Volatility contagion in the Asian crisis: New evidence of volatility tail dependence

Abstract

In this paper, we analyze empirically the existence and extent of financial contagion by means of extreme value theory in the Asian crisis. We analyze two key markets, the stock exchange and the foreign exchange over the daily period of 1992-2001. We define financial contagion as a significant increase in the tail dependence among different asset volatilities. To this end, we introduce a semi-parametric estimator for volatility tail dependence in the framework of regularly varying strictly stationary time series. According to the results of our analysis, for any Asian country, with exception of Japan, the crisis event led to stronger co-movements among the asset markets. The wave of currency depreciations, starting with the Thai baht, made foreign exchange markets of small countries more likely to co-move with foreign exchange markets of large economies, especially Hong Kong and Singapore, but not Japan. Large currency markets seem to be robust in case of regional currency turbulences. In the case of stock markets, the mini-crash of October 1997 in Hong Kong is reflected in increasing volatility tail dependencies, conducting to contagion when related to the stock markets of Hong Kong or Singapore.

Keywords: Asian Crisis, Contagion, Interdependence, Tail dependence, Multivariate Extreme Value Theory.

JEL Classification: E44, F36

1 Introduction

The Asian Crisis 1997/98 provocated many economists to analyze the regional economic and especially financial markets to better understand the linkages across markets and across countries. A common understanding is its regional character with non-significant impact to large economies outside the region, like the USA or the EU, and the prominent role of regional financial linkages across markets as well as across countries, mainly attributed to portfolio rebalancing effects of financial investors. But there is still an ongoing debate of the Forbes (2002) type "no contagion, only interdependence" and how to identify extreme co-movements of financial markets. And, finally in terms of an extreme value theory (EVT), what can be said about the impact of economic or institutional characteristics on financial linkages during the Asian crisis.

In the literature there are different approaches to define contagion and distinguishing this concept from interdependence. The most accepted definition is the Forbes (2002) approach. They defined <u>contagion</u> as a significant increase in co-movement of markets after initial shock. Our definition of contagion is based on the Forbes (2002) approach. Contagion in this paper should be interpreted as a significant increase in the tail dependence function of squared log-returns, as a proxy to the <u>volatility tail dependence</u> (VTD) , that takes place during a turmoil period. On the contrary, if two markets show high tail dependence of squared log-returns during the period of stability and continue to be highly tail dependent after a shock to one market, this constitutes <u>interdependence</u>. Thus, the idea of risk contagion is based on the idea of large volatility dependence.

The concept of (volatiliy) contagion and in particular VTD is not new in finance, for instance Edwards and Susmel (2001) using weekly stock market data for a group of Latin American countries analyze the behavior of volatility through time. They find strong evidence of volatility co-movements across countries, especially among the Mercosur countries. Dirk and Baur (2003) propose a new test that is based on a regression model that differentiates between mean contagion and volatility contagion in an asymmetric way. Empirical results for 11 Asian stock markets show that there is mean and volatility contagion in the Asian crisis. Brailsford et al. (2006) investigate risk and return in the banking sector in three Asian markets of Taiwan, China and Hong Kong. The study focuses on the risk-return relation in a conditional factor GARCH-

M framework that controls for time-series effects. The factor approach is adopted to incorporate intra-industry contagion and an analysis of spillovers between large banks and small banks. Finally, the study provides evidence on these relations before and after the Asian financial crisis of 1997. Dungey et al. (2010) propose an identified structural GARCH model to disentangle the dynamics of financial market crises. They apply the method to data from the 1997–1998 Asian financial crisis which consists of a complicated set of interacting crises. They find significant hypersensitivity and contagion between these markets but also show that links may strengthen or weaken. Chiang and Wang (2011) propose a new approach to evaluate volatility contagion in financial markets. The approach proposed is applied to the stock markets of the G7 countries to investigate the volatility contagion due to the subprime mortgage crisis. Empirical evidence shows that volatility is contagious from the US market to several markets examined. Engle et al. (2012) model the interrelations of equity market volatility in eight East Asian countries before, during, and after the Asian currency crisis. Using a new class of asymmetric volatility multiplicative error models based on the daily range, they find that dynamic propagation of volatility shocks occurs through a network of interdependencies, and shocks originating in Hong Kong may be amplified in their transmission throughout the system, posing greater risks to the region than shocks originating elsewhere.

There is no shortage of research on estimating contagion volatility. However, there are key aspects of the relation between the two main classes of volatility models; the generalized autoregressive conditional heteroscedasticity (GARCH) and the stochastic autoregressive volatility (SARV) models. While GARCH model allows one to incorporate volatility spillovers in the model, it does not allow one to incorporate volatility in all markets at once and it does not allow for the endogeneity of all return or volatility measures. In addition, from the point view of EVT, the study of dependence under periods of turmoil may reveal contrasts which are obscured when we only concentrate on examining the volatility of a time series. Interestingly, and unlike the situation for GARCH processes (see Davis and Mikosch, 2009), there is no extremal clustering for SARV processes in either the light- or heavy-tailed cases. That is, large values of the processes do not come in clusters, which mean that the large sample behaviour of maxima is the same as that of the maxima of the associated iid sequence. While GARCH and SARV models imply some information about extreme events, still little is known about the extremes per se.

In this paper we will consider that the asset markets returns analyzed are strictly stationary sequence of random vectors whose finite-dimensional distributions are jointly regularly varying with some positive tail index. Under the theory of regular variation in EVT only the tail of financial returns is modeled, i.e., the estimation uses data just from the tail area of the distribution function and, hence, is not biased toward the center. This means that EVT only provides asymptotic results, but offers the benefit that its asymptotic results hold for a wide range of parametric distributions. This representation allows to derive a tail dependence function for non iid observations and to infer their extremal behaviour. The assumption of regularly varying log-returns is very general and not too restrictive, due the most of stock, bond and foreign exchange markets show these features. This class of processes includes, among others, GARCH processes with normally or Student-distributed noise and SARV models with regularly varying multiplicative noise.

The main question in this paper asks for evidence in favor of (volatility) contagion vs. interdependence with respect to extreme co-movements in the Asian markets before, during and after the financial crisis. Our sample consists of stock market (S) and foreign exchange (FX) observations, in terms of daily log-returns as proxies of volatility, from the following eight countries, ordered according to size of stock market capitalization (similarly to Forbes (2002)): the Phillipines, Indonesia, Thailand, South Korea, Singapore, Malaysia, Hong Kong, Japan. Thereby we contrast the pre-crisis period January 1, 1992 - July 1, 1997 with the crisis period July 2, 1997 - July 31, 1999 and the post-crisis period August 1, 1999 - December 31, 2001.

We focus on the two financial markets of stocks and currencies to test the hypotheses of different authors on the nature of contagion and on economic/institutional factors influencing the strength of financial linkages. First, addressing the "no-contagion, only interdependence" question, how likely is a contagious infection during the Asian crisis? Next, is contagion rather a temporary phenomenon calming down in the aftermath of a crisis? This argument parallels the statement of a V-shaped recovery among Asian economies (see, e.g. Yang and Lim, 2004). According to the standard argument that during crisis international financial investors pull out there local investments, do we observe contagion to systematically effect local stock as well as currency markets, first within countries (see Dungey et al. 2006, p. 52). But this may also hold across countries: if we observe stock markets in two Asian countries to strongly co-move, we shall also observe strong co-movements in the respective local currency markets. Or, are there signs that stock markets are more prone to contagion than exchange rate markets as being more protected by governmental interactions? And is the level of contagious co-movements in vola returns higher for stock markets than for currency markets, as earlier studies suggest?

With regard to economic and institutional factors, we address the following question: what exactly is the role of large vs. small regional economies in the process of contagion transmission? What was the role of Japan and Hong Kong, the countries with the largest stock market in the region, in spreading the crisis? Which contagion effects can be identified for two prominent episodes: the precipitous drop of the Thai baht at the beginning of July 1997 and the mini-crash in Hong Kong's financial markets of October 1997? And did capital controls mitigate the propagation of shocks (see, e.g. Yang and Lim, 2004).

