may be due to both its idiosyncratic component and the non-observable variables. In the simulation realized by F-R, the results show that, whenever a significant part of the increase in volatility stems from the heteroskedasticity of the common non-observable variable, the F-R theoretical coefficient is often inferior[7] to the one observed over the period of high volatility and generated through simulation. This is due to the fact that the F-R coefficient is unable to capture the increase in volatility caused by the common variables: this makes an erroneously leaning towards contagion.

On the contrary, whenever a significant part of the increase in volatility is due to the idiosyncratic component of the generator market, the F-R theoretical coefficient is too high in relation to the one of the period of high volatility (the latter is calculated by simulation, keeping the parameters of the model constant). For this reason, the test will erroneously lean towards the loss of interdependence[8] (C-P-S, introducing their theoretical coefficient, aim at solving this problem).

The parameter β of the F-R model plays an important role in reducing the distortion due to common non-observable shocks. Independently from the variable which causes the increase in variance of r_j, whether β is high, that is whether the dependence of r_i on r_j is marked, the theoretical coefficient is very similar to the one generated by simulation, keeping the parameters constant.

F-R argue that their theoretical coefficient is a good approximation of what should be observed during a crisis, even in the presence of non-observable variables and endogeneity, whether the so-called "quasi-identification" conditions hold. This means that a significant increase in the variance of the market *j* (δ should be high) has to occur, it has to be possible to identify the country which generates the crisis, and the comparison between the correlations has to be made considering the

[6] Given the increase in volatility and ρ^c, F–R compute an adjusted correlation coefficient (ρ^a) which is depurated of the distortion produced by the increase in volatility, and they compare it with the one observed during the tranquil period (ρ).

[7] In their simulation study, F-R consider the adjusted coefficient (ρ^a , see footnote 6), that is the coefficient which does not include the distortion caused by the heteroskedasticity . This coefficient has to be compared with the coefficient of the tranquil period (ρ) set to 0.2. Then, they find $\rho^a > \rho$.

[8] In terms of the adjusted coefficient, F-R find $\rho^a < \rho$.

country which generates the crisis and the one which receives it. Moreover, if there are common non-observable shocks, they have to be homoskedastic and, if they are not homoskedastic, the increase in their variance has to be negligible in comparison with the increase in the variance of the idiosyncratic shocks of the generator market. Later, we propose a simple approach to evaluate the reliability of the results of the test.

3.2 Corsetti, Pericoli and Sbracia test

C-P-S assume that the rates of return of the stock markets in country *i* and country *j* are generated by the process:

$$r_{it} = \alpha_i + \gamma_i f_t + \varepsilon_{it}$$
$$r_{jt} = \alpha_j + \gamma_j f_t + \varepsilon_{tj}$$

where *f* is a common (global) factor, usually approximated with a world index. They also assume that *f* and the idiosyncratic shocks are mutually independent random variables with finite and strictly positive variance.

Starting from this model, C-P-S build up their theoretical correlation coefficient that we should observe during crisis:

$$\phi = \rho \left[\left(\frac{1+\lambda_j}{1+\lambda_j^c} \right)^2 \frac{1+\delta}{1+\rho^2 \left[(1+\delta) \frac{1+\lambda_j}{1+\lambda_j^c} - 1 \right] (1+\lambda_j)} \right]$$

where $\lambda_j = \dfrac{\mathrm{var}(\varepsilon_j)}{\gamma_j^2 \, \mathrm{var}(f)}$, $\lambda_j^c = \dfrac{\mathrm{var}(\varepsilon_j / C)}{\gamma_j^2 \, \mathrm{var}(f / C)}$ and *C* is the event “Crisis in country *j*”.

It is useful to simplify this coefficient assuming that $\lambda_j^c = \lambda_j$. A constant ratio λ_j means that the variance of the global factor and the variance of the country specific risk increase by the same proportion during the crisis in *j*:

$$\frac{\mathrm{var}(r_j / C)}{\mathrm{var}(r_j)} = \frac{\mathrm{var}(f / C)}{\mathrm{var}(f)} = \frac{\mathrm{var}(\varepsilon_j / C)}{\mathrm{var}(\varepsilon_j)} = 1 + \delta \; .$$

Then the coefficient of C-P-S can be expressed as:

$$\phi(\lambda_j) = \rho\left[\frac{1+\delta}{1+\delta\rho^2+(1+\lambda_j)}\right]^{1/2}.$$

Following C-P-S, the latter is the correlation coefficient that we should observe during a crisis.
If we put λ_j equal to zero, the coefficient of C-P-S coincides with the F-R coefficient. When λ_j is equal to zero, country *j* suffers no idiosyncratic shock ($(\mathrm{var}(\varepsilon_j) = 0)$ and, if this is the case, we define *j* as a global factor: every single shock in *j* has global or regional consequences.
We can also observe that the theoretical coefficient of F-R is always equal to or larger than the C-P-S coefficient unless $\rho<0$. The difference between the two theoretical coefficients depends on λ_j.
If the correlation observed during tranquil periods is positive, then it is more likely that the C-P-S coefficient will reflect contagion than the F-R coefficient, because of their underlying relationship. If the correlation during tranquil periods is negative, we get the opposite relationship.
Indeed, it is important to observe that the conditions under which the C-P-S theoretical coefficient is a good description of the correlation observed during a crisis period are the same that have to hold in the F-R model. The change that C-P-S introduce aims at reducing the distortion of the F-R coefficient in the case in which the idiosyncratic component of the generator market is the main source of heteroskedasticity (in this case, the test realized by F-R erroneously leans towards the loss of interdependence).

3.3 Rigobon's DCC test

The two previous tests are biased if the data suffers from simultaneous equations or omitted variable problems. Rigobon (2002a) proposes a new test that is robust to the presence in the data of simultaneous equations, omitted variables, and heteroskedasticity: the DCC test.
Suppose that the stock market returns of *N* countries are described by the following latent factor model:

$$\underset{NxN}{A}\ \underset{Nx1}{R_t} = \underset{Nxk}{\Gamma}\ \underset{kx1}{Z_t} + \underset{Nx1}{\varepsilon_t}$$

where:
Z are *k* unobservable shocks;

Γ is the matrix containing the coefficients of the common shocks (the first row is normalised to one);

ε_t is the vector of idiosyncratic shocks; ε_t i.i.d.; $\varepsilon_t \approx WN(0, \Omega_t^{\varepsilon})$ where Ω_t^{ε} is diagonal;

$E(\varepsilon_t Z_t) = 0$, i.e. the idiosyncratic risks and the common shocks are not correlated;

$E(Z_t) = 0$ and $E(Z_t Z_t') = \Omega_t^Z$, where Ω_t^Z is diagonal.

Rigobon also supposes that $E(R_t) = 0$ and R_t is serially uncorrelated. If R_t is stationary, the results are independent of these assumptions. Rigobon (2000) wrote:

"*…The problem of a simultaneous equation is summarised in the assumption that A is not block diagonal, the problem of omitted variables is modelled as the unobservable common shocks and the heteroskedasticity is built into the covariance matrix of both the structural and the common shocks.*"

Given the increase in volatility during crises, we can divide our dataset into two subsets, one containing stock market returns in the period of low volatility (tranquil period) and one containing stock market returns in the high volatility period (crisis). We compute two variance/covariance matrices, one for each period:

$\Omega_t^l =$ variance/covariance matrix for the low volatility period;

$\Omega_t^h =$ variance/covariance matrix for the high volatility period.

Then the DCC statistic is defined as follow:

$$\text{DCC} = DET(\Omega_t^h - \Omega_t^l) = DET(\Delta\Omega_t)$$

.

The test consists in verifying if the DCC statistic is equal to zero.

It can be shown that if the heteroskedasticity is only in a subset of the idiosyncratic shocks (ε) or only in a subset of the common shocks (Z) (not in both) and the parameters are stable across the sub sample, then the DCC statistic is equal to zero. The DCC is different from zero if the parameters are not stable but also when the specific assumption of heteroskedasticity is not satisfied and here rises the major problem of the DCC test, since rejections can due to parameters instability or to the violations of heteroskedasticity assumptions. As for the previous tests, it is necessary to know exactly the timing of a crisis or when there is a period of high volatility.

With this test we are not able to find episodes of loss of interdependence like those in which correlation falls, because the test finds only structural breaks and tells us nothing about the direction of the change. For this purpose we have to look at the correlations.

4 Application and results

First of all, we have analysed the tests based on the correlation analysis and propose some approaches to study the robustness of these tests. Then, we consider the DCC test which has been proposed to solve some of the correlation test problems.

4.1 Correlation analysis

We have taken into account the Asian financial crisis considered by F-R and C-P-S to show the performances of their tests. Since we need to compute ρ_t^c and the increase in volatility during the crisis, and ρ, during the tranquil period, we have to define the crisis and tranquil windows. For this purpose, we have considered respectively a tranquil and a crisis window chosen by monitoring jointly index returns and volatility dynamics. Then we have divided the Asian crisis in a set of turmoil periods and for each one we have defined a crisis window. The windows used are reported in table 1: windows A, B, C, D are a subset of those used by F-R, window L is selected by us and the other windows are used by Rigobon (2001). For simplicity we have used only two different low volatility periods. We have performed the test for each window to point out when there is a break.

F-R focused on the 1997 East Asian crisis, the 1994 Mexican crisis and the 1987 Wall Street crash and their analysis provided little evidence of contagion. In particular, during the Asian crisis the test based on their adjusted correlation coefficient between Hong Kong and 27 other stock markets, gave only one rejection of the hypothesis of stability in the parameters.

C-P-S ran their test only during the Asian crisis and, using two-days moving averages of the daily stock returns, studied the stability of the correlation coefficients between Hong Kong and 17 other markets finding 8 rejections.

As C-P-S did, we have analysed only the Asian crisis[9] and have used the F-R and C-P-S tests to verify if the propagation mechanisms between Hong Kong and Eurostoxx, Dow Jones and Nikkei have changed during this period. We have used both daily returns and two-days moving averages.

Unlike F-R and C-P-S, we exploit the symmetric property of the tests also to find evidence of the so-called "loss of interdependence" phenomenon, which happens when the theoretical coefficient is larger than the one observed during the crisis[10]. Indeed, even if they cannot be accounted as contagion, correlation falls[11] support the thesis of the discontinuity of the propagation mechanisms.

