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TESTING FOR ASSET MARKET LINKAGES: A NEW APPROACH BASED ON TIME-VARYING COPULAS

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Abstract. This paper proposes a new approach based on time-varying copulas to test for the presence of increases in stock market interdependence (also known as shift contagion) after a financial crisis. We discuss the importance of considering simultaneously separate breaks in volatility and dependence. Without such consideration, the contagion test turns out to be biased. A sequential algorithm is proposed to tackle this problem. Applied to the recent 1997 Asian crisis, the analysis confirms that breaks in variances always precede those in the dependence parameter. Moreover, a significant 'J-shape' evolution of the dependence parameter is detected, supporting the idea of shift contagion.

1. INTRODUCTION

The recent financial crises have renewed debate regarding the vulnerability of international financial markets and the propagation of foreign shocks. These crises originate from crashes in 'ground-zero' countries,[1] which spread across the world, despite the fact that the other countries were considered by market analysts to have been 'healthy' before the crises.

Financial market linkages are fostered by the trend towards an almost complete capital market liberalization and, consequently, are at the heart of the recent crises. Emerging countries wishing to finance domestic investments can find the capital they require in foreign capital markets. Therefore, they are no longer bounded by their national saving and can accelerate their growth. However, rapid growth is achieved at the cost of a higher risk of financial instability: a negative shock in a 'ground-zero' country will be quickly and strongly transmitted to its financial partners. Crisis-contingent theories explain the increase in market cross-correlation after a shock issued in a 'ground-zero' country in several ways: as resulting from multiple equilibria based on investor psychology; endogenous liquidity shocks causing a portfolio recomposition; and/or political disturbances affecting the exchange rate regime. The transmis-

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[1] The devaluation of the Thai baht in July 1997 is considered to be the event that initiated the Asian crisis.

sion of a crisis and the subsequent increase in cross-correlation between markets is thus characterized by a 'spillover' or 'shift contagion' process.[2] These crisis-contingent theories do not specify the channels of transmission. In contrast, according to the non-crisis-contingent theories, the propagation of shocks does not lead to a shift from a good to a bad equilibrium, but the increase in cross-correlation is the continuation of linkages (trade and/or financial) existing before the crisis.

Empirical analyses for 'shift contagion' avoid the identification of transmission channels and focus their attention on changing patterns of cross-market correlation. For example, the propagation of the Asian crisis from Thailand to Indonesia is revealed by a higher correlation between returns of these financial markets during the crisis period. This correlation breakdown has been considered in several empirical studies.[3]

The concept of 'shift contagion' appeared to be a robust standard stylized fact until the publication of the influential paper of Forbes and Rigobon (2002). Considering a simple linear framework, they show that any increase in spurious correlation is detected in the presence of a change in volatility. As during a crisis financial markets are subject to high volatility regimes, Forbes and Rigobon (2002) propose a stability test for correlation, which corrects for the influence of volatility changes. Applied to the 1994 Mexican and the 1997 Asian crises, the hypothesis of higher cross-market linkages is ruled out. Several recent studies have extended the framework proposed by Forbes and Rigobon (2002), ruling out the idea of absence of contagion (see, among others, Candelon *et al.*, 2005, Corsetti *et al.* 2005 and Dungey and Zhumabekova, 2001).

The linear framework used in Forbes and Rigobon (2002) has also been subject to strong criticism. Ramchand and Susmel (1998) and Ang and Bekaert (2002), for example, prefer to consider a nonlinear framework, such as the Markov-switching approach. They test for differences in the sample correlations among different volatility regimes identified as crisis and non-crisis periods.

Rodriguez (2007) uses 'copulas' to investigates contagion. A copula is the part of a joint distribution that completely describes its dependence structure. Copulas allow the modelling of the dependence between variables in a flexible way and independently of the marginal distribution (see, for example, Embrechts *et al.*, 2003). Using copulas, it is possible to model different dependencies for losses and gains (asymmetric dependence) and dependence of extreme events (tail dependence). Therefore, they appear to allow for a more general characterization of contagion than linear correlation. Using asymmetric copulas and assuming that the same regimes govern the volatility and the (tail-)dependence structure, Rodriguez (2007) finds support for changing tail-dependence during periods of turmoil.

[2] Masson (1999) considers the particular case of 'false' shift contagion, where the increase in cross-correlation may be due to the simultaneous occurrence of macroeconomic shocks across countries. According to the 'monsoonal effect' theory, this artefact for shift contagion is likely to occur as macroeconomic shocks are correlated.

[3] See *inter alia* King and Wadhwani (1990), Calvo and Reinhart (1995) and Baig and Goldfajn (1998).

The present paper proposes using copulas to investigate asset market shift contagion. Contagion is defined here as a significant increase in dependence, or correlation, as in Forbes and Rigobon (2002). This point of view differs from Rodriguez (2007), who focuses on tail-dependence. Moreover, we do not impose the change in dependence to coincide with the changes in volatility regime. It may be that both dates are identical, supporting the idea that changes in dependence are synchronized with changes in the volatility regime. However, because of propagation time or information transfer, they are, in our opinion, unlikely to perfectly coincide. Typically, when tensions occur in the 'ground zero' market we expect the linkage with the other markets to remain constant or to even decrease slightly until the transmission of the crisis is complete. Consequently, interdependence would rise to become higher than before the turmoil. The existence of such a 'J-shape' can be addressed within the framework proposed in this paper.

For this reason, the present paper contributes to the published literature by setting up a sequential algorithm. Based on a time-varying copula, it allows for the efficient joint estimation of distinct breakpoints in dependence and volatility. We elaborate on Dias and Embrechts (2004), who propose a formal test for the presence of a structural break in the dependence at an unknown period of time. The sequential algorithm also includes a formal estimation of the date of the break in the variance parameters. A Monte-Carlo study shows that the sequential algorithm exhibits correct size and power properties, whatever the type of copula. In the empirical application, which deals with the Asian 1997 crisis, it turns out that contagion, defined as an increase in correlation, is a dominating feature among the Asian economies. Furthermore, the assumption that dependence and volatility exhibit a simultaneous change in regime is rejected. The date of the change in regime is different, supporting the idea that the transmission process might take some to advance after the occurrence of a financial crisis.