We contribute to the literature by introducing a semiparametric estimator for the VTD function in a more general framework. We take a different tack and study the extremal dependence structure of general strictly stationary time series. The key point is that for the asset markets whose distributions are jointly regularly varying, their extremal behaviours are determined by a limit measure. Therefore, any quantity trying to capture tail properties of these assets should be a function of this limit measure. The main difference between our methodology and the classical tail dependence methodology, is that we do not impose the iid assumption of the returns[1]. Hence, this model seems a more natural approach to study volatility contagion risk. In addition, due to the fact that the VTD is a conditional measure of extremal dependence this is also a difficult measure to estimate and does not always yield satisfactory results, even for moderate sample sizes, so that its estimation cannot be based on standard empirical process techniques. For this reason, we adopt a stationary bootstrap approach in which the block sizes are given by independent geometric random variables. This will allow us to construct asymptotical errors for the estimates.

Our empirical results show significant changes of vola returns during crisis to hold in almost half of the cases considered showing that contagion as well as interdependence are of similar prevalence, a result well in line with more recent contributions to literature. Contagion is typically a temporary phenomenon, i.e. volatility first increases to calm down in the aftermath of the crisis, thus supporting the view of a rather quick recovery of the Asian economies. Within-country contagion prevails while across-country contagion is typically symmetric, in line with capital-flight arguments: financial investors affecting local stock markets also affect local currency markets. This also points to the high vulnerability of Asian foreign exchange markets despite announcements

[1] As consequence, the estimation of this tail dependence function depends on the marginals.

of pegged exchange rate regimes (see also Haile and Pozo, 2006). Moreover, the first episode of currency depreciations, with sudden breaks of currency arrangements, may also explain why large stock markets were infected by exchange rate shocks from smaller economics like Thailand, the Phillipines and Indonesia. In this sense, the Thai bath drop may still be understood as a 'weak up call' for the region. Nonetheless, the size of market capitalization seems to play a somewhat limiting factor for volatility contagion transmission, as larger stock markets do not tend to co-move closely with each other. For Japan, the largest economy in this study, both financial markets do not seem to interact contagiously with the respective other financial markets considered, hence questioning the often cited role of Japan as a regional shock transmitter during the Asian crisis. With respect to capital control, our result shows some evidence that a decisive tightening of measures during crisis may be beneficial: Malaysia, the country showing the largest number of across-country reactions from pre-crisis to crisis-period and reacting with the strongest increase in capital account restrictions in our sample, experienced throught highly significant reductions of co-movements in the aftermath of the Asian crisis.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework of extreme dependence, as needed in the sequel. Based on the notion of multivariate regular variation we propose a tractable estimator of conditional probabilities of extreme events. The empirical application and the results are discussed in section 3. Section 4 concludes.

2 Methodology

Contagion is often investigated by testing how closely markets move together during turbulent periods. A natural approach to measure extreme dependence is by means of the tail dependence coefficient. For simplicity, let (X, Y) be iid random vectors with common distribution function. The tail dependence is defined as

$$\lambda(x, y) := \lim_{x,y\to\infty} \mathbb{P}(X > x \mid Y > y). \tag{1}$$

for $\lambda \in [0, 1]$, where $\lambda = 0$ means that X and Y are independent or asymptotically independent. The larger the value of λ, the larger the extremal dependence between X and Y. For more details on tail dependence based on Copulas, see Joe (1997) or Nelsen (2006). Note that (1) describes the tail dependence of (X, Y) in any direction of the bivariate distribution on the positive quadrant of $\mathbb{R}^2$.

However, the results of more than half a century of empirical studies on financial time series indicate that there exists a set of stylized statistical facts, which are common to a wide set of financial assets. For instance, the distribution of returns seems to display volatility clustering, which basically means the events tend to cluster in time. In addition, extreme events and serial dependence typically violate the assumptions of independence. Thus, a direct estimation of this coefficient is not possible. A common alternative is to utilize a two step procedure. First, a parametric model is used to extract the volatility present in the data, as for example, GARCH model of Engle (1982) or the SARV model Clark (1973). Second, one estimates the tail dependence coefficient of the pseudo iid residuals.

In this paper, contrary to earlier work on multivariate extreme models or copulas, the temporal dependence structure of each underlying marginal is not treated within a stochastic volatility model, which certainly would affect the dependence properties among the marginals. Instead of forcing the entire sample to have a parametric model, it is possible to investigate only the tails of the sample distribution.

We will review the notion of regular variation mentioned above, and by means of some simple examples illustrate how it may help to answer many questions about extremal dependence. See Resnick (2006) for a survey in regular variation.

2.1 Multivariate regular variation

In the multidimensional case we adopt the following definition for strictly stationary sequences whose finite-dimensional distributions have power law tails in some generalized sense. In particular, we will assume that the finite-dimensional distributions of the d-dimensional process $\mathbf{X}$ have *regularly varying distributions with tail index* $\alpha > 0$, if for some norm $|\cdot|$ on $\mathbb{R}^d$ satisfies the relation

$$\lim_{x\to\infty} \frac{\mathbb{P}(x^{-1}\mathbf{X})}{\mathbb{P}(|\mathbf{X}| > x)} \xrightarrow{v} v\,(\cdot)\,. \tag{2}$$

for a Radon measure v on $\overline{\mathbb{R}}^d \setminus \{\mathbf{0}\}$, where $\overline{\mathbb{R}} = \mathbb{R} \cup \{-\infty, \infty\}$. The symbol $\xrightarrow{v}$ stands for vague convergence of finite measues (see Kallenberg (1983))[2].

[2]Notice, that the definition of regular variation does not depend on the particular norm chosen in the sense that (2) holds for some norm if and only if it holds for every norm.

Intuitively, this measure means that asymptotically the d-dimensional process $\mathbf{X}$ can be represented by a product measure between a spectral measure, which describes the way how extreme movements of univariate marginals are related to each other, and a radial measure which has power decay. Knowledge of this measure facilitates the estimation of joint and conditional probabilities as the tail dependence coefficient.

In addition, the limiting measure has the scaling property

$$v\left(t\cdot\right) = t^{-\alpha} v\left(\cdot\right) \;\; t > 0. \tag{3}$$

As a consequence this measure does not put any mass on hyperplanes through infinity. In the next section we will make use of this property, which is often one of the most important effects of heavy tailed behavior, to propose an estimator for the tail dependence function for stationary sequences.

The multivariate definition (2) is crucial for the understanding of the finite-dimensional distributions of stock and foreign exchange markest, which are normally modelled by means of GARCH or stochastic volatility models. For instance, Davis and Mikosch (2009) for GARCH process and Davis and Mikosch (2008) for stochastic stochastic volatility model. Resnick and Starica (1998) show that the weak convergence of the tail empirical measure $v\left(\cdot\right)$ implies the consistency of Hill's estimator for a stationary sequence $\mathbf{X}$ whose marginal distribution is regularly varying, i.e, $\alpha > 0$. Using this results Starica (1999) propose a semiparametric estimates for the tail empirical measure of Constant Conditional Correlation GARCH, which embeds bivariate tail dependence information.

For our purposes it will be convenient to use a sequential definition of a regularly varying sequence $\mathbf{X}$ which is equivalent to the definition above: there exists a sequence $a_n \rightarrow \infty$ such that $\mathbb{P}\left(|\mathbf{X}| > a_n\right) \sim n^{-1}$, and an intermediate order sequence $k = o(n)$ ($n \to \infty$, $k/n \to 0$ as $k \to \infty$). Then, (2) holds for non-null Radon measures $v\left(\cdot\right)$ such that

$$\frac{n}{k}\mathbb{P}\left(a_n^{-1}\mathbf{X} \in \cdot\right) \xrightarrow{v} v\left(\cdot\right) \text{ for } k = o(n) \text{ as } n \to \infty, \tag{4}$$

Relation (4) is referred as the sequential definition of regular variation. Resnick and Starica (1998) suggest a naive estimate based on the empirical tail distribution. Different normalizations a_n are possible, yielding different limit measures ; however, all possible normalizations are asymptotically equivalent, and the limit measures only differ up to multiplicative constants. For instance for a bivariate vector (X, Y) the empirical estimate is given by

$$v_n = \frac{1}{k}\sum_{i=1}^{n} I\left\{X > X_{k,n}, Y > Y_{k,n}\right\} \tag{5}$$

where $X_{k,n}$ is the k-th upper order statistic of a sample $X_{n,n} \leq .... \leq X_{1,n}$, and this approximates a_n. In particular $v(\cdot)$ is a Poisson random measure whose mean depends on (X, Y) and is determined by the vague limit (4) (See Proposition 3.21 in Resnick, 1987). Consistency of this empirical measure is proved via the continuos maping theorem by applying two almost surely continuos maps in (5).

