Contagion Detection with Switching Regime Models:
a Short and Long Run Analysis

M. Billio
University of Venice

M. Lo Duca
European Central Bank

L. Pelizzon
University of Venice

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MONICA BILLIO*
University of Venice

MARCO LO DUCA
European Central Bank

LORIANA PELIZZON*
University of Venice

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Abstract

The paper evaluates the potentialities of Markov switching models (MS) in contagion analysis. We intend contagion as a break that produces non-linearities in the linkages among financial markets. The MS approach allows the detection of contagion in a more general framework since, differently from the previous literature, (i) the crisis period are endogenously defined by the MS model rather than arbitrarily and are specific for each country, (ii) we investigate the flight to quality effect, i.e. when the non-linear relationship among markets who implies a significant reduction of the link among markets during a crisis period, and (iii) we distinguish between short and long run breaks using Markov switching ECM models.

We analyse the period of the Hong Kong stock market crash in 1997. The results show that (i) the relationship between developed markets strengthens, as that between the Hong Kong market and the US and European markets (i.e. contagion) and (ii) the factor loading of the error correction term shows a flight to quality effect suggesting that investors during crisis potentially ignore economic fundamentals.

JEL: Classification Numbers: C22, G15,F36
Keywords: Contagion, stock market crises, international financial markets, financial integration, Markov switching models, long run analysis.

* Dipartimento di Scienze Economiche, University Ca' Foscari of Venice, Fondamenta San Giobbe 873, 30121 Venezia, Italy

Introduction

Deregulation, globalization and advances in information technology have dramatically changed the structure of domestic and world financial markets. There is sufficient evidence that information is now shared more intensively across the world's major equity markets and that markets have become increasingly integrated. The advantages of having integrated markets are well known: investors can share their consumption risk much more efficiently, which in turn decreases the cost of capital the firms will face, hereby stimulating investment and economic growth (see Beck et al (2000), Bekaert et al. (2002) and Henry (2000a, 2000b)).

However, in the aftermath of the recent financial crises, many authors have argued that increased financial integration has intensified contagion effects across markets, causing severe welfare losses to large geographic regions. As a result, analysis of market integration and shock spillover across countries are important for many parties including investors, risk managers and regulatory and monetary authorities.

The literature focused on the question whether the relationships among markets during tranquil periods are different from those during periods of crisis and whether there is any contagion effect.

In this work, "contagion" – as opposed to "interdependence" – conveys the idea that international propagation mechanisms are discontinuous and during a crisis period the linkages among markets could strengthen. We define the opposite of contagion as loss of interdependence (or flight to quality effect) and happens when there is a structural break during the crisis and the relationship among markets weakens[1].

Since under the approach we follows contagion or loss or interdependence are structural breaks in the data-generating process during crisis periods, we can use tests to check the stability of parameters to find it.

To perform this analysis we take an asset pricing perspective as in Bekaert et al. (2005) where, for a given factor model, increased correlation is expected if the volatility of a factor increases. The size of the increased correlation will depend on the factor loadings. We test if the factor loadings in the crises periods are statistically different from those during the tranquil periods. The novelty of our approach for testing contagion is the use of an asset

[1] There is no agreement on these definitions and many other definitions have been proposed. See Forbes and Rigobon (2001b) for a review of the different definitions and theoretical and empirical approaches proposed for analysing contagion.

pricing model based on a regime-switching model as in Billio and Pelizzon (2000) and Ang and Bekaert (2002) to which we add a latent factor that capture the long run relationship between stock markets and represents the historical link between economic fundamentals.

Our approach provides the econometric framework to analyze whether financial crises and contagion are intrinsically linked, and contagious effects arise when crises are propagated across countries or markets after controlling for fundamental linkages and interdependencies, and these transmissions may spread further through mechanisms such as cross-market hedging. In particular, our approach is able to cope with one key aspect on the concerns about contagion analysis based on correlation measurement i.e. that they are generally founded on the presumption that there is something different about large negative events that leads to irrational outcomes, excess volatility and even panics. In the context of stock returns, this means that if panic grips investors as stock returns fall and lead them to ignore economic fundamentals, one would expect large negative returns to be contagious or loss of interdependence (flight to quality effect) in a way that small negative returns are not and the role of economic fundamentals will weakens. The use of a switching regime model with an error correction term that capture economic fundamentals through the long run relationship among markets allow to us to deeply analyze contagion among different markets in line with the above economic explanation of contagion.

Many papers have recently investigated interdependence and volatility spillover between equity markets (King and Wadhwani (1990), Hamao et al. (1990) and Lin et al. (1994), Karolyi (1995) and Koutmos and Booth (1995), Ng (2000), Fratzscher (2001), Baele (2004), Billio and Pelizzon (2003a)). Most of these studies and the experience of recent financial crises suggest (see, for instance, Baig and Goldfajn (1999), Favaro and Giavazzi (2002), Bae et al. (2003) and Bekaert et al. (2005)) that the international propagation of financial shocks may be non linear.

A number of papers (e.g. Baig and Goldfajn (1999), Forbes and Rigobon (2002), Corsetti et al. (2002), and for a survey see Dungey et al. (2004)) provide measures of "contagion", which allow to measure correlation taking into consideration the bias introduced by changing volatility in market returns. However, these approaches have been criticized (among other see Favero and Giavazzi (2002), Billio and Pelizzon (2003b)) and the debate is still open, since there is no professional consensus on how to measure contagion and even on the appropriate definitions of what constitutes a financial crisis or contagion, despite substantial research progress towards these goals.

In this paper we focus on switching regime models to detect contagion or loss on interdependence because this approach is able to cope not only with some important theoretical issues like economic fundamentals and non linearity in links between markets but also because this approach is able to deal with a series of econometric issues, which are extremely important for assessing the appropriate policy response to prevent crises and adequately managing those that occur.

This aspect has been well recognized by Bekaert et al. (2005) where they argue that GARCH models fail to capture fully asymmetric volatility (higher volatility in bear markets) and the potential effects it has on correlations during crisis periods and they suggests for further research a regime switching model[2].

In particular, our approach addresses a series of econometric problems that arise when dealing with contagion among financial markets:

(i) Crises are in some way associated with an increase in the conditional volatility of financial market returns, thus it is necessary to deal with heteroskedasticity;

(ii) Control for fundamentals, which often implies an omitted variables problem in existing approaches;

(iii) Endogenous identification of crisis and non-crisis periods from sample data and definition of country specific crisis periods;

(iv) limited-information estimator proposed by Forbes and Rigobon (2002) is less efficient, thus it is necessary to cope with non linearity with a full-information technique.

There is no agreement on how to treat data when these difficulties are simultaneously present. A variety of analyses use different assumptions to solve those problems and reach different conclusions on contagion. In our work, we focus on the use of switching regime models, which apply state dependent coefficients to detect contagion. This method also allows us to solve the problem of the crisis period definition (see Forbes and Rigobon 2002, Billio and Pelizzon 2003a) and, with Markov switching ECM models, we are able to check whether a crisis in a market that produce large negative returns may affect investors in other markets through a rational or irrational change in the behaviour and lead them to ignore economic fundamentals.

