EAST ASIAN FINANCIAL CONTAGION UNDER DCC-GARCH

J. H. Cho and A. M. Parhizgari
Florida International University

Abstract

We reconsider the definition and measurement of contagion by analyzing the 1997 East Asian financial crisis in the equity markets of eight countries using dynamic conditional correlation (DCC). Taking Thailand and Hong Kong as alternative sources of contagion, a total of fourteen source-target pairs is analyzed. We define contagion as the statistical break in the computed DCCs as measured by the shifts in their means and medians. In the DCC process, the parameters of each pair of source-target country contagion are allowed to vary and be dictated by the data. Contagion is tested using DCC means and medians difference tests. Our findings indicate the presence of contagion in the equity markets across all the fourteen pairs of source-target countries that are considered.
Key words: Contagion, East Asian financial markets, Dynamic conditional correlation

JEL Classification Codes: G15, F36, C51

1. Introduction

Defining an evolutionary process in the context of cross-country analyses, the term contagion has gone through a gradual refinement and measurement process only in the last two decades or so. In the early days, a simple (static) measure of correlation, for instance, between the stock return series of two countries, was deemed informative enough to establish the relation between their respective equity markets, and thereby aid in decisions on cross-country portfolio diversification. The construction of such portfolios has indeed been geared, for the most part, to a static measure of correlation.

Further developments in correlation analyses have progressively led into new measures and techniques including co-movements, causality, error-correction models, and co-integration among cross-country return series (see, among others, Pascual, 2003; Darbar and Deb, 1997; Karolyi and Stulz, 1996; and Parhizgari et al., 1994). By now, it is well recognized that estimates of correlations may require further statistical refinements (Forbes and Rigobon,

2002) and that such estimates should consider the dynamic, i.e., the time-varying, aspect of correlations (Engle, 2002). This latter feature may be exploited in identifying and measuring contagion among cross-country markets.

The anatomy of a cross-country financial crisis and thereby contagion is not expected to be the same in all instances and for all time periods. Yet, given a set of countries with some common interaction variables, financial distress or bad news in a segment of a county's market, for instance in its equity market, generally leads into gradual increases in the volatility in the returns of that country. During the early periods, the changes in the volatilities and its associated variables are confined within each country. Not much cross-border effect is discerned during the early periods. With the spread of the news, the global aspects of such changes in volatility start brewing, leading possibly into contagion. It is often hard to pinpoint when, and sometimes where, exactly the cross-border transmission starts. The global transmission, if any, resembles more of a gradual or an evolutionary process with bi-feedback than a sudden one-time transmission.

The above process can not be fully captured by a simple or static measure of correlation. It needs a different type of analysis, i.e. one that is dynamic enough to account for the continuous changes in the market. We thus start with the assumption of time-varying correlations and resort to Engle's (2002) dynamic conditional correlations (DCC, henceforth). We believe DDC, particularly with GRCH(1,1), fits the transmission process of contagion very well.

The application of DCC to contagion in general, and to the East Asian financial markets in particular, is fairly recent. The existing literature on contagion includes one study (Chiang et al., 2005) using DCC for the Asian markets. Though we also employ DCC, our approach is somewhat different from theirs. For example, they assume the same parameters for each pair of contagion source and target countries in the correlation process while we do let the parameters to differ across pairs of countries. Furthermore, our approach for testing contagion is very different. They use regression method with dummy variables to examine if there are any significant increases in DCC. We use mean difference t-tests and median difference z-tests for this purpose. Finally, the length of the period under our coverage is different (longer).

The remaining parts of this paper are organized as follows. Section 2 provides a brief review of the literature. Section 3 presents the methodology that is employed. Section 4 provides information on the data input and section 5 contains the empirical results. The last section offers the summary and conclusions.

2. Prior literature

Contagion is variously defined (see, for instance, Pericolo and Sbracia, 2001). Among the several definitions, the most commonly prevailed one is the existence of some degree of excess co-movement which cannot be explained by the

fundamentals. This type of contagion is often referred to as pure contagion (see Kumar and Persaud, 2002).