2.2 Extremal dependence in a strictly stationary sequence

The extremal behavior of a regularly varying vector (X, Y) is always determined by the limit measure $v(\cdot)$. It is therefore reasonable that any quantity trying to capture the tail dependence function should be a function of v. Observe that the definition of tail dependence function is directly related with the definition of regular variation. Indeed, the Radon measure in (4) is conected with the tail dependence function defined in (1) as follows

$$\begin{aligned} \lambda(x,y) &= \lim_{x,y\to\infty} \mathbb{P}\left(X > x \mid \; Y > y\right) \\ &= \lim_{x,y\to\infty} \mathbb{P}\left(X \in (x,\infty] \mid Y \in (y,\infty]\right) \end{aligned} \tag{6}$$

It is worth noting that standard arguments in regular variation allow one to replace $x = x_n a_n$ and $y = y_n b_n$ for suitably chosen of a_n, b_n in the second limit appearing in the last relation with any x_n and y_n sequence of numbers tending to ∞.

$$\begin{aligned} \lambda(x,y) &= \lim_{n\to\infty} \frac{\frac{n}{k}\mathbb{P}\left(a_n^{-1}X \in (x_n,\infty], b_n^{-1}Y \in (y_n,\infty]\right)}{\frac{n}{k}\mathbb{P}\left(b_n^{-1}Y \in (y_n,\infty]\right)} \\ &= \frac{v\left((x_n,\infty] \times (y_n,\infty]\right)}{v\left((x_n,\infty]\right)}. \end{aligned} \tag{7}$$

Observe that the above approach in the empirical application to the tail dependence function might not even be ocurrences falling into the set $(x_n,\infty] \times (y_n,\infty]$ for x_n, y_n large and will probably not do well estimating $\lambda(x,y)$. Even though there might be occurrences in the set $(x_n,\infty] \times (y_n,\infty]$, these are probably very few and the resulting estimate will be highly sample dependent.

The key point in our methodology is the scaling property (3) of the measure $v(\cdot)$. With this in mind we restart the previous derivation from (7) making use of the scaling property to estimate the same probability on an infinite square whose lower left corner always falls on the unit triangle, regardless how large x_n and y_n are chosen, guaranting enough obervations for good estimates. A valid estimate for such large quantiles x_n and y_n is proposed by De Haan and Ronde (1998) $x_n := \lim_{p\to 1} x_p = (k/n(1-p))^{1/\alpha_1}$ and $y_n := \lim_{q\to 1} y_q = (k/n(1-q))^{1/\alpha_2}$, where $\alpha_1, \alpha_2 > 0$ are tail indeces. Observe that now we deal with values $x_p$band y_q defined by means of quantile functions $p, q \in (0,1)$.

Replacing this estimates in (7) we obtain

$$
\begin{aligned}
\lambda(x,y) &= \frac{\frac{n}{k}\mathbb{P}\left(a_n^{-1}X \in (x_n,\infty], b_n^{-1}Y \in (y_n,\infty]\right)}{\frac{n}{k}\mathbb{P}\left(b_n^{-1}Y \in (y_n,\infty]\right)} \\
&= \frac{\frac{n}{k}\mathbb{P}\left(a_n^{-1}X \in (x_p,\infty], b_n^{-1}Y \in (y_q,\infty]\right)}{\frac{n}{k}\mathbb{P}\left(b_n^{-1}Y \in (y_q,\infty]\right)} \\
&= \frac{k}{n(1-q)}\frac{n}{k}\mathbb{P}\left(a_n^{-1}X \in \left(\left(\frac{k}{n}(1-p)\right)^{1/\alpha_1},\infty\right], b_n^{-1}Y \in \left(\left(\frac{k}{n}(1-q)\right)^{1/\alpha_2},\infty\right]\right)
\end{aligned}
$$

Define $m = \frac{k}{n}\left(\frac{2-p-q}{(1-p)(1-q)}\right)$, notice that due to the scaling property

$$
\begin{aligned}
\lambda(x,y) &= \frac{k}{n(1-q)}\frac{n}{km}\mathbb{P}\left(a_n^{-1}X \in \left(\left(\frac{k}{nm}(1-p)\right)^{1/\alpha_1},\infty\right], b_n^{-1}Y \in \left(\left(\frac{k}{nm}(1-q)\right)^{1/\alpha_2},\infty\right]\right) \\
&= \frac{k}{n(1-q)}\frac{n}{km}\mathbb{P}\left(a_n^{-1}X \in \left(\left(\frac{1-q}{2-p-q}\right)^{1/\alpha_1},\infty\right], b_n^{-1}Y \in \left(\left(\frac{1-p}{2-p-q}\right)^{1/\alpha_2},\infty\right]\right) \\
&= t\frac{n}{k}\mathbb{P}\left(a_n^{-1}X \in \left((1-t)^{1/\alpha_1},\infty\right], b_n^{-1}Y \in \left(t^{1/\alpha_2},\infty\right]\right) \\
&= tv\left(\left((1-t)^{1/\alpha_1},\infty\right] \times \left(t^{1/\alpha_2},\infty\right]\right) =: \lambda(t)
\end{aligned}
$$

where $t(2-p-q) = 1-p$, with $t \in (0,1)$. Thus, when $t \to 0$ in $\lambda(t)$ means that in (6) $x \to \infty$, $y = o(x)$ which implies that $\lambda(x,y) \to 0$, while in the other case, when $t \to 1$, implies that $y \to \infty$, $x = o(y)$ and $\lambda(x,y) \to 1$. Oberve that when $t = 0.5$ our methodology is equivalent to the classical definition of tail dependence for the same threhold levels, i.e., when $\lim_{x\to\infty} \mathbb{P}(X > x \mid Y > x)$.

In a bivariate framework, we propose the following empirical estimation of the tail dependence function based on (5)

$$\begin{aligned}\hat{\lambda}_n(t) &= tv_n\left(\left((1-t)^{1/\hat{\alpha}_1},\infty\right]\times\left(t^{1/\hat{\alpha}_2},\infty\right]\right)\\ &= \frac{t}{k}\sum_{i=1}^{n} I\left\{\frac{X}{X_{k,n}}>(1-t)^{1/\hat{\alpha}_1},\frac{Y}{Y_{k,n}}>t^{1/\hat{\alpha}_2}\right\} \quad t\in(0,1) \end{aligned} \tag{8}$$

We can see that this methodology is more sophisticated than the empirical distribution method. In addition the visualization of the tail dependence in different directions $t \in (0,1)$ is much more informative. Notice that the estimators are ready to use as soon as the parameter k is specified. However, the approach depends on the k-th upper order statistic of the sample to estimate the tail indices α_1, α_2. In practice, the choice of the number of exceedances k is a delicate matter. The reasonable choices can be identified by letting k vary over a suitable range and hoping for stability in estimates for small changes in k. The formal requirements on $k = o(n)$ are not much help in practice. One way to circumvent is given by the scaling property in (3) of the measure v. Observe that given a optimal number of exceedances k_n we can consequently estimate tail indices $\hat{\alpha}_1, \hat{\alpha}_2$, the empirical measure v_n and finally the conditional probability $\hat{\lambda}_n(t)$. The procedure steps with an example are given in the Appendix.

A major difficulty for the robustness of this methodology is the construction of credible standard errors for the tail empirical measure for the stationary case. In this paper, we employ the stationary bootstrap to overcome this problem. Moreover, we introduce hypotesis testing to distinguish constant VTD between periods from varying VTD functions. The use of the stationary bootstrap for the VTD functions and the resulting interpretations are illustrated in the empirical investigation.

2.3 Hypothesis testing

A key point to identify contagion is a significant increase in the VTD during the crisis episode. To this end, we define an equality test for the estimates of the tail dependence parameter $\lambda(t) = \lambda$ for $t \in (0,1)$. This will be based on the following T-statistics

$$T = \frac{\lambda_i - \lambda_j}{\sqrt{\hat{\sigma}^2(\lambda_i) + \hat{\sigma}^2(\lambda_j) - 2\widehat{cov}(\lambda_i, \lambda_j)}} \to N(0,1), \tag{9}$$

where i and j are two subsequent time periods. The null hypothesis is constant VTD for two different time periods ($H_0 : \lambda_i = \lambda_j$ for $i \neq j$). The asymptotic standard errors and covariances are obtained via a block bootstrap. The number of bootstrap replications is set equal to 1000. The limiting distribution of (9) directly follows from the limiting behaviour of the tail indices and the empirical measure v_n (see Resnick, 2006; Resnick and Starica, 1998). However, in the last case, the asymptotic normality still holds but with higher asymptotic variance. Because closed-form expression for the asymptotic standard deviations in the denominators of the test does not exist under general nonlinear time dependence, we applied a block bootstrap procedure[3].