To show the potentiality of switching regime models to detect contagion, we concentrate on the Asian crisis. To bring by hand the reader we move from (i) a simple one chain switching regime model to (ii) a two chain switching regime model and (iii) to the Markov

[2] See Bekaert et al (2005) section 3.5 on contagion and footnote 8.

switching error correction models (MS ECM). The one chain switching regime model is very simple and its methodological purpose is to show how the Forbes and Rigobon (2002) test fits within switching regime models. We show that one of the advantages of using switching regime models with respect to the methodologies previously used is their ability to find candidate crisis periods on the basis of the volatility pattern exhibited by the data.
The second branch of models considered are the two chain switching beta models with the aim to capture the change in the link between markets, better measured by factor loading rather than simple correlation measures. The results show that the relationship between homogeneous markets (developed markets) strengthens, while there is evidence of loss of interdependence in the relationships between inhomogeneous markets (i.e. the relationship between developed and emerging or underdeveloped markets).
In the last part of the paper we concentrate on Markov switching error correction models. The analysis of the short and long run relationships among markets show that during crisis periods, not only there is partial evidence of contagion in the short term but also there is loss of interdependence in the long run. This result seems to support the economic theories that argue that crises lead investors to ignore economic fundamentals.

The paper is organised as follows: Section 1 introduces Markov Switching basic models. Section 2 describes some simple switching correlation models and shows their ability to detect contagion events during the period of the Hong Kong crash in 1997. Section 3 presents a more appropriate approach to describe the volatility transmission process and to test the links among the high volatility phases exhibited by financial markets: the two chain switching regime models and reports the empirical results. Section 4 introduce the Markov switching error correction models and shows their ability in detecting changes in the short and long run relationship among markets during the Asian crisis. The final section provides a summary and conclusions.

1. Switching regime asset pricing models and contagion: the base model and the Data

The model we propose is an extension of Forbes and Rigobon (2002), in a sense that we distinguish between global shocks and regional sources of shocks instead of one world shock, and of Bekaert and Harvey (1995) as we allow for regime-switches in the risk factors. For simplicity, the following presentation focuses on the two-market case. More specifically, the base specification of asset returns used in our paper is:

$$y_t = \mu_y + \lambda_y w_t + \beta x_t + \sigma_y u_{yt}$$
(1)
$$x_t = \mu_x + \lambda_x w_t + \sigma_x u_{xt}$$

where y and x are the returns of the two markets, μ_y and μ_x are constants, w represents the common factor, u_y and u_x are the idiosyncratic factors and βx is the explicit link between market y and market x.

1.1 One chain switching regime model

In the spirit of the correlation tests run by Forbes and Rigobon (2002), the simplest model that we are going to use is a bivariate model with state dependent covariance matrix and, thus, state dependent correlation. The only difference with the correlation test approach is that with this model the crisis windows are not arbitrarily chosen but they are selected by the model on the basis of the features exhibited by the data. Let again x_t and y_t the returns of two markets, the model used is the following:

(2)
$$y_t = \mu_y(s_t) + \lambda w_t + \beta(s_t) x_t + \sigma_y(s_t) u_{yt}$$
$$x_t = \mu_x(s_t) + \lambda w_t + \sigma_x(s_t) u_{xt}$$

with $u_t \sim WNN\left(\begin{bmatrix}0\\0\end{bmatrix};\begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}\right)$

where: s_t is a Markov Chain with k state and transition probability matrix P.

For example, if k=2 (state labels are 0 or 1), the model can be represented as follows:

(3) $x_t = \begin{cases}\mu_0 + \sigma_0 u_t & \text{in state } 0\\ \mu_1 + \sigma_1 u_t & \text{in state } 1\end{cases}$

where:
$u_t - IIN(0,1)$
and the Markov chain k_t is described by the following transition probabilities:

(4)
$$P(k_t = 0 | k_{t-1} = 0) = p \qquad P(k_t = 1 | k_{t-1} = 0) = 1 - p$$
$$P(k_t = 1 | k_{t-1} = 1) = q \qquad P(k_t = 0 | k_{t-1} = 1) = 1 - q$$

The parameters p and q determine the probability to remain in the same regime[3]. This model allows for a change in the variance of returns only in response to occasional, discrete events.

In this model there exists only one latent variable that determines the shifts in the covariance matrix of the two markets. Our aim is to interpret the state of this variable as crisis periods, when the volatility is high, and non crisis periods, when the volatility is low. Once we have identified the crisis and non crisis periods, via smoothed probabilities, we test the equality between the correlation coefficients in the two regimes and evaluate the contagion hypothesis.

The main advantage of switching regime models with respect to ARCH and GARCH models is their ability to capture extreme events and the fact that changes of regimes can be intended as breaks. Moreover, they have other advantages with respect to traditional models: first, they are able to produce features of the distribution of financial data as kurtosis and skewness and they are able to treat with unconditional non normal distributions also by simply combining conditional (to a regime) normal distributions; second, they can take into account unobserved variables that affect the endogenous ones; third, they are able to describe volatility clusters.

As we will see, one of the advantages of switching regime models is their ability to produce endogenously defined crisis periods and, thus, partially solve the problem rising with the first generation of contagion tests (i.e. correlation tests) that required an arbitrary selection of the tranquil and crisis windows in order to run the test.

The possibility to separate high and low volatility regimes is the main advantage of this kind of models, also for contagion analysis: in fact we are able to infer at each point in time the state of the market and to determine endogenously the contagion periods. In this way we can overcome the problem one has with the widely used correlation tests (see Forbes and Rigobon 2002 or Billio and Pelizzon 2003a for a review of this methodology).

1.2 Windows estimation and contagion test.

In our empirical analysis we consider the Asian crisis of 1977. We evaluated the relationship among the Hong Kong stock market (represented by the HS index), which is supposed to be the crisis generator country as in Forbes and Rigobon (2002), and two other

[3]For ease of exposition, we assume that there are only two states of the volatility process. The analysis, however, generalises naturally to the case of multiple states for the volatility process.

markets: the European stock market, represented by the Eurostoxx index, and the American stock market, represented by the Dow Jones index.

Stock market returns are calculated as daily returns based on each country's aggregate stock market index as in Forbes and Rigobon (2002). The sample is January 1996-February 1998. We calculated returns based on US dollars. We focus on US dollar returns since these where most frequently used in past work on contagion. All of the data is from Datastream.

The common factor is captured as in Forbes and Rigobon (2002) by interest rates in order to control for any aggregate shocks and/or monetary policy coordination. For simplicity we analyze our multifactor model by two steps. First we estimate a one factor model with the common factor and the residual are recovered. Second the residuals are used as dependent variable in the estimation of the switching regime model (without in this case the common factor).