Apart from the variety of the definitions that could be forwarded as viable alternatives (see Moser, 2003; Pasquariello, 2007; Castiglionesi, 2007), the measurement of contagion has also proved to go far beyond the simple static estimate of the correlation coefficients (see, for instance, Diebold andYilmaz, 2007; Forbes and Rigobon, 2002; and Boyer et al., 1999). For example, Boyer et al. (1999) make some adjustments in the correlations to account for volatility. Forbes and Rigobon (2002), examining the 1994 Mexican peso crisis and the 1997 Asian financial crisis, estimate a set of cross-market correlation coefficients to measure the extent of co-movements between a contagion source country and a group of target countries. They correct the bias in the correlation coefficient that arises from the increased volatility during the turmoil period. Their results indicate the presence of contagion when the correlation coefficients are not adjusted for volatility. This finding is reversed when the volatility-adjusted correlation coefficients are considered. Under such adjustment, the co-movements among the source and the target countries do not increase significantly during the turmoil periods. Forbes and Rigobon's interpretation is that the continued high level of market correlation is not contagion; it arises simply due to strong linkages among them.

Considering the complexities in measuring contagion, there are two main issues with Forbes and Rigobon's (2002) approach that deserve reconsideration. First, they do not adjust volatility ***continuously***. It has increasingly been accepted that time-varying volatility is one of the stylized facts of stock returns (see Tse and Tsui, 2002). Second, their test results of co-movement difference between the stable and turmoil periods can be different for different lengths of the turmoil period (see, Chiang *et al*., 2005).

Other complexities have also presented themselves. First, nearly all stock returns exhibit some degree of skewness and kurtosis (see, for instance, Chiang, Table 1, p. 38). This violates the assumption of normality that underlies some of the tests that are employed. Second, identification of the break point to establish the beginning of the contagion period could carry some ambiguity. Most prior research starts with pre-assigned break points. Third, the period of study, i.e., the length of the overall, stable, and turmoil periods, could make a difference in the results (see, for instance, Forbes and Rigobon, 2002 and Chiang, 2005). Fourth, differences in time zones and operating hours have raised questions about the accuracy of contagion measurement. This has prompted the researchers to examine them separately. Fifth, inclusion or exclusion of global variables has also expanded the dimension of contagion analysis. Finally, the currency factor has posed an additional problem. Some studies have used indices in local currencies, a practice that suffers from the lack of consistency in units of measurement.

3. Methodology

DCC(1,1)–GARCH(1,1) developed by Engle (2002) and Engle and Sheppard (2001) are employed to examine the time-varying correlation coefficients. Mean

difference t-test and median difference Wilcoxon z-test are used to investigate whether there are significant differences in the estimated time-varying correlation coefficients between the stable and the turmoil periods. Since the volatility is adjusted by the procedure, the time-varying correlation (or dynamic conditional correlation or DCC) does not have any bias from volatility. Unlike the volatility-adjusted cross-market correlations employed in Forbes and Rigobon (2002), DCC-GARCH continuously adjusts the correlation for the time-varying volatility. Hence, DCC provides a superior measure of correlation.

Estimation of the dynamic correlation coefficients follows three steps. The first step consists of a demeaning process (see Engle and Sheppard, 2001) whereby the residual returns are obtained. The regression model that we have employed for this process is:

$$r_t = a_0 + a_1 r_{t-1} + a_2 r_{t-1}^{S\&P} + \varepsilon_t \tag{1}$$

where r_t is the returns of local stock index and $r_{t-1}^{S\&P}$ is the U.S. S&P 500 composite index. Inclusion of the latter variable is to capture the effect of a global market factor. The existing literature supports a near consensus position that the U.S. equity markets have statistically significant influence on the Asian markets.

In the second step, the parameters in the variance models are estimated using the residual returns (ε_t) from the first step. A standard GARCH model is employed such that:

$$\varepsilon_t = D_t v_t \sim N(0, H_t) \tag{2}$$

where ε_t is a k x 1 column vector of residual returns of r_t, k is the number of countries considered, v_t and is k x 1 a column vector of standardized residual returns. H_t is a k x k matrix of time-varying variances. Specifically,

$$H_t = D_t R_t D_t \tag{3}$$

where R_t is a k x k matrix of time-varying correlations. D_t is a k x k diagonal matrix of time-varying standard deviations of residual returns. The variances are obtained with univariate GARCH (1,1) processes. Specifically,

$$h_t = b_0 + b_1 \varepsilon_{t-1}^2 + b_2 h_{t-1}^2 \tag{4}$$

The log-likelihood function to determine the parameters in (4) and (6) is given below.

