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Tequila crisis

Measuring financial contagion: A Copula approach

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Abstract

This paper models dependence with switching-parameter copulas to study financial contagion. Using daily returns from five East Asian stock indices during the Asian crisis, and from four Latin American stock indices during the Mexican crisis, it finds evidence of changing dependence during periods of turmoil. Increased tail dependence and asymmetry characterize the Asian countries, while symmetry and tail independence describe the Latin American case. Structural breaks in tail dependence are a dimension of the contagion phenomenon. Therefore, the rejection of the correlation breakdown hypothesis should not be considered, without further investigation, as evidence of a stable dependence structure.

JEL classification: G100; F3
Keywords: Financial crises; Contagion; Copulas

1. Introduction

A central issue in asset allocation and risk management is whether financial markets become more interdependent during financial crises. This issue acquired dramatic importance during the five major crises of the 1990s.[1] Common to all these episodes was the fact that the turmoil that originated in one market extended to a wide range of markets and countries in a way that was hard to explain on the basis of changes in fundamentals. The word "contagion" became popular, both in the press and in the academic literature, to refer to this phenomenon.

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[1] These were the ERM attacks (1992), the Mexican devaluation (1994), the East Asian crisis (1997), the Russian default (1998), and the devaluation of the Brazilian real (1999).

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During the 1990s, the study of financial contagion, defined in a recent influential paper[2] as "a significant increase in cross-market linkages after a shock to one country (or group of countries)", was conducted mostly around the notion of "correlation breakdown": a statistically significant increase in correlation during the crash period. Examples of this literature are the works by Bertero and Mayer (1989) and King and Wadhwani (1990), who find evidence of an increase in the correlation of stock returns at the time of the 1987 crash. Also, Calvo and Reinhart (1996) report correlation shifts during the Mexican crisis, while Baig and Goldfajn (1999) find significant increases in correlation for several East Asian markets and currencies during the East Asian crisis.

The studies of contagion based on structural shifts in correlation were challenged by Boyer, Gibson and Loretan (1999),[3] who pointed to biases in tests of changes in correlation that do not take into account conditional heteroskedasticity. Boyer et al. (1999) argued that the estimated correlation coefficient between the realized extreme values of two random variables will likely suggest structural change, even if the true data generation process has constant correlation. Forbes and Rigobon (2002) generalized the approach of Boyer et al. (1999) and applied it to the study of three major crises (the 1987 crash, the Mexican devaluation, and the East Asian crisis). They were unable to find evidence of correlation breakdown in any of these crises after adjusting for heteroskedasticity and concluded that the phenomenon that has been labeled as "contagion" is nonexistent, but just the continuation in times of increased volatility of the strong dependence among international markets that exists in tranquil times.

In this way, by the end of the decade of 1990 the literature was far from having reached a consensus about the very existence of contagion. Some authors began to recognize the necessity to go beyond the linear approach to address the issue. For example, Longin and Solnik (2001), Hartman, Straetmans and de Vries (2000) and Bae, Karolyi and Stulz (2003) presented models based on extreme value theory, while others, like Ramchand and Susmel (1998), Ang and Bekaert (2002) and Chesney and Jondeau (2000), explored Markov switching models. These works cope with the Forbes and Rigobon critique either by studying tail correlation (extreme value models), or by providing a consistent model to accommodate structural breaks in the variance (Markov switching models). An additional advantage of Markov switching models in the study of contagion is that they do not rely on an ad hoc determination of the crisis period. As Dungey and Zhumabekova (2001) have shown, tests of contagion can be seriously affected by the size of the "crisis" and "non-crisis" periods.

Markov switching models, like the ones mentioned in the above paragraph, have been limited to analyze the case of bivariate normality.[4] As a result, they have missed a potentially important dimension of the contagion phenomenon such as nonlinear dependence. As Bae et al. (2003) have pointed out: "The concerns (about contagion) are generally founded on the presumption that there is something different about extremely bad 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 leads them to ignore economic fundamentals, one would expect large negative returns to be contagious in a way that small negative returns are not."[5]

On the other hand, models based on extreme value theory, even those that have tested for some form of nonlinearity, have implicitly assumed an asymptotically dependent structure. There are

[2] See Forbes and Rigobon (2002).

[3] See also Loretan and English (2000).

[4] An exception is Ang and Chen (2002), who considered mixtures of normals.

[5] Bae et al. (2003, page 2). See also Longin and Solnik (2001) for a paper that addresses directly this issue.

two forms of extreme value dependence for random variables: asymptotic dependence and asymptotic independence, and both allow for dependence between relatively large realizations of each variable. But to be asymptotically dependent, the random variables must be associated in the very tails of the distribution. In a recent paper, Poon, Rockinger and Tawn (2004) could not find evidence of asymptotic dependence in daily stock market returns for the US, Japan, Germany and France after filtering the series from GARCH effects. An important conclusion of this work is that assuming asymptotic dependence can lead to serious overestimation of financial risks. Another potential shortcoming of Extreme Value models is that there is always discretion when defining what an extreme observation is.[6]

This paper studies financial contagion using a methodology that goes beyond the simple analysis of correlation breakdowns and, at the same time, is careful in the characterization of nonlinearity and asymptotic dependence. It also avoids discretion in the identification of the contagious episodes and in the definition of extreme outcomes. It accomplishes these objectives by the use of copulas with Markov switching parameters.

Nelsen defines copulas as “functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions” (Nelsen, 1999, page 5). Copulas contain all the information about the dependence structure of a vector of random variables. They can capture nonlinear dependence, while correlation is only a linear measure of dependence. In particular, copulas contain information about the joint behavior of the random variables in the tails of the distribution,[7] which should be of primary interest in a study of contagion of financial crises.[8] Moreover, copulas are able to capture tail behavior without the need of using discretion to define extreme outcomes.

Copulas enable the modeler to construct flexible multivariate distributions exhibiting rich patterns of tail behavior, ranging from tail independence to tail dependence, and different kinds of asymmetry. They are an alternative to correlation in the modeling of financial risks. This is important in Finance, as correlation is the canonical measure of dependence only in the case of the multivariate normal distribution (or, more in general, of spherical and elliptical distributions), but there is mounting evidence that distributions in Finance are outside of this class.[9] Moreover, research in multivariate extreme value theory has shown that it is possible to construct multivariate distributions with identical correlations but otherwise completely different dependence structures.

Fitting copulas with different tail behavior makes it possible to test whether times of increased dependence can be also characterized by changes in one or both tails of the distribution. However, in order to capture shifts in the dependence structure, the copula that describes it must be time-varying. Patton (2006a,b) pioneered the study of time-varying copulas.[10] He introduced the concept of conditional copula, and applied it to the study of asymmetries in the dependence structure of a set of exchange rates.

In this paper I explore whether financial crises can be described as periods of change in the dependence structure between markets. I model the dependence structure as a mixture of

[6] For a critical assessment of extreme value theory in finance, see Diebold, Schuerman and Stroughair (2000).

[7] Section 3 of this paper provides a short survey on copulas. For an introduction to copulas, see Nelsen (1999).

[8] Multivariate normality *assumes* tail independence, which is another reason to look for better models to study financial crises.

[9] For an analysis of the shortcomings of the use of correlation as the main measure of dependence in finance and insurance, see Embrechts, McNeil, and Straumann (1999).

[10] See also Rockinger and Jondeau (2001).

copulas,[11] with parameters changing over time according to a Markov switching model. I study two classes of copulas: a finite mixture of the Frank, Gumbel, and Clayton copulas,[12] which can capture asymmetries in tail dependence, and the bivariate Student's t copula, which exhibits symmetric tail dependence and has the tail-independent Normal copula as a special case.