Figures 1 and 2 show the window identified by our model. The crisis windows identified by the states of the latent Markov chain are close to the periods when a shock occurred. For example, the crash of the Hong Kong market is detected by the model. Moreover the crisis windows are also connected with periods to which the contagion literature has referred as crisis periods. In particular the periods detected by the model are largely similar to the windows considered by Forbes and Rigobon (2002) and by Corsetti et al. (2002).

Following Dungey et al (2004), we simply derive by regression the Forbes and Rigobon contagion test for our one chain switching regime model, which by construction is able to cope with heteroschedasticity. In particular, from the estimation of the beta coefficients we determine the correlation coefficients used in the Forbes and Rigobon test. Results are shown in Tables 1 and 2.

Regarding the relationship between the Europe and the Hong Kong stock markets, Table 1 shows that in the high volatility regime (the parameters of this regimes are denoted by 0) there is an increase also in the correlation (ρ_0 is higher than ρ_1) but if we adjust the correlation in tranquil periods in order to take into account the rise in the volatility[4], as suggested by Rigobon (see coefficient RIG), there is no evidence of contagion, as with the correlation test based on arbitrary windows.

Concerning the analysis on the relationship between the American and the Hong Kong stock markets, we draw the same conclusions. First, the high volatility regime is associated with periods of financial turbulence or specific shocks as the Hong Kong stock market

[4] We used the adjustment proposed by Forbes and Rigobon (2002). See the article for formulas.

crash (see figure 2). Second (see table 2), an higher correlation is observed in the high volatility regime, but when we correct for the increase in the volatility as suggested by Forbes and Rigobon (2002) there is no evidence of contagion, but little evidence of a loss of interdependence. In fact, table 2 shows that the expected correlation during the crisis (RIG) is greater than that we have observed (ρ_0).

3. The two chains switching regime βeta model

The one chain switching regime model is able to deal with heteroschedasticity. However, as done by all the correlation tests, the same crisis periods are arbitrarily imposed for both countries, i.e. there is a single Markov chain. This model is unable to cope with the presence of different latent variables that potentially may affect stock returns.

Since we want to investigate contagion events we need a model able to describe a time varying relationship among markets without imposing the same crisis windows. Thus we consider a model with specific Markov chains: one for the country risk factor and a second one who affects the crisis market that characterized the link among the two markets. This allow for a (i) specific window selection and (ii) specific heteroskedasticity. Formally equation (2) becomes:

$$\begin{aligned} y_t &= \mu_y(s_t) + \lambda w_t + \beta(s_{xt}, s_{yt})x_t + \sigma_y(s_{yt})u_{yt} \\ x_t &= \mu_x(s_{xt}) + \lambda w_t + \sigma_x(s_{xt})u_{xt} \end{aligned} \tag{5}$$

with s_{yt} and s_{xt} are two independent two state Markov chains.

The returns of the y market are driven by an idiosyncratic component and by the crisis generator market x: the linkage is described by the parameter β. The volatility state of each market is determined by a specific Markovian latent variable, s_{it}, $i=y,x$, that can assume two values: 0 in the high volatility state, 1 otherwise. The two Markov chains are assumed to be independent.

The β model is useful in contagion analysis because it allows the parameter β to change depending on the Markovian state variables: once we have separated crisis (i.e. periods when at least one market is in the high volatility state) from tranquil periods we can check if β changes during the crises. As anticipated, each market has two states; hence the joint process of the two markets is described by the following Markov chain, denoted by S_t, with four states:

S_t=0 if $\begin{cases} s_{xt} = 1 \\ s_{yt} = 1 \end{cases}$ low volatility for both chains: regime 0.

S_t=1 if $\begin{cases} s_{xt} = 0 \\ s_{yt} = 1 \end{cases}$ low volatility only for the follower market: regime 1.

S_t=2 if $\begin{cases} s_{xt} = 1 \\ s_{yt} = 0 \end{cases}$ low volatility only for the leader market: regime 2.

S_t=3 if $\begin{cases} s_{xt} = 0 \\ s_{yt} = 0 \end{cases}$ high volatility for both chains: regime 3.

The hypothesis of independence of the specific Markov chain allows us to compute in an easy way the transition matrix, denoted P, of the joint process defined by the variable S_t.

$$P = P_x \otimes P_y = \begin{bmatrix} p_{00,00} & p_{00,01} & p_{00,10} & p_{00,11} \\ p_{01,00} & p_{01,01} & p_{01,10} & p_{01,11} \\ p_{10,00} & p_{10,01} & p_{10,10} & p_{10,11} \\ p_{11,03} & p_{11,01} & p_{11,10} & p_{11,11} \end{bmatrix}.^{5}$$

Where P_i, $i=x,y$, is the transition matrix of a specific chain, i.e.:

$$P_i = \begin{bmatrix} p_{00}^i & p_{01}^i \\ p_{10}^i & p_{11}^i \end{bmatrix} \text{ with } i = x,y.$$

The model offers the opportunity to identify different phases of the crisis on the basis of the state variable S_t. For example, it is possible that the crisis first strikes the crisis market, thus we have the discordant regime were only the crisis market is in the high volatility state (S_t

[5] $p_{00,00}$ is the probability that S_t is equal to 3 in t-1 and in t ($S_t = 3$ if $s_{xt} = 0 \cap s_{yt} = 0$), thus it refers to the probability to remain in the high volatility state for both markets.

=1) and then strikes also the other market, thus we go in the regime characterised by high volatility for both the markets (S_t =3). To detect contagion, we look at the coefficient β in the regime 1 and regime 3 and compare them with the β that has been estimated for the tranquil periods.

As our second analysis of how the test for contagion could be affected by the model misspecification, we apply the two chains switching regime β model to the Asian Crisis.
Concerning the relationship between the European stock market and the Hong Kong stock market, figure 3 shows that also in this case the crisis windows detected by the model are very similar to those periods widely recognised as crisis periods. However, the regime with high volatility for both the markets is related to the same shocking events for the Hong Kong market but for a restricted period. This peculiarity is even more relevant for the relationship among the Hong Kong stock market and the American one as shown in Figure 4. The results suggest that the period when both the markets are in crisis is extremely limited and is a sub-sample of the windows used by Forbes and Rigobon (2002) for detecting contagion. This indicates a potential bias in the analysis previously performed.
The test on contagion in this model could be easily performed by testing the null hypothesis that betas in the different regimes are equal.
Tables 3 and 4 report the estimated parameters. Looking at the estimated β in different regimes, there is no evidence of contagion but there is little evidence of loss of interdependence in discordant phases for the European market. The null hypothesis that betas in different regimes are equal is rejected because the coefficients in the discordant regimes are statistically equal to zero and the other two cases are statistically different from zero.
Regarding the relationship between the Hong Kong stock market and the American one, we draw almost the same conclusions. There is little evidence of loss of interdependence: the estimated β for discordant regimes and for the high volatility regime for both the markets, are lower than that estimated one for the tranquil period. The null hypothesis that betas in tranquil periods is equal to the one when at least one market is facing a crisis is rejected because the coefficients when the Hong Kong market is in the high volatility regimes are statistically equal to zero and the other two cases are statistically different from zero.
One of the issue addressed in the literature is not only if a crisis in an emerging market is able to affect developed markets but how the volatility spillover from an emerging market