As first analysis, we have used the windows proposed by F-R and Rigobon (2001). Table 2, 3 and 4 report the results of the analysis performed on Nikkey (Nik), Dow Jones (DJ) and Eurostoxx (EU). The columns of each table show the test on the correlations between the return obtained with the closing time price of Hong Kong[12] and the return obtained with the closing time of the other market. DAILY indicates that we have considered daily returns while MA2D means we have used two-days moving average data.

As the tables show, there are many cases where the correlation falls and few cases where the correlation observed during the crisis is significantly bigger than the theoretical coefficient.

As we can expect, the C-P-S test finds more episodes of contagion than the F-R test because of its set up (see paragraph 3.2), instead the F-R test finds more episodes of falls in correlation. As anticipated in the des3(o)0.w(□we have used .7 -1.72gF-R te0.0001 Tc)

In particular, looking at table 2 (relation between HK and DJ), we can notice that the results are sensitive to the frequency of analysed data (daily returns or two-days moving average of these returns) and also that, when we analyse two-days moving averages of market returns, the number of rejections are higher. This sensitivity may stem from the remarkable existing difference of time zone in the two considered markets.

The rejections are almost entirely composed of losses of interdependence. C-P-S and F-R do not take this event into account. Nevertheless, it is an aspect that needs to be analysed more deeply since it represents cases where an increase of volatility is characterized by a reduction of correlation between markets.

As we could observe in table 2, the test realized by F-R is not very sensitive to the change in windows, while the one realized by C-P-S is more sensitive to this change. We can notice that the latter does not identify any break in windows A, C and D, which are those used by F-R.

Regarding Eurostoxx (the results are reported in table 3), it is easy to observe that the two tests provides opposite evidence about contagion. However, the most reliable test is certainly the one realized by C-P-S, which takes into account the fact that the rise in volatility of the idiosyncratic component of the market generating the crisis cannot imply an increase in the expected correlation over the crisis period. On the contrary, the test realized by F-R does not consider this fact. That is why the expected correlation is too high and it is often greater than the correlation observed over the crisis period. Therefore, the results of F-R test are biased and this test leans towards the loss of interdependence. However, even if the C-P-S test is more appropriate, it could be biased because of the arbitrary assumptions on λ_j.

Even though breaks in the cross-market linkages are identified, the shortcoming of these tests is their inability to identify a suspicious period. Indeed, they are methodologies that proceed on the basis of attempts. The rejections obtained by means of the F-R test in windows B and C make the break starting respectively in June 1997 and in August 1997: the difference is remarkable. The effect of the choice of which window to use is detailed in the following.

Concerning the Nikkey index (table 4), the results are sensitive neither to frequency of data nor to definition of windows. Because of the previously mentioned distortion, the test realized by F-R identifies a considerable amount of rejections due to the loss of interdependence. The test realized by C-P-S highlights that the relationships between the two markets have not been influenced by the

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$$\hat{\lambda}_j = \frac{\hat{\text{var}}(\varepsilon_j)}{\hat{\gamma}^2\ \hat{\text{var}}(f)} \quad .$$

crisis. This means that we do not observe any structural break during the crisis period, the relation between the two markets, usually quite high, remain almost unaffected by this event.

4.1.1 Variance analysis

As mentioned above, we propose a simple methodology to analyse whether there is potentially the presence of omitted variables in the analysis performed. Because omitted variables bias the test, in this way we are able to evaluate the performance of the tests on correlation.

The approach we propose is to compare the increase rate of the variance of the follower index (denoted by Δ) with the one that may be explained by means of the F-R model (without common non-observable shocks and denoted by $\rho^2\delta$). If $\Delta>\rho^2\delta$, we conclude that the increase rate of the variance of the follower is partly due to other causes. Note that the opposite does not apply. We cannot indeed sustain that if the increase of the variance is highly explained by the market generating the crisis that we are not omitting variables since other potential factors may have affected the increase of the variance in the follower market.

Applying this rough methodology to the markets considered, we obtain the results presented in table 5. From this table we observe that the increase rate of the variance of the follower market explained by means of the F-R model is extremely low in the case of Dow Jones. This means that there are potentially some omitted variables and indeed the analysis is biased.

On the contrary, the variance explained is extremely high for Eurostock. This is in some ways surprisingly. One potential interpretation could be the fragility of the European capital markets with respect to the US market. Concerning the Nikkei index, the increase of volatility observed is highly explained by the increase of volatility in the HK market.

4.1.2 Window analysis

To evaluate the test sensitivity to the change in the analysed periods, we have used a number of crisis windows and also two tranquil periods.

Windows A, B, C and D are a subset of those used by F-R. In their work, at first, they use window A, then, in order to evaluate the test sensitivity, they use also periods B, C and D. We also consider a longer window L. The other windows considered, which are usually shorter, are derived from

Rigobon (2001), and we use them in order to try to date break periods more precisely (refer to table 1 for the definition of the windows). C-P-S use windows similar to the A and HK+K.

The choice of the windows is based on the observation that, if the windows are too long or too short, the test loses power. Suppose, for example, that there are a crisis regime and a tranquil regime, and that in each regime there is a different correlation between markets. Whether the test is based on a crisis window too long, which includes observations generated by different regimes (and not only by the crisis regime), the estimated correlation coefficient for the crisis is a linear combination of the population coefficients in the two regimes. In this situation, differences between the estimated correlation coefficients of the two chosen periods (tranquil and crisis period) are less marked and it is unlikely that we will find a rejection of the stability test.

On the other hand, when the test is based on a shorter crisis window, the risk of including different regimes is lower, but the standard error of the statistic we use could be too high because we have a small crisis sample. Moreover, we consider the asymptotic distribution of the statistic and there is literature (Dungey and Zhumabekova (2001)) that show, if the windows used are too short, there is the risk of a loss of the power of the test.

The use of predetermined windows therefore implies a series of disadvantages: first of all, the risk of not identifying a break because the windows are not well defined; second, it is very difficult, maybe impossible, to identify break periods precisely.

In order to try to solve these problems, the carrying out of the test has been modified.

Once the tranquil period is defined, which, however, remains arbitrary as to the beginning and final date, the correlation coefficient and the variance of the generator market are estimated on the basis of this period. The correlation coefficient observed over the crisis period and the increase in variance are, instead, estimated on the basis of a moving window with a fixed size equal to 20 observations. We considered this moving window for the whole Asian crisis period and we roll it starting from June 1997 till February 1998.

By means of the p-value of the test statistic, we can therefore constantly monitor the time in which the difference between the two coefficients is significant. This method partly allows us to obviate the arbitrary definition of windows over crisis periods, thus reducing the consequent disadvantages, such as, for example, the loss of the power of the test. This methodology allows evaluation of whether there are episodes of contagion and whether it is correct using long period or whether the phenomenon concerns only with a period of few weeks.

The results of the sequential correlation analysis (figures 1, 2 and 3) for Dow Jones, Eurostoxx and Nikkei show that in the first period of the sample (till October/November 1997) the F-R and C-P-S tests provide almost the same result and both identify a loss of interdependence[14]. In the rest of the sample we observe that the C-P-S test differs from the F-R test and identifies contagion for Dow Jones, starting from November 1997, and for Eurostoxx the test weakly rejects stability in December 1997 and rejects it in February 1998. Moreover, the results show that the windows of contagion are short and that, over a first phase (June 1997 and then September 1997) the tests lean towards the loss of interdependence and, over a later phase, the p value of C-P-S test is very different from the one of the F-R test, especially near to contagion.

We control even for different tranquil periods and generate the test distribution by bootstrap and for larger moving windows. However, neither of these approaches significantly influences the results.

4.2 DCC test analysis

We have ran the DCC test on the windows reported in table 6 which are those used in Rigobon (2002a). As in the correlation analysis, the choice of the windows is based on the observation that, if the windows are too long or too short, the test loses power (see section 4.1.2). Concerning the DCC test, Rigobon argues that with long windows, it is more likely that most of the shocks are heteroskedastic and this increases the chance that the test is rejected because all shocks are heteroskedastic and not because the parameters are unstable. Moreover, in Rigobon's opinion, using longer windows also increases the probability that heteroskedasticity should be exhibited by different kinds of shocks (ε and Z).

On the other hand, when the test is based on narrower windows, the risk of including different regimes is lower, but the estimated covariance matrix are too noisy and the test loses power. Rigobon claims that the heteroskedasticity assumptions are likely to be satisfied in narrower windows and so a rejection found in those windows is probably due to parameter instability: in any case there is no way to be sure of that.

Therefore, as reported in the correlation analysis, the use of predetermined windows implies a series of disadvantages. We then modify the implementation of the test by suggesting a sequential analysis in which we use a crisis moving window of a fixed size of 60 observations. We considered this moving window for the whole Asian crisis period and we roll it starting from June 1997 till February 1998. By means of the p-value of the test[15], we can constantly monitor when the DCC

[14] When the p-value of the test is bigger than 0.95 there is evidence of loss of interdependence, when it is lower than 0.05 there is evidence of contagion.

[15] Following Rigobon (2002a), we bootstrapped the distribution of the DCC and then we evaluated the proportion of realisations for which the DCC is below zero (mass below zero) which are a sort of p-value: the test is rejected if that mass is lower than 0.1 or greater than 0.9.

becomes statistically different from zero and then evaluate if there are rejections and the timing of these rejections.

The test is executed on the residuals of a VAR, as suggested by Rigobon (2002a), where the endogenous variables are two days moving averages of the stock markets returns. We analysed the relationship between Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI indexes.

First of all, the test is ran on the predetermined windows reported in table 6, which are the same used by Rigobon (2002a)[18]. Since the test allows us to operate in the presence of omitted variables, differently from the correlation analysis we do not test the stability of the propagation mechanism between the generator of the crisis and another market but we start analysing the relationship between Eurostoxx and Dow Jones during the Asian crisis. In fact, during the periods of financial turmoil it is possible that cross market linkages change not only between the market generator of the crisis (Hong Kong for example) and the market that receipt the crisis, but also among the markets that receipt the crisis.

As Rigobon (2002a) argues, since we are analysing Eurostoxx (EU henceforth) and Dow Jones (DJ) and the crisis rises in Asia, we are not including the generator market in the regression and so the crisis depends on the increase of variance of an unobservable shock. It is then possible (but there is no way of being sure of that) that the heteroskedasticity involves only Z and so the rejections should be due to the parameter instability. Using the correlation it is not possible to test the stability of the linkages among the markets which receipt the crises because the presence of omitted variables biases this kind of tests as we showed for the F-R test.