A straightforward view of contagion is to observe a notable increase in co-movements to vanish in the aftermath of the crisis. A key point of analysis is therefore to identify significant changes in the tail dependence λ_i between the episodes of before-crisis (i=1), during-crisis (i=2) and after-crisis (i=3) period.

We will use the following notions: contagion as a significant increase in the VTD during the crisis period, i.e., for $\lambda_1 < \lambda_2$ the null hypothesis $H_0 : \lambda_1 = \lambda_2$ is rejected (write: $\lambda_1 \ll \lambda_2$). In contrast, any case where $H_0 : \lambda_1 = \lambda_2$ is not rejected will be called interdependence (write: $\lambda_1 \sim \lambda_2$). Temporary contagion is a sequence of a significant increase followed by a significant decrease of VTD (write: $\lambda_1 \ll \lambda_2 \gg \lambda_3$). The case of a significant decrease is also called a calming down tail dependence. As will be seen in our empirical results, there are few cases of lasting (write: $\lambda_1 \ll \lambda_2 \sim \lambda_3$), accelerating (write: $\lambda_1 \ll \lambda_2 \ll \lambda_3$), or finally accelerating (write: $\lambda_1 \sim \lambda_2 \ll \lambda_3$) type. Similarly, we observe also sequences of finally calming down type (write: $\lambda_1 \sim \lambda_2 \gg \lambda_3$).

3 Empirical application to the Asian Crisis

The set of results established in the last sections provides reliable and practical inference for extremal events. In this section we apply these results to the Asian financial markets. In this investigation we concentrate on daily observations of stock and foreign exchange returns evaluated in U.S. dollar from Thailand (BANGKOK S.E.T) [Th], the Philippines (PSEi) [Ph], Malaysia (JKSE) [Ma], Indonesia (KLSE) [In], Hong Kong (HANG SENG) [HK], South Korea (KOSPI) [SK], Singapore (STI) [Si] and Japan (NIKKEI) [Ja] as potential candidates for contagion. For the stock market The study of these two markets has important implications[4] from the point of view of interna-

[3]In order to obtain an optimal size for the block length, we follow the procedure proposed in Politis and White, 2004

[4]For instance, the dollar exchange rate has often been used to analyze stock prices in the belief that corporate earnings are significantly affected by fluctuations in the currency value (see, e.g, Kim, 2003)

tional diversification and, therefore, management of multi-currency equity portfolios. Furthermore, there exists a natural explanation to emphasize the relationship between equity and currency markets in each country. For instance, a collapse in equity values can lead to an outflow of foreign investment, which exerts downward pressure on the domestic currency. On the other hand, currency devaluation can disrupt the domestic financial sector, then the entire domestic economy, finally bringing the equity market to a collapse.

Other important aspect in this paper is the inclusion of developed markets in estimating the effects of contagion helps to provide a clearer picture of the propagation mechanisms. For example, during the Asian crisis, the behaviour of Japanese banks is said to play a role in spreading the crisis particularly to Indonesia, Malaysia and South Korea (Kaminsky and Reinhart 2001). In particular, when following the Thai devaluation those banks began to drastically curtail their lending to the affected Asian countries.

To make the difference between the tail dependence in assets within country and cross-country, we will define two types of tail dependence. The tail dependence between stock and foreign exchange markets in the same country will be called *intra-tail dependence*, while the tail dependence between stock and foreign exchange markets of different countries will be named *cross-tail dependence*. The full sample consists of 2632 daily return observations, from January 1, 1992 to December 31, 2001, which allow us to identify a sufficient number of extreme return observations to estimate statistical models for these rare events.

All return series were generated using the continuous compounding formula $X_t = \ln(\frac{P_t}{P_{t-1}})^2$, where P_t represents the price series at time t and X_t the squared log-returns as proxy for the volatiliy. In addition, the size sample also allows comparing results between the crisis period and the pre- and post- period of crisis. We follow the chronology of the IMF (Lindgren, 1999) to define the period of crisis from 2 July 1997 to 31 July 1999. In each period of analysis, for the definition of extremes events, we consider the 0.95- quantile of the squared of the returns as the threshold, i.e., $k_n = 132$. All data are taken from Datastream.

Different directions in the measure represented in (8) allow to capture a better measure of extreme events, however, in the following we concentrate on the directions 1/2 (the diagonal), since we are more interested in the dynamic aspect of strong co-movements. In order to analyze potential changes in co-movement of different markets, we consider three sub-samples. The period before the crisis is from January 1, 1992 to

1 July 1997, the period of crisis is from 2 July 1997 to 31 July 1999, and the period after the crisis is from 1 Agust 1999 to December 31, 2001.

Chronology of the Asian Financial Crisis

The Asian financial crisis was initiated by two episodes of currency depreciation that have occurred in March 1997. The first episode was a precipitous drop in the values of Thai baht, Malaysian ringgit, Philippine peso and Indonesian rupiah. As these currencies stabilized, the second episode began with downward pressures hitting the South Korean won, Singapore dollar, and Hong Kong dollar.

According to the International Monetary Fund (IMF)[5], the crisis was triggered by the floating of the Thai baht in 2 July 1997 followed by devaluations of other currencies and by the attack on the Hong Kong dollar in October 1997. Changing expectations led to the depreciation of most other currencies in the region, to bank runs and rapid withdrawals of foreign private capital, and to dramatic economic downturns. Finally, the end of the tremors of crisis was in July 1999.

In this complex framework of the 1997 financial crisis in Southeast Asia, two events stand out. The first one is the abandonment of the fixed exchange rate system in Thailand in mid of July. The second event was the Hong Kong stock market crash, at the end of October. Though part of the same process, the crash and its contagion effect on markets all over the world ended for good all hopes that the crisis could be circumscribed on a local level. Most European, American and Asian stock markets endured heavy losses.

In relation to the chronology of the crisis, only Thailand may be considered as the likely origin, due to the fact that Thailand was forced to abandon the exchange rate peg on 2 July 1997, a move that caused the Thai baht to plunge immediately as much as 15.2 % against the U.S. dollar. Within the period of July and August 1997, the Philippine peso, the Indonesian rupiah and the Malaysian ringgit were floated. The rapid and sharp depreciation of the ringgit subsequently led to the adoption of the pegged exchange rate regime in September 1998 and the imposition of capital controls by the government of Malaysia till February 1999, when control was replaced by graduating taxation. Figures 1 and 2 display the evolution of the stock and the foreign exchange

[5]See, e.g., C. Lindgren, Balino T., Enoch C, Gulde A.,Quintyn M. and Teo L. (1999).”Financial Sector Crisis and Restructuring Lessons from Asia”, Occasional Paper N° 188. International Monetary Fund

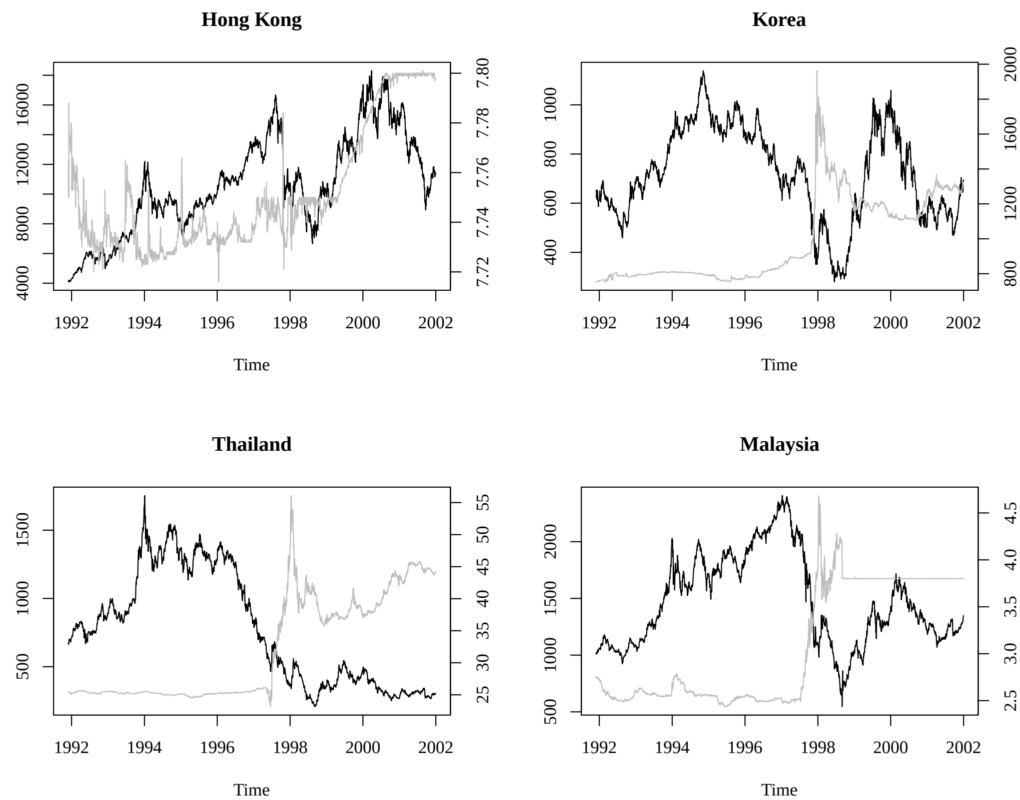

Figure 1: Stock and foreign exchange market indices for the countries under study. The line in black colour denotes the stock markets and the axes on the left shows the scale. The line in gray colour represents the foreign exchange index, where the scale on the right indicates the scale.