The rest of the paper is organized as follows. Methodological tools are introduced in Section 2. Section 3 is devoted to an extensive Monte-Carlo analysis. Section 4 presents the results of our empirical study in the case of the Asian crisis and Section 5 offers some conclusions.

2. METHODOLOGY

2.1. *Copulas*

Copulas are multivariate distribution functions, which have uniform marginal distributions. They capture dependence between the random variables of interest independently of their marginal distributions and, hence, are scale invariant. Copulas find their applications mainly in finance when calculating the Value-at-Risk of a portfolio, pricing exotic options and credit derivatives, or for simply estimating the joint distribution of asset returns.[4] In this study we only focus on bivariate copulas, but definitions and most results of bivariate copulas carry over to the multivariate setting. In practice, however, the extensions are trivial

[4] For a good exposition of financial applications of copulas, see Cherubini *et al*. (2004).

only for very specific cases and we thus limit the analysis to the bivariate case. The most important result on copulas, Sklar's theorem, can be found with a proof in Nelsen (2006) and states the following. Let F be the marginal distribution function of X, G be the marginal distribution function of Y, and let H be the joint distribution function of (X, Y). Then there exists a copula C such that:

$$H(x, y) = C(F(x), G(y)), \forall (x, y) \in \bar{\mathbf{R}} \times \bar{\mathbf{R}}, \tag{1}$$

where $\bar{\mathbf{R}}$ denotes the extended real line. If F and G are continuous, then C is unique. Conversely, if we have distribution functions F and G and a copula C, then H is a bivariate distribution function. Hence, a copula is no more than a multivariate distribution function with uniform marginals. It captures all the dependence between random variables of interest, as all the dynamics of the marginal distributions are captured by F and G for X and Y, respectively. For formal introductions to copulas and related functions, as well as a large number of examples of copulas, we refer to the books by Joe (1997) and Nelsen (2006).

Patton (2006) extends the theory by allowing the copula to be time-varying and to depend on a conditioning set $\mathcal{F}_{t-1}$. In this way, both the functional form of the copula and the copula parameter may vary over time. It is crucial, however, that the conditioning set is the same for marginal distributions as for the copula, because otherwise the extension of Sklar's theorem to conditional distributions is not valid.

2.2. *The model*

The present paper opts for a model of contagion and interdependence between two asset markets. The conditional mean process is a simple linear process and the error terms are time-varying copula-based distributions, evolving with volatility and correlation regimes.

To this aim, the class of semi-parametric copula-based multivariate dynamic models by Chen and Fan (2006) is considered. Chen and Fan propose a parametric estimation of the conditional mean and variance of multivariate time series (using vector autoregressive (VAR) or autoregressive and generalized autoregressive conditional heteroskedasticity (GARCH) models). Theoretically, this class of model allows for dynamic dependence of higher moments (e.g. the conditional variance of one series depending on the past of the other one). As far as we know, this general form has not been previously implemented in the published literature until now. The multivariate distribution of the innovations standardized by the conditional standard deviation is estimated via a semi-parametric copula model. Surprisingly, the estimation of the first step model asymptotically does not influence the estimation of the copula parameter, provided it is correctly specified. The model for the conditional mean is given by the following stationary VAR model:

$$\boldsymbol{R_t} = \boldsymbol{\Gamma}(\boldsymbol{L}) \cdot \boldsymbol{R_{t-1}} + \varepsilon_t, \tag{2}$$

where $\boldsymbol{R_t}$ are the stacked returns in markets r_1 and r_2, $\boldsymbol{R_t} = [r_1' \quad r_2']'$ and $\Gamma(\boldsymbol{L})$ is a lag polynomial with roots lying outside the unit circle. Potential dynamic interactions in the mean are then taken into account. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ are the VAR errors, which have the following conditional distribution:

$$\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \Bigg| \mathcal{F}_{t-1} \sim C(F(\varepsilon_{1t}; \boldsymbol{\eta}_t), G(\varepsilon_2; \boldsymbol{\eta}_t); \boldsymbol{\theta}_t), \qquad (3)$$

where $\mathcal{F}_{t-1}$ is the σ field generated by the past returns. The variances of the marginal series σ^2 are included in the parameter vector $\boldsymbol{\eta}_t = [\sigma_t^2, \boldsymbol{\xi}']'$, where ζ captures the other moments of the marginal distribution, which are assumed constant over time and are treated as nuisance parameters. The copula is chosen to provide the best fit to the data, which is the one giving the smallest value for the Akaike information criterion. The dimension of the copula parameter θ_t depends on which copula is considered.

The marginal distributions F and G may be specified parametrically or non-parametrically. We allow the conditional volatility to follow a GARCH process, but we leave the distribution of the standardized innovations unspecified and model it by the empirical distribution function:

$$\hat{F}(x) = \frac{1}{T} \sum_{t=1}^{T} \mathbf{1}_{\{X_t \le x\}}.$$

Furthermore, we allow for a single breakpoint in the unconditional variance. Similarly, the copula parameter θ_t is characterized by a single (unknown) breakpoint. Alternatively, it can dynamically evolve over time, as proposed in Patton (2006) and as described below. Both the breakpoints in volatility and in correlation are determined endogenously. Therefore, changes in volatility and correlation induced by the regime shift are captured in the conditional distribution of the VAR residuals.

Using copulas has three main advantages compared to using a known multivariate distribution such the multivariate normal or the Student t-distribution. First, the individual series are likely to not be normally distributed, often being leptokurtic and skewed. The marginals underlying standard multivariate distributions do not allow for these features. Leaving the marginal distributions unspecified eliminates the risk of misspecification, which might influence the estimation of the dependence parameter.[5] Second, the dependence between two stock markets might reveal tail dependence (dependence of extreme losses), which may be modelled by several types of copulas.[6] Third, using a copula representation as in equation 3 allows sequential estimation of the marginal distribution as well as of the copula itself, which is the basis of our test for a breakpoint in the dependence parameter conditional on a break in volatility. It also leads to a significant decrease in the computing time.

A test for contagion can then be performed as follows. First, one searches for a breakpoint in the dependence parameter. If correlation does not increase,

[5] The advantage of not having to specify the marginal distributions comes at the cost of less efficient estimation of the copula parameter (see Genest *et al*., 1995).