To identify the crisis episodes, I model the marginals using the SWARCH structure introduced by Hamilton and Susmel (1994). In a SWARCH model, the variance of the series under study is subject to occasional shifts, which are the outcome of a random variable that follows a Markov process. In this way, I can explore whether different dependence structures are associated to different variance regimes. In the mixture, the shifting parameters of the dependence structure are the weights. Otherwise, the remaining parameters of the mixture are assumed constant.[13] In the Student copula, the changing parameters are the correlation coefficient and the degrees of freedom.

This paper is related to Patton (2006a,b) and Rockinger and Jondeau (2001) in that it models dependence using copulas with time-varying parameters. But unlike these authors, I allow the parameters of the copula to change with the states of the variance to identify shifts in the dependence structure in times of crisis. In order to do this, I build a multivariate SWARCH model along the lines of Ramchand and Susmel (1998). The key difference with Ramchand and Susmel (1998) is that I model the dependence structure using switching copulas instead of assuming bivariate normality. A switching copula can capture increases in tail dependence, reflecting that, for example, the probability of markets crashing together is higher in periods of financial turmoil, while a model based on multivariate normality *imposes* tail independence. This is the first paper that uses "switching copulas" to study contagion of financial crises.

Using daily returns on stock indices from five East Asian countries (Thailand, Malaysia, Indonesia, Korea and Philippines), during the Asian Crisis, and from four Latin American countries (Mexico, Argentina, Brazil and Chile) during the Mexican Crisis, I find evidence of changing dependence structures during periods of financial turmoil. I also test whether these changes are best described using copulas with tail dependence and asymmetry compared to symmetric and also to tail-independent copulas. Increased tail dependence and asymmetry in times of high volatility characterize the Asian countries, while increased dependence with symmetry and tail independence describes Mexico–Brazil. Mexico–Argentina and Mexico–Chile are the only cases in which a stable dependence structure could not be rejected.

These results contribute to the ongoing debate on the existence of contagion. They show that times of financial turmoil are indeed times of increased dependence. Most cases studied in this paper exhibit contagion in the sense of Forbes and Rigobon's (2002) definition. However, although overall dependence increases, patterns of tail dependence change differ widely across markets. The cases of Thailand–Indonesia and Thailand–Korea, in which a tail-independent structure is found in the tranquil period, while a tail-dependent and asymmetric structure characterizes the crisis time suggest that the prevalence of tail independence found

[11] Mixtures of copulas are copulas. See Nelsen (1999). Finite mixtures of distributions are discussed in Hamilton and Susmel (1994) in the context of Markov switching models. See also Everitt and Hand (1981).

[12] The Frank copula exhibits tail independence, while the Gumbel and Clayton copulas exhibit upper and lower tail dependence, respectively. See Section 3 for a detailed description of these copulas.

[13] Under these assumptions, I can construct parsimonious models in which the change in the dependence structure is captured by the shift in only one parameter.

by Poon et al. (2004) may not be general. On this regard, excessive reliance on tail independence, although harmless in stable times, may lead to the underestimation of financial risks in periods of crisis. From an asset allocation perspective, recent results by Ang and Bekaert (2002) and Das and Upal (2004) on portfolio selection establish that the costs of ignoring regime shifts can be substantial, especially in the presence of highly correlated jumps between markets.

The organization of the paper is the following. Section 2 presents the data and shows descriptive statistics. Section 3 presents univariate results for the SWARCH model, exploring whether the variances of the series studied are state dependent. Section 3 gives a short summary of copulas. Sections 4 and 5 present results for the Asian and Mexican crises, respectively. Section 6 concludes.

2. Data

This paper uses daily data (in US dollars) of stock indices from five Asian countries: Thailand, Malaysia, Indonesia, Korea and Philippines. The series go from 1/1/96 to 30/6/98 (652 observations, Fig. 1). Also, four Latin American countries are studied (Mexico, Argentina,

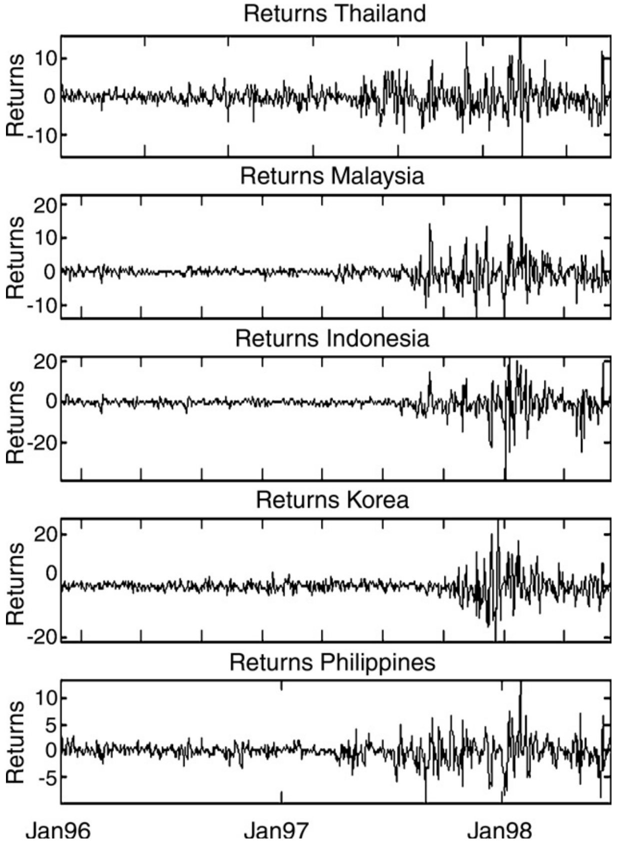

Fig. 1. Asian markets returns.

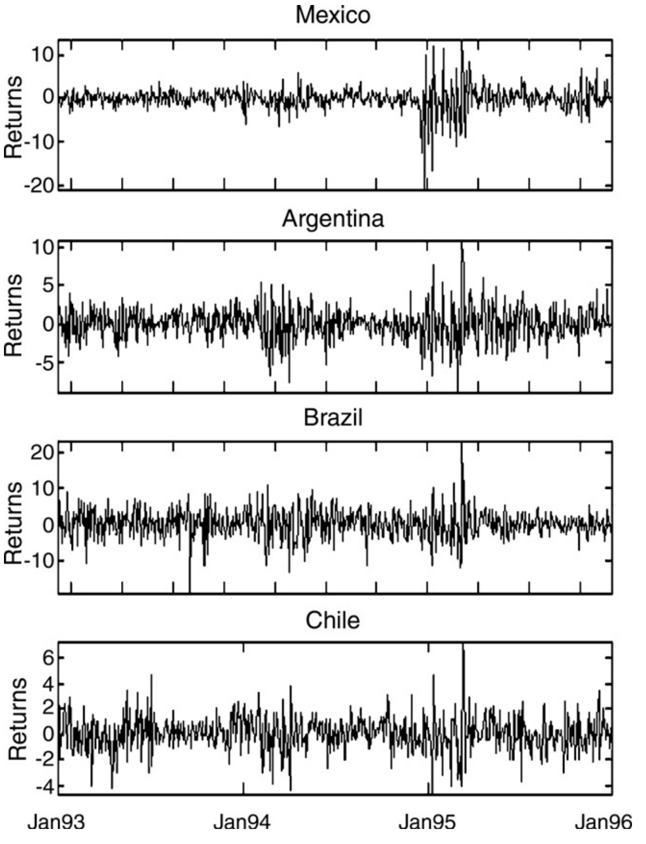

Fig. 2. Latin American markets returns.

Brazil and Chile), the series going from 1/1/93 to 31/12/95 (781 observations, Fig. 2). Only regional contagion is considered. The variable of interest is daily returns, which are calculated as 100 times the difference in the log of the indices. All data come from Datastream. Table 1a shows descriptive statistics of the series. The non-normality of the data is apparent from the coefficients of skewness and kurtosis. Also, the Jarque-Bera test (reported in the last line of the table) strongly rejects normality.[14] Results from Latin American markets (Table 1b) exhibit a similar pattern.