As one can see from the first three columns of table 7 there are many rejections of the null of stability. The results seem to be stable even using different lags in the initial VAR specification. Anyway, we are not sure that these rejections are due to parameter instability because, as one can observe from table 9, the residuals exhibit auto-correlation and also ARCH effects which could cause rejections. Looking at the first three columns of table 7 one can see that the rejections in windows HK and K, related to the crises of Hong Kong and Korea, are stable: anyway it is a surprising that using VAR(3) residuals (column 2) we reject the null in the windows HK and K but we accept it in the window HK+K which is the sum of HK and K. Even in the simplest bivariate

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[18] Rigobon argues that the power of the test depends on the average increase in volatility. Rigobon ran a simulation using a sample of 60 observations and assuming that α and β are lower than 0.8 and the unconditional correlation is lower than 0.85. If the increase in the volatility in the crisis period is bigger than five times, then the power of the DCC test is higher than 90%. Since the power of the tests depends on the increase in the variance we constantly monitor it. In table 8 it is reported the average increase in the variance in each predetermined window, while all the figures concerning the DCC test report the average increase in the variance calculated in the moving window.

case it is difficult to state the cause of a rejection, but following Rigobon we should state that rejections are due to the shift in the parameters.

To evaluate the power of the test we firstly add to the analysis the Nasdaq index (NA henceforth) and secondly also the Nikkei (NI). Since none of those markets is the generator of the crisis, as in the case of EU and DJ, we are allowed to suppose that the heteroskedasticity assumptions are satisfied. As shown in table 7 (column 4 to 9), the rejections diminish when we increase the number of markets and the number of lags in the VAR specification: when we analyse the residuals of a VAR(3) and a VAR(5) modelled on four markets (EU, DJ, NA, and NI) (columns 8 and 9), the rejections disappear in the predetermined windows. This is surprising because, if the propagation mechanism between EU and DJ changes, as we found in the bivariate analysis, we should find the same rejections also in the multivariate analysis. Either the DCC is misleading in the bivariate analysis, or it is powerless in the multivariate set up.

To empirically evaluate the power of the test we finally add to the analysis the HSI index. In this way we introduce the Hong Kong market in the analysis. Since we include the generator market, the crisis consists in the increase of the variance of the idiosyncratic shock of Hong Kong. Anyway, since Hong Kong is not the only generator, we should expect that also an unobservable shock exhibits heteroskedasticity: if this is true we expect that the number of rejections increase due to the different types of heteroskedasticity. As one can see from table 7 (column 10 to 12) no rejections are found. This fact suggests that the test have very little power in the multivariate set up.

However, as already observed, the predetermined window analysis proceeds by attempts and, even if breaks in the parameters occurred, we could not be able to find them because the crisis windows are bad specified. To avoid this problem we ran sequential analysis using a fixed size crisis window of 60 observations[19]. This enable us to verify if there are breaks in some periods not analysed with the predetermined windows and to approximate the starting and ending dates of a break in the cross market linkages. Figure 4 refers to the analysis with the EU and DJ indexes and reports the mass below zero and the average increase in variance at every observation from June 1997 to February 1998. As one can see, the test rejects the stability since August 1997 till the end of our sample period. Anyway, as already underlined it is difficult to take the rejection as a proof of parameter instability. By extending the analysis to other markets we see that the "instability" window found in the bivariate analysis narrows: first of all, by adding the NA index (figure 5), it starts from August 1997 and ends at the beginning of February 1998; then by adding the NI index (figure 6) and at last the HSI index (figure 4), it starts at the beginning of November 1997 and ends at the beginning of

[19] We choose this length to minimise noisy signals. We repeat the analysis with fixed windows of different size (40 and 50 observations), and as one can see by comparing figures 7, 8 and 9, the results are not sensitive to this change, but in the shorter windows there are more false signals.

December 1997. As we have said, including the Hong Kong stock market in the regression should add a cause of rejection due to heteroskedasticity assumptions that are violated, but as one can see from figure 7 nothing changes in the instability window after HSI is introduced. We ran the test on filtered data (with a VAR(3) and a VAR(5))[20] and we changed the size of the moving window but, even if the rejection periods are shorter, the conclusions are the same. It is important to underline that the predetermined window analysis is misleading: looking at table 7, in the case of multivariate analysis, one can conclude that the Asian crisis is a stable period. On the contrary, using a moving window analysis we always find periods of rejections and we are able to approximate their duration.

4.2.1 Multivariate analysis: power of the test

To assess the power of the DCC test we run a simple experiment. In particular we analyse if the increase in the number of markets under analysis has an impact on the power of the test. We simulate the returns of five financial markets from a simple linear simultaneous equation model with, heteroskedasticity and without omitted variables. We generate two sub-samples: a tranquil sample of 100 observations and a crisis one of 60 observations. The model satisfies the heteroskedasticity assumptions and we allow the propagation mechanism during the tranquil period to be different from that of crisis. The model has the following form:

$$AX_t = \Phi X_{t-1} + \mathrm{E}_t$$

A is a *5x5* matrix that allows for a simultaneous relationship among the endogenous variables; X_t is a *5x1* vector and contains the endogenous variables; X_{t-1} contains the lagged values of *X* and Φ is a *5x5* matrix containing the coefficients of the lagged variables. E_t is a *5x1* vector and contains the idiosyncratic components of the analysed markets. The matrix Φ is the same during the two subset (crisis and non crisis) and is the following:

$$\Phi = \begin{pmatrix} 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \end{pmatrix}.$$

[20] Figures 12 and 13 report the result in the case of EU and DJ.

Contagion is modelised by differentiating the matrix A between the two periods. In the tranquil period the matrix A is the following:

$$A^{I} = \begin{pmatrix} 1 & -0.05 & -0.05 & -0.05 & -0.05 \\ -0.05 & 1 & -0.05 & -0.05 & -0.05 \\ -0.05 & -0.05 & 1 & -0.05 & -0.05 \\ -0.05 & -0.05 & -0.05 & 1 & -0.05 \\ -0.05 & -0.05 & -0.05 & -0.05 & 1 \end{pmatrix}.$$

We keep the simulation study as simple as possible by setting the relations across markets equal in each equation of the model. Contagion occurs in the first market and it is modelled with a shift in the parameter $\alpha_{1,5}$ which switches from -0.05 to -0.2. The crisis is represented by a 3 time increase in the standard error of the idiosyncratic component of the fifth market. The standard error of the country specific component of each market is arbitrary set to 0.01. After generating the samples we run the DCC test to evaluate if the power of the test changes when the number of market under analysis increases. In each simulation we run 1000 replications.

The model is calibrated to asymptotically obtain the correlation matrices reported in table 12 and 13**,** and to increase the variance as reported in table 14. Moreover, we calibrate the model to get an increase in the correlation between markets and an increase volatility if the generator market of nine times: these conditions are similar to those we found in the empirical analysis.

Firstly we analyse the relationship between the generator market and the one which is subject to contagion. These markets have some linkages with those not included in the regression, so we are running the test in the presence of omitted variables. Since the generator market is included in the regression, the crisis is assimilated to an increase in the variance of the idiosyncratic shock of this market, then the heteroskedasticity assumptions are satisfied and the only cause of rejection is the parameter instability. As one can see from table 15 the proportion of realisations greater than 0.9 and lower than 0.1 in 1000 replication is 18,3%, which represents the power of the test.

We increased the number of markets and we evaluated if the power of the test changes. Table 15 shows that the power of the test diminishes when the number of the analysed markets increases. The test has almost no power against the parameter shift when we analyse simultaneously the five markets.

Since there is evidence that in the multivariate set up the test loses power, it may be useless to study a large set of markets to support the thesis of no contagion during the crisis.. In summary, the results suggest that the test properties in the multivariate set up, require further study.

5. Conclusions

In this paper we analyse three different methods proposed in the literature to verify the null hypothesis of interdependence against contagion between financial markets. Following many authors we define contagion as an increase in the cross market linkages during a financial crisis. We sustain that it is useful to take into account the hypothesis of a fall of correlation during crises.

We show that the inference based on conditional correlation coefficient, even if adjusted for heteroskedasticity (F-R and C-P-S methods), can be misleading and depends highly on the window used. We demonstrate that these tests are biased because in most of the cases we observe the presence of omitted variables. To demonstrate this, we have proposed a simple analysis of volatility. In order to solve the problems which arise when predetermined windows are used, we modify the execution of the test by considering a sequential analysis. In this way, we show that the analysis based on predetermined windows is misleading because it proceeds by attempts and some rejections are not found because the windows are not well specified.

Then, we have ran the DCC test and have observed that even if it operates in the presence of omitted and endogenous variables, it is unable to cope with some types of heteroskedasticity that could be exhibited by the data. It is thus impossible to state whether the rejections we found are due to shifts in the parameters (contagion) or to the type of heteroskedasticity. We have also noticed that, when the number of market under analysis increases, the rejections disappear by using predetermined windows even if it is likely that the heteroskedasticity assumptions are violated. Finally, we have ran a simulation study to evaluate the loss of power of the DCC test in the multivariate framework. We show that, other things equal, increasing the number of analysed markets diminishes the power of the test against a parameter shift. Since there is evidence that in the multivariate set up the test loses power, it may be useless to study a large set of markets to support the thesis of no contagion during the crisis.

The DCC sequential analysis also shows that the predetermined windows are misleading because they proceeds by attempts and many rejections are not found because windows are not well specified. By using a sequential analysis, rejections are always found and the results are stable to changes in the test implementation. However, our work is only a preliminary analysis of contagion tests. Further work is needed to find an approach that appropriately measure contagion among financial markets.

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TABLE 1: Definition of the windows. They are the same analysed in Rigobon (2001) and a subset of those in Forbes and Rigobon (2002). We also consider a longer window L.

PERIOD	TRANQUIL WINDOW	CRISIS WINDOW
Hong Kong (HK)	2/1/97-2/6/97	27/10/97-14/11/97
Korea (K)	2/1/97-2/6/97	1/12/97-9/1/98
Thailand (T)	2/1/97-2/6/97	10/6/97-29/8/97
HK+K	2/1/97-2/6/97	27/10/97-9/1/98
HK+K+T	2/1/97-2/6/97	10/6/97-9/1/98
A	1/1/96-16/10/97	17/10/97-16/11/97
B	1/1/96-31/5/97	1/6/97-16/11/97
C	1/1/96-16/10/97	17/10/97-23/12/97
D	1/1/96-16/10/97	17/10/97-1/3/98
L	1/1/96 – 31/5/97	1/6/97-31/1/98

TABLE 2: Synthesis of the results of the F-R and C-P-S tests run on Dow Jones and HSI indexes. LI = Loss of Interdependence; C = Contagion; N= Null hypothesis.