would affects the link among developed market. For this reason we investigate the relationship between the American and the European markets.
The asset pricing model we consider in this case has the same structure of the model presented in the equation (5) where x are the returns of the Dow Jones and y are the returns of the Eurostoxx, in line with the model proposed by Bekaert et al. (2005) whom consider the return of a region represented by a two factor models: the US market and a particular region local factor.
The intuition is that US stock market has an important role in determining the behaviour of many markets in the world and the aim is to investigate if during the Asian crisis the role of this market has changed and more specifically, if the link among these two markets has increased.
The crisis windows detected by the model are reported in figure 5, the estimated parameters are shown in table 3 and the test on β in order to detect contagion is described in table 4.
Figure 5 shows that the crises windows, with at least one market in the high volatility state, identified by the model are related to some important events of the Asian crisis as the devaluation in Korea and the Hong Kong stock market crash in October 1997. Moreover, there are narrow windows in which both markets display the high volatility regime.
The estimated beta coefficients shown in Table 5 suggest that β is equal to 0.65 during the tranquil period while, during the periods when at least one market is in the high volatility state the betas are largely higher.
Since all the coefficients are statistically different than zero, we perform a proper test of the null hypothesis that coefficients are equal. The results of the tests on the links among the markets are reported in Table 6. All the coefficients when at least one of the markets is in the high volatility regimes are different than the beta during the tranquil period. This result suggests that non-linearities in the links were a general phenomenon during the Asian crisis even for developed markets. Nevertheless, these non-linearites show an opposite sign. The markets seems more integrated when one of the market is in the high volatility regime.
We can conclude that during the Asian crisis there were periods of structural break and the European stock market increased its dependence on the American stock market. In particular, we had contagion in the periods when both the markets are in the high volatility regime. These periods are associated to important events of the Asian crisis.
Over all countries considered display some evidence of non-linearity in the transmission of the crisis. Such non-linearities imply a change in the transmission mechanism across countries of financial crises, which normally amounts to a stronger effect in the same

direction (as confirmed for links among developed markets), as most of the previous literature on contagion has concentrated on. However, following different approaches, previous studies that concentrates on the Asian Crisis have failed to detect contagion from the emerging markets of the East Asia to the developed markets such as US and Europe (see Forbes and Rigobon (2002), Bae et al. (2003), Bekaert et al (2005)). Nevertheless, as our results show, they fail to consider another potential effect: that a crisis could generate a non linearity in the crisis transmission which implies a significant effect in the opposite direction. This effect has been recognized by Favaro and Giavazzi (2000) for the Exchange Mechanism Crises of the European Monetary System. Our results suggest that this effect could characterize even the transmission of a crisis among financial markets. This outcome has important policy implications and is relevant for portfolio diversification. Nevertheless, this result contrasts with previous empirical analyses that detect no changes in the links among markets and the other branch of the literature that provides evidence of contagion during the Asian crisis. One possibility to explain the different previous findings is a model that disentangles between short and long term relationships among markets.

4. The switching regime ECM

Previous models take into account only short term movements, but as stressed in previous literature on crisis (see Malliaris and Urutia (1992)) links between international stock markets need also to take into consideration long run relationship among markets, i.e. cointegration among price movements on the different markets. Such long run relationship is well recognized as representing economic fundamentals links among the different countries. Nevertheless, its effect on return patterns may change as sustained by a large variety of models that describe alternative mechanisms which may lie behind such non-linearities on the effects of long run relationship on returns process: multiple equilibria due to expectation shifts, herd behaviour, etc. In fact a crisis in a country, for example Honk Kong, may change the medium term expectations for this market: since the crisis is specific to that country and it is not expected to affect other countries, link with the common factor characterized by the long term relationship among countries could be affected. In particular, we expect that an error correction model (ECM) with Markov switching is able to capture this effect. In such a situation, we expect that a break affects the factor loading of the error correction term. Other studies on contagion have considered the potential misspecification that could come from ignoring the cointegration among prices in different countries (see

Favero and Giavazzi (2000) or Forbes and Rigobon (2002)). Neverthelss, neither of previous researches have allowed for a break on the factor loading of the error correction term as supported by theoretical models.

Following[6] Krolzig (1997), we estimate and error correction model with coefficients and variance depending on a latent Markov variable but with state independent long run attractor. However, differently from Krolzig (1997) we consider that also the strength with which the equilibrium errors are corrected vary across regimes. The chosen specification is the following:

$$\Delta EU = \beta_0 + \beta_1(s_t)\Delta HSI + \beta_2(s_t)\Delta HSI_{-1} + \beta_3(s_t)\Delta DJ_{-1} - h(s_t)co\,\mathrm{int}_{-1} + \sigma(s_t)\varepsilon_t$$

where ε_t~N(0,1) and *coint* are the equilibrium errors.

For the estimation of this model, as suggested by Krolzig (1997), a two stage maximum likelihood procedure can be applied. In the first step the Johansen procedure is applied to finite VAR approximations of the model. This is possible because as shown by Krolzig (1996) the MS-VAR model has a VARMA representation and thus can be approximated by a finite VAR. In the second step, conditional to the estimated cointegration rank and matrix, the remaining parameters of the VECM representation are estimated via a maximum likelihood procedure.

We then consider a trivariate VAR and identified the cointegration rank with the Johansen trace and maximum-eigenvalue tests (see table 7). Since the cointegration rank is one[7] , thus there is a single cointegration relationship, we estimate the equilibrium errors with the residuals we got from the following static regression:

$$EU = c_0 + c_1 HSI + c_2 DJ_{-1} + \eta_t$$

where EU, DJ and HSI are the log-levels of the stock indexes Eurostoxx, Dow Jones and Hong Kong respectively, and ΔEU, ΔDJ, ΔHSI are their daily returns.

After checking the stationarity of the residual of the static regression the ECM model has been estimated. The coefficient of the long run term is negative as expected. The estimated parameters are reported in table 8. Figure 6 shows that the periods of the high volatility

[6] See also Krolzig (1996), Krolzig (2001), Krolzig, Marcellino and Mizon (2002), Krolzig and Sensier (2000).

[7] The cointegration analysis considers a shorter sample. In fact if we include the Hong Kong crises there is no clear evidence of cointegration relationship.

regime are related to the Asian crisis and this allows us to evaluate whether contagion happened or not looking at the estimated loading coefficients. Table 8 reports the estimated parameters and shows first that the short term relationship between Eurostoxx and Dow Jones is stable: in the low volatility regime the punctual estimate of β_{DJ} is 0.31 while during the high volatility regime is equal to 0.36.

Second, the short term relationship between Eurostoxx and HSI at the same date strengthens during the high volatility period increasing from β_{HSI}=0.09 in the low volatility period to β_{HSI}=0.21 in the high volatility period. Differently from the conclusion drawn with the two chain switching beta model, now we have evidence of contagion during the Asian crisis.