3. Copulas

Copulas are "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions."[15] The most important result in copula theory is Sklar's theorem:

[14] Under the null of normality, the Jarque-Bera test statistics follows a chi-squared distribution with two degrees of freedom.
[15] Nelsen (1999).

Table 1
Descriptive statistics

(a) Asian markets

	Thailand	Malaysia	Indonesia	Korea	Philippines
Mean	−0.296	−0.183	−0.267	−0.224	−0.116
Standard deviation	2.968	2.631	4.382	3.514	1.998
Skewness	0.673	1.064	−1.305	0.644	0.116
Kurtosis	8.87	17.29	19.73	15.991	9.70
Jarque-Bera *	973.6	5616.8	7723.1	4588.5	1207.0

(b) Latin American Markets

	Mexico	Argentina	Brazil	Chile
Mean	−0.057	0.031	0.137	0.107
Standard deviation	2.613	2.012	3.672	2.476
Skewness	−1.022	−0.002	−0.036	0.317
Kurtosis	15.952	5.531	6.468	8.680
Jarque-Bera *	5553.0	205.8	387.2	1053.4

Under the null of normality, the Jarque-Bera test statistics follows a chi-squared distribution with two degrees of freedom.

Theorem 3.1. (Sklar, 1959): *Let D be an n-dimensional distribution function with margins $F_1,\ldots,F_n$. Then there exists an n-copula C such that for al x in* $\bar{\Re}^n$,

$$D(x_1,\ldots,x_n) = C(F_1(x_1),\ldots,F_n(x_n)). \tag{1}$$

If $F_1,\ldots,F_n$ are all continuous, then C is uniquely determined on $RanF_1 \times\ldots\times RanF_n$. Conversely, if C is an n-copula and $F_1,\ldots,F_n$ are distribution functions, the function D defined above is an n-dimensional distribution function with margins $F_1,\ldots,F_n$.[16]

Therefore, if D is a continuous multivariate distribution function, Sklar's theorem says that it is possible to separate the univariate margins from the dependence structure. The dependence structure is represented by the copula. This can be seen more clearly if we assume the F_i's are differentiable, and C and D are n times differentiable. Then, deriving both sides of (1) to get the density of D, we get

$$\frac{\partial^n D(x_1,\ldots,x_n)}{\partial x_1,\ldots,\partial x_2} = \frac{\partial^n C(F_1(x_1),\ldots,F_n(x_n))}{\partial x_1,\ldots,\partial x_2} \times f_1(x_1) \times \ldots \times f_n(x_n)$$

That is, the density of D has been expressed as the product of the copula density and the univariate marginal densities. It is in this sense that we say that the copula has all the information about the dependence structure.

Copulas have certain properties that are very useful in the study of dependence. First, copulas are invariant to strictly increasing transformations of the random variables. Second, widely used measures of concordance[17] between random variables, like Kendall's tau and Spearman's rho, are

[16] For a proof, see Nelsen (1999).

[17] Nelsen's (1999) informal definition of concordance:"Two random variables X and Y are concordant if "large" values of X tend to be associatied with "large" values of Y, and "small" values of X tend to be associated with "small" values of Y. For a formal treatment, see Nelsen (1999) and also Joe (1997).

properties of the copula. Third, and of the greatest importance in the study of financial contagion, asymptotic tail dependence is also a property of the copula.

In what follows, I provide formal definitions of asymptotic tail dependence and of a concordance measure, Kendall's tau, which will be widely used in the rest of the paper.

Intuitively, asymptotic tail dependence is a measure of the propensity of markets to crash (or boom) together. More formally,[18] let (X,Y) be a vector of continuous random variables with marginal distribution functions F and G. Let $u=F(X)$, an $v=G(Y)$.[19] The coefficient of upper tail dependence of (X,Y) is

$$\lim_{u\uparrow 1} P\{Y>G^{-1}(u)|X>F^{-1}(u)\} = \lambda_U.$$

The coefficient of upper tail dependence can be expressed in terms of the copula between X and Y as follows:

Definition 3.1. If a bivariate copula C is such that $\lim_{u\uparrow 1} \frac{1-2u+C(u,u)}{1-u} = \lambda_u$ exists, then C has upper tail dependence if $\lambda_U \in (0,1]$, and upper tail independence if $\lambda_U=0$.

In the same way, the coefficient of lower tail dependence can be defined as

$$\lim_{u\downarrow 0} P\{Y<G^{-1}(u)|X<F^{-1}(u)\} = \lambda_L.$$

In terms of copulas,

Definition 3.2. If a bivariate copula C is such that $\lim_{u\downarrow 0} \frac{C(u,u)}{u} = \lambda_L$ exists, then C has lower tail dependence if $\lambda_L \in (0,1]$ and lower tail independence if $\lambda_L=0$.

Kendall's tau is a measure of concordance between random variables. Two points (x_1, x_2), (y_1, y_2) in R^2 are said to be concordant if $(x_1-y_1)(x_2-y_2)>0$ and to be discordant if $(x_1-y_1)(x_2-y_2)<0$. In a similar way two-random vectors (X_1, X_2), $(\tilde{X}_1, \tilde{X}_2)$ are said to be concordant if $P[(X_1-\tilde{X}_1)(X_2-\tilde{X}_2)>0]-P[(X_1-\tilde{X}_1)(X_2-\tilde{X}_2)<0]>0$, that is, if X_1 tends to increase with X_2, and discordant otherwise. Kendall's tau measures this difference of probabilities:

$$\rho_\tau(X_1,X_2) = P[(X_1-\tilde{X}_1)(X_2-\tilde{X}_2)>0]-P[(X_1-\tilde{X}_1)(X_2-\tilde{X}_2)<0].$$

It is possible to express Kendall's tau in term of the copula that joins X_1 withX_2:

$$\rho_\tau(X_1,X_2) = 4\iint_{[0,1]^2} C(u_1,u_2)\mathrm{d}C(u_1,u_2)-1.$$

As a measure of concordance based on copulas, which means that it is invariant to increasing transformations of its arguments, Kendall's tau can capture nonlinear dependences that are not possible to measure with linear correlation. As contagion is most likely a nonlinear phenomenon, Kendall's tau will be the main measure of association studied in this paper.

[18] This is based on Embrechts et al. (2003).

[19] Note that $u=F(X)$ and $v=G(Y)$ belong to [0,1]. Furthermore, they are uniformly distributed. For a proof of this last result, see, for example, Casella and Berger (1990, page 52).

Table 2
Copulas

	Student	Frank	Clayton–Gumbel
λ_L	$2t_{v+1}\left(\sqrt{(v+1)(1-\rho)/(1+\rho)}\right)$	0	$2^{-\frac{1}{\delta\theta}}$
λ_U	$2t_{v+1}\left(\sqrt{(v+1)(1-\rho)/(1+\rho)}\right)$	0	$2-2^{\frac{1}{\delta}}$
Kendall's τ	$\tau=\frac{2}{\pi}\arcsin(\rho)$	$1-\frac{4}{\alpha}\left(1-\int_0^{\alpha}\frac{t}{e^t-1}\mathrm{d}t\right)$	$\frac{(2+\theta)\delta-2}{(2+\theta)\delta}$
Clayton			$\delta=1$
Gumbel			$\theta=0$
Independence	$\rho=0$ and $\upsilon\rightarrow\infty$	$\alpha\rightarrow 0$	$\theta=0$ and $\delta=1$

Definitions: λ_L is the coefficient of lower tail dependence. λ_U is the coefficient of upper tail dependence. Independence refers to the restrictions on the parameters that render the independent copula. In the Student copula, ρ is the coefficient of linear correlation, and υ are the degrees of freedom. The Clayton (lower tail dependence, upper tail independence) copula is obtained as the special case of the Clayton–Gumbel copula in which $\delta=1$. The Gumbel (upper tail dependence, lower tail independence) copula is obtained as the special case of the Clayton–Gumbel copula in which $\theta=0$.