markets in each country for the sample under investigation. The figures clearly show for some countries increasing stock prices a few years before the Asian currency crisis while for other countries the behaviour of stock prices was relatively stable . Notice, that in all countries the stock market indices show price to decrease before the currencies were forced to abandon the exchange rate peg.

3.1 Intra-tail dependence

The question in this section is whether there are signs that the local stock market (foreign exchange market) tend to affect the current returns of its foreign exchange market (local stock market) in the crisis period. To this end, we analyse for each country the changes of structure in tail dependence between stock and foreign exchange

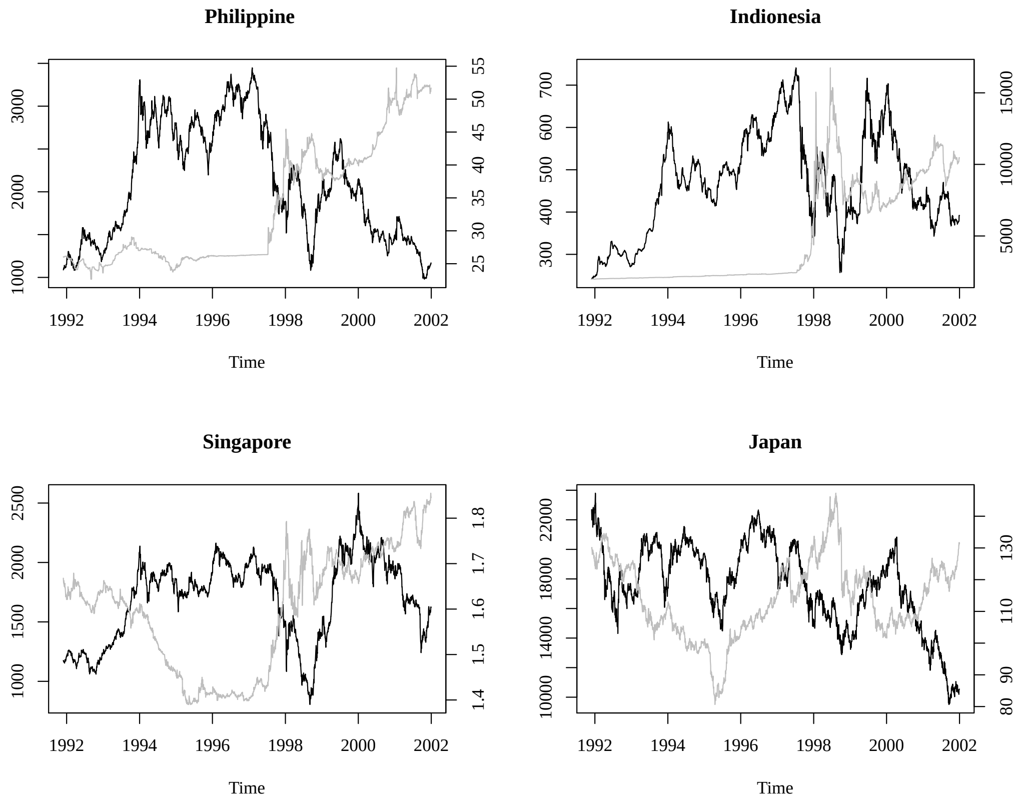

Figure 2: Stock and foreign exchange market indices for the countries under study. The line in black colour denotes the stock markets and the axes on the left shows the scale. The line in gray colour represents the foreign exchange index, where the scale on the right indicates the scale.

markets within country. The typical channel in which an extreme linkage between these two markets would arise is through the portfolio effect (see Gerlach and Smets 1995; Caramazza et al. 2004). For instance, if there were a sustained depreciation of the foreign exchange rate in a country, investors would substitute this currency for US Dollars, thus drawing liquid funds from the local stock exchange. The opposite occurs when a rising stock market attracts capital flows which increases the demand for domestic currency and causes exchange rates to appreciate.

We are interested in whether there was a change in the intra-tail dependence behaviour of the stock and foreign exchange markets during the period of crisis and whether this change can be interpreted as contagion or interdependence. Table 1 displays the results on the estimation of the tail dependence between asset classes for the three periods. The general trends in tail dependence between stock market and foreign exchange returns from 1997 to 1999 suggest several observations. First, the results indicate that extreme currency market returns and stock market returns are not tail independent events in all countries and periods. Furthermore, in contrast to Japan, all countries show an increasing intra-tail dependence at the beginning of the crisis period. Second, the most important intra-tail dependences are found for the Philippines, South Korea and Indonesia. The Hong Kong and Malaysian markets also show an increment in intra-tail dependence having a lasting effect after the crisis. Finally, the results for Thailand, Japan and Singapore show only interdependence as result of the dynamic intra-tail dependence estimation. These results between stock market and foreign exchange market are consistent with the observation that a capital flight of foreign investors leads first to crashing domestic stock markets, which is followed by a depreciation of the domestic currency if they pull theirs money out of this country.

3.2 Cross-tail dependence

In this section we are interested in determining whether contagion is presented among stock and foreign exchange markets from different countries. Our findings reveal fairly high level of cross-tail dependence during the period of investigation. The results for the foreign exchange and stock market combinations are displayed in tables 2 and 3.

For all country-pairs analysed, we observe asymptotic dependence, i.e., tail dependence greater than zero, in all cases during the period under study. In particular, the number of cases being asymptotically dependent increased sharply at the beginning of the crisis period, which has important consequences for portfolio managers who would particularly need the opportunities for diversification during such periods.

Cross-tail dependence between foreign exchange markets

The results of the test of constant tail dependence among foreign exchange markets are displayed in table 2. We found one pair displaying contagion: Hong Kong - Singapore and five pairs with strong contagion during the sample period: the Philippines - Indonesia, Philippines - South Korea, Indonesia - Malaysia, and Malaysia - Singapore. Notice that smaller economies tend to be more vulnerable to contagion, while larger economies do not tend to move closely. However, contagion is propagated through large economies (e.g., South Korea, Hong Kong and Singapore).

Considering the period of pre-crisis, we observe that among the pairs: the Philippines - Malaysia, South Korea - Malaysia, Thailand - Malaysia, the Philippines - Thailand, South Korea - Thailand, and South Korea - the Philippines, there exists marked cross-tail dependence which corresponds to the peg system adopted by the respective currencies. In the case of the pairs Japan - Singapore, Singapore - Thailand and, in minor degree, the pairs Thailand - Indonesia and Singapore - Indonesia we observe high tail dependence. This may be the consequence that the yen depreciated against the dollar in 1996 causing a general export slowdown in many Asian economies in the pre-crisis period calming down the respective currency demands (see Kochar et al., 1998).

For the period of crisis we find two defined patterns. The most pair combinations are characterized by an increase in the tail dependence which can be associated with the devaluation of the Thai baht in July 1997. Countries most affected were smaller countries (see e.g., the Philippines and Malaysia). In case of strong contagion the tail dependence increased about 20%. While for the majority of country combinations increasing tail dependence holds (17 out of 28). All the others do not show significant changes, so that we conclude for interdependence. This holds especially for the relation between yen, and the others Asian currencies: large currency markets seem to be relatively robust in case of regional foreign exchange turbulences.

Cross-tail dependence between stock markets

While most attention in the literature has been paid to currency markets where the contagion effects are rather limited according to our findings, least attention has been given to equity markets, where substantial contagion effects can be supposed. The results obtained in different investigations are mixed in relation to the methodology used and the importance of contagion effects found, (see e.g., Dungey et al., 2006 for a resume).