[6] However, tail dependence analysis is not the focus of the present paper.

there is clearly no evidence for shift contagion. When a breakpoint in the dependence parameter is detected, it might support the hypothesis of contagion, but it might also simply be due to an increase in volatility (see Forbes and Rigobon, 2002). To discriminate between these possibilities, several methods are available. First, it is possible to compare the confidence intervals for the breakpoint in variance in the 'ground-zero' country and those for the breakpoint in correlation. Second, equation 3 can be extended to allow the dependence parameter to vary over time, conditional on volatility. It then becomes possible to build a likelihood ratio test to determine whether the level or the regime of the conditional variance can explain the variation of the dependence parameter.

The tests for contagion based on correlation proposed by Forbes and Rigobon (2002) consist of estimating the VAR model (eqn 2)[7] and restricting the distribution of the error terms to a bivariate normal distribution, which is estimated over two predetermined periods (one preceding and the other one during the turmoil). A significant increase in the correlation of the error term during the turmoil (i.e. $\rho_1 < \rho_2$) indicates the presence of contagion. There are several drawbacks associated with this approach. First, it may be subject to sample selection bias as the tranquil and crisis periods are chosen prior to the analysis. Second, the test assumes that the residuals are normally distributed. It is obvious that such a condition is violated in our case. Comparing the models before and during the crisis leads to the introduction of nonlinearities, and transforms equation 2 into a regime-dependent model. Forbes and Rigobon (2002) associate these regimes with volatility stance, and propose a correction of the original test. As a result, however, other explanatory factors might be missed and an endogeneity bias introduced again as the volatility regimes are determined beforehand.

2.3. *Testing for structural breaks in copula models*

A formal test for the presence of a breakpoint in the dependence parameter of a copula is developed by Dias and Embrechts (2004). They assume an independent sample $(x_1, y_1) \ldots (x_T, y_T)$, where $t = 1, \ldots,$ and T is generated by the bivariate distribution functions $H(x, y, \theta_1, \eta_1) \ldots H(x, y, \theta_T, \eta_T)$. The '$\theta_t$'s are the parameters of the underlying copula, whereas the 'η_t's are the parameters of the marginal distributions and are treated as nuisance parameters. Formally, the null hypothesis of no structural break in the copula parameter becomes:

$$H_0 : \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2 = \cdots = \boldsymbol{\theta}_T \text{ and } \boldsymbol{\eta}_1 = \boldsymbol{\eta}_2 = \cdots = \boldsymbol{\eta}_T,$$

whereas the alternative hypothesis of the presence of a single structural break is formulated as:

$$H_1 : \boldsymbol{\theta}_1 = \cdots = \boldsymbol{\theta}_k \neq \boldsymbol{\theta}_{k+1} = \cdots = \boldsymbol{\theta}_T \equiv \boldsymbol{\theta}_k^* \text{ and } \boldsymbol{\eta}_1 = \boldsymbol{\eta}_2 = \cdots = \boldsymbol{\eta}_T.$$

[7] Forbes and Rigobon (2002) also add the interest rate as an exogenous control variable.

In the case of a known breakpoint k, the test statistics can be derived as a generalized likelihood ratio test. Let $L_k(\theta, \eta)$, $L_k^*(\theta, \eta)$ and $L_T(\theta, \eta)$ be the log-likelihood functions of our copula given in equation 3 using the first k observations, the observations from $k + 1$ to T and all observations, respectively. Then the likelihood ratio statistic can be written as:

$$LR_k = 2[L_k(\boldsymbol{\theta}_k, \boldsymbol{\eta}_T) + L_k^*(\boldsymbol{\theta}_k^*, \boldsymbol{\eta}_T) - L_T(\boldsymbol{\theta}_T, \boldsymbol{\eta}_T)],$$

where a hat denotes the maximizer of the corresponding likelihood function. Note that $\hat{\boldsymbol{\theta}}_k$ and $\hat{\boldsymbol{\theta}}_k^*$ denote the estimates of θ before and after the break, whereas $\hat{\boldsymbol{\theta}}_T$ and $\hat{\boldsymbol{\eta}}_T$ are the estimates of θ and η using the full sample. In the case of an unknown break date k, a recursive procedure similar to the one proposed by Andrews (1993) can be used. The test statistic is the supremum of the sequence of statistic for known k:

$$Z_T = max_{1 \le k < T} LR_k. \tag{4}$$

Dias and Embrechts (2004) recommend obtaining critical values using the approximation provided by Gombay and Horváth (1996). The asymptotic distribution turns out to be equivalent to the one proposed by Andrews (1993). Therefore, we use his critical values and a trimming value of 15%. For a discussion on the choice of the trimming value we refer the reader to Gombay and Horváth (1996) and references therein.

2.4. *Testing for a structural break in unconditional volatility*

We test for and locate a breakpoint in volatility using a quasi-likelihood ratio test. To this end, we model the return data with a normal distribution that has a structural break in variance at an unknown point in time, p. This does not mean that we assume the return data to be normally distributed, but the maximum likelihood estimate of the variance parameter σ^2 converges in probability to its pseudo-true value, which is the unconditional variance of the (sub-)sample.

Let $L_p(\sigma)$, $L_p^*(\sigma)$ and $L_T(\sigma)$ be the log-likelihood function of the Gaussian distribution using the first p observations, the observations from $p + 1$ to T and from the whole sample, respectively. Again, $\hat{\sigma}_p$ and $\hat{\sigma}_p^*$ stand for the estimates of σ before and after the candidate breakpoint and $\hat{\sigma}_T$ is the estimate of σ using the whole sample. Similar to the approach for testing for a breakpoint in correlation denoting

$$LR_p = 2[L_p(\hat{\sigma}_p) + L_p^*(\hat{\sigma}_p^*) - L_T(\hat{\sigma}_T)],$$

the test statistic of interest is

$$Z_T = max_{1 \le p < T} LR_p. \tag{5}$$

In practice, series should be demeaned over both subsamples, to remove the possible problems induced by different means. The asymptotic theory driving the behaviour of the statistic Z_T for i.i.d. data is similar to the test above and the same critical values can be used.

However, it is quite likely that conditional volatility exhibits clusters and then follows a GARCH process. In such a case, previous asymptotic theory is no longer valid: the time variation of conditional volatilities affects the estimates of the unconditional volatilities in finite (sub-)samples and, therefore, also the distribution of the test statistic under the null hypothesis. Therefore, in such a case, critical values will be simulated using the estimated GARCH model.