To capture different patterns of tail dependence, I use in this paper three out of the many copulas that have been studied in the literature:[20] the Student, Frank, and Gumbel–Clayton copulas. The Student and Frank copulas describe situations of symmetric tail dependence and tail independence, respectively, while the Gumbel–Clayton copula describes situations of asymmetric tail dependence. The definitions and properties of these copulas are summarized in Table 2.

Fig. 3 shows the scatter plots of simulated bivariate copulas: Gumbel, which is a special case of the Clayton–Gumbel copula that exhibits only upper tail dependence (left-top panel), Clayton, which is a special case of the Clayton–Gumbel copula that exhibits only lower tail dependence (right-top panel),[21] Frank (left-bottom panel) and Student (right-bottom panel). In all cases, 1000 observations were generated, and margins were selected as standard normal. The parameters of the copulas were chosen to give a Kendall's tau equal to 0.3. Therefore, the simulated random variables in Fig. 3 differ only on the dependence structure, with the Clayton copula showing strong association in the left tail, while the Gumbel copula shows strong association in the right tail. It is in this sense that the Clayton and Gumbel copulas describe asymmetric dependence. On the other hand, the Student copula exhibits dependence in both tails, while no clear association in the tails can be observed for the Frank copula.

4. Univariate results

The models for the marginal distributions are based on the SWARCH model of Hamilton and Susmel (1994). In this section, I show results that document the presence of different variance regimes in the series analyzed in this paper.

[20] For a catalog of copulas and their properties, see Nelsen (1999), and also Joe (1997).

[21] See Table 2 for a description of the Clayton–Gumbel copula and its special cases.

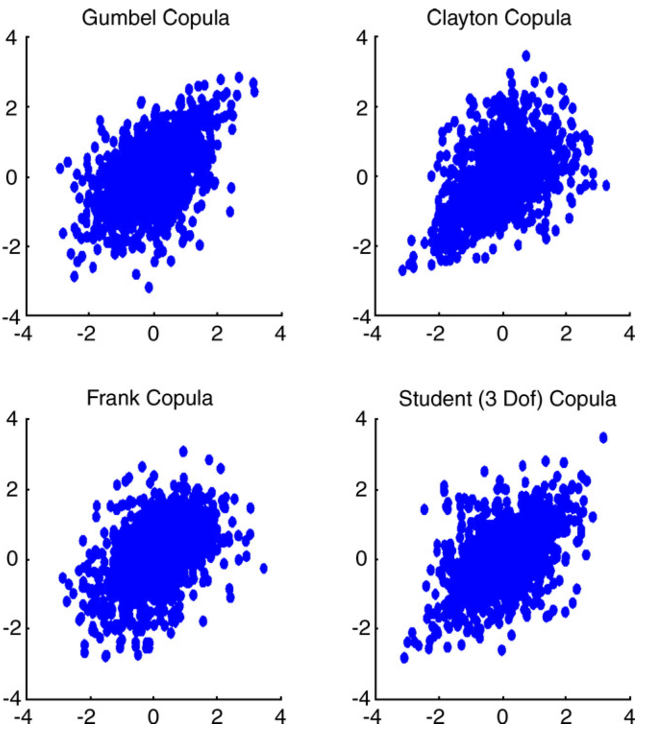

Fig. 3. Simulated Copulas scatter plots of simulated Gumbel, Clayton, Frank, and Student Copulas. All marginal are standardized normals. The parameters of the copulas were chosen to give a Kendall's tau equal to 0.3.

The general formulation of an AR(p)−GARCH(q,r) model for the stochastic process y_t is

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + u_t, \tag{1}$$

where

$$u_t = \sqrt{h_t} v_t,$$

and

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t=i}^2 + \sum_{i=1}^{r} \beta_i h_{t-i}.$$

The distribution of the residual v_t has in general been assumed standard normal, although the usefulness of the standardized Student's t is also well documented in the literature,[22] especially to deal with heavy-tailed, high-frequency data of financial returns.

One shortcoming of ARCH models is that they are not well suited to describe structural breaks in the variance. Moreover, some authors have suggested that structural breaks are

[22] Another popular distribution is the GED. For a comprehensive survey of ARCH models, see Bollerslev et al. (1992).

the reason of the high persistence found in ARCH models (see Lamoreux and Lastrapes (1990)).

As a way to introduce regime switches in variance, Hamilton and Susmel (1994)[23] presented the Switching ARCH (SWARCH) model, in which the residual u_t in Eq. (1) is modelled as

$$u_t = \sqrt{g_{st}} \times \overline{u}_t, \tag{2}$$

and $\bar{u}_t$ follows a standard ARCH(q) process:

$$\overline{u}_t = \sqrt{h_t} v_t, \tag{3}$$

where h_t obeys

$$h_t = \alpha_0 + \alpha_1 \overline{u}_{t-1}^2 + \alpha_2 \overline{u}_{t-2}^2 + \ldots + \alpha_q \overline{u}_{t-q}^2.$$

From Eqs. (2) and (3), we see that the level of the variance can occasionally change, depending on the values of $g_{st} \cdot g_{st}$ is a scaling parameter that changes in time as a function of a latent variable s_t. This latent variable is assumed to take values 1,2,…, K, and to be described as a Markov Chain:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{k1} \\ p_{12} & p_{22} & \cdots & p_{k2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{1k} & p_{2k} & \cdots & p_{kk} \end{bmatrix},$$

where $p_{ij}=p(s_t=i|s_{t-1}=j)$. s_t is regarded as the "state" or "regime" that the process is in at date t. So, a SWARCH(K,q) is a model in which the variable s_t can be in any K possible states at time t, and q is the number of lags in the conditional variance. Therefore, the variable u_t is multiplied by $\sqrt{g_1}$ in state 1, $\sqrt{g_2}$ by in state 2, and so on. Hamilton (1989) describes how to estimate the parameters in (2) through the maximization of a likelihood function and also how to do inference about the state in which the process has been at date t. Inferences based on information up to time t are called "filtered probabilities", while inferences based on information from the full sample are called "smoothed probabilities."[24]

The model selected to investigate the presence of different volatility regimes in the markets considered in this paper, is a SWARCH(2,1). Although the selection of the number of states and lags has been based on practical reasons of avoiding overparameterization and cumbersome computation in the multivariate case,[25] specification tests on the copulas reported in Section 5 suggest that the AR(1)−SWARCH(2,1) performs well in describing the structure of the marginals.

[23] There is also a contribution by Cai (1994).

[24] This methodology is described in Hamilton and Susmel (1994). See also the original papers: Hamilton (1989), and Hamilton and Susmel (1994).

[25] Adding just one more state for the variance would imply to estimate 18 additional parameters in the bivariate model.

Therefore, I model returns in country i as

$$y_t^i = \mu + \phi y_{t-1}^i + u_t^i,$$

where

$$u_t^i = \sqrt{g_{st}^i} \times \overline{u}_t^i,$$

and $\overline{u}_t^i$ follows a standard ARCH(q) process:

$$\overline{u}_t^i = \sqrt{h_t^i} v_t^i,$$

where h_i^t obeys

$$h_t^i = a_t^i + a_1^{i2} \overline{u}_{t-1}^{i2}.$$

The residual v_t^i is assumed to have a Student's t distribution with n degrees of freedom, which must also be estimated.

Table 3 shows univariate results for five Asian markets: Thailand, Malaysia, Indonesia, Philippines, and Korea. Note that, in all cases, the variance in the high-volatility state is far higher than the one in the low volatility state (from 7 times higher in the case of Thailand to 26 times higher in the case of Indonesia). The scaling variable g is always significantly different from 1, even at the 1% level. Also, all markets exhibit positive autocorrelation. Asian markets (with the exception of Korea) exhibit strong ARCH effects, together with Mexico and Chile (see Table 4).