Third, the coefficient of long run term is significant in the low volatility period but it is no more significant during the crisis. This provides evidence of a non-linear relationship with the long run factor suggesting a flight to quality effect.

Over all the results suggest that ignoring long term relationships among markets can cause a bias in the contagion test. As our analysis shows, we could detect with a models without the error correction term with a time varying factor loading either loss of interdependence or no contagion (see Forbes and Rigobon (2002), Bae et. al (2003), Bekaert et al (2005) and our previous results) that could be easily generated by the contemporaneous presence of contagion in the short term and a flight to quality effect on the link with the long the relationship.

5. Discussion and conclusions

The paper evaluates the role of Markov switching models in detecting contagion. Following many authors we define contagion as an increase in the cross market linkages during a financial crisis. We sustain that it is also useful to take into account the hypothesis of a fall of correlation during crises (i.e. loss of interdependence or flight to quality effect).

The aim of the paper is to shed light on the critiques moved by many works (among others Billio and Pelizzon, 2003a) on the correlation analysis performed in the literature. In particular, Billio and Pelizzon (2003a) show that the inference based on conditional correlation coefficient, even if adjusted for heteroskedasticity (Forbes and Rigobon, 2002 and Corsetti *et al.*, 2002), can be misleading since it highly depends on the window selected and, in most of the cases, these tests are biased because we observe the presence of omitted variables.

In this paper we use an innovative approach based on Markov switching models to detect contagion. This approach is relevant because it is able to solve some of the drawbacks of the contagion detection methods used in the previous literature. In particular, using MS models we have the following advantages: (i) we easily deal with heterosckedasticity, (ii) candidate contagion windows are self detected and not arbitrarily chosen like in the correlation test approach, (iii) we perform more efficient estimation because of the full-information approach and (iv) using a Markov switching ECM, we are able to control for fundamentals by distinguish between short and long run breaks in the factor loadings of short and long run factors risk.

The potentialities in using MS models for detecting contagion are presented by considering the period of the Hong Kong stock market crash in 1997. For this purpose we estimate and compare several models. First we analyse a simple one chain Markov switching model with regime dependent correlation. With this approach we are able to find candidate contagion windows drawn with more precision then standard methodologies that requires the arbitrary selection of the periods to be tested. Our methodology takes into account the bias introduced by the increase in volatility during the crisis and makes an appropriate correction as suggested by Forbes and Rigobon (2002). The results show little evidence of loss of interdependence.

Second, we estimate a switching regime beta model that allows us to observe how the loading coefficients change during the period of crisis. Our analysis shows the presence of non-linearities during the Asian crisis. In particular the link among developed countries strengthen and the European stock market increased its dependence on the American stock market while both the American and European stock market shown a loss of interdependence from the Hong Kong stock market (i.e. a flight to quality effect).

Finally, we have considered a MS-ECM model that has a more complex specification than the other models. The justification of using this approach is based on the theories whom argue that if panic grips investors as stock returns fall and lead them to ignore economic fundamentals than there could be changes in the factor loading that links returns to short term and long term. Our analysis shows that the dependence of the Eurostoxx returns on economic fundamentals that links Hong Kong market to the European market weakened and has strengthened the link to the innovation of such market, i.e. the short term risk factor.

Our work can be extended in several directions in a multivariate framework. In particular, multiple Markov chains VAR models with country specific Markov chains which affect the variance of each market could be useful (see Anas *et al*., 2003). The relationships among the specific Markov chains could provide additional information, helpful in understanding how volatility spreads across markets. In fact, by modelling the transition matrix, different hypotheses can be considered for studying the relationship between specific chains. This analysis is left for future research.

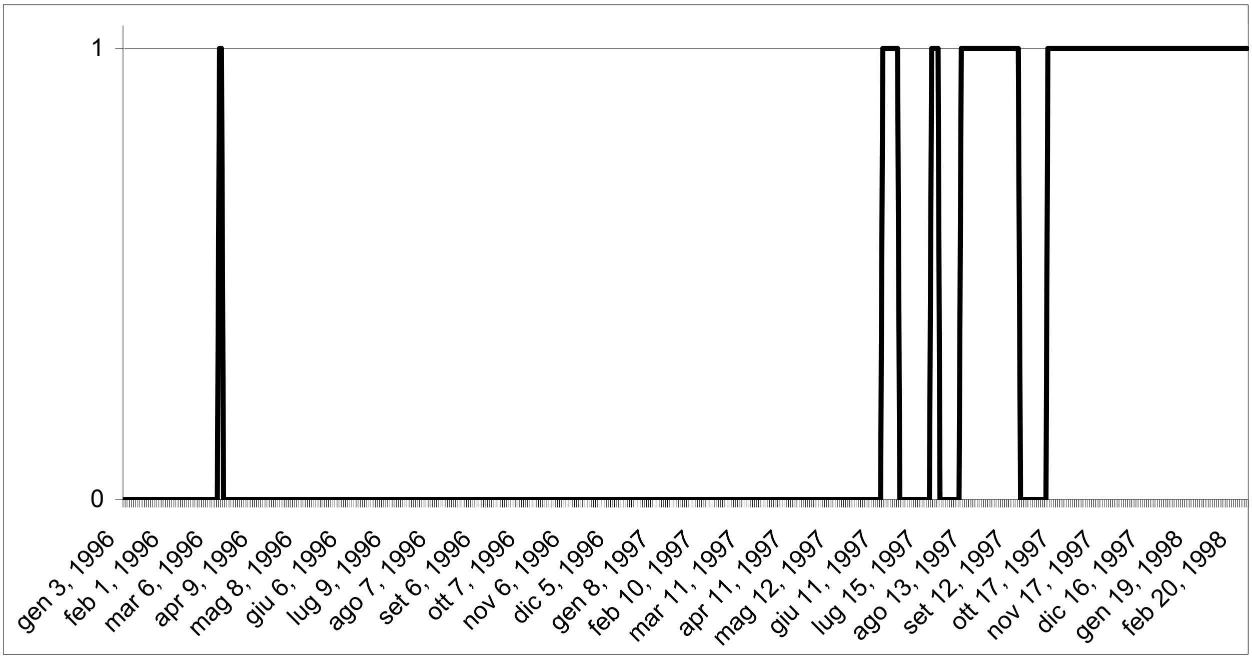

Figure 1: Eurostoxx/HSI, inference on the regime: 1 means high volatility/crisis. The model is estimated on a sample from January 1996 to February 1998.