WINDOWS	HSI/DOWJONES			
	C-P-S		FORBES-RIGOBON	
	DAILY	MA2D	DAILY	MA2D
HK	C	N	N	LI
K	N	N	N	N
T	N	N	N	LI
HK+K	N	N	N	N
HK+K+T	N	N	N	LI
A	N	N	LI	LI
B	N	LI	N	LI
C	N	N	N	LI
D	N	N	N	LI
L	N	LI	N	LI

TABLE 3: Synthesis of the results of the F-R and C-P-S tests run on Eurostoxx and HSI indexes. LI = Loss of Interdependence; C = Contagion; N= Null hypothesis.

WINDOWS	HSI/EUROSTOXX			
	C-P-S		RIGOBON	
	DAILY	MA2D	DAILY	MA2D
HK	C	C	N	N
K	N	N	N	N
T	N	N	N	LI
HK+K	C	C	LI	N
HK+K+T	N	N	LI	LI
A	C	N	N	N
B	N	LI	LI	LI
C	C	C	N	N
D	C	C	N	N
L	N	N	LI	LI

TABLE 4: Synthesis of the results of the F-R and C-P-S tests run on Nikkei and HSI indexes. LI = Loss of Interdependence; C = Contagion; N= Null hypothesis.

WINDOWS	HSI/NIKKEI			
	C-P-S		FORBES-RIGOBON	
	DAILY	MA2D	DAILY	MA2D
HK	N	N	N	N
K	N	N	N	LI
T	N	N	N	N
HK+K	N	N	LI	LI
HK+K+T	N	N	LI	LI
A	N	N	LI	LI
B	N	N	LI	LI
C	N	N	LI	LI
D	N	N	LI	LI
L	N	N	LI	LI

TABLE 5: Increase rate of the variance of the follower market(Δ), expected increase rate *($\rho^2\delta$)* on the basis of F-R model and percentage of that increase (exp%) explained by the market generating the crisis.

	DJ			**EU**			**NIK**		
WINDOW	Δ	$\rho 2\delta$	exp%	Δ	$\rho 2\delta$	exp%	Δ	$\rho 2\delta$	exp%
HK	6.08	0.30	5%	6.90	4.24	61%	0.83	2.88	349%
K	0.38	0.04	11%	1.00	0.59	59%	0.78	0.45	58%
T	0.14	0.01	8%	0.82	0.16	19%	-0.48	0.12	-25%
HK+K	1.89	0.04	2%	2.71	5.93	219%	1.77	1.13	64%
HK+K+T	0.80	0.06	8%	1.54	0.87	56%	0.35	0.61	177%
A	6.20	0.21	3%	6.81	2.63	39%	2.14	2.04	95%
B	1.77	0.06	3%	3.23	1.27	39%	0.41	0.85	206%
C	2.96	0.11	4%	3.89	1.35	35%	4.36	1.08	25%
D	1.72	0.09	5%	2.29	1.12	49%	2.84	0.91	32%
L	1.45	0.06	4%	2.88	1.28	44%	1.53	0.85	56%

TABLE 6: Definition of the windows used to run the DCC test. They are the same analysed in Rigbon (2002a).

PERIOD	**TRANQUIL WINDOW**	**CRISIS WINDOW**
HK	1/2/97-6/2/97	10/27/97-11/28/97
K	1/2/97-6/2/97	12/1/97-1/30/98
HK+K	1/2/97-6/2/97	10/27/97-1/30/98
THAI	1/2/97-6/2/97	6/10/97-29/8/97
HK+K+THAI	1/2/97-6/2/97	6/10/97-1/30/98

TABLE 7: DCC test results. R means that we found a rejection, N means that we accepted the null of parameter stability.

PERIOD	**EU DJ**			**EU DJ NA**			**EU DJ NA NI**			**EU DJ NA NI HK**		
lag	*1*	*3*	*5*	*1*	*3*	*5*	*1*	*3*	*5*	*1*	*3*	*5*
HK	**R**	**R**	**R**	**R**	**R**	**R**	N	N	N	N	N	N
K	**R**	**R**	**R**	N	N	N	**R**	N	N	N	N	N
HK+K	**R**	N	**R**	**R**	N	N	N	N	N	N	N	N
THAI	**R**	N	**R**	**R**	N	N	N	N	N	N	N	N
HK+K+THAI	N	N	N	**R**	N	N	N	N	N	N	N	N

TABLE 8: Average increase rate of the residuals variance during the analysed crisis windows. We refer to the VAR(1) residuals.

PERIOD	EU DJ	EU DJ NA	EU DJ NA NI	EU DJ NA NI HK
HK	3,7841	3,1040	3,3891	4,6963
K	1,5779	1,5979	1,7000	3,0886
HK+K	2,3727	2,1626	2,3410	3,6278
THAI	1,6624	1,3231	1,1021	1,4025
HK+K+THAI	2,1009	1,8846	1,6751	2,5576

TABLE 9: Eurostoxx and Dow Jones residual tests. We checked for the presence of autocorrelation in mean (Box Pierce test, rows BP1 in the table), in variance (Box Pierce test, rows BP2 in the table), and ARCH effects (LM test, rows LM) in every equation of the different VARs from which the residuals are obtained. Columns (1), (3) and (5) refer to the lags included in the VAR specification. Columns 5, 10 and 20 refer to the lag included in the diagnostic tests.

	VAR	(1)			(3)			(5)		
	lag	5	10	20	5	10	20	5	10	20
eq. 1 (EU)	BP 1	0,00	0,00	0,00	0,00	0,00	0,00	0,10	0,16	0,07
	BP 2	0,21	0,01	0,00	0,06	0,05	0,01	0,70	0,10	0,11
	LM	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,05	0,04
eq. 2 (DJ)	BP 1	0,00	0,00	0,00	0,01	0,00	0,00	0,24	0,00	0,00
	BP 2	0,00	0,00	0,00	0,21	0,66	0,93	0,34	0,67	0,92
	LM	0,00	0,00	0,00	0,00	0,00	0,00	0,17	0,00	0,01

TABLE 10: Eurostoxx, Dow Jones and Nasdaq residual tests. We checked for the presence of autocorrelation in mean (Box Pierce test, rows BP1 in the table), in variance (Box Pierce test, rows BP2 in the table), and ARCH effects (LM test, rows LM) in every equation of the different VARs from which the residuals are obtained. Columns (1), (3) and (5) refer to the lags included in the VAR specification. Columns 5, 10 and 20 refer to the lag included in the diagnostic tests.

	VAR	(1)			(3)			(5)		
	lag	5	10	20	5	10	20	5	10	20
eq. 1 (EU)	BP 1	0,00	0,00	0,00	0,00	0,00	0,00	0,34	0,32	0,12
	BP 2	0,01	0,00	0,00	0,00	0,00	0,00	0,11	0,11	0,06
	LM	0,00	0,00	0,00	0,00	0,00	0,00	0,18	0,25	0,17
eq. 2 (DJ)	BP 1	0,00	0,00	0,00	0,11	0,00	0,01	0,75	0,01	0,05
	BP 2	0,00	0,00	0,00	0,36	0,84	0,90	0,45	0,75	0,83
	LM	0,00	0,00	0,00	0,05	0,00	0,02	0,70	0,01	0,11
eq. 3 (NA)	BP 1	0,00	0,00	0,00	0,03	0,04	0,13	0,47	0,24	0,47
	BP 2	0,00	0,00	0,00	0,00	0,03	0,04	0,00	0,01	0,03
	LM	0,00	0,00	0,00	0,01	0,01	0,15	0,37	0,23	0,48

TABLE 11: Eurostoxx, Dow Jones, Nasdaq and Nikkei residual tests. We checked for the presence of autocorrelation in mean (Box Pierce test, rows BP1 in the table), in variance (Box Pierce test, rows BP2 in the table), and ARCH effects (LM test, rows LM) in every equation of the different VARs from which the residuals are obtained. Columns (1), (3) and (5) refer to the lags included in the VAR specification. Columns 5, 10 and 20 refer to the lag included in the diagnostic tests.

	VAR	**(1)**			**(3)**			**(5)**		
	lag	**5**	**10**	**20**	**5**	**10**	**20**	**5**	**10**	**20**
eq. 1 (EU)	**BP 1**	0,00	0,00	0,00	0,10	0,05	0,11	0,62	0,31	0,37
	BP 2	0,79	0,05	0,11	0,83	0,41	0,09	0,79	0,48	0,20
	LM	0,00	0,00	0,00	0,07	0,02	0,03	0,51	0,22	0,20
eq. 2 (DJ)	**BP 1**	0,00	0,00	0,00	0,35	0,09	0,06	0,93	0,17	0,05
	BP 2	0,00	0,00	0,00	0,72	0,96	0,96	0,69	0,93	0,95
	LM	0,00	0,00	0,00	0,21	0,06	0,02	0,88	0,16	0,02
eq. 3 (NA)	**BP 1**	0,00	0,00	0,01	0,35	0,26	0,79	0,98	0,87	0,98
	BP 2	0,00	0,00	0,00	0,05	0,12	0,18	0,04	0,10	0,18
	LM	0,00	0,00	0,00	0,20	0,19	0,66	0,92	0,80	0,97
eq. 4 (NI)	**BP 1**	0,00	0,00	0,00	0,00	0,00	0,00	0,63	0,52	0,74
	BP 2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	LM	0,00	0,00	0,00	0,00	0,00	0,00	0,48	0,41	0,54

TABLE 12: Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI residual tests. We checked for the presence of autocorrelation in mean (Box Pierce test, rows BP1 in the table), in variance (Box Pierce test, rows BP2 in the table), and ARCH effects (LM test, rows LM) in every equation of the different VARs from which the residuals are obtained. Columns (1), (3) and (5) refer to the lags included in the VAR specification. Columns 5, 10 and 20 refer to the lag included in the diagnostic tests.