Table 3
Univariate results, SWARCH(2,1) model: Asian markets

	Thailand	Malaysia	Indonesia	Korea	Philippines
P_{11}	0.997[a] (0.003)	0.998[a] (0.002)	0.998[a] (0.002)	0.998[a] (0.002)	0.992[a] (0.006)
P_{22}	1.000 (See text)	1.000 (See text)	1.000 (See text)	0.994[a] (0.006)	0.992[a] (0.007)
g	7.278[a] (1.207)	23.743[a] (3.868)	26.871[a] (5.237)	15.498[a] (1.003)	9.965[a] (1.279)
a0	1.898[a] (0.281)	0.653[a] (0.091)	1.018[a] (0.181)	2.037[a] (0.193)	0.560[a] (0.082)
a1	0.212[a] (0.082)	0.160[a] (0.067)	0.421[a] (0.114)	0.053 (0.053)	0.284[a] (0.02)
v	4.321[a] (0.797)	4.021[a] (0.715)	3.612[a] (0.566)	5.542[a] (1.008)	4.447[a] (0.887)
mu	−0.233[a] (0.064)	0.001 (0.035)	0.041 (0.043)	−0.1095 (0.062)	0.007 (0.037)
phi	0.172[a] (0.042)	0.185[a] (0.042)	0.227[a] (0.041)	0.166[a] (0.039)	0.283[a] (0.043)
Kendall's tau (low)		0.162	0.130	0.023	0.119
Kendall's tau (high)		0.242	0.222	0.130	0.217
LF	−1444.1	−1159.8	−1348.7	−1403.0	−1117.1
LF*	−1492.3	−1268.8	−1434.8	−1466.6	1163.0
p-value	0.00	0.00	0.00	0.00	0.00

Kendal's tau (low/high) is the empirical Kendal's tau between Thailand and the corresponding country calculated from the residuals of the low/high variance state.
LF = maximum value of the likelihood function.
LF* = maximum value of the restricted likelihood function (no regime switching).
p-value = probability value of a standard LR test (null = no regime switching).
[a] Significant at the 5% level.

Table 4
Univariate results, SWARCH(2,1) model: Latin American markets

	Mexico	Argentina	Brazil	Chile
P_{11}	0.997 [a] (0.004)	0.995 [a] (0.004)	0.988 [a] (0.009)	0.969 [a] (0.019)
P_{22}	0.978 [a] (0.025)	0.986 [a] (0.009)	0.979 [a] (0.013)	0.980 [a] (0.013)
g	15.188 [a] (5.057)	3.823 [a] (0.557)	3.496 [a] (0.497)	3.400 [a] 0.614
a0	1.896 [a] (0.203)	2.109 [a] (0.194)	6.251 [a] (0.655)	0.485 [a] (0.091)
a1	0.210 [a] (0.105)	0.068 (0.049)	0.050 (0.051)	0.218 [a] (0.061)
v	5.552 [a] (1.097)	17.696 (1.000)	11.592 [a] (1.010)	8.303 [a] (2.700)
mu	0.021 (0.052)	0.073 (0.061)	0.184 (0.111)	0.083 [a] (0.037)
phi	0.218 [a] (0.042)	0.105 [a] (0.039)	0.071 (0.038)	0.172 [a] (0.040)
Kendall's tau (low)		0.238	0.120	0.134
Kendall's tau (high)		0.372	0.268	0.297
LF	−1524.4	−1572.7	−2053.1	−1213.5
LF*	−1555.0	−1598.1	−2073.0	−1223.1
p-value	2.26×10^{-23}	$5.24\times10^{-}11$	21.17×10^{-08}	2.49×10^{-04}

Kendal's tau (low/high) is the empirical Kendal's tau between Mexico and the corresponding country calculated from the residuals of the low/high variance state.
LF = maximum value of the likelihood function.
LF* = maximum value of the restricted likelihood function (no regime switching).
p-value = probability value of a standard LR test (null = no regime switching).
[a] Significant at the 5% level.

However, even in the countries exhibiting strong ARCH effects, the persistence of the variance is low. This is consistent with the remark made by Lamoreux and Lastrapes (1990) that the high persistence found in ARCH models is due to structural breaks. The estimated degrees of freedom are also higher than 2, which guarantees that the variance of the residuals are well defined.[26] Smooth probabilities (Fig. 4) show that Thailand was the first country to enter in the high-variance regime (5/12/1997), while Korea entered the last (9/26/1997). Results for Latin American countries are similar (see Table 4). Interestingly, smooth probabilities (Fig. 5) show that, in the Mexican crisis, all countries entered into the high-volatility state almost simultaneously, with Mexico leading the other countries, as expected. From the smooth probabilities, Mexico entered into the high volatility state on December 19, 1994. Interestingly, this is the same day that Forbes and Rigobon (2002) define as the start of the turmoil period in their paper. Mexico stayed in the high volatility period during 72 days. Argentina and Brazil entered into the high volatility state on December 20. Argentina remained in that state until June 29, 1995, and Brazil until April 4, 1995.

Tables 3 and 4 also show empirical Kendal's tau between the originator and the country in the corresponding column, calculated from the residuals in both the low and high variance states. In all cases, the change in Kendall's tau shows that times of financial turmoil are also times of increased dependence. In the Asian case, the range of Kendall's tau increases goes from 50% (Thailand–Malaysia) to 465% (Thailand–Korea). In the Latin American case, it goes from 56% (Mexico–Argentina) to 122% (Mexico–Brazil and Mexico–Chile). The significance of these changes will be analyzed in the next section.

In the cases of Thailand, Malaysia and Indonesia, the maximum-likelihood estimates of the transition probabilities of the high-variance state turn to be one. The reason for this is that, in the

[26] If v has a Student distribution with n degrees of freedom, the variance of $v=n/(n-2)$ if $n>2$. Otherwise, the variance of v is either infinite (if n ε(0,1]) or nonexistent (if $n<1$).

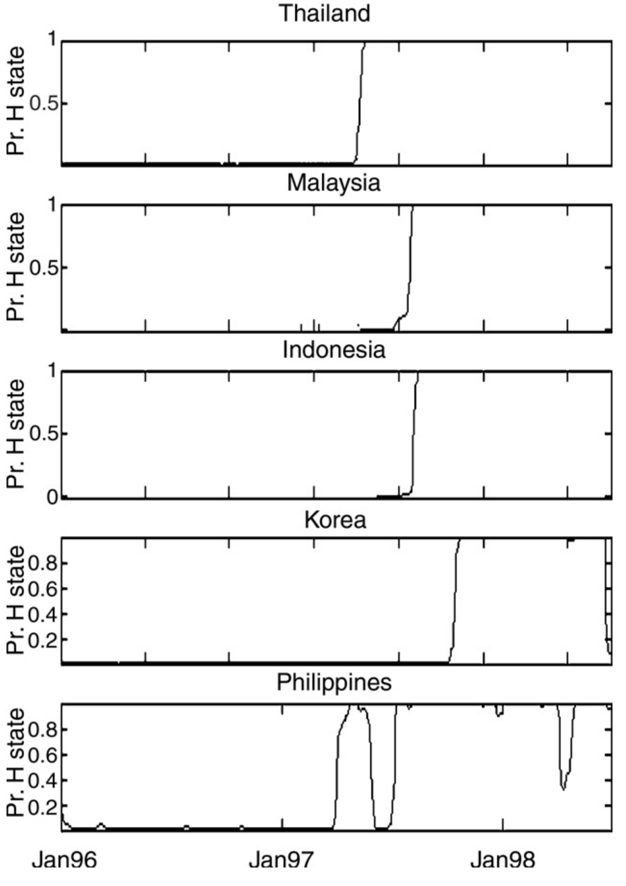

Fig. 4. Asian case. Smooth probabilities, high volatility state.

sample, once the series enter in the high volatility state, they do not abandon it. This characteristic of the sample is clearly seen in Fig. 4, which shows the smooth probabilities of the high volatility state. In these cases I follow Hamilton and Lin (1996) and impose the value of one with the purpose of calculating the standard errors of the remaining parameters.