One possible explanation to the cause of contagion in stock markets can be due to the "wake-up call hypothesis" (see Kaminsky and Reinhart, 2000), which suggests that the initial crisis in a country serves as a wake-up call, leading investors to reassess the risks of other countries which share similar characteristics with the crisis country.

In this analyse, we share some results found by previous researches. In table 2 we resume the results of the estimation of the tail dependence for the three periods and the tests of constancy tail dependence. A particular result is that on average the tail dependence in stock markets is higher than in foreign exchange market for the sample under investigation. One explanation for the high degree of tail dependence in stock markets may be that the value of stocks is subject to common risk factor, which-according to theory- should be the same for different stock markets. On the contrary, foreign exchange markets depend on country-specific fundamentals, which probably deviate from each other, particularly in times of crisis. Thus, tail dependence of stock markets should be higher than for foreign exchange markets.

In the crisis period we observe an increment in the tail dependence for 20 out of 28 pairs of countries which seems to be associated with the turmoil in Hong Kong. After this mini crash, other extreme events quickly spread among Asian stock markets making contagion quite likely to hold. Though there was always higher tail dependence between the Hong Kong and the other stock markets in the region, none of these increases can be characterized as contagion. In total, only five combinations indicate statistically significant changes, all in terms of strong contagion: Thailand - South Korea, the Philippines - Singapore, Malaysia - Indonesia, Malaysia - South Korea, and Hong Kong - Singapore.

The extreme events in each stock market return occur in the months of October 1997 through January 1998. In fact, the extreme jumps on October 28, when the Hong Kong market collapses, with seven out of the nine countries posting losses averaging about 9.1 percent. During November and December, a total of 51 large movements have been observed, of which 29 were negative.

We observe that the most of the cross-tail dependences varying between 0.22 and 0.51 among the affected countries. We also emphasise the role of Singapore and Malaysia markets in helping to transmit the contagion effects around the region. Before the crisis Singapore had only increasing tail dependence with Malaysia and the Philippines while in the crisis period the number had been increased to other four countries.

Further, contagion between Hong Kong and Singapore is found to be highly significant. In particular, cross-tail dependence in equity markets during the Asian crisis is always stronger among the Singapore and the other Asian economies. This result is consistent with the hypothesis that developed markets are a conduit for financial contagion to under developing markets as suggested in Kaminsky and Reinhart (2007). However, contrary to this work, where Japan is seen as the financial center, in this paper surprisingly Japan does not play any role in the crisis transmission showing only interdependence among all countries.

Cross-tail dependence between stock and foreign exchange markets

One of the most remarkable features of the Asian crisis is the simultaneous fall of currency and stock prices in the region. Rigobon and Sack (2003) investigated these contemporaneous responses of daily return of stock prices from 1994 to 2001 in Latin American and Asian countries. They found that the contemporaneous interactions between stock prices and exchange rates of these two markets are stronger when markets are more volatile.

Our results are displayed in table 3. When passing from pre-crisis to crisis period, 43 of 56 pairs of combinations show an increment in the cross-tail dependence. Furthermore, 36 of the 46 pairs show some degree of decrease in cross-tail dependence when passing to the post-crisis period. However, only 20 pairs show strong contagion in relation to the test hypothesis. Notice that according to the chronology of the crisis the first countries to be affected by the crisis were Thailand, Malaysia and the Philippines, all showing contagious effects to other countries' asset markets.

A major result in observing the tail dependence between the two asset markets in different countries is the increasing interaction of the Hong Kong stock market and the foreign exchange markets of all other countries except Japan, after the mini-crash. This increase was significant for Malaysia and Indonesia where, in addition, contagion holds within country (see table 1) and also between their domestic stock markets and the Hong Kong market (table 2). A similar result holds for Singapore showing strong contagion of stock markets with respect to Hong Kong. For the other Asian countries we observe this increase typically being accompanied by respective country contagion (intra-tail dependence) or stock market contagion with respect to Hong Kong. The only exception is Thailand where the asset markets had been pulled down earlier.

4 Conclusions

This paper presents a semiparametric framework to evaluate contagion by means of tail dependence analysis. We introduce a new dependence function, which allows us to capture the complete extreme dependence structure and does not impose the iid assumption. Thus, we test for the presence of contagion in the international propagation of financial shocks during the episode of financial turmoil in the Asian crisis.

According to the tail dependence analysis, we can distinguish between interdependence and contagion. For any Asian country, with exception of Japan, the crisis event led to stronger co-movements among the asset markets calming down thereafter, revealing cases of contagion for the majority of countries.

Similarly, the wave of currency depreciations, starting with the Thai baht, made foreign exchange markets of small countries more likely to co-move with foreign exchange markets of large economies, especially Hong Kong and Singapore, but not Japan. Large currency markets seem to be more robust in case of regional currency turbulences.

In the case of stock markets, the mini-crash of October 1997 in Hong Kong is reflected in increasing tail dependencies, conducting to contagion when related to the stock markets of Hong Kong or Singapore. This result is consistent with Kaminsky and Reinhart (2007).

Finally, in the wave of the mini-crash, we observe Hong Kong's stock market inducing strong co-movements with the foreign exchange markets of all other Asian countries, except Japan, typically accompanied by contagion within the respective country or by stock market contagion among the respective country and Hong Kong.

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A Estimation procedure to estimate empirical estimation of the tail dependence function

The procedure steps to estimate the empirical VTD function based on (5) are as follows:

1. Replace k for a fixed and optimal k_n, then estimate the tail indices $\hat{\alpha}_j$ based on the k-th upper order statistic of each marginal. This can be done by methods such as the Hill or Pickand estimator (see Embrechts et al., 1997).

2. Substitute the estimators $\hat{\alpha}_j$ into (8).

3. If k_n is chosen wisely, for any value of $w \in (0, \infty]$ the scaling property should hold

$$v_n(w\cdot) = w^{-1} v_n(\cdot).$$

In our case, we defined the Radon measure as

$$v_n\left(\left((1-t)^{1/\hat{\alpha}_1}, \infty\right] \times \left(t^{1/\hat{\alpha}_2}, \infty\right]\right).$$

Then, for fixed t and a good choice of k_n we graph

$$\left\{ \frac{v_n\left(\left((w-tw)^{1/\hat{\alpha}_1}, \infty\right] \times \left(tw^{1/\hat{\alpha}_2}, \infty\right]\right)}{wv_n\left(\left((1-t)^{1/\hat{\alpha}_1}, \infty\right] \times (t^{1/\hat{\alpha}_2}, \infty]\right)}, w \in (0, 5] \right\}, \tag{10}$$

which we call Starica plot[6].

The idea is that the ratio should be roughly constant for any $w > 0$ in a neighbourhood of 1 if k_n is chosen wisely. The plots will look differently for different values of k_n. Therefore we will choose the k_n for which the scaling property is more evident. Thus, we obtain a simultaneous solution for the problem of estimation of k, α and v_n.

A toy example

In this section we show how to estimate the VTD function by means of the empirical measure (8). To this end we estimate the VTD function between two stock markets,

[6]From a theoretical point of view the homogeneity property should hold for each value of w in the interval $w \in (0, \infty]$. However, because the results are obtained asymptotically in a finite sample, we defined arbitrary a small interval for the range w where the homogeneity property holds.

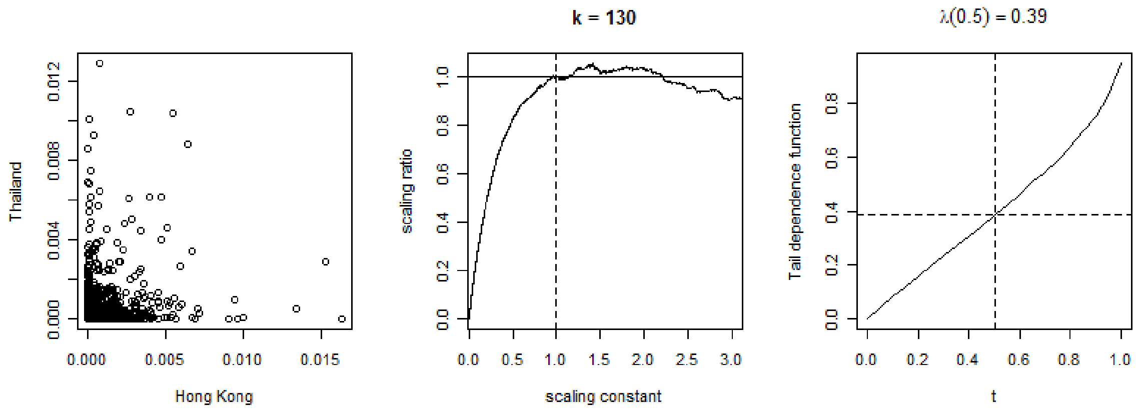

Figure 3: From left to rigth: Scatter plots of the squared log-returns of the Hong Kong and Thailand stock markets, Starica plot for $k_n = 130$, and the estimated Tail dependence function.