	VAR	(1)			(3)			(5)		
	lag	5	10	20	5	10	20	5	10	20
eq. 1 (EU)	BP 1	0,00	0,01	0,02	0,39	0,49	0,45	0,90	0,74	0,84
	BP 2	0,54	0,00	0,02	0,35	0,00	0,00	0,14	0,00	0,00
	LM	0,00	0,00	0,00	0,36	0,30	0,26	0,88	0,63	0,67
eq. 2 (DJ)	BP 1	0,00	0,00	0,01	0,87	0,58	0,50	0,99	0,43	0,20
	BP 2	0,00	0,00	0,00	0,34	0,42	0,73	0,40	0,28	0,63
	LM	0,00	0,00	0,00	0,85	0,42	0,38	0,98	0,40	0,18
eq. 3 (NA)	BP 1	0,00	0,00	0,07	0,75	0,93	0,95	1,00	0,97	0,95
	BP 2	0,00	0,00	0,00	0,53	0,09	0,18	0,45	0,21	0,19
	LM	0,00	0,00	0,00	0,67	0,85	0,89	0,99	0,95	0,95
eq. 4 (NI)	BP 1	0,00	0,00	0,00	0,02	0,01	0,01	1,00	0,91	0,83
	BP 2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	LM	0,00	0,00	0,00	0,01	0,07	0,07	0,99	0,89	0,61
eq. 5 (HK)	BP 1	0,01	0,02	0,13	0,18	0,18	0,38	0,99	0,49	0,46
	BP 2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	LM	0,00	0,00	0,04	0,11	0,14	0,41	0,99	0,55	0,52

TABLE 13: Correlation matrix in the tranquil period**.** We generated 1000 tranquil period samples of 1000 observations.

market	**1**	**2**	**3**	**4**	**5**
1	1	0,26	0,27	0,27	0,27
2	0,26	1	0,26	0,26	0,26
3	0,27	0,26	1	0,27	0,27
4	0,27	0,26	0,27	1	0,27
5	0,27	0,26	0,27	0,27	1

TABLE 14: Correlation matrix in the crisis period. We generated 1000 crisis samples of 1000 observations.

market	**1**	**2**	**3**	**4**	**5**
1	1	0,51	0,52	0,52	0,58
2	0,51	1	0,49	0,49	0,33
3	0,52	0,49	1	0,49	0,33
4	0,52	0,49	0,49	1	0,33
5	0,58	0,33	0,33	0,33	1

TABLE 15: Average increase in the variance and in the standard error during the crisis in the simulation.

market	**1**	**2**	**3**	**4**	**5**
variance	1,9	1,4	1,4	1,4	8,2
std err	1,4	1,2	1,2	1,2	2,9

TABLE 16: Power of the test against the alternative hypothesis of a shift in the parameters. The test is rejected if the mass below zero is greater than 0.9 or lower than 0.1.

Markets	**power of the test**
1-5	0.183
1-2-5	0.083
1-2-3-5	0.012
all markets	0.002

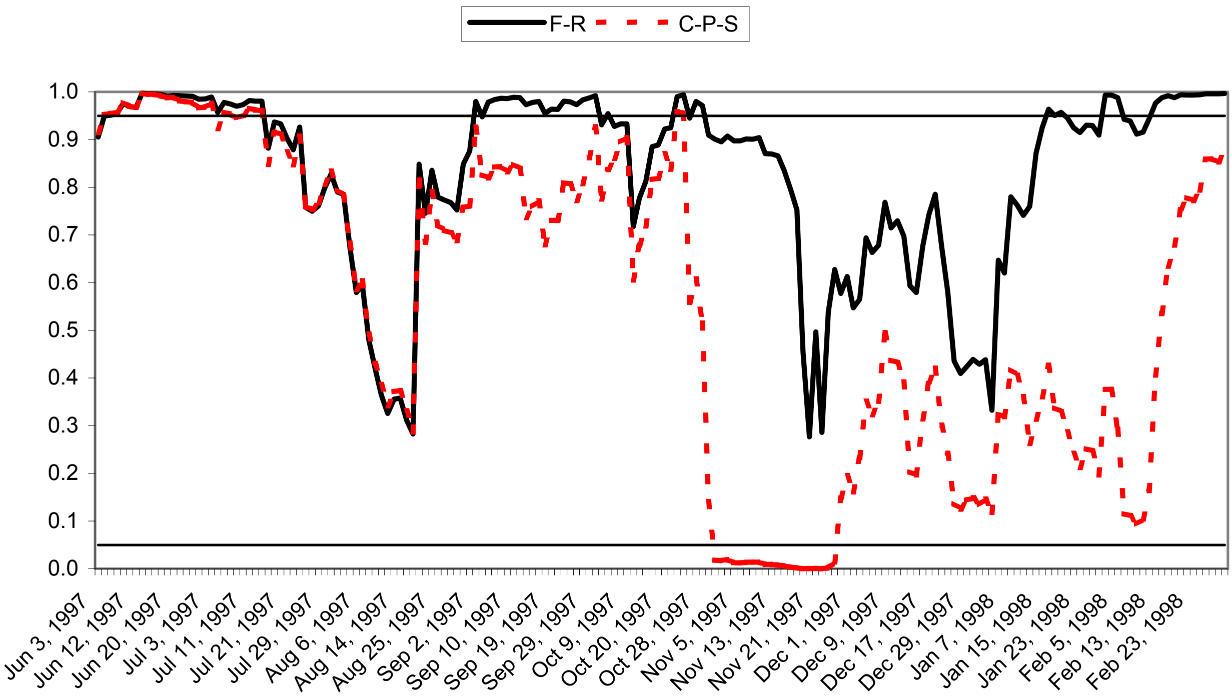

Figure 1 – Rolling window result for Dow Jones and HSI. The figure shows the p-values of the two tests at every observation, starting from June 1997 till February 1998. If the p-value is greater than 0.95 we reject the null of interdependence in favour of loss of interdependence. If the p-value is lower than 0.05 we reject the null in favour of contagion.

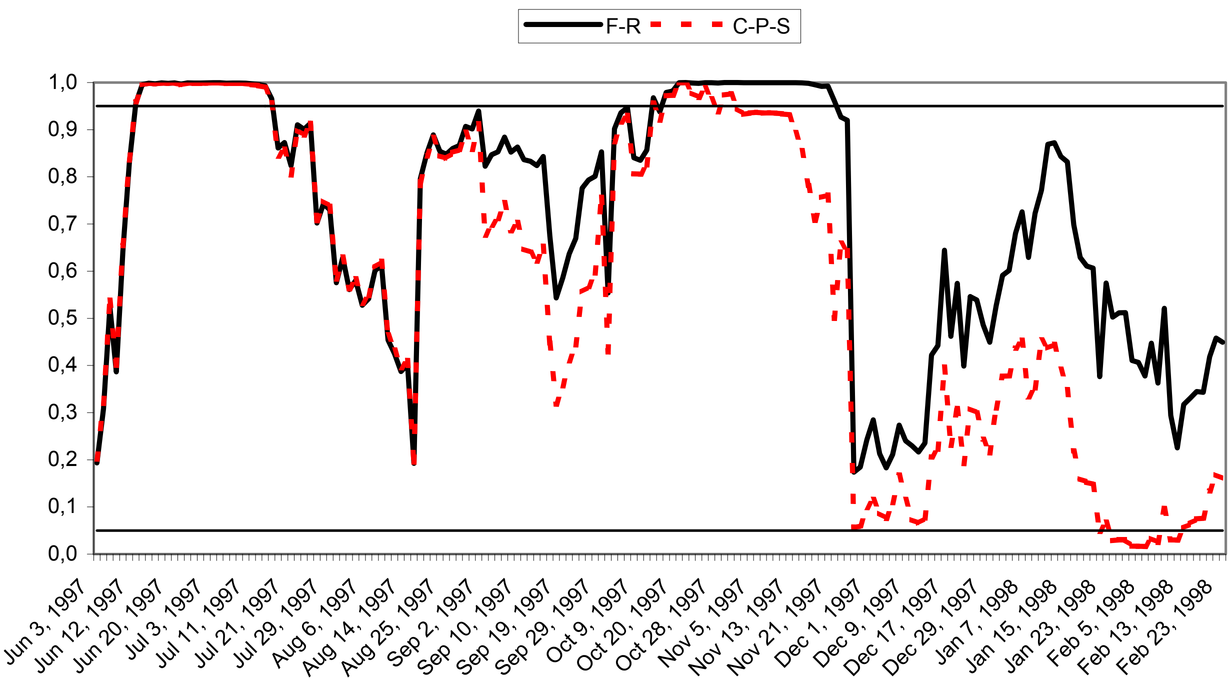

Figure 2 – Rolling window result for Eurostoxx and HSI. The figure shows the p-values of the two tests at every observation, starting from June 1997 till February 1998. If the p-value is greater than 0.95 we reject the null of interdependence in favour of loss of interdependence. If the p-value is lower than 0.05 we reject the null in favour of contagion.

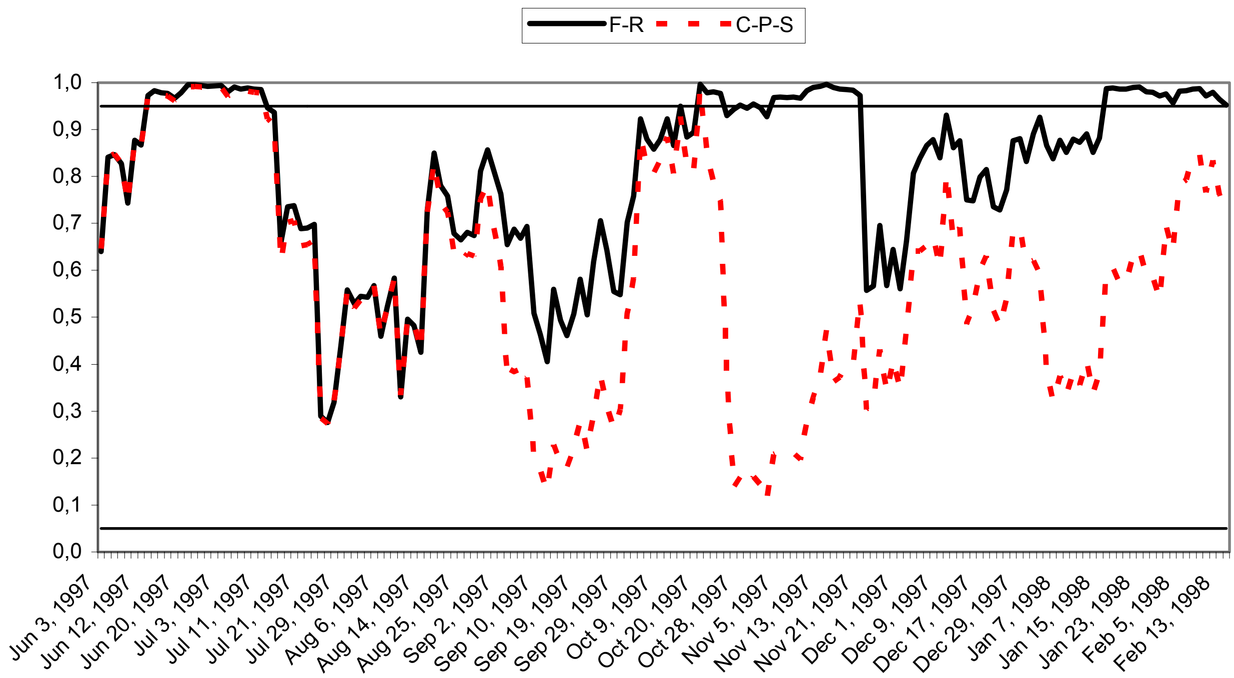

Figure 3 – Rolling window result for Nikkei and HSI. The figure shows the p-values of the two tests at every observation, starting from June 1997 till February 1998. If the p-value is greater than 0.95 we reject the null of interdependence in favour of loss of interdependence. If the p-value is lower than 0.05 we reject the null in favour of contagion.