Also, it is important to note that, in the Asian case, countries are simultaneously in the high variance state during approximately 40% of the sample (see Fig. 4), while in the Latin American case countries are simultaneously in the high variance state during approximately 10% of the sample (see Fig. 5).

In Tables 3 and 4 LF is the value of the maximized log-likelihood of the SWARCH(2,1) model, while LF* is the value of the maximized log-likelihood under the restriction that there is only one state (this is equivalent to estimate an ARCH(1) model). Although a standard likelihood-ratio test is not appropriate, because under the null hypothesis of no regime change the parameters of the high variance regime are not identified, I still provide the p-values of such a test in both tables for each country. Although this is an informal test, the extremely small p-values obtained should be considered as fairly convincing evidence of regime switching.[27]

[27] Hamilton and Lin (1996) discuss informal tests of regime switching.

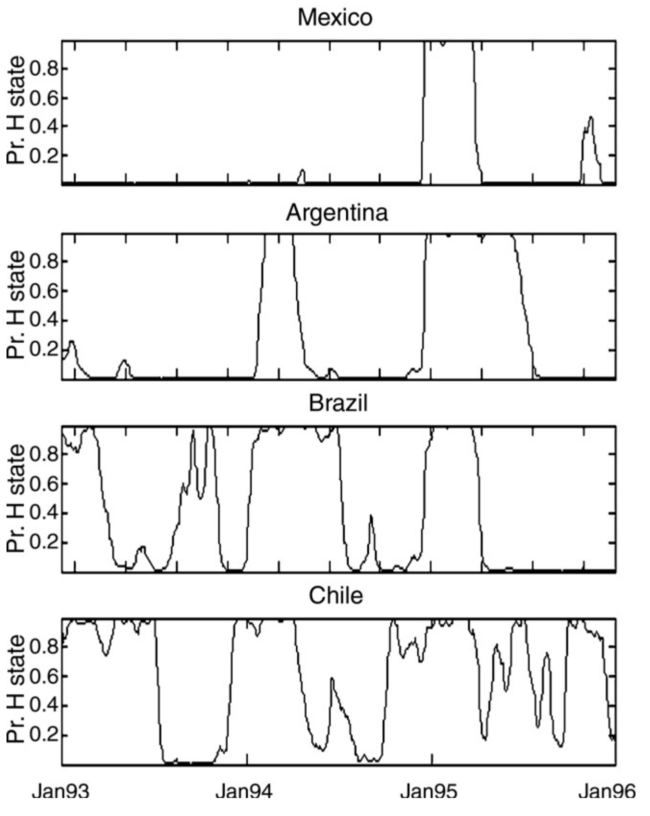

Fig. 5. Latin American case. Smooth probabilities, high volatility state.

The univariate results provide evidence of structural breaks in the variances of the series during the crisis periods. Moreover, markets seem to be simultaneously in the high variance regime. However, to assess whether the crisis periods are also times of change in the dependence structure, the analysis must be extended to the multivariate case. This will be done in the next section.

5. Bivariate results

Following Ramchand and Susmel (1998), I consider only the bivariate case to keep the models tractable for estimation. However, given that each univariate series can be in one of two variance regimes, the bivariate case will be a Markov Switching Model with four states. For example, two countries, Malaysia and Thailand, will be at one of four states s_t at time t:

s_t=1 Malaysia, Low volatility; Thailand, Low volatility.
s_t=2 Malaysia, High volatility; Thailand, Low volatility.
s_t=3 Malaysia, Low volatility; Thailand, High volatility.
s_t=4 Malaysia, High volatility; Thailand, High volatility.

I also follow Ramchand and Susmel (1998) in considering one of the countries as the generator of the turmoil. For the Asian crisis, that country is Thailand. Thailand was the first Asian country to be hit in the process that led to the Asian crisis.[28] It was also the first country to enter in the high volatility state in the sample. I will further assume that the dependence structure can change only between states 1 and 2 (Thailand's low volatility states) and 3 and 4 (Thailand's high volatility states). For obvious reasons, Mexico will be considered the generator country in the Latin American case, and I assume that the dependence structure between Latin American markets can change only between the high and low volatility states of Mexico.

As it was shown in Section 3, a bivariate density can be decomposed as the product of the copula and the univariate marginals. This is convenient in maximum likelihood estimation, because it permits to estimate the parameters of the density in two steps: first the parameters of the marginals, and then the parameters of the copula. The two-step approach saves computer time, although it has a cost in terms of efficiency. Unfortunately, when the copula and marginal parameters change simultaneously according to a Markov Switching process, the two-step approach cannot be used. All parameters must be estimated simultaneously. Assuming a two-state Markov Chain for each country, the likelihood of each observation can be written as

$$\begin{aligned} q_t(x_t, y_t|I_{t-1};\Theta) = \sum_{i=1}^{4} & P(s_t = i|I_{t-1};\Theta) \times f_t(x_t|s_t = i, I_{t-1};\Theta) \times g_t(y_t|s_t = i, I_{t-1};\Theta) \\ & \times C_{12}(u_t, v_t|s_t = i, I_{t-1};\Theta), \end{aligned}$$

where $P(s_t=i|I_{t-1};\Theta)$ is the probability of state i, conditional on past information, f, g and C_{12} are the marginals and copula densities, respectively, Θ is a vector of parameters, and $u_t=F_x(x_t|s_t, I_{t-1};\theta)$, $v_t=F_y(y_t|s_t, I_{t-1};\theta)$. Then, the likelihood function to be maximized is

$$L(\theta) = \sum_{t=1}^{T} \log[q(x_t, y_t|I_{t-1}, \theta)].$$

To find the copula that best fits the data I estimated two models: a mixture of Frank, Clayton and Gumbel, and the Student's t copula with switching correlation and degrees of freedom. The mixture (model 1) admits asymptotic tail dependence and asymmetry, while the Student's t copula (model 2) is also symmetric and has the property of asymptotic tail dependence. The normal copula obtains as a special case of the Student copula as the degrees of freedom go to infinity.

In model 1, to find the "right" mixture, I estimated for all cases, a mixture of threecopulas (Frank, Clayton, Gumbel):

$$\begin{aligned} C(u, v; \alpha, \delta, \theta) = {} & \pi_{Fs_t} C_F(u, v; \alpha) + \pi_{Cs_t C_C}(u, v; \theta) + (1 - \pi_{Fs_t} - \pi_{Cs_t}) C_G(u, v; \delta), \ \ 0 \le \pi_{is_t} \le 1, \\ & i = F, C. \end{aligned}$$

where π_{Cs_t} is the weight of the Clayton copula, π_{Gs_t} is the weight of the Gumbel copula, and π_{Fs_t} is the weight of the Frank copula. Note that the weights depend on the states: this is the way in which

[28] Forbes and Rigobon (2002) also use the figure of the country generator, but in the case of the Asian Crisis they chose Hong Kong. I keep Thailand as country generator because it was the first to enter into the high volatility phase, but using Hong Kong as the country generator does not modify the qualitative result of changing dependence structures between pairs of countries.

I try to capture changes in tail dependence. For example, after an increase in π_{Cs_t} , the copula will assign more probability mass to the left tail.

In the Thailand–Malaysia case $\hat{\pi}_{Fs_t}$ reached the boundary of zero, so the mixture estimated was Clayton and Gumbel:

$$C_G^C(u,v;\delta,\theta) = \pi_{s_t} C_C(u,v;\theta) + (1-\pi_{s_t}) C_G(u,v;\delta), \quad 0 \le \pi_{s_t} \le 1.$$

Note that here π_{s_t} is the only shifting parameter. Lower tail dependence increases as π_{s_t} goes from zero to one.