Once the break in variance $\hat{p}$ is estimated, it is necessary to build its confidence interval at a certain level. To this aim, we develop a bootstrap procedure. We draw two bootstrap samples from our data set before and after $\hat{p}$. The test for a structural break in the variance is then performed on the complete bootstrap sample, leading to the detection of a variance breakpoint $\hat{p}^b$, which may be different from $\hat{p}$. This procedure is repeated a sufficiently large number of times (B) and the empirical 95% confidence interval is calculated from the distribution of $\hat{p}^b$, where $b = 1, \ldots , B$.

2.5. *Testing for structural breaks in dependence conditional on a break in volatility: A sequential algorithm*

The problem of testing for a structural break in the dependence parameter becomes more complicated when there is a breakpoint in the variances of the individual series. We take this into account by allowing for a breakpoint in the volatility parameter σ_t^2 at an unknown point in time p both under the null of no change in dependence and under the alternative. The other moments of the marginal distribution, captured by ζ, are still treated as nuisance parameters and are not allowed to change over time. Consequently, we test for a break in dependence conditional on the fact that a break in volatility has occurred. Formally, the null hypothesis of our conditional test is

$$H_0 : \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2 = \cdots = \boldsymbol{\theta}_T \text{ conditional to}$$

$$\boldsymbol{\xi}_1 = \boldsymbol{\xi}_2 = \cdots = \boldsymbol{\xi}_T \equiv \boldsymbol{\xi},$$

$$\sigma_1 = \cdots = \sigma_p \neq \sigma_p + 1 = \cdots = \sigma_T \equiv \sigma_p^*,$$

versus

$$H_1 : \boldsymbol{\theta}_1 = \cdots = \boldsymbol{\theta}_k \neq \boldsymbol{\theta}_{k+1} = \cdots = \boldsymbol{\theta}_T \equiv \boldsymbol{\theta}_k^* \text{ conditional to}$$

$$\boldsymbol{\xi}_1 = \boldsymbol{\xi}_2 = \cdots = \boldsymbol{\xi}_T \equiv \boldsymbol{\xi},$$

$$\sigma_1 = \cdots = \sigma_p \neq \sigma_p + 1 = \cdots = \sigma_T \equiv \sigma_p^*.$$

Under the alternative, a single break is present in both the dependence (at time k) and the variance (at time p). A time-varying copula model allows for a simultaneous estimation of the break in the variance and in the dependence parameter. Intuitively, the loglikelihood ratio (LR) statistics are calculated for all possible points k and p. We then retain the supremum and compare the LR value to the simulated critical value at a fixed nominal size. More precisely, let us assume without loss of generality that $p < k$, and let $L_{k/p}(\theta, [\sigma, \zeta])$ be the likelihood function of the joint distribution in our model (eqn 3) using the observations between p and k. In this situation, the LR statistic becomes:

$$LR_{k,p} = 2[L_p(\hat{\boldsymbol{\theta}}_k, [\hat{\sigma}_p, \boldsymbol{\xi}]) + L_{k\setminus p}(\hat{\boldsymbol{\theta}}_k, [\hat{\sigma}_p^*, \hat{\boldsymbol{\xi}}]) + L_k^*(\hat{\boldsymbol{\theta}}_k^*, [\hat{\sigma}_p^*, \hat{\boldsymbol{\xi}}]) - L_T(\hat{\boldsymbol{\theta}}_T, [\hat{\sigma}_T, \boldsymbol{\xi}])].$$

The test statistic then has the following form:

$$S_T = max_{\substack{1 \le k < T \\ 1 \le p < T}} LR_{k,p}.$$

This supremum statistics becomes more complicated when the variances of the two series exhibit a breakpoint at distinct points p_1 and p_2. In any case, it is not obvious what the asymptotic distribution of S_T might be, as it also depends on the estimation of the breakpoint in the variance parameter. The approximations provided by Andrews (1993) and Gombay and Horváth (1996) should be modified to take the uncertainty in the estimation of the variance break into account. Although we believe that the influence of the estimation of the variance break is likely to disappear asymptotically, we leave a formal analysis for future research. Appropriate critical values will be obtained using the parametric bootstrap algorithm outlined below.

Estimating all three breakpoints jointly is computationally very demanding and we opt for a sequential procedure to estimate the variance and dependence breaks. The copula decomposition of a joint distribution allows us to first estimate the marginal distributions, including the breakpoint in variance, followed by the estimation of the copula, which greatly reduces the computational burden. Therefore, we apply a conditional test in the second step, estimating a breakpoint in the copula parameter, conditional on a break in the variance. The breaks in variance as well as the 95% confidence intervals I_{p1} and I_{p2} are estimated in a first step using the method introduced in Subsection 2.4.[8] In a second step, both series are transformed into uniform variables ($\tilde{u}$, $\tilde{v}$) such that $\tilde{u} = \hat{F}(x)$ and $\tilde{v} = \hat{F}(y)$. $\hat{F}(\cdot)$ is the empirical probability integral transform, which has to evaluated separately before and after the estimated breaks $\hat{p}_1$ and $\hat{p}_2$.

Finally, the structural break test of the copula parameter proposed by Dias and Embrechts (2004) is applied to the transformed data ($\tilde{u}$, $\tilde{v}$). Thus, we compute a similar test statistic with the following form

$$S_T = max_{1 \le k < T} LR_k.$$

[8] p_1 and p_2 refer to the breaks in the first and second series, respectively.

Assuming that the variance breaks are consistently estimated, the resulting estimate of the break in the correlation coefficient is also consistent. However, the nuisance caused by the estimation error in the first step must be taken into account when obtaining the critical values for the sup *LR* statistic in the second step. Furthermore, the stability test may exhibit a size bias when the breaks are close to the trimming value (see Candelon and Lütkepohl, 2001). To tackle these potential problems, the following parametric bootstrap algorithm is set up:

1 Sequentially estimate first the variance breaks p_1 and p_2, and then the correlation break conditional on the estimated variance breaks $k|\hat{p}_1, \hat{p}_2$. Use the 95% confidence intervals $I_{\hat{p}_1}$ and $I_{\hat{p}_2}$ for the variance breaks.
2 Estimate the time constant copula parameter $\bar{\theta}$.
3 Randomly draw two points p_1' and p_2' for the variance breaks from the confidence intervals $I_{\hat{p}_1}$ and $I_{\hat{p}_2}$.
4 Estimate GARCH parameters $\boldsymbol{\omega}_{p_i'}$ and $\boldsymbol{\omega}_{p_i'}^*$ before and after the drawn breaks for both series.
5 Generate two random series (u, v) from a time constant copula $C(u, v, \bar{\theta})$) and transform the marginal series into heteroscedastic variables using the estimated GARCH parameters before and after that break.
6 Apply the sequential breakpoint test to this series and compute the sup LR Z^* statistic for the correlation break.
7 Repeat steps 3–6 m times (m being sufficiently large) and obtain the desired empirical quantile from the bootstrapped test statistics.