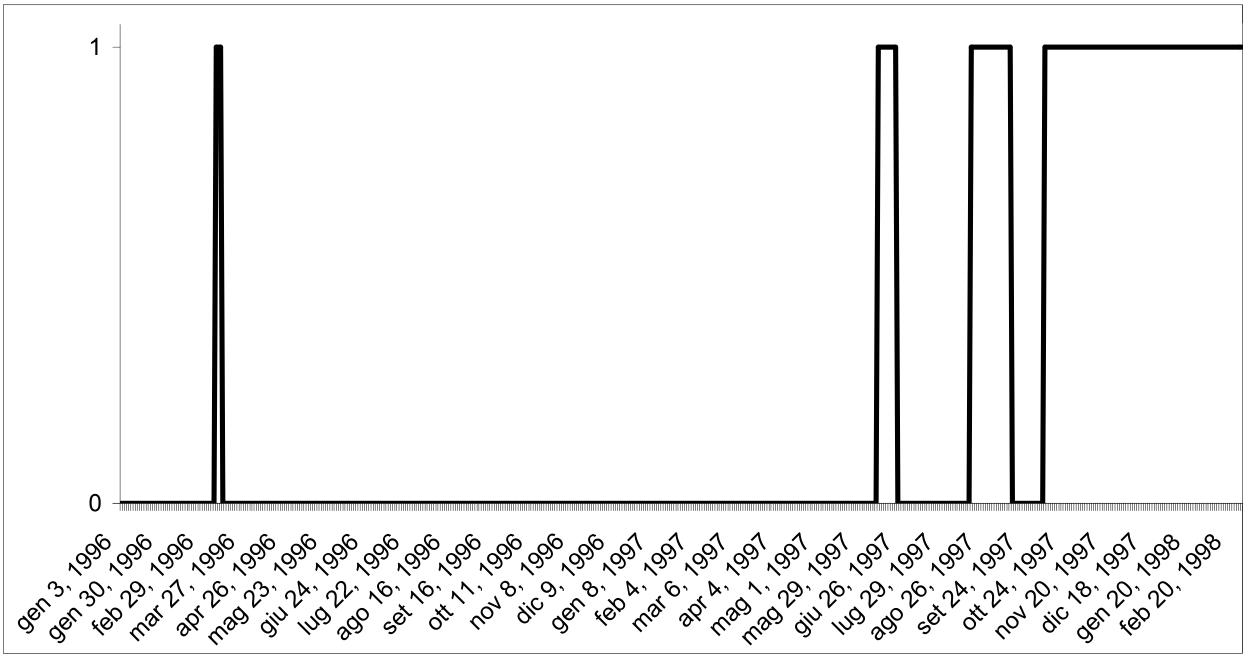

Figure 2: Dow Jones/HSI, inference on the regime: 1 means high volatility/crisis. The model is estimated on a sample from January 1996 to February 1998.

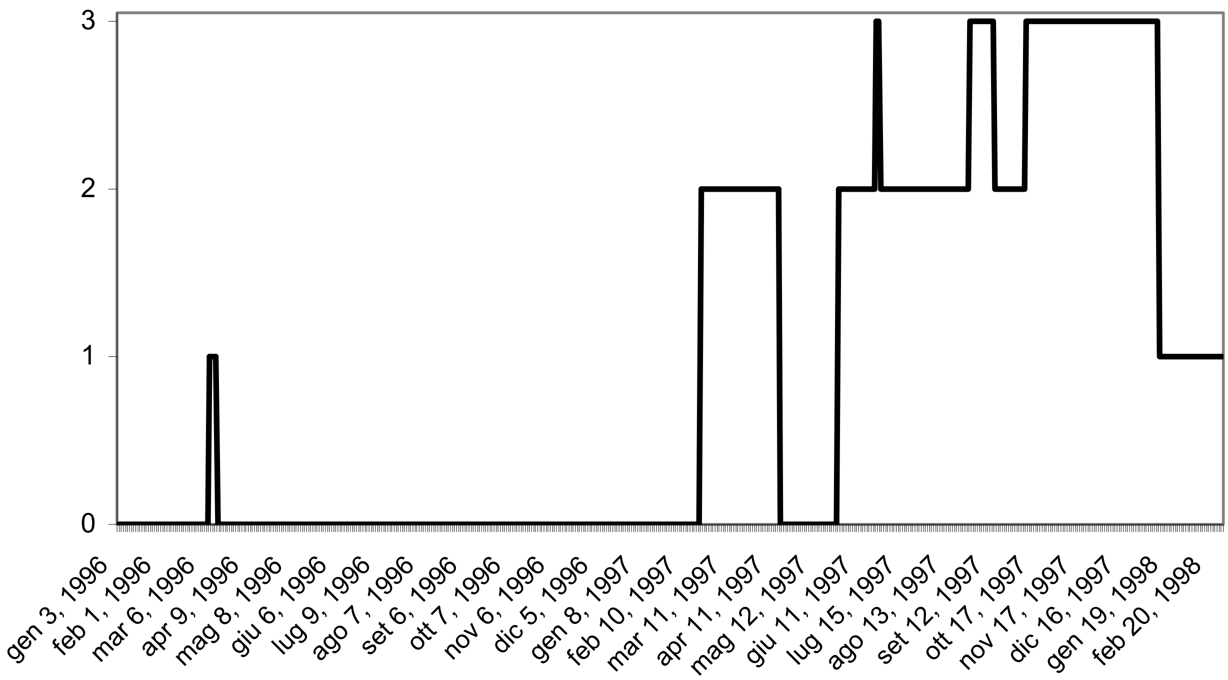

Figure 3: HSI/Eurostoxx, inference on the regimes: 0 means low volatility for both the markets, 1 high volatility only for the HSI, 2 high volatility only for EU, 3 high volatility for both markets. The model is estimated on a sample from January 1996 to February 1998.