Hong Kong (Hang Seng) and Thailand (Bangkok SET). In this example we concentrate on daily observations from January 1, 1992 to 1 July 1997. The length of this serie is 2631. Time series of financial returns often show little dependence when returns are small. However, when returns are larger and more extreme in squared value, then there is more pronounced dependence between the components.

Figure 3 gives on the left, a scatter plot of the squared log-daily returns for the two stock markets. The key point in the estimation is the selection of the number of exceedances k_n. First, we concentrate on $t = 0.5$ and we make a plot based on (10) for various values of k_n and choose the k_n which seems to have the plost most closely hugging the horizontal line at height 1. As a result of our diagnostics we fixed $k_n = 130$, which represents about 5 % of the data[7]. Based on this number of exceedances we estimate both tail indices by means of the Hill's estimator. We obtain $\hat{\alpha}_1 = 1.57$ for Hong Kong and $\hat{\alpha}_2 = 1.65$ for Thailand. With these results we are in conditions to estimate the VTD function, in Figure 3 we can see the resulting estimated tail dependence function for differents values of $t \in (0, 1)$.

[7]We observe for this example that for $k_n \in [120, 140]$, the tail empirical measure gives the same results.

B Tables

Tail dependence	Pre-Crisis		Crisis		Post-Crisis		T-test	
	λ_1	std	λ_2	std	λ_3	std	$\lambda_1 = \lambda_2$	$\lambda_2 = \lambda_3$
Thailand	0.22	0.08	0.23	0.11	0.25	0.07	-1.05	-1.21
The Philippines	0.28	0.10	0.41	0.15	0.29	0.11	**-1.95	*1.91
Malaysia	0.21	0.07	0.31	0.12	0.32	0.13	*-1.76	-1.09
Indonesia	0.24	0.10	0.36	0.13	0.21	0.11	**-1.97	**1.96
Hong Kong	0.27	0.14	0.46	0.11	0.38	0.17	*-1.65	1.59
South Korea	0.19	0.09	0.41	0.16	0.21	0.07	**-2.01	**1.99
Singapore	0.22	0.12	0.31	0.14	0.24	0.15	-1.43	1.35
Japan	0.21	0.07	0.19	0.06	0.18	0.08	1.51	1.43

Table 1: Results for the intra-tail dependence for the Asian countries. The test is asymptotically normal in large samples and two-sided rejections at the 10, 5 and 1 percent significance level are denoted by *, ** and ***, respectively. We assume before July 1997 (January 1992 - July 1997) to be the pre-crisis period and after August 1999 (August 1999 - December 2001) the post-crisis period. The approximated crisis period is from 2 July 1997 to 31 July 1999.

Country pair	Asset pair	Pre-Crisis λ_1	std	Crisis λ_2	std	Post-Crisis λ_3	std	T-test $\lambda_1 = \lambda_2$	$\lambda_2 = \lambda_3$	Country pair	Asset pair	Pre-Crisis λ_1	std	Crisis λ_2	std	Post-Crisis λ_3	std	T-test $\lambda_1 = \lambda_2$	$\lambda_2 = \lambda_3$
Th vs Ph	FX - FX	0.58	0.21	0.41	0.11	0.35	0.09	**1.98	1.56	Ma vs In	FX - FX	0.24	0.06	0.41	0.12	0.21	0.08	**-2.01	**2.14
	S - S	0.39	0.12	0.40	0.09	0.39	0.12	-0.91	0.81		S - S	0.35	0.09	0.39	0.13	0.28	0.15	*-1.88	**1.98
Th vs Ma	FX - FX	0.51	0.21	0.38	0.12	0.33	0.13	1.92	0.98	Ma vs HK	FX - FX	0.23	0.11	0.24	0.09	0.19	0.08	-0.98	1.61
	S - S	0.37	0.11	0.27	0.08	0.25	0.11	1.56	1.09		S - S	0.31	0.10	0.29	0.11	0.24	0.09	1.05	1.41
Th vs In	FX - FX	0.31	0.15	0.35	0.14	0.32	0.12	-1.45	1.41	Ma vs SK	FX - FX	0.39	0.09	0.41	0.13	0.29	0.12	-1.54	*1.89
	S - S	0.39	0.10	0.38	0.09	0.31	0.13	1.06	1.42		S - S	0.19	0.07	0.35	0.11	0.26	0.07	**-1.98	**1.96
Th vs HK	FX - FX	0.21	0.09	0.22	0.10	0.20	0.07	-0.88	0.95	Ma vs Si	FX - FX	0.36	0.14	0.40	0.11	0.32	0.16	*-1.91	**1.99
	S - S	0.39	0.13	0.38	0.11	0.36	0.14	0.97	1.31		S - S	0.42	0.15	0.41	0.09	0.34	0.10	0.98	**1.98
Th vs SK	FX - FX	0.29	0.12	0.28	0.12	0.29	0.13	0.85	-0.81	Ma vs Ja	FX - FX	0.21	0.08	0.23	0.12	0.24	0.07	-1.01	-0.83
	S - S	0.21	0.07	0.29	0.10	0.32	0.11	**-1.98	*-1.68		S - S	0.22	0.09	0.26	0.11	0.25	0.12	-1.56	0.91
Th vs Si	FX - FX	0.37	0.15	0.38	0.08	0.37	0.09	-1.08	1.21	In vs HK	FX - FX	0.21	0.07	0.22	0.08	0.23	0.09	-0.65	-0.76
	S - S	0.41	0.09	0.38	0.11	0.35	0.12	1.33	1.45		S - S	0.36	0.11	0.38	0.13	0.37	0.12	-0.92	0.84
Th vs Ja	FX - FX	0.42	0.14	0.19	0.12	0.22	0.11	**1.98	-0.94	In vs SK	FX - FX	0.32	0.09	0.33	0.05	0.32	0.07	-0.51	0.60
	S - S	0.25	0.09	0.29	0.13	0.28	0.10	-1.43	0.87		S - S	0.28	0.05	0.29	0.07	0.30	0.03	-0.65	-0.71
Ph vs Ma	FX - FX	0.61	0.21	0.45	0.15	0.21	0.08	*1.91	*1.93	In vs Si	FX - FX	0.42	0.12	0.43	0.15	0.40	0.14	-0.98	1.11
	S - S	0.39	0.12	0.41	0.11	0.31	0.08	-1.05	**1.97		S - S	0.41	0.11	0.42	0.09	0.37	0.13	-1.02	1.39
Ph vs In	FX - FX	0.23	0.08	0.41	0.14	0.21	0.09	**-2.31	**2.42	In vs Ja	FX - FX	0.31	0.13	0.27	0.10	0.22	0.11	1.43	1.56
	S - S	0.39	0.13	0.38	0.15	0.31	0.10	0.74	*1.75		S - S	0.27	0.08	0.29	0.07	0.28	0.08	-0.91	1.03
Ph vs HK	FX - FX	0.31	0.07	0.33	0.16	0.25	0.12	-1.05	1.24	HK vs SK	FX - FX	0.23	0.08	0.24	0.10	0.22	0.08	-1.02	0.97
	S - S	0.38	0.09	0.42	0.11	0.36	0.14	-1.45	1.43		S - S	0.27	0.11	0.29	0.13	0.34	0.10	-0.92	-1.64
Ph vs SK	FX - FX	0.31	0.13	0.34	0.16	0.30	0.15	-1.65	1.76	HK vs Si	FX - FX	0.28	0.09	0.31	0.14	0.25	0.13	*-1.65	1.54
	S - S	0.23	0.07	0.25	0.08	0.27	0.09	-0.91	-0.88		S - S	0.40	0.12	0.51	0.14	0.45	0.11	*-1.87	*1.77
Ph vs Si	FX - FX	0.30	0.18	0.29	0.15	0.23	0.14	0.89	1.55	HK vs Ja	FX - FX	0.21	0.05	0.19	0.09	0.17	0.07	0.94	0.91
	S - S	0.35	0.12	0.42	0.14	0.36	0.10	*-1.91	**2.21		S - S	0.27	0.10	0.30	0.11	0.36	0.12	-1.43	-1.36
Th vs Ja	FX - FX	0.21	0.07	0.22	0.08	0.23	0.07	-0.93	-0.89	SK vs Si	FX - FX	0.31	0.08	0.30	0.09	0.28	0.11	0.97	1.21
	S - S	0.24	0.11	0.25	0.09	0.23	0.08	-1.02	1.24		S - S	0.21	0.09	0.31	0.08	0.38	0.15	-1.49	-1.89
Ma vs In	FX - FX	0.24	0.06	0.41	0.12	0.21	0.08	**-2.01	**2.14	SK vs Ja	FX - FX	0.33	0.15	0.21	0.13	0.19	0.11	1.01	1.23
	S - S	0.35	0.09	0.39	0.13	0.28	0.15	*-1.88	**1.98		S - S	0.25	0.12	0.27	0.10	0.29	0.09	-0.92	-0.83