Note that simulating data with changing parameters for the GARCH models, but with a constant copula parameter $\bar{\theta}$ ensures that we are bootstrapping under the null hypothesis.

Until now, for the sake of generality, no specific type of copula is assumed. Nevertheless, in empirical work we suggest using the simple and well known Gaussian copula. Its distribution function is given by:

$$C^{Gaussian}(u, v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp\left(-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right) dsdt,$$

where ρ is the linear correlation coefficient of the corresponding bivariate normal distribution. The simulation results in the next section will show that breakpoints in the dependence parameter can be found consistently using the Gaussian copula, even when the data are issued from data generating processes (DGP) producing tail dependence or volatility clusters. The procedure is then quite robust to misspecification. Restricting the attention to the Gaussian copula is also justified by the fact that the asymmetric dependence often encountered in financial data and modelled by more flexible copulas partly seems to be taken into account by time-varying dependence.

3. MONTE CARLO STUDY

The purpose of this section is to study the performance of our testing procedure in small samples. To this aim, we retain three of the most frequent data generating processes encountered in empirical works.

The first DGP (*DGP*(1)) corresponds to a simple Gaussian copula with i.i.d. Gaussian marginals (i.e. a bivariate normal distribution). Thus, the series $Y_{1,t}$, $Y_{2,t}$ have the distribution:

$$F(Y_{1,t}, Y_{2,t}) = C^{Gaussian}(\Phi(Y_{1,t}), \Phi(Y_{2,t}), \rho_t),$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. This distribution is the same as the one used in the sequential approach. Therefore, it is expected that under this DGP the LR approach for detecting a break in variance and dependence performs the best in terms of size and power.

The Monte Carlo experiments should also analyse the behaviour of this testing procedure in front of DGP relaxing the normality assumption. To this aim, *DGP*(2) assumes volatility clusters in stock market returns series generated by univariate GARCH processes, whereas *DGP*(3) allows for asymmetric dependence structures and tail dependence. To be more precise, in *DGP*(2), let $(\Phi(\varepsilon_{1t}), \Phi(\varepsilon_{1t})) \sim C^{Gaussian}$. Then $Y_{i,t}$ follows a GARCH process:

$$Y_{i,t} = \sqrt{h_{i,t}}\,\varepsilon_{i,t},$$

where

$$h_{i,t} = \omega_{i,t} + \alpha Y_{i,t-1}^2 + \beta h_{i,t-1}.$$

Such a process is frequent for financial series, which exhibit volatility clustering.

DGP(3) corresponds to Clayton Copula with i.i.d. normal marginals and has the following form. The Clayton copula is given by

$$C_\theta^{Clayton}(u, v) = max\left(u^{-\theta} + v^{-\theta} - 1\right)^{\frac{-1}{\theta}}, 0\Big],$$

with $\theta > 0$. To ensure comparability of the degree of dependence with the DGP using the Gaussian copula, the parameter for the Clayton copula is chosen such that the two copulas have the same value for the concordance measure, Kendall's τ. The Clayton copula is characterized by asymmetric and lower tail dependence.

In a first experiment, the DGP are simulated under the null hypothesis of no break in the dependence parameter (i.e. size analysis). Nevertheless, it is assumed that a single break in the variance occurs at date p, where $p = (1/4, 1/2, 3/4)T$ and T is the sample size. The unconditional standard deviations before and after the breakpoint are set to $\sigma_l = 1$ and $\sigma_h = 3$, corresponding more or less to the estimates found in our empirical part. The sample sizes investigated are 500, 1000 and 2000.

Table 1 reports the rejection frequency of the test for a structural break in the dependence parameter for three cases. First, the break in variance is ignored, and the original Dias and Embrechts (2004) test is applied. Second, this break is taken into account and the sequential testing approach developed in Subsection 2.5 is followed. Third, the volatility regimes are known and Forbes and Rigobon's (2002) test is used. In all cases, the nominal size is fixed at 5%.

It turns out that ignoring the break in variance leads to severe size distortion whatever the DGP considered. The rejection frequencies are always above the nominal size, indicating that the presence of a break in the dependence parameter is too often supported by Dias and Embrechts in the presence of a volatility break. The importance of the size distortion increases with the sample size, but is not affected by the location of the variance break, indicating inconsistency of the test. This result corroborates the initial findings of Forbes and Rigobon (2002), who show that tests for dependence stability are heavily biased in the presence of volatility regimes. Nevertheless, Forbes and Rigobon's (2002) method does not appear as an adequate alternative when the DGP is copula based. Columns 8–10 of Table 1 show that the rejection frequency of the Forbes and Rigobon test is strongly undersized. The null hypothesis of stability in dependence is then too often supported, leading to rejection of the presence of shift contagion in almost all cases.

Columns 5–7 of Table 1 report the rejection frequency using the sequential testing approach, which takes into account the variance break. It turns out that the size is close to the nominal size of the test when considering *DGP*(1). Such a result is not surprising for *DGP*(1), as the Gaussian hypothesis is at the basis of the sequential procedure. More interestingly, the size is also quite correct, even if slightly higher than 5% in the case of the Clayton copula (*DGP*(3)). It shows the that sequential testing approach is very affected by the presence of lower tail dependence. Intuitively, the dependence parameter of the Gaussian copula measures the overall degree of dependence. Nevertheless, the size distortions increase with sample size, which is most likely a result of using a misspecified model. It is thus likely that stability tests are not affected by symmetric heavy tails and are only marginally affected by asymmetric lower or higher tails. To conclude, the type of copula does not constitute a limiting factor for the sequential testing approach and, therefore, the Gaussian copula will be used in the rest of the paper. The size of the sequential testing approach in the case of *DGP*(2) is also close to 5%. Such an outcome is also expected as the critical values used in the test for a structural break in unconditional volatility are obtained by simulations allowing for GARCH dynamics.[9] Note that all these conclusions hold whatever the sample size and the location of the variance break.