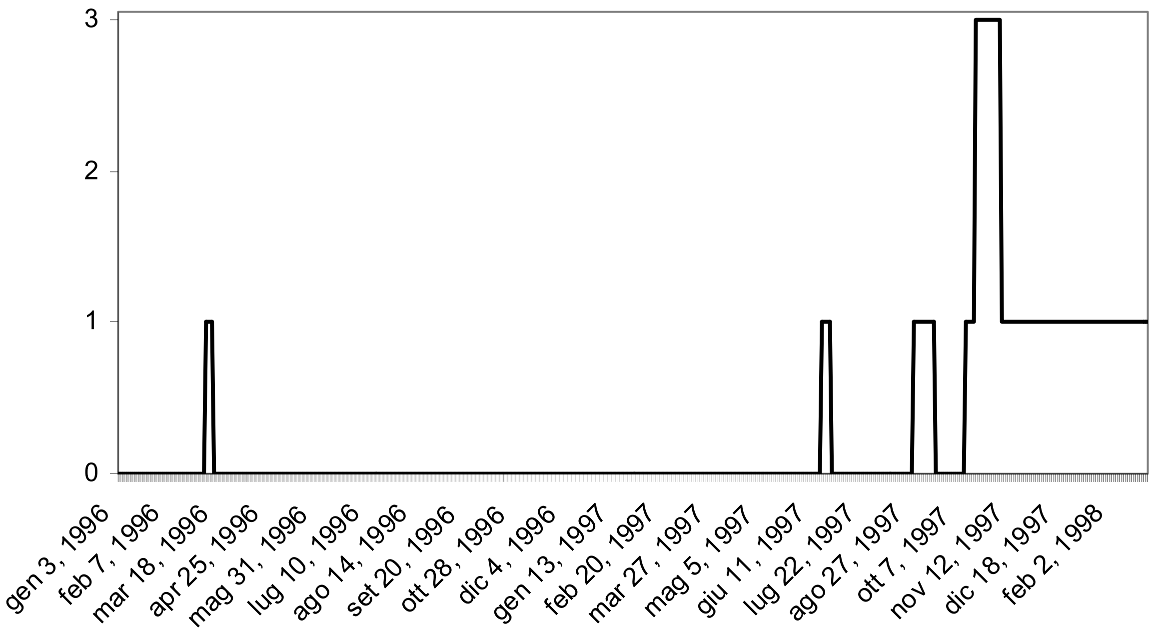

Figure 4: HSI/Dow Jones, inference on the regimes: 0 means low volatility for both markets, 1 high volatility only for the HSI, 2 high volatility only for DJ, 3 high volatility for both the markets. The model is estimated on a sample from January 1996 to February 1998.

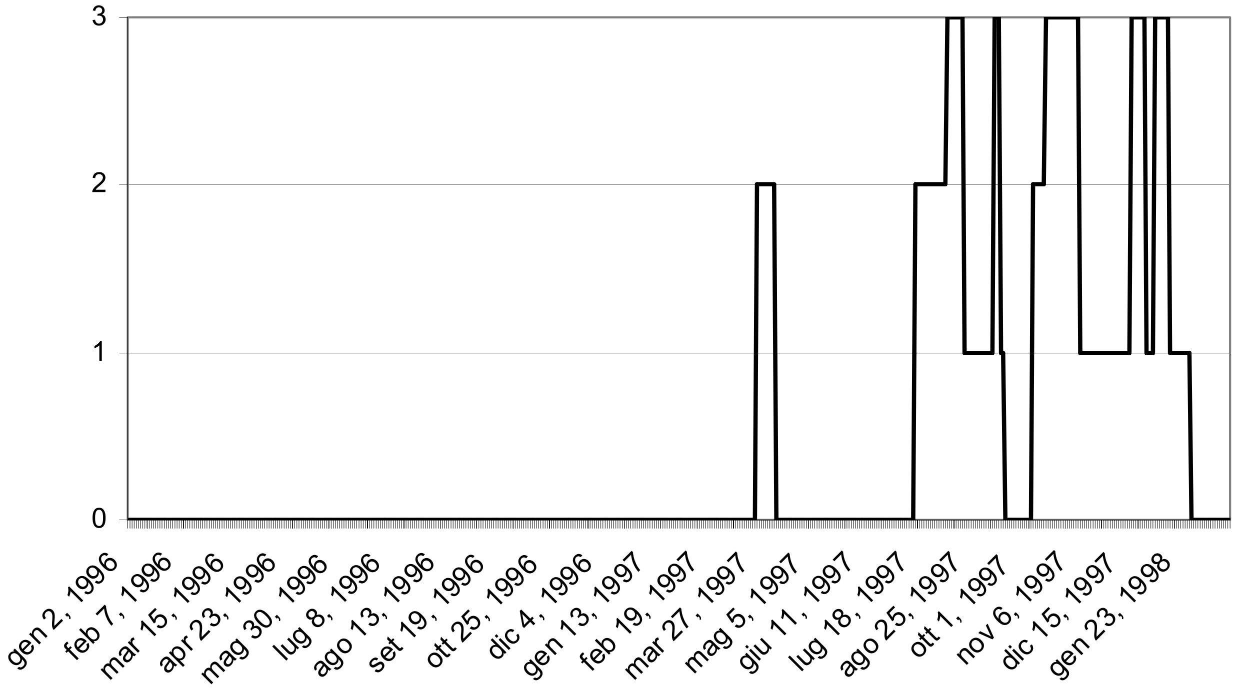

Figure5: Dow Jones/Eurostoxx, inference on the regimes: 0 means low volatility for both the markets, 1 high volatility only for the DJ, 2 high volatility only for EU, 3 high volatility for both the markets. The model is estimated on a sample from January 1996 to February 1998.

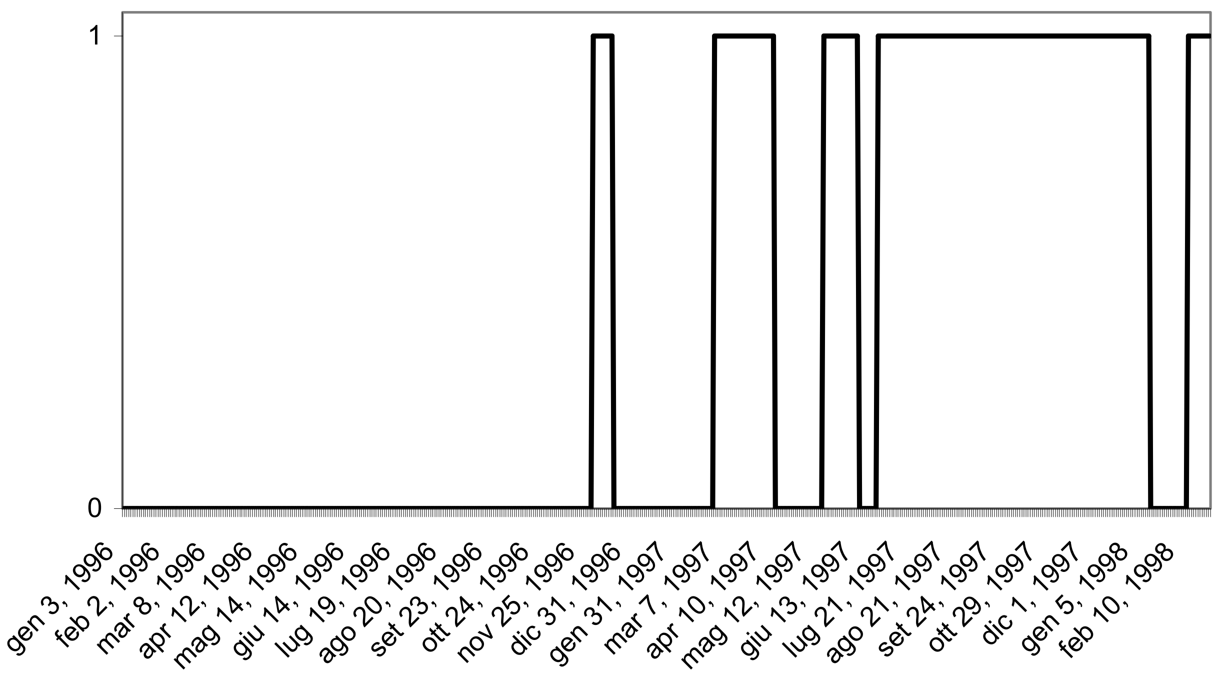

Figure 3: MS-ECM for Eurostoxx returns, inference on the regime: 1 means high volatility/crisis. The model is estimated on a sample from January 1996 to February 1998.