$$l = -0.5 \sum_{t=1}^{T} \left(n \log(2\pi) + \log\left(|H_t|\right) + \varepsilon_t' H_t \varepsilon_t \right)$$

$$= -0.5 \sum_{t=1}^{T} \left(n \log(2\pi) + \log\left(|D_t R_t D_t|\right) + v_t' D_t^{-1} R_t^{-1} D_t^{-1} v_t \right)$$

Since , $\varepsilon_t' D_t^{-2} \varepsilon_t = \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t = \left(D_t^{-1}\varepsilon_t\right)' D_t^{-1}\varepsilon_t = v_t' v_t$,

$$l = -0.5\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log\left(|D_t|\right) + \varepsilon_t' D_t^{-2}\varepsilon_t\right) - 0.5\sum_{t=1}^{T}\left(\log\left(|R_t|\right) + \varepsilon_t' R_t^{-1}\varepsilon_t - v_t' v_t\right)$$
$$= l_1 + l_2 \tag{5}$$

Where:

$$l_1 = -0.5\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log\left(|D_t|\right) + \varepsilon_t' D_t^{-2}\varepsilon_t\right) \tag{6}$$

$$l_2 = -0.5\sum_{t=1}^{T}\left(\log\left(|R_t|\right) + \varepsilon_t' R_t^{-1}\varepsilon_t - v_t' v_t\right) \tag{7}$$

As is shown above, log-likelihood function is separated into log-likelihood function of variances and that of correlations. The parameters of variances in l_1 are determined without simultaneous determinations of the correlation parameters by maximizing l_1.

In the third step, correlation coefficients are estimated. The correlation coefficients between stock index returns *i* and *j* at time t are defined as:

$$\rho_{ijt} = \frac{E_{t-1}\left[\varepsilon_{it}\varepsilon_{jt}\right]}{\sqrt{E_{t-1}\left[\varepsilon_{it}^2\right]}\sqrt{E_{t-1}\left[\varepsilon_{jt}^2\right]}} = \frac{E_{t-1}\left[\sqrt{h_{it}}v_{1t}\sqrt{h_{jt}}v_{jt}\right]}{\sqrt{E_{t-1}\left[h_{it}v_{it}^2\right]}\sqrt{E_{t-1}\left[h_{jt}v_{jt}^2\right]}} = \frac{E_{t-1}\left[v_{it}v_{jt}\right]}{\sqrt{E_{t-1}\left[v_{it}^2\right]}\sqrt{E_{t-1}\left[v_{jt}^2\right]}} = E_{t-1}\left[v_{it}v_{jt}\right].$$

where:

$$E_{t-1}\left[v_{it}^2\right] = E_{t-1}\left[h_{it}^{-1}\varepsilon_{it}^2\right] = h_{it}^{-1}E_{t-1}\left[\varepsilon_{it}^2\right] = 1.$$

The correlations ρ_{ijt} constitute the correlation matrix R_t of which diagonal elements are unity.

Let $Q_t = E_{t-1}\left[v_t v_t'\right]$. Then,

$$R_t = \left\{diag\left(Q_t\right)\right\}^{-\frac{1}{2}} Q_t \left\{diag\left(Q_t\right)\right\}^{-\frac{1}{2}} \tag{8}$$

In order to parameterize the correlation coefficient ρ_t, it is assumed that Q_t follows an autoregressive process. Specifically,

$$Q_t = \bar{Q}\left(1-\alpha-\beta\right) + \alpha v_{t-1}v_{t-1}' + \beta Q_{t-1} \tag{9}$$

where $\bar{Q}$ is an unconditional correlation coefficient matrix. The unconditional correlations are determined in the second step and are used as

predetermined values in this step[1] (see Engle and Sheppard, 2001, p. 5). The parameters for the time-varying correlations are determined by maximizing the log-likelihood function l_2. Since $v'_t v_t$ does not involve the determination of the parameters, the log-likelihood function is reduced to

$$l_2 = -0.5 \sum_{t=1}^{T} \left(\log \left(|R_t| \right) + \varepsilon'_t R_t^{-1} \varepsilon_t \right) \tag{10}$$

We implement the correlation model in (9) for each pair of contagion source and target countries to allow the parameters α and β to be different for each pair. In this regard, our approach is different from Chiang et al. (2005) who keep these parameters constant across all country pairs.