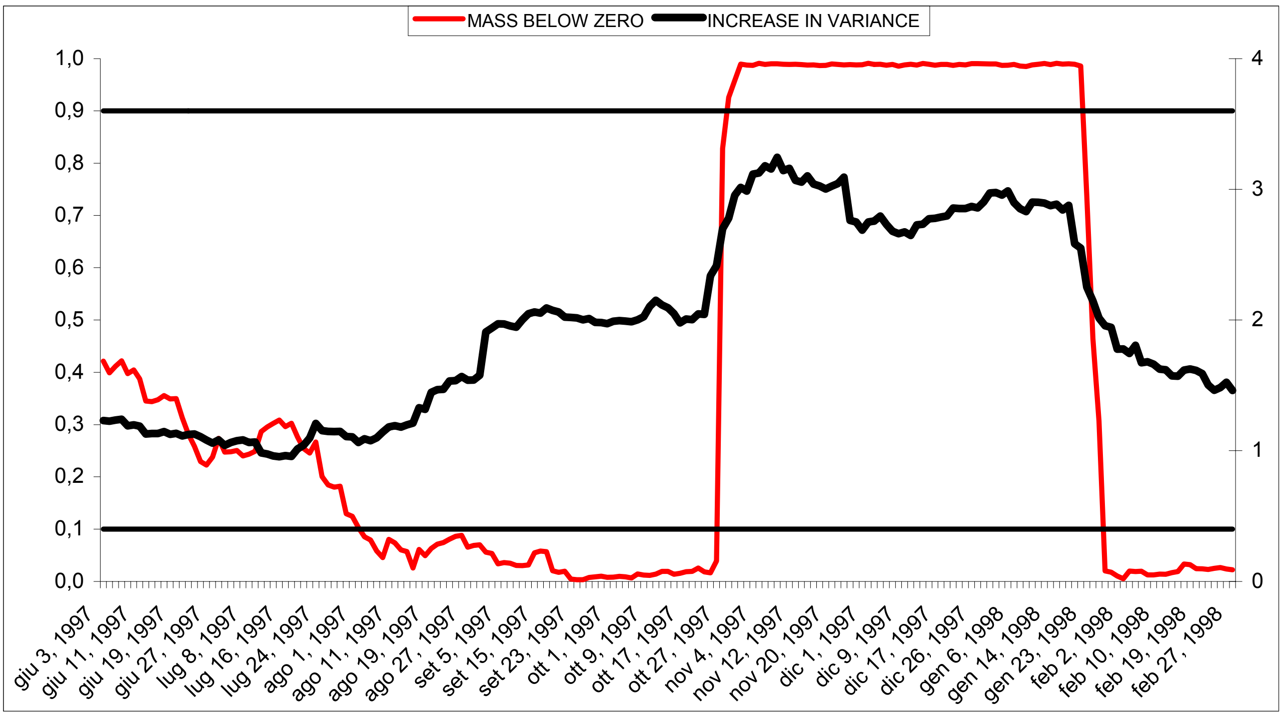

Figure 4: DCC moving window result for Eurostoxx and Dow Jones. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations.

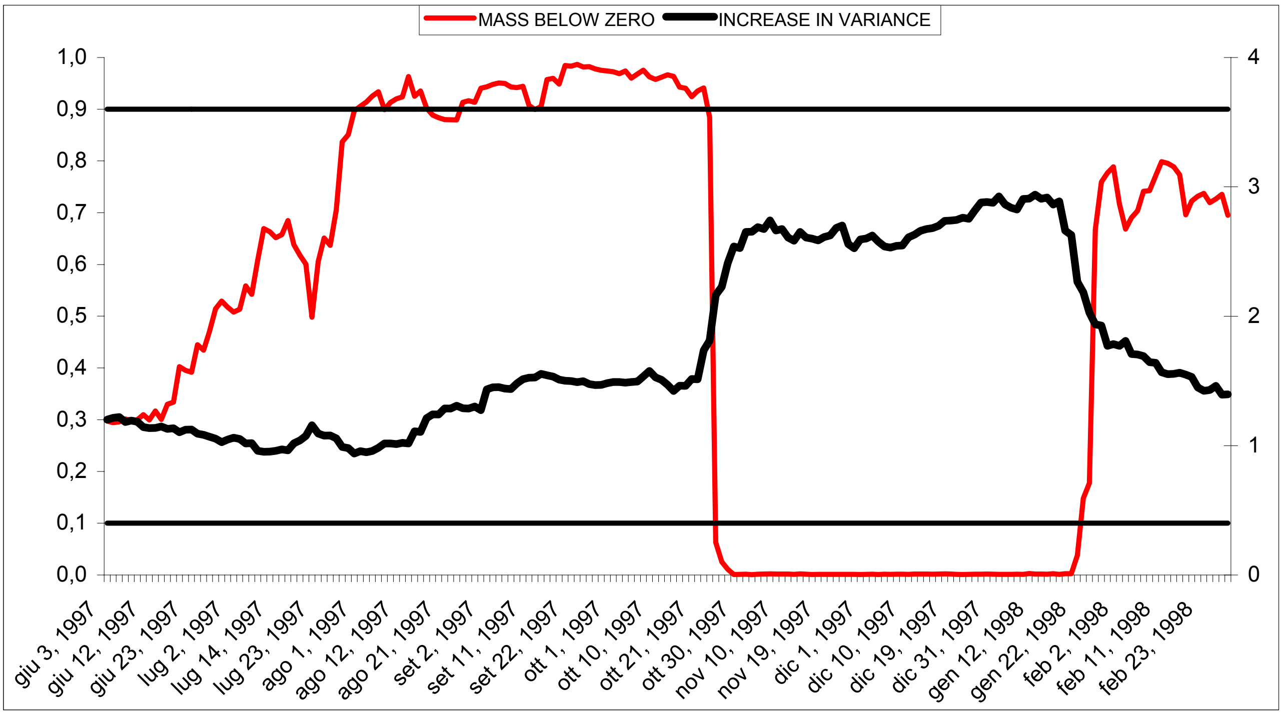

Figure 5: DCC moving window result for Eurostoxx, Dow Jones and Nasdaq. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations.

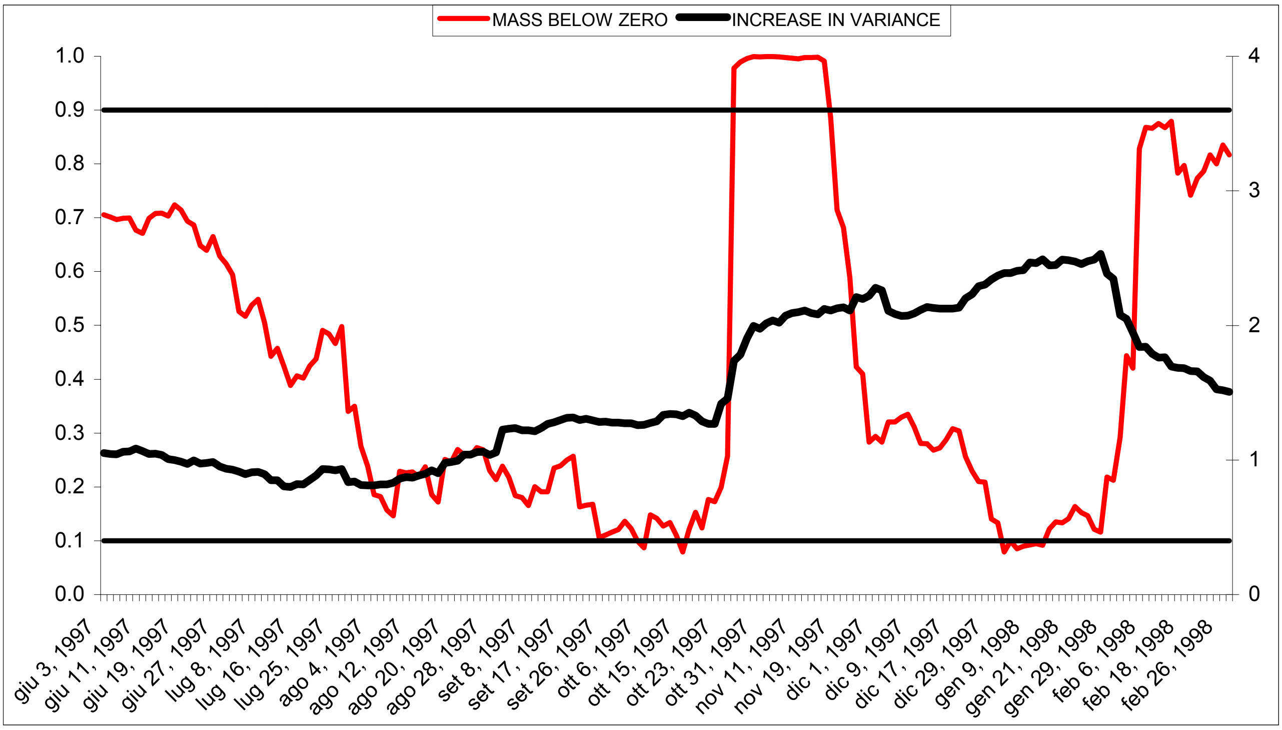

Figure 6: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq and Nikkei. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations.