[9] The test for a structural break in unconditional volatility can also be modified accordingly if one suspects an asymmetric or a fat-tailed GARCH process. Critical values can be obtained by modifying the simulation technique and are available upon request for the case of a GARCH model with Student-*t* innovations.

Table 1. Size of the stability test using Dias and Embrechts' approach and sequential testing approach

Break in variance (p)	Dias and Embrechts ignored			Taking sequential testing approach into account			Forbes and Rigobon's (2002 test known; Dias and Embrechts and below unknown		
Break date T^*	1/4	1/2	3/4	1/4	1/2	3/4	1/4	1/2	3/4
DGP1									
$T = 500$	0.601	0.605	0.543	0.051	0.059	0.06	0	0	0
$T = 1000$	0.731	0.758	0.667	0.061	0.052	0.064	0	0	0
$T = 2000$	0.850	0.860	0.788	0.053	0.048	0.055	0	0	0
DGP2									
$T = 500$	0.528	0.484	0.335	0.049	0.049	0.053	0.001	0	0
$T = 1000$	0.598	0.565	0.466	0.053	0.035	0.036	0	0	0
$T = 2000$	0.670	0.651	0.547	0.049	0.062	0.054	0	0	0
DGP3									
$T = 500$	0.611	0.656	0.564	0.073	0.061	0.083	0.002	0	0.002
$T = 1000$	0.752	0.767	0.699	0.079	0.06	0.075	0	0	0
$T = 2000$	0.832	0.857	0.798	0.083	0.074	0.068	0	0	0

Notes: The size of the copula breakpoint test by Dias and Embrechts (2004) ignoring changes in volatility (columns 2 to 4) and the size of our copula breakpoint test procedure (columns 5 to 7). Nominal size is 5% and the number of replications is equal to 1000. DGP, data generating processes.

In a second experiment, the three DGP and designs are kept identical, except that the dependence parameter is subject to a structural break occurring at date k, where $k = (1/4, 1/2, 3.4)\ T$. Before the break $\rho_l = 0.3$, which then increases to $\rho_h = (0.5, 0.6, 0.7)$. Therefore, we are now investigating the power of the sequential testing approach.

Table 2 reports the rejection frequency of the test for a structural break in the dependence parameter using the sequential testing approach. The power of the sequential testing approach turns out to be quite high and of the same magni-

Table 2. Power of the stability test using sequential testing approach

	Break ρ: 1/4*T			Break ρ: 1/2*T			Break ρ: 3/4*T		
Break σ*T	1/4	1/2	3/4	1/4	1/2	3/4	1/4	1/2	3/4
DGP1									
$T = 500$									
$\rho_h = 0.5$	0.509	0.528	0.532	0.642	0.646	0.654	0.496	0.464	0.525
$\rho_h = 0.6$	0.917	0.938	0.928	0.973	0.977	0.975	0.917	0.917	0.924
$\rho_h = 0.7$	0.999	1	0.999	1	1	1	1	0.999	0.999
$T = 1000$									
$\rho_h = 0.5$	0.838	0.831	0.829	0.922	0.92	0.94	0.843	0.83	0.834
$\rho_h = 0.6$	0.999	0.999	1	1	1	1	0.999	0.997	0.997
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1
$T = 2000$									
$\rho_h = 0.5$	0.995	0.992	0.994	1	1	1	0.99	0.99	0.989
$\rho_h = 0.6$	1	1	1	1	1	1	1	1	1
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1
DGP2									
$T = 500$									
$\rho_h = 0.5$	0.418	0.443	0.458	0.566	0.611	0.613	0.427	0.432	0.484
$\rho_h = 0.6$	0.879	0.883	0.874	0.946	0.963	0.96	0.846	0.87	0.889
$\rho_h = 0.7$	0.997	0.993	0.993	1	1	0.999	0.997	0.996	0.997
$T = 1000$									
$\rho_h = 0.5$	0.783	0.776	0.751	0.88	0.896	0.88	0.755	0.786	0.817
$\rho_h = 0.6$	0.997	0.992	0.994	0.999	1	1	0.989	0.998	0.997
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1
$T = 2000$									
$\rho_h = 0.5$	0.977	0.972	1	0.994	0.999	0.997	0.964	0.976	0.98
$\rho_h = 0.6$	1	1	0.999	1	1	1	1	1	1
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1
DGP3									
$T = 500$									
$\rho_h = 0.5$	0.495	0.523	0.539	0.622	0.673	0.642	0.448	0.487	0.505
$\rho_h = 0.6$	0.888	0.901	0.894	0.943	0.948	0.95	0.873	0.867	0.901
$\rho_h = 0.7$	0.995	0.997	0.997	0.999	1	1	0.994	0.993	0.994
$T = 1000$									
$\rho_h = 0.5$	0.804	0.818	0.822	0.91	0.911	0.925	0.773	0.811	0.821
$\rho_h = 0.6$	0.992	0.995	0.997	1	1	0.999	0.998	0.99	0.995
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1
$T = 2000$									
$\rho_h = 0.5$	0.985	0.977	0.987	0.997	1	0.997	0.977	0.979	0.988
$\rho_h = 0.6$	1	1	1	1	1	1	1	1	1
$\rho_h = 0.7$	1	1	1	1	1	1	1	1	1

Notes: Power of sequential testing approach for all three data generating processes (DGP). Nominal size is 5% and the number of replications is equal to 1000. DGP, data generating processes.

tude for the three DGP under scope.[10] Besides, as already noted, it does not seem to depend on the location of the variance break. Finally, as expected, the power increases with the sample size T and is at a maximum for breakpoints in the dependence parameter located in the middle of the sample.

To conclude, the sequential testing approach based on a Gaussian copula appears to be an adequate approach for testing for a structural break in the dependence parameter, while accounting for a possible structural break in volatility.