4. Data

The East Asian countries and their stock indices that are considered are Hong Kong (Hang Seng Index), Thailand (Bangkok SET Index), South Korea (Korea SE Composite Index), Malaysia (Kuala Lumpur SE Index), Singapore (Singapore SE Index), Taiwan (Taiwan SE Weighted Index), The Philippines (Philippines SE Composite Index), and Indonesia (Jakarta SE Composite Index). Daily stock price indices for these exchanges are obtained from *Datastream*.

The period of the analysis is from January 1, 1996, through March 1, 2005. The starting date of January 1, 1996, is considered as the beginning of the stable period and is the same as in Forbes and Rigobon (2002). This date appears to be a suitable starting point for the Asian countries since it is relatively distanced from the December 1994 Mexican peso crisis. Hence, estimates of the dynamic correlation coefficients will not be confounded with the effects of the Mexican peso crisis. The ending date of the turmoil period is assumed to be December 30, 1998. Given our choice of the break points (see below), it is a preferred date since it results in equal number of days in the stable and the turmoil periods.

Kaminsky, Lyons, and Schmukler (2000) provide evidence that mutual fund firms started to pull out their capital from the Asian countries upon the outburst of the currency crisis. To capture the effect of such capital outflows requires the turmoil period be long enough to allow the co-movements among the financial markets occur. Forbes and Rigobon (2002) assume one month for the length of the turmoil period. Chiang, *et al.* (2005) extend it and obtain different results. We have selected two dates that are often identified as the inception of the turmoil period. The first is July 2, 1997, when Thailand baht was devalued. The second is October 17, 1997, when the Hong Kong stock market crashed. Forbes and Rigobon, among others, have selected the October date as well.

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[1] To provide stable and long term static measures, the unconditional correlations are computed using data from January 1, 1990, through December 30, 2003.

5. Empirical application

In terms of considering further details in our analysis, we rely on the results of prior studies. For example, much effort has gone into a consideration of differences in time zones and the operating hours of the markets. At a given time zone, the opening hours among the Asian markets differ by a maximum of three hours. The difference in the closing hours is higher since the operating market hours are unequal. For example, the Philippines market is open only for two and a half hours (from 9:30 a.m. to 12:00 noon). Forbes and Rigobon (2002), for instance, average the returns over two consecutive days to overcome this problem. Their results indicate no significant difference. We thus assume that a consideration of time-zone and operating-hour differences in our analyses is not going to have significant effects on the results.

To visualize the computed DCCs, we have graphed them in Figures 1 through 3. Figures 1 and 2 provide individual DCC plots for pair-wise countries when the contagion source countries are Thailand and Hong-Kong, respectively. The break-point dates are represented by vertical dash lines. The increases in DCCs beyond the break points in nearly most cases are obvious. The estimated DCCs for the pairs of Hong Kong - Malaysia and Hong Kong - Indonesia do not appear to rise considerably, yet they exhibit large innovations over the turmoil period.

Figure 3 provides another insight into the overall contagion effects during the sample period. It shows the ***average*** of the estimated dynamic conditional correlations (DCC) for Thailand and Hong-Kong as the contagion source countries. Prior to calculating these averages, the DCCs are normalized by dividing each country's DCC by the value of its DCC on the day prior to the crisis break point. It is apparent from Figure 3 that there are surges in the DCCs. There are also some unusual sharp decreases in the DCCs right after the start of the turmoil dates. These are, however, very immediate and short-lived. These quick and temporary decreases could be attributed to the need to quickly rebalance and adjust portfolios as explained by Kaminsky, et al. (2000).

Table 1 show the estimation results of the mean, variance, and correlation models as given in relations (1), (4), and (9). All the estimates are statistically significant at the one percent or below. The statistical significance in this table is not indicated by asterisks, but rather by the p-values that are in parentheses under the estimates. As shown by the magnitude of the estimated parameter β, the DCC processes exhibit a high degree of persistency in general, except for Thailand - Malaysia (0.888 in column 10) and to some extent, for Hong Kong - Malaysia and Hong Kong - Indonesia (0.900 and 0.902 in the very last column). Additionally, our results show that the DCC processes for each pair have different innovation and persistency. Therefore, it is evident that restricting the parameters α and β to be the same for all pairs of the countries may lead to different estimation results. Chiang *et al.* (2005) restrict the correlation parameters α and β to be equal for all the pairs.[2] Their estimates are 0.006 for α and 0.989 for β.