In the remaining Asian cases, all three copulas were found significant, with the weights of Clayton and Gumbel increasing from the low variance to the high variance state. This means that both lower and upper tail dependence increase in the crisis period. In this case, a mixture of only two copulas (Frank and Clayton–Gumbel) can capture the implied change in tail dependence:

$$C_{CG}^F(u,v;\alpha,\delta,\theta) = \pi_{s_t} C_{GC}(u,v;\delta,\theta) + (1-\pi_{s_t}) C_F(u,v;\alpha), \quad 0 \le \pi_{s_t} \le 1,$$

and this was the mixture estimated for the remaining Asian cases. This is convenient, because now an increase in tail dependence (upper and lower) can be captured as just one parameter, π_{s_t}, goes from zero to one.

In the Latin American case, the Model 1 copulas were selected following the criteria described above. In Mexico–Argentina, the copula estimated was Frank, Clayton:

$$C_G^C(u,v;\alpha,\theta) = \pi_{s_t} C_F(u,v;\alpha) + (1-\pi_{s_t}) C_G(u,v;\delta), \; 0 \le \pi_{s_t} \le 1$$

Here, again, lower tail dependence increases as π_{s_t} goes from zero to one. In Mexico–Brazil the best fitting copula was Frank, Clayton–Gumbel. Finally, in the Mexico–Chile case, the best fitting dependence structure was a mixture of three copulas (Clayton, Frank, Gumbel).

The mixtures were compared to the Student switching (model 2) to find the best fitting model. As the models are nonnested, it is necessary to find a criterion to choose among them. In this paper, I use the Akaike Criterion[29] adjusted for small sample bias[30]:

$$\mathrm{AIC}_c = -2\log L\left(\hat{\theta}\right) + 2K + \frac{2K(K+1)}{n-K-1},$$

where log $L(\hat{\theta})$ is the maximized log likelihood function, K is the number of estimated parameters, and n is the sample size. As the purpose of this study is to get an understanding of the structure of the data, and not prediction, the Akaike Information Criterion is preferred to other criteria that are also widely used in Economics, like the Schwartz Information Criterion. The adjustment for small sample bias is recommended when $n/K<40$.[31] According to this criterion, the best fitting model is the one that minimizes AICC.

Results are presented in Tables 5 (Asian case) and 7 (Latin American case). To save space, I show only the parameters of the best fitting copulas.[32] Tables 6 and 8 summarize all the results obtained in the above-mentioned tables for the Asian and Mexican case, respectively.

[29] Breymann et al. (2003) also use the Akaike criterion to select best fitting copulas.

[30] For a survey of model selection and inference, see Burnham and Anderson (1998).

[31] See Burnham and Anderson (1998).

[32] The tables with details for all models are available from the author upon request.

Table 5
Bivariate results: Asian case, estimation of Copula models

	Thailand–Malaysia		Thailand–Indonesia		Thailand–Korea		Thailand–Philippines	
	Cl&Gumb	Std Error	F&Cl–Gumb	Std Error	F&Cl–Gumb	Std Error	F&Cl–Gumb	Std Error
π_L	0.091	0.057	0.000	See text	0.000	See text	0.245[a]	0.090
π_H	0.277	0.079[a]	1.000	See text	0.301	0.126	0.463[a]	0.102
α	–		1.201	0.331[a]	0.000	See text	0.000	See text
θ	3.860	1.072[a]	0.235	0.103[a]	0.000	See text	0.913[a]	0.416
δ	1.152	0.046[a]	1.158	0.064[a]	1.888	0.529	1.400[a]	0.220
LF	−2552.7		−2761.5		−2835.7		−2520.0	
Param.	21		19		19		20	
p-value	0.032		0.000	See text	0.000	See text	0.0359	
K-S test	0.090		0.441		0.881		0.919	
A-D test	0.107		0.361		0.862		0.930	

The table gives estimates for the copulas for the Asian case. For Malaysia the best fitting copula was a mixture of Clayton and Gumbel. For the rest of the Asian countries it was a mixture of Frank and Clayton–Gumbel. π_L is the weight of the Clayton–Gumbel copula (Clayton in the case of Malaysia) in the low volatility state, π_H is the weight of the Clayton–Gumbel copula (Clayton in the case of Malaysia) in the high volatility state. Tail dependence increases with π, α, θ and δ are the parameters of the Frank, Clayton, and Gumbel copulas, respectively.
LF is the maximized log likelihood function.
Param. is the number of estimated parameters.
p-value is the probability value of a Likelihood Ratio test of constancy of the weights. A p-value lower than 0.05 indicates rejection of the hypothesis that the copulas are invariant across regimes.
K-S test is the Kolmogorov–Smirnov test to assess the copula specification.
A-D test is the Anderson–Darling test to assess the copula specification.
In the K-S and A-D tests, an entry lower than 0.05 indicates rejection of the hypothesis that the conditional copula is standard uniform.
[a] Significant at the 5% level.

The best-fitting copula for Thailand–Malaysia is the Clayton and Gumbel mixture. This means that the increase in dependence between periods of different volatility is best described as an increase in asymmetric tail dependence. Note that the weight of the Clayton copula increases, which means that more probability mass is assigned to the event of both markets crashing together when the markets are simultaneously in the high variance regime. A standard likelihood-ratio test rejects the hypothesis of constant weights at the 5% level (p-value = 0.032). The first column of

Table 6
Summary of results: Asian case (generator: Thailand)

	Malaysia (Cla&Gu)	Indonesia (Fr&,Cla-Gu)	Korea (Fr&,Cla-Gu)	Philippines (Fr&,Cla-Gu)
↑ Dependence	Yes	Yes	Yes	Yes
↑ Tail dependence	Yes	Yes	Yes	Yes
τ_L (empirical)	0.162	0.130	0.023	0.119
τ_H (empirical)	0.242	0.222	0.130	0.217
τ_L (estimated)	0.178	0.132	0.023	0.125
τ_H (estimated)	0.269	0.228	0.148	0.236
λ_L (low variance)	0.078	0.000	0.000	0.148
λ_L (high variance)	0.224	0.078	0.000	0.280
λ_U (low variance)	0.155	0.000	0.000	0.091
λ_U (high variance)	0.125	0.180	0.167	0.171

τ_i is Kendall's tau in state i (i = low, high).
λ_j is the tail probability in the low/high variance state (j = lower, upper).

Table 6 shows dependence parameters associated to the different π_{s_t}s. Dependence (as measured by Kendal's tau) increases in the high volatility state. Estimates are close to the empirical Kendal's tau calculated in Table 3. Lower tail dependence increases also in the high volatility state, while upper tail dependence decreases.

For Thailand–Indonesia the best fitting copula is the Frank, Clayton–Gumbel mixture. The maximum likelihood estimates of the weights are in the boundaries, suggesting that a Frank copula describes the structure of dependence in tranquil periods, while the Clayton–Gumbel copula, with more probability mass in the tails, provides a better description of high volatility periods. Following Hamilton and Lin (1996), I imposed those values and re-estimated the model with the purpose of calculating the standard errors of the remaining parameters. In a test of constancy of weights, the constant weight mixture estimates more parameters, and gives a lower value of the likelihood function than the switching weights mixture. The second column of Table 6 shows dependence parameters associated to the different π_{s_t}s. Note again that the estimates are close to the empirical Kendall's tau shown in Table 3. Dependence and both upper and lower tail probabilities increase in the high volatility period.