4. EMPIRICAL APPLICATION

The financial turmoil that affected Asian countries in 1997 has fuelled the empirical literature on contagion (see Dungey *et al*., 2006 or Candelon *et al*., 2008). Its main feature is that Asian countries were assumed to be well-behaved (i.e. to possess strong macroeconomic fundamentals) before the occurrence of the crisis, leaving market analysts or modellers of the first generation without any voice. Therefore, the importance of the transmission of the crisis from Thailand, which was first hit, to the rest of Asia is at the core of this global crisis. The conclusion of Forbes and Rigobon (2002) rejects the presence of contagion in this crisis, and has left analysts sceptical.[11] However, their test tends to be biased if the break in variance and correlation are erroneously assumed to be identical. In such a case, the sequential procedure based on a time-varying copula presented in Section 2 is a good alternative.

4.1. *Data*

In this empirical application, stock returns for eight Asian countries are considered.[12] Daily series are used, and are extracted from Datastream market indices, labelled in US$ and cover the period from 1 January 1996 to 30 June 1998 (i.e. 652 observations).

To shed new light on the question of the possible contagious characteristic of the Asian crisis, the sequential testing approach, presented in Subsection 2.5, is applied. We consider both Thailand and Hong Kong as the 'ground-zero' countries at the origin of the financial crisis. It is well-documented in the literature (see e.g. Dungey *et al*., 2006) that the Asian crisis was initiated by the Thai baht devaluation, and then by the crash of the Hong Kong stock market. These

[10] It is noticeable that power is not corrected for size. Nevertheless, as the size distortion is small (see Table 1) using the sequential testing approach, such a conclusion will remain valid when considering size-adjusted power.

[11] Some other empirical papers extending the Forbes and Rigobon's (2002) test reach a different conclusion. See Corsetti *et al*. (2005) and Candelon *et al*. (2005).

[12] These countries are Thailand, Malaysia, Japan, Hong Kong, Taiwan, Indonesia, South Korea (hereafter simply referred to as 'Korea') and the Philippines.

Table 3. Breakpoints in variance

Thailand	12 May 1997 (24 April 1997, 2 June 1997)
Malaysia	30 July 1997 (28 July 1997, 6 August 1997)
Japan	3 December 1996 (22 November 1996, 26 December 1996)
Japan second break	20 October 1997 (1 September 1997, 5 February 1998)
Hong Kong	15 August 1997 (14 July 1997, 5 September 1997)
Indonesia	12 August 1997 (5 August 1997, 18 August 1997)
Taiwan	18 July 1997 (24 January 1997, 8 December 1997)
Korea	13 October 1997 (9 October 1997, 22 October 1997)
Philippines	18 April 1997 (11 April 1997, 1 May 1997)

Notes: This table reports the date of the structural break in volatility found using the sequential approach, described in Subsection 2.4. Confidence bounds are bootstrapped (1000 replications) and are indicated between brackets.

shocks have to be analysed separately to draw a global picture of the shift contagious process during the Asian crisis.[13]

4.2. *Sequential testing approach*

For each bivariate system of the other six Asian countries with both Thailand and Hong Kong (i.e. 13 models), we estimate the VAR given in equation 2 and then steps 1–7 are performed on the residuals.[14] Note that following the earlier discussion and the outcomes of the Monte Carlo experiments, only Gaussian copulas are considered, for simplicity. Table 3 reports the dates for the structural breaks found in all univariate systems, and Table 4 gathers the dates for the structural breaks in the conditional copula, together with confidence intervals, which together allow for a conclusion regarding whether contagion has occurred.

It first turns out that point estimates for the dates of the break in variance generally precede the ones from the conditional correlations.[15] There are two cases, one where the confidence intervals of the variance and correlation breaks overlap and one where they do not. Therefore, assumption of concomitance between the change in volatility and dependence is not always supported. It supports the intuition that some time elapses between the occurrence of the crisis, the increase in volatility and its spillover developments. This delay finds its justification in the time for information to be spread over the region. Typically, tensions occurring at ‘ground zero’ reduce the dependence with the other markets until the transmission of the crisis. Then, linkages rise to become higher

[13] It is possible to find country-specific analyses of the Asian crisis (e.g. see Chou *et al.* (2002) for Taiwan).

[14] The study is limited to bivariate systems to avoid the possible effect of indirect contagion or third-country effects. The Johansen cointegration tests reject the presence of cointegration relationships for the bivariate systems composed by the indices, allowing us to specify the VAR for the return series. Furthermore, optimal lag length is determined according to the Schwarz information criterion.

[15] Besides comparison of break dates in the variance and the conditional correlation, the ‘J-shape’ of the conditional correlations, which is plotted in Figure 1, supports this conclusion.

Table 4. Breakpoints in correlation

	Malaysia	Japan	Hong Kong	Indonesia	Taiwan	Korea	Philippines
Thailand	4 December 1997***	8 December 1997***	2 December 1997***	2 September 1997***	2 December 1997***	14 October 1997***	22 October 1997***
Lower	23 September 1997	30 December 1996	15 October 1997	15 May 1997	19 September 1997	2 October 1996	29 July 1997
Upper	30 December 1997	3 February 1998	8 January 1998	3 November 1997	14 January 1998	27 November 1997	30 December 1997
Hong Kong	1 December 1997***	9 December 1997(N.S.)	–	30 September 1996**	28 November 1997***	4 February 1998(N.S.)	10 October 1997***
Lower	24 June 1997	13 June 1996	–	24 May 1996	3 October 1997	4 August 1997	8 January 1997
Upper	29 January 1998	6 February 1998	–	25 August 1997	13 January 1998	12 February 1998	20 January 1998

Notes: This table reports the date of the structural break in the conditional copula found using the sequential approach presented in Subsection 2.5 and the 95% confidence bounds for the correlation break considering both Thailand and Hong Kong as the crisis country. This table reports the date of the structural break in the conditional copula found using the sequential approach presented in Subsection 2.5 considering both Thailand and Hong Kong as the crisis country. ** and *** indicate significance at 5% and 1% levels, respectively.

than prior to the turmoil. Moreover, such a result justifies our sequential testing procedure, which tends to support contagion for all the systems except (Hong Kong; Japan) and (Hong Kong; Korea), for which no significant change in conditional correlation is detected. Nevertheless, it is clear that these two systems are a minority compared to the 11 other exhibiting a significant break. Thus, the main picture delivered by our study is clearly in favour of the existence of contagious characteristics of the Asian 1997 crisis, confirming the results of previous studies (*inter alia* Wirjanto, 2002).