Table 2: Results for the cross-tail dependence for the Asian countries between the same asset classes. The test is asymptotically normal in large samples and two-sided rejections at the 10, 5 and 1 percent significance level are denoted by *, ** and ***, respectively. We assume before July 1997 (January 1992 - July 1997) to be the pre-crisis period and after August 1999 (August 1999 - December 2001) the post-crisis period. The approximated crisis period is from 2 July 1997 to 31 July 1999.

Country	Asset	Pre-Crisis		Crisis		Post-Crisis		T-test		Country	Asset	Pre-Crisis		Crisis		Post-Crisis		T-test	
pair	pair	λ_1	std	λ_2	std	λ_3	std	$\lambda_1=\lambda_2$	$\lambda_2=\lambda_3$	pair	pair	λ_1	std	λ_2	std	λ_3	std	$\lambda_1=\lambda_2$	$\lambda_2=\lambda_3$
Th vs Ph	FX - S	0.22	0.07	0.31	0.12	0.24	0.10	**-1.99	*1.87		S - FX	0.24	0.09	0.31	0.11	0.21	0.09	**-1.96	*1.91
	S - FX	0.21	0.09	0.26	0.10	0.24	0.11	*-1.85	0.91	Ma vs HK	FX - S	0.21	0.08	0.29	0.09	0.23	0.07	**-1.99	*1.92
Th vs Ma	FX - S	0.21	0.08	0.25	0.07	0.23	0.09	-1.35	1.22		S - FX	0.29	0.14	0.28	0.16	0.38	0.13	0.75	*-1.97
	S - FX	0.22	0.07	0.24	0.08	0.23	0.04	-1.02	0.97	Ma vs SK	FX - S	0.21	0.11	0.29	0.10	0.19	0.12	**-1.96	**2.10
Th vs In	FX - S	0.23	0.08	0.26	0.10	0.23	0.09	-0.98	1.10		S - FX	0.20	0.08	0.33	0.13	0.25	0.10	**-2.21	**2.11
	S - FX	0.20	0.10	0.23	0.09	0.19	0.08	-1.09	1.25	Ma vs Si	FX - S	0.21	0.07	0.25	0.09	0.27	0.11	-1.64	-1.43
Th vs HK	FX - S	0.25	0.12	0.27	0.17	0.42	0.16	-0.97	**-1.97		S - FX	0.27	0.09	0.30	0.10	0.25	0.13	*-1.84	*1.91
	S - FX	0.23	0.09	0.31	0.11	0.21	0.08	*-1.76	*1.88	Ma vs Ja	FX - S	0.21	0.06	0.22	0.06	0.23	0.05	-0.73	-0.81
Th vs SK	FX - S	0.22	0.07	0.21	0.07	0.23	0.06	0.82	-0.89		S - FX	0.19	0.07	0.23	0.05	0.19	0.06	-1.08	1.05
	S - FX	0.23	0.08	0.22	0.04	0.24	0.07	0.78	-0.76	In vs HK	FX - S	0.23	0.09	0.29	0.11	0.24	0.08	*-1.87	*1.79
Th vs Si	FX - S	0.21	0.11	0.29	0.13	0.24	0.12	*-1.95	*1.90		S - FX	0.32	0.12	0.35	0.14	0.41	0.12	-1.32	-1.44
	S - FX	0.23	0.09	0.24	0.12	0.25	0.09	-0.98	-0.91	In vs SK	FX - S	0.21	0.06	0.29	0.12	0.23	0.11	*-1.87	*1.89
Th vs Ja	FX - S	0.28	0.14	0.25	0.11	0.24	0.09	1.43	0.78		S - FX	0.23	0.09	0.27	0.11	0.23	0.11	*-1.82	*1.78
	S - FX	0.23	0.08	0.25	0.09	0.24	0.08	-1.37	1.32	In vs Si	FX	0.23	0.10	0.32	0.09	0.26	0.09	**-2.21	*1.97
Ph vs Ma	FX - S	0.21	0.16	0.33	0.12	0.27	0.09	**-1.97	*1.85		S	0.24	0.12	0.31	0.08	0.25	0.11	**-2.02	*1.96
	S - FX	0.23	0.07	0.26	0.10	0.25	0.08	*-1.76	1.53	In vs Ja	FX - S	0.31	0.07	0.28	0.08	0.29	0.12	0.96	-0.87
Ph vs In	FX - S	0.26	0.09	0.41	0.13	0.24	0.08	**-2.03	**2.23		S - FX	0.19	0.09	0.20	0.09	0.22	0.10	-0.86	-1.22
	S - FX	0.22	0.08	0.26	0.11	0.23	0.09	-1.03	0.97	HK vs SK	FX - S	0.25	0.08	0.24	0.07	0.26	0.11	0.87	-0.98
Ph vs HK	FX - S	0.29	0.11	0.32	0.12	0.27	0.13	-0.97	1.45		S - FX	0.31	0.12	0.33	0.15	0.42	0.12	-1.02	-1.89
	S - FX	0.30	0.13	0.31	0.14	0.40	0.10	-0.82	**-2.01	HK vs Si	FX - S	0.39	0.15	0.31	0.13	0.38	0.14	**1.99	**-2.01
Ph vs SK	FX - S	0.31	0.11	0.32	0.09	0.21	0.08	-1.01	*1.65		S - FX	0.28	0.08	0.37	0.10	0.25	0.09	**-2.25	**2.31
	S - FX	0.25	0.09	0.24	0.08	0.23	0.10	0.89	0.81	HK vs Ja	FX - S	0.31	0.11	0.25	0.09	0.39	0.12	1.12	-2.02
Ph vs Si	FX - S	0.39	0.15	0.40	0.11	0.28	0.12	-1.57	**2.21		S - FX	0.23	0.09	0.22	0.08	0.23	0.11	0.87	-0.81
	S - FX	0.30	0.13	0.32	0.10	0.27	0.09	*-1.89	**1.96	SK vs Si	FX - S	0.25	0.14	0.27	0.11	0.29	0.09	*-1.79	-1.17
Th vs Ja	FX - S	0.25	0.12	0.23	0.08	0.24	0.07	0.94	-0.71		S - FX	0.24	0.12	0.28	0.15	0.22	0.13	*-1.89	**1.96
	S - FX	0.18	0.07	0.21	0.09	0.19	0.07	-1.43	1.31	SK vs Ja	FX - S	0.22	0.07	0.30	0.10	0.25	0.09	**-1.98	*1.67
Ma vs In	FX - S	0.23	0.09	0.34	0.12	0.24	0.07	**-2.01	**1.99		S - FX	0.24	0.09	0.21	0.11	0.22	0.08	1.04	-0.94
	S - FX	0.24	0.09	0.31	0.11	0.21	0.09	**-1.96	*1.91	Si vs Ja	FX - S	0.22	0.11	0.31	0.12	0.27	0.10	**-1.99	*1.65
Ma vs In	FX - S	0.23	0.09	0.34	0.12	0.24	0.07	**-2.01	**1.99		S - FX	0.31	0.14	0.22	0.10	0.24	0.12	*1.95	-1.48

Table 3: Results for the cross-tail dependence for the Asian countries between different asset classes. The test is asymptotically normal in large samples and two-sided rejections at the 10, 5 and 1 percent significance level are denoted by *, ** and ***, respectively. We assume before July 1997 (January 1992 - July 1997) to be the pre-crisis period and after August 1999 (August 1999 - December 2001) the post-crisis period. The approximated crisis period is from 2 July 1997 to 31 July 1999.