For Thailand–Korea, the best fitting copula is a mixture of Gumbel and the independent copula. The copula estimated originally was Frank, Clayton–Gumbel, but θ attained its

Table 7
Bivariate results: Latin American case, estimation of Copula models

	Mexico–Argentina		Mexico–Brazil		Mexico–Chile	Mexico–Chile	
	(Student)	Std Error	(Student)	Std Error	Param.	Fr&Cl&Gu	Std Error
ρ_L	0.378[a]	0.035	0.197	0.041	π_{CL}	0.103[a]	0.059
ρ_H	0.495[a]	0.078	0.412	0.086	π_{GL}	0.401[a]	0.188
ν_L	>35		>35		π_{CH}	0.000	See text
ν_H	>35		>35		π_{GH}	1.000	See text
					θ	2.801[a]	1.554
					δ	1.268[a]	0.094
					α	0.000	See text
LF	−3030.5		−3550.9			−2704.8	
Param	19		19			21	
p-value	0.180		0.028			0.1797	
K-S test	0.999		0.930			0.457	
A-D test	0.994		0.945			0.782	

This table gives estimates for the copulas in the Latin American case. For Argentina and Brazil, the best fitting copula was Student. ρ_H, and ν_L and ν_H are the correlation coefficients and the degrees of freedom in the low and high variance states, respectively. For Chile, the best fitting copula was a mixture of Frank, Clayton and Gumbel copulas. π_{CL} is the weight of the Clayton copula in the low volatility state, π_{CH} is the weight of the Clayton copula in the high volatility state. π_{CL} is the weight of the Clayton copula in the low volatility state, π_{CH} is the weight of the Clayton copula in the high volatility state. Lower tail dependence increases with πC. Lower tail dependence increases with π_G. θ, δ and α are the parameters of the Clayton, Gumbel, and Frank copulas, respectively.
LF is the maximized log likelihood function.
Param. is the number of estimated parameters.
p-value is the probability value of a Likelihood Ratio test of constancy of the weights. A p-value lower than 0.05 indicates rejection of the hypothesis that the copulas are invariant across regimes.
K-S test is the Kolmogorov–Smirnov test to assess the copula specification.
A-D test is the Anderson–Darling test to assess the copula specification.
In the K-S and A-D tests, an entry lower than 0.05 indicates rejection of the hypothesis that the conditional copula is standard uniform.
[a] Significant at the 5% level.

Table 8
Summary of results: Latin American case (generator: Mexico)

	Argentina (Student)	Brazil (Student)	Chile (Fra,Cla,Gu)
↑ Dependence	No	Yes	No
↑ Tail Dependence	No	No	No
τ_L (empirical)	0.238	0.120	0.134
τ_H (empirical)	0.372	0.268	0.297
τ_L (estimated)	0.247[a]	0.126	0.145[a]
τ_H (estimated)	0.330[a]	0.270	0.211[a]
λ_L (low variance)	0.000	0.000	0.008
λ_L (high variance)	0.000	0.000	0.000
λ_U (low variance)	0.000	0.000	0.109
λ_U (high variance)	0.000	0.000	0.273

τ_i is Kendall's tau in state i (i=low, high).
λ_j is the tail probability in the low/high variance state (j=lower, upper).
[a] These values were not found significantly different from each other.

lower bound of zero. Also, the independent copula was obtained because the parameter of the Frank copula was not found significantly different from zero. Note that the weight of the Clayton–Gumbel copula attained its lower bound, suggesting that the series were independent in the non-crisis period. The hypothesis of constant weight is rejected: as in Thailand–Indonesia, the constant-weight copula estimates at least the same number of parameters and gives a lower log likelihood value. This result makes the Thailand–Korea case the most dramatic in the sample, as it evolves from independence in stability to upper tail dependence in turmoil. The third column of Table 6 shows dependence parameters associated to the different π_{s_t}s.

For Thailand–Philippines the best fitting copula is also the Frank, Clayton–Gumbel mixture. The weights move in the direction of increased tail dependence between volatility regimes. This case also provides strong evidence of switching parameters between volatility regimes. The likelihood ratio test presented rejects the hypothesis of constant weights at the 5% level (p-value = 0.0359). Results in Table 6 (fourth column) show dependence and both upper and lower tail probabilities increasing in the high volatility period.

Results for the Mexican crisis are shown in Table 7. Perhaps surprisingly, in the Latin American case there was no evidence of changes in tail dependence. Although the Student copula was chosen as the best fitting model for Mexico–Argentina and Mexico–Brazil, the estimates of the degrees of freedom turned out to be too high (180 and 200 for Mexico–Argentina in the low and high volatility states, respectively; 44 and 49 for Mexico–Brazil). Therefore, the Normal copula was estimated in these two cases. A mixture of three copulas (independent, Clayton and Gumbel) gave the best fit for Mexico–Chile. In the case of Mexico–Brazil, the correlation coefficient increases from 0.197 to 0.412, and this change is significant (p-value = 0.028). Note that this corresponds to an increase in Kendall's tau from 0.126 to 0.270, which is very close to the empirical results shown in Table 4. Mexico–Argentina and Mexico–Chile were the only cases in which I found evidence of a stable dependence structure across variance regimes. Mexico and Argentina appear highly interdependent even in the period of tranquillity (the correlation coefficient in the low variance state is 0.378), so one possible explanation for this finding is the Forbes and Rigobon (2002) argument. On the other hand, and this is relevant also for Mexico–Chile, the crisis period is short relative to the entire sample (about 10% of the observations), and therefore, the Dungey and Zhumabekova (2001) observation could also be applicable. Table 8 shows implied measures of dependence for the Latin American case.

Tables 5 and 7 provide also tests on the specification of the best fitting copulas. If $C(u,v)$ is a copula, where $u=F(x)$ and $v=G(y)$, it is a well known result[33] that the conditional distribution of $Y|X=x$ is

$$H_{Y|X}(y|x) = \frac{\partial C(u,v)}{\partial u},$$

where $\partial C/\partial u$ is uniformly distributed in [0,1]. This suggests to test the adequacy of the copula specification by testing its first derivative with respect to each of its arguments. The last two rows of Tables 5 and 7 show the results of Kolmogorov–Smirnov and Anderson–Darling tests. The Kolmogorov–Smirnov test is a standard goodness of fit test. The Anderson–Darling test gives more weight to the tails of the distribution, and for this reason some authors have advocated its use in the evaluation of the copula specification.[34] The copulas pass both tests, which suggests that they are well specified.[35]

6. Conclusions

This paper provides evidence that the dependence structure between stock market returns of countries in Asia and Latin America changed during the Asian and Mexican crises. Although dependence (as measured by Kendal's tau) is low after filtering the series from state-varying volatility, changes in dependence during high variance regimes are statistically significant in most cases. In this way, most cases studied in this paper exhibit contagion in the sense of Forbes and Rigobon's (2002) definition. However, although overall dependence increases, patterns of change in tail behavior differ widely across markets, with tail dependence being more prevalent in times of financial turmoil.

This paper makes the case that structural breaks in tail dependence are an actual dimension of the contagion phenomenon. Changes in tail dependence should be taken into account in the design of any sound asset allocation strategy. Failing to do so can be expensive, as recent theoretical literature has demonstrated.[36] Moreover, it is important to note that these changes are not necessarily captured by correlation shifts. If contagion is a nonlinear phenomenon, as the results in this paper suggest, it is dangerous to consider, without further investigation, the rejection of the "correlation breakdown" hypothesis as evidence of a stable dependence structure.

Acknowledgement

I have benefited from insightful comments and suggestions from Raul Susmel, Andrew Karolyi, Roberto Rigobon, and seminar participants at Eurandom, Lancaster University, Tilburg

[33] See Klugman and Parsa (1999).

[34] See Malevergne and Sornette (2001).

[35] The specification of the copulas was also investigated using *QQ* plots. The results were in line with the aforementioned tests, and for reasons of space are not included in the paper. They are available from the author upon request.

[36] See Ang and Bekaert (2002) and Das and Upal (2004).

University and the 2004 American Finance Association Meeting, San Diego. All remaining errors are mine.

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Further Reading

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