4.3. *Time-varying dependence*

As a final step in our analysis, we use conditional copulas to model the path of the correlation coefficient of a Gaussian copula for the standardized VAR-tGARCH residuals, transformed by the empirical distribution function. Recall that p is the breakpoint in variance of the 'ground-zero' country and k is the break of the copula parameter estimated previously. Define two dummies $D_t(\rho)$ and $D_t(\sigma)$ as: $D_t(\sigma) = 0$ for $t < p$, $D_t(\sigma) = 1$ for $t \geq p$, $D_t(\rho) = 0$ for $t < k$ and $D_t(\rho) = 1$ for $t \geq k$. Following Patton (2006) to capture dynamics, ρ_t evolves over time according to

$$\rho_t = \Lambda\left(\alpha + \gamma_1 \cdot \rho_{t-1} + \gamma_2 \cdot \frac{1}{p}\sum_{j=1}^{p} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j}) + \beta_1 \cdot D_t(\sigma) + \beta_2 \cdot D_t(\rho)\right),$$

where $\Lambda(x) = \dfrac{1-e^{-x}}{1+e^{-x}}$ is the modified logistic transformation to keep ρ in $(-1, 1)$. The two dummies are included to determine whether the breakpoint in volatility contains additional information about the correlation dynamics not included in the correlation dummy. We perform likelihood ratio tests for the significance of β_1 and β_2 and only keep the significant dummies in the model. In most cases only the correlation dummies remained in the model, but in some cases either both dummies (e.g. Thailand *vs* Hong Kong) or none (Hong Kong *vs* Japan) were significant.

The conditional correlations are plotted in Figure 1. Recall that our earlier analysis revealed that the volatility break occurred before the correlation break. One can see that conditional correlations vary quite a lot over time, increasing after the 'correlation' break. The evolution of the conditional correlation after the 'volatility break' reveals a more shadowed picture. On one hand, it turns out that dependence decreases for some system leading to a 'J-shape' evolution of the conditional correlations. Such a shape remains difficult to explain, even if it is confirmed by other studies using different techniques (Cappiello *et al*., 2005). On the other hand, some pairs of countries exhibit a constant increase in the conditional correlation, stressing that dependence begins to increase with the volatility break. Nevertheless, Figure 1 supports our previous conclusions that the break in variance generally precedes the one in correlation. This is thus further evidence that high volatility is not always concomitant to an increase in

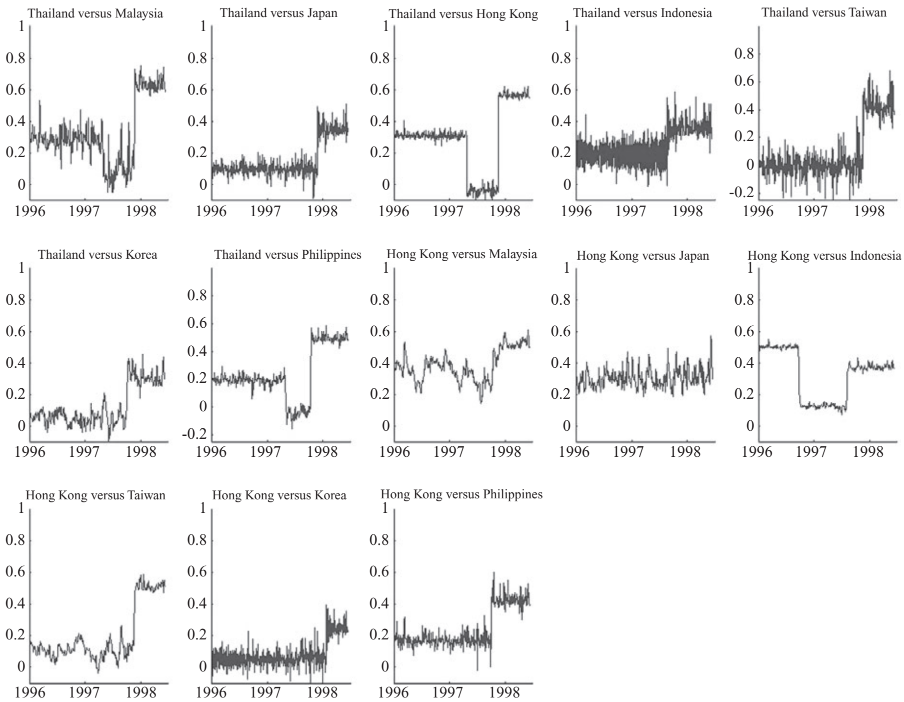

Figure 1. Conditional correlation.

correlation. Taken together, these results support the previous finding of shift contagion, irrespective of the presence of a change in volatility.

5. CONCLUSION

In this paper we propose a new sequential procedure using time-varying copulas to test for the presence of an increase in stock market dependence after a financial crisis (i.e. shift contagion). We show that it is very important to consider simultaneously separate breaks in volatility and dependence, as otherwise the contagion test can be severely biased. In order to offer a better approach, we develop a sequential algorithm, which allows for different breakpoints in the variance and correlation. Moreover, the proposed contagion test is a sequential 'all-in-one' procedure that takes into account the uncertainty in the determination of the variance regime. The formal stability test is elaborated from the one proposed by Dias and Embrechts (2004) and a bootstrap procedure is implemented to tackle the distortion in the asymptotic distribution due to the presence of a breakpoint in the nuisance parameters. Applied to the recent 1997 Asian crisis, the results produced by our sequential algorithm support that assuming the same break date for the variance and the conditional correlation is an erroneous assumption: breaks in variances generally precede those in conditional correlation. Nevertheless, the Asian crisis turns out to have been characterized by a regional contagious transmission of the Thai shock. The robustness of the results (with respect to, for example, the mean dynamics and the choice of the copula) has been checked.[16]

Beyond the separate analysis of the effect of the volatility regime on the evolution of asset market dependence, tail-dependence might be also interesting to consider as a complementary measure for contagion (Rodriguez, 2007). Future research would include another step in the sequential procedure that would allow for lower tail dependence (see Joe (1997) for a definition) as well as changing types of dependence over time (as studied by Rodriguez, 2007). This could be performed using a more flexible copula model that additionally allows for conditional tail dependence. Even if such an analysis were to bring about a complementary insight into the tail dependence time path, it would not modify the previous results.

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