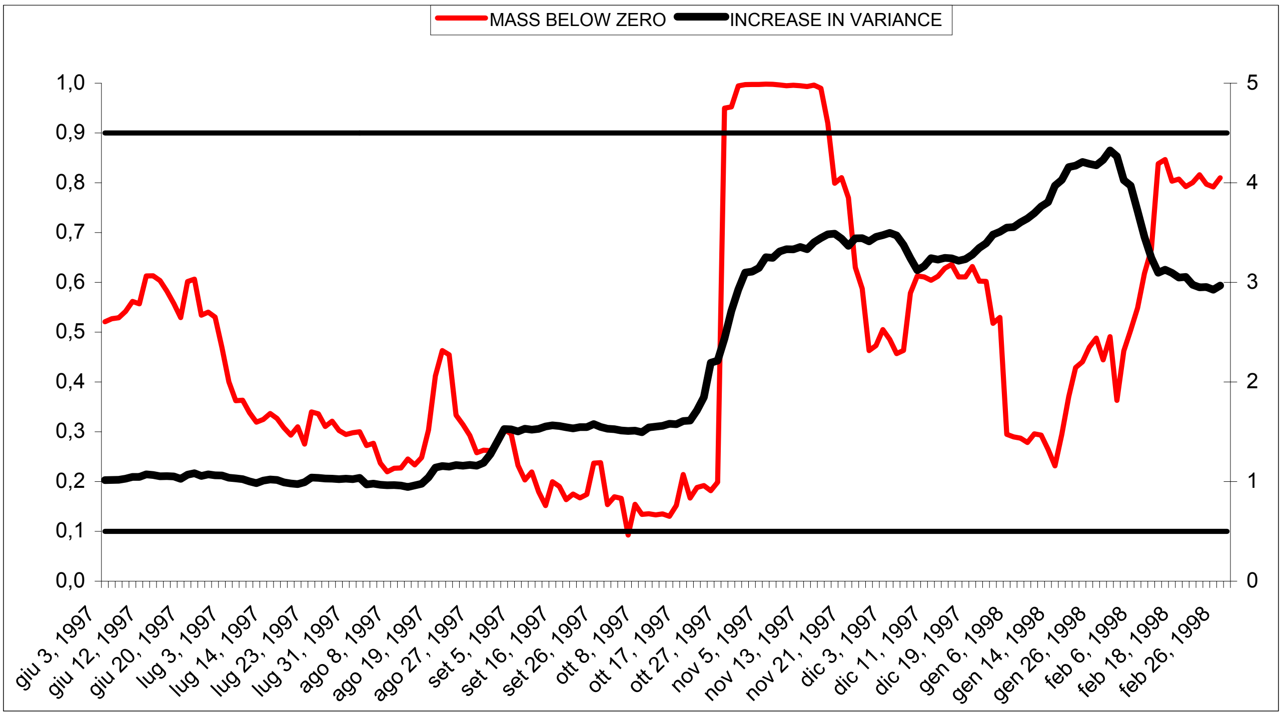

Figure 7: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations.

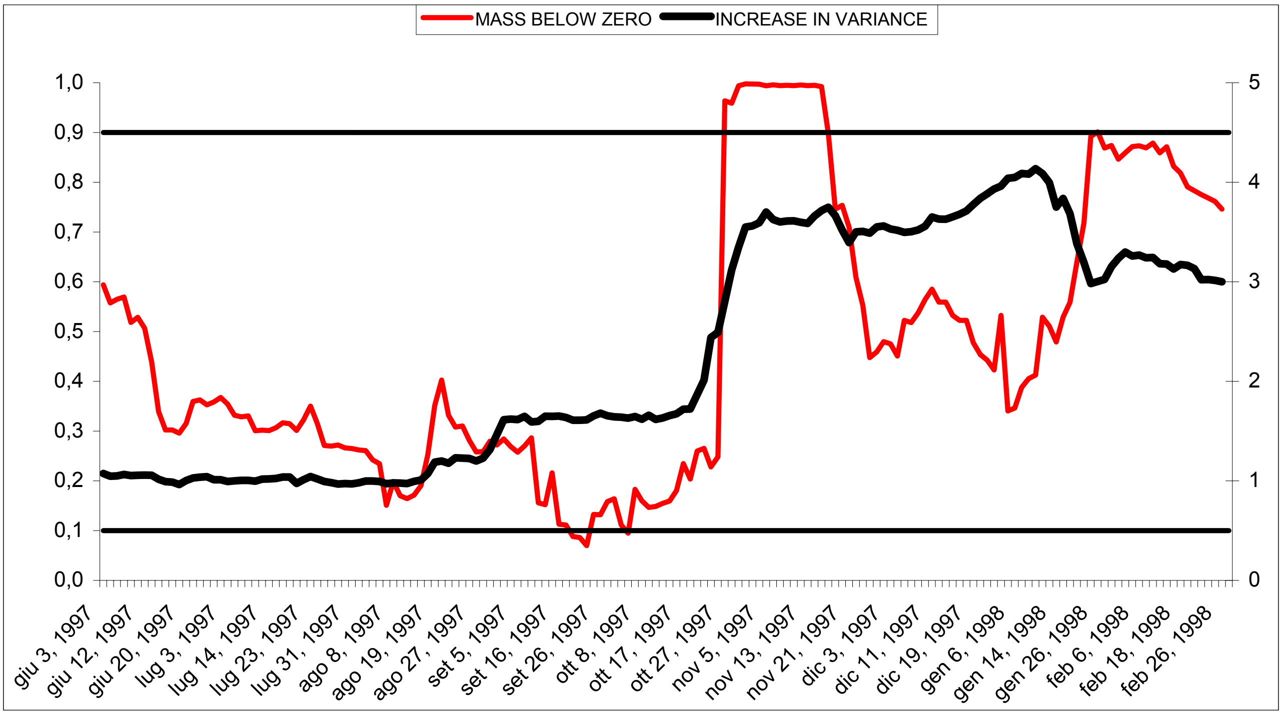

Figure 8: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 50 observations.

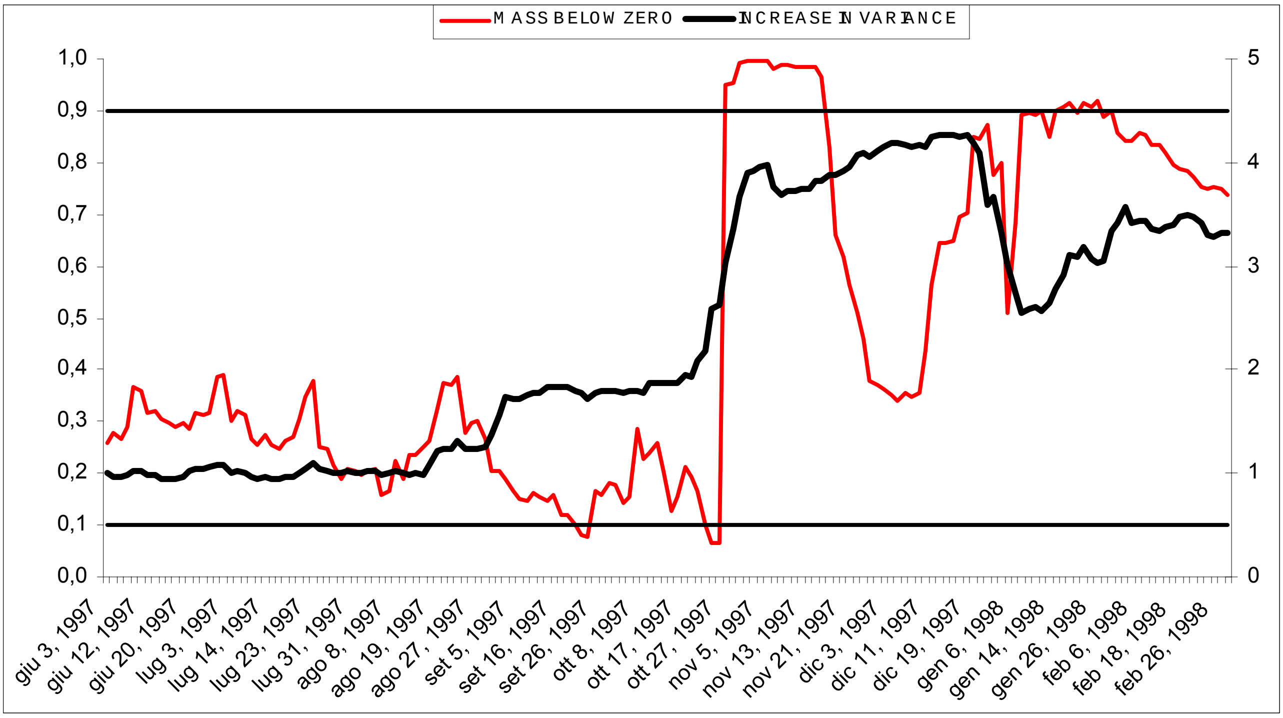

Figure 9: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 40 observations.

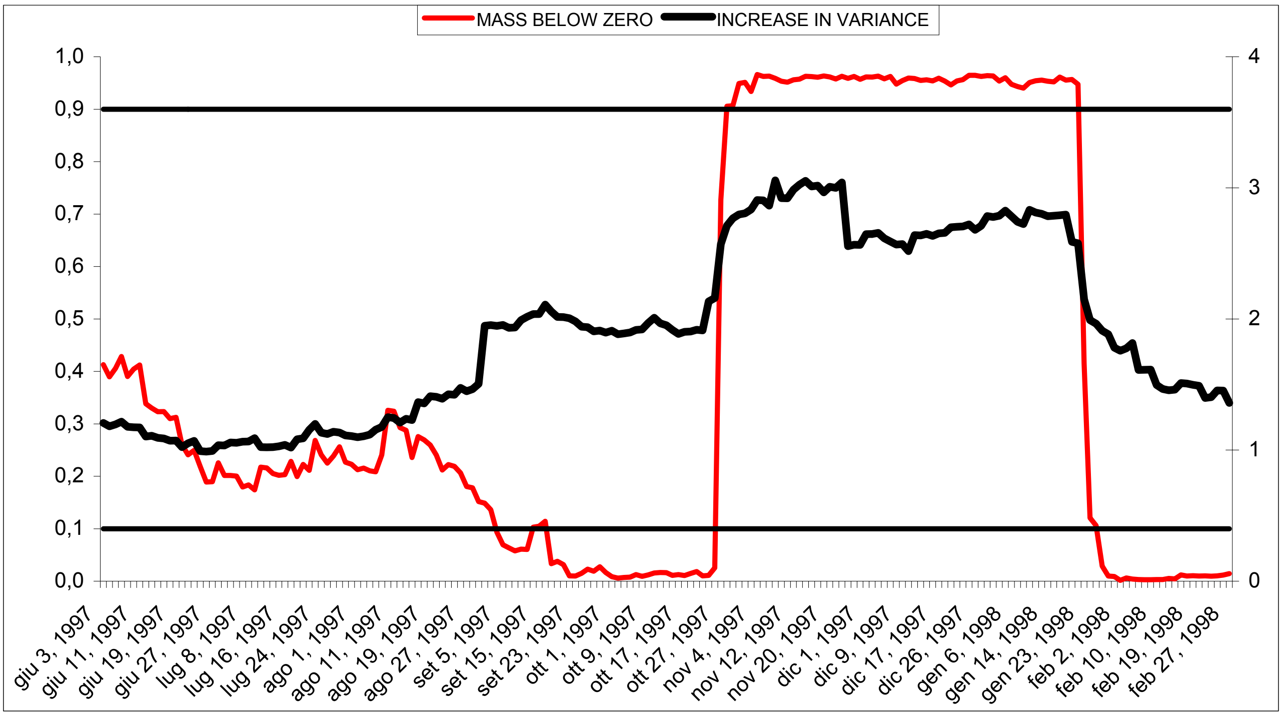

Figure 10: DCC moving window result for Eurostoxx and Dow Jones. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations. The test is ran on the residuals of a VAR with 3 lags.