Table 1: Eurostoxx/HSI analysis. The model is estimated on a sample from January 1996 to February 1998. Table shows the estimates of each parameter of the model and their standard error: μ is the average daily return of the market (HK for Hong Kong, EU for Eurostoxx), σ is the standard deviation in regime 0 and 1, ρ is the correlation in regime 0 and 1, and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively. The correlation coefficient, adjusted as suggested by Forbes and Rigobon (2002), is reported (denoted by RIG). This coefficient is computed using the correlation coefficient estimated by the model in non crisis periods (ρ 1) and the estimated increase in the variance in the two regimes.

	estimate	std dev
M HK	0.001376	0.000372
M EU	0.001481	0.000244
σ 0 HK	0.025921	0.001808
σ 1 HK	0.007166	0.000284
σ 0 EU	0.010867	0.000712
σ 1 EU	0.004848	0.000214
ρ 0	0.569121	0.057822
ρ 1	0.308453	0.05095
P (0,0)	0.952882	0.022642
P(1,1)	0.981434	0.00812
RIG	0.506012	

Table 2: Dow Jones/HSI analysis. The model is estimated on a sample from January 1996 to February 1998. Table shows the estimates of each parameter of the model and their standard error: μ is the average daily return of the market (HK for Hong Kong, DJ for Dow Jones), σ is the standard deviation in regime 0 and 1, ρ is the correlation in regime 0 and 1, and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively. The correlation coefficient, adjusted as suggested by Forbes and Rigobon (2002), is reported (denoted by RIG). This coefficient is computed using the correlation coefficient estimated by the model in non crisis periods (ρ 1) and the estimated increase in the variance in the two regimes.

	estimate	std dev
μ HK	0.001084	0.000286
μ EU	0.001266	0.000372
σ 0 HK	0.009669	0.000659
σ 1 HK	0.006004	0.000220
σ 0 EU	0.026990	0.001908
σ 1 EU	0.007253	0.000281
ρ 0	0.403330	0.076913
ρ 1	0.271906	0.050387
P (0,0)	0.964364	0.020841
P(1,1)	0.987845	0.006428
RIG	0.464493	0.000286

Table 3: HSI/Eurostoxx analysis. The model is estimated on a sample from January 1996 to February 1998. Table shows the estimates of each parameter of the model and their standard error: μ is the average daily return of the market (HK for Hong Kong, EU for Eurostoxx), σ is the standard deviation in regime 0 and 1, β is the dependence of Eurostoxx in the four possible regimes, and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively for a specific chain.

	estimate	std dev
μ HK	0.00112	0.000372
μ EU	0.00104	0.000241
β3 (0,0)	0.25987	0.033433
β1(0 HK)	0.15601	0.03406
β2 (0 EU)	0.18929	0.10434
β0 (1,1)	0.26471	0.04608
σ 0 HK	0.02807	0.00199
σ 1 HK	0.00745	0.000298
σ 0 EU	0.00835	0.000528
σ 1EU	0.00415	0.000247
P(0,0) HK	0.97136	0.017357
P(1,1) HK	0.99062	0.005261
P(0,0) EU	0.98459	0.010428
P(1,1) EU	0.99171	0.006955

Table 4: HSI/Dow Jones analysis. The model is estimated on a sample from January 1996 to February 1998. Table shows the estimates of each parameter of the model and their standard error: μ is the average daily return of the market (HK for Hong Kong, DJ for Dow Jones), σ is the standard deviation in regime 0 and 1, β is the dependence of Eurostoxx in the four possible regimes, and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively for a specific chain.

	estimate	std dev
μ HK	0.00115	0.00037
μ DJ	0.00088	0.00028
β3 (0,0)	0.08220	0.09529
β1(0 HK)	0.18521	0.02758
β2 (0 DJ)	-0.16836	0.87558
β0 (1,1)	0.20982	0.05335
σ 0 HK	0.02737	0.00212
σ 1 HK	0.00736	0.00031
σ 0 DJ	0.01653	0.00442
σ 1DJ	0.00596	0.00025
P(0,0) HK	0.97100	0.01781
P(1,1) HK	0.99027	0.00537
P(0,0) DJ	0.87116	0.11300
P(1,1) DJ	0.99562	0.00606

Table 5: Dow Jones/Eurostoxx analysis. The model is estimated on a sample from January 1996 to February 1998. Table shows the estimates of each parameter of the model and their standard error: μ is the average daily return of the market (EU for Eurostoxx, DJ for Dow Jones), σ is the standard deviation in regime 0 and 1, β is the dependence of Eurostoxx in the four possible regimes, and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively for a specific chain.

	estimate	std dev
μ DJ	0.00117	0.00028
μ EU	0.00086	0.00022
β3 (0,0)	0.65562	0.13629
β1(0 DJ)	1.07191	0.07830
β2 (0 EU)	0.94669	0.27727
β0 (1,1)	0.39982	0.03893
σ 0 DJ	0.01038	0.00079
σ 1 DJ	0.00597	0.00021
σ 0 EU	0.00923	0.00111
σ 1EU	0.00421	0.00021
P(0,0) DJ	0.97487	0.01694
P(1,1) DJ	0.99484	0.00383
P(0,0) EU	0.88788	0.08954
P(1,1) EU	0.97834	0.01470

Table 6: Equality tests for β in the Dow Jones/Eurostoxx analysis.

H_0	std err	stat	pvalue
β3=β0	0.143727	1.7797646	**0.04**
β2=β0	0.085816	7.8317271	**0.00**
β1=β0	0.283024	1.9322335	**0.03**

Table 7: Cointegration analysis for the trivariate VAR model. The sample running from January 1996 to the 10th October 1997 (it ends just before the Hong Kong crisis).

Lags interval: 1 to 2

Data Trend:	None	None	Linear	Linear	Quadratic
Rank	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations					
Trace test	1	1	0	0	1
Max-Eig test	1	0	1	1	1

Table 8: model estimated coefficients for the MS ECM. The model is estimated on a sample from January 1996 to February 1998. The endogenous is the Eurostoxx daily return and exogenous are the returns of the Dow Jones (DJ) and the Hang Seng (HSI) indexes. σ is the standard deviation in regime 0 and 1, βs are the loading coefficients in regime 0 and 1 and P(0,0) and P(1,1) are the probabilities to stay in high volatility and low volatility regime respectively.

	estimate	std dev
μ EU	0.0009	0.0003
β0 HSI	0.0883	0.0262
β1 HSI	0.2054	0.0348
β0 HSI_{t-1}	-0.0589	0.0236
β1 HSI_{t-1}	-0.0623	0.0279
β0 DJ_{t-1}	0.3146	0.0444
β1 DJ_{t-1}	0.3605	0.0779
β0 coint	-0.0159	0.0094
β1 coint	-0.0343	0.0267
σ 0 EU	0.0054	/
σ 1EU	0.0108	/
P(0,0)	0.9833	/
P(1,1)	0.9761	/

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