[2] See Chiang *et al.* (2005), Table 3, p. 41.

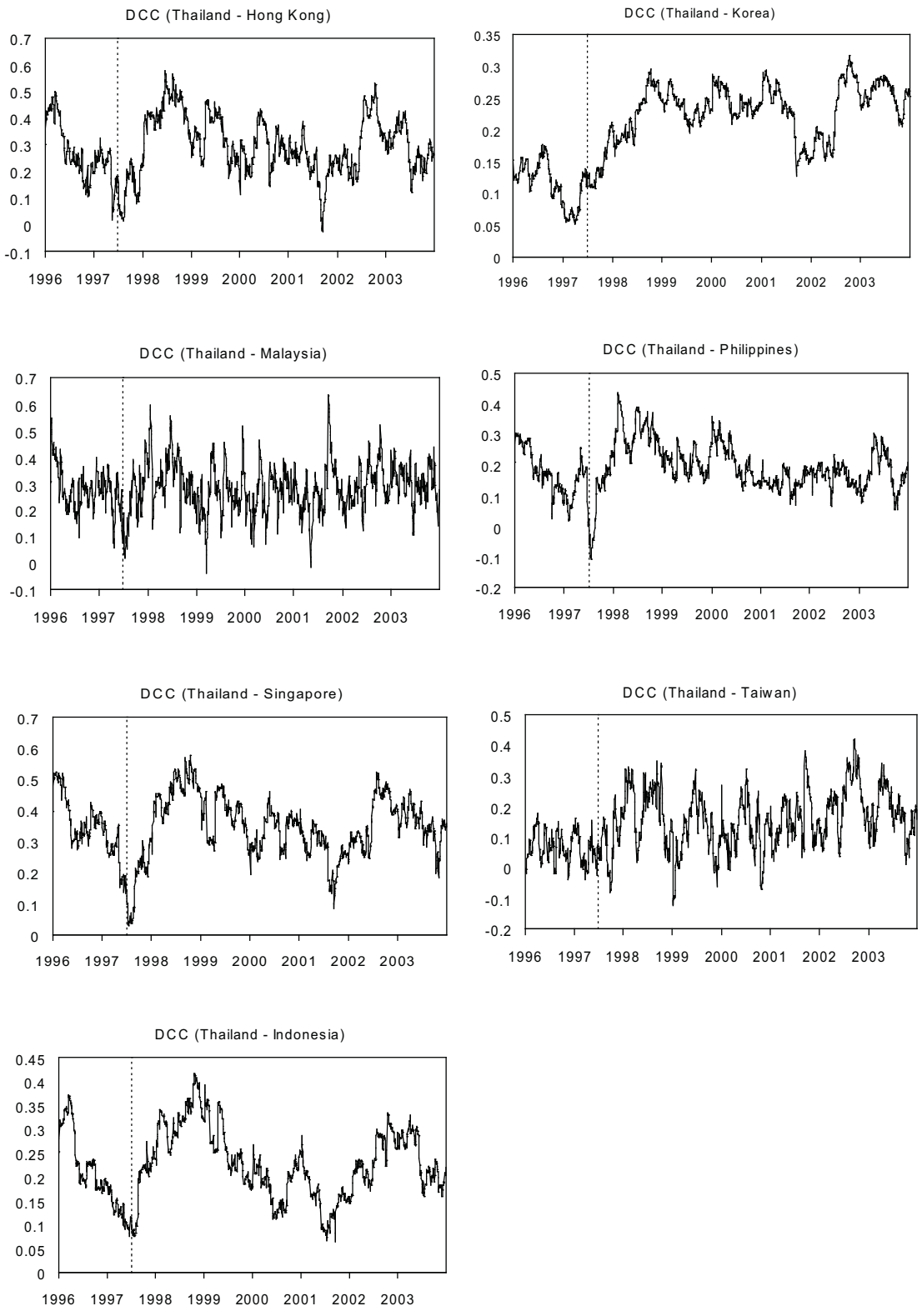

Figure 1: The estimated dynamic correlation coefficients (Contagion source: Thailand)

This figure shows the estimated dynamic correlation coefficients (DCC) for each pair of the contagion source (Thailand) and target country. The vertical dash line in each plot indicates July 2, 1997.