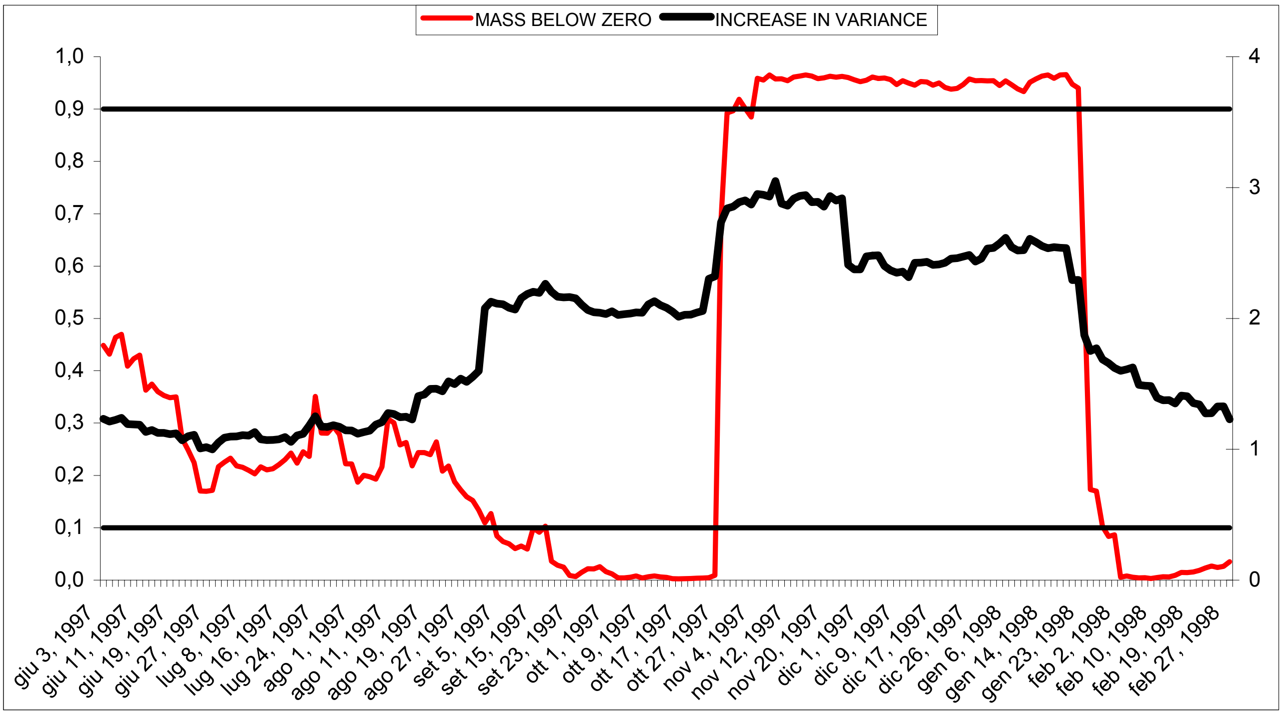

Figure 11: DCC moving window result for Eurostoxx and Dow Jones. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is grater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations. The test is ran on the residuals of a VAR with 5 lags.

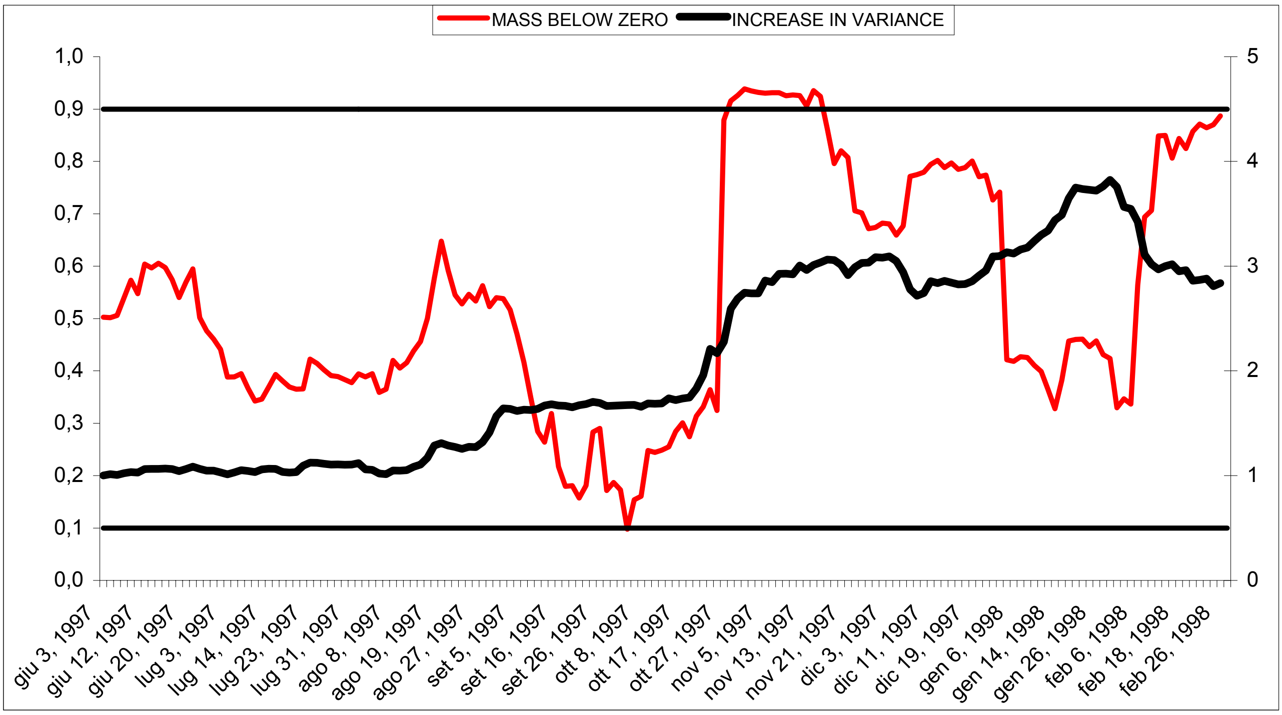

Figure 12: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations. The test is ran on the residuals of a VAR with 3 lags.

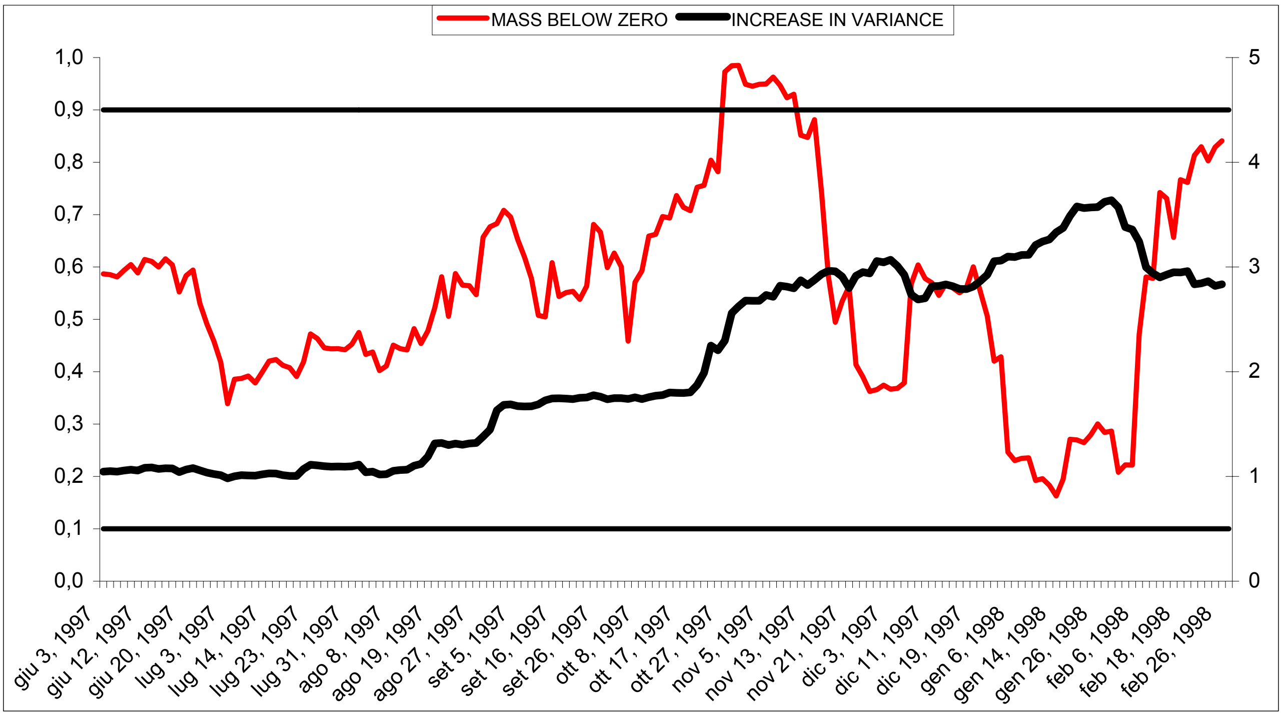

Figure 13: DCC moving window result for Eurostoxx, Dow Jones, Nasdaq, Nikkei and HSI. The figure shows the mass below zero of the DCC and the average increase of the variance at every observation, starting from June 1997 till February 1998. If the mass is greater than 0.9 or lower than 0.1 we reject the null of interdependence. We considered a moving window of 60 observations. The test is ran on the residuals of a VAR with 5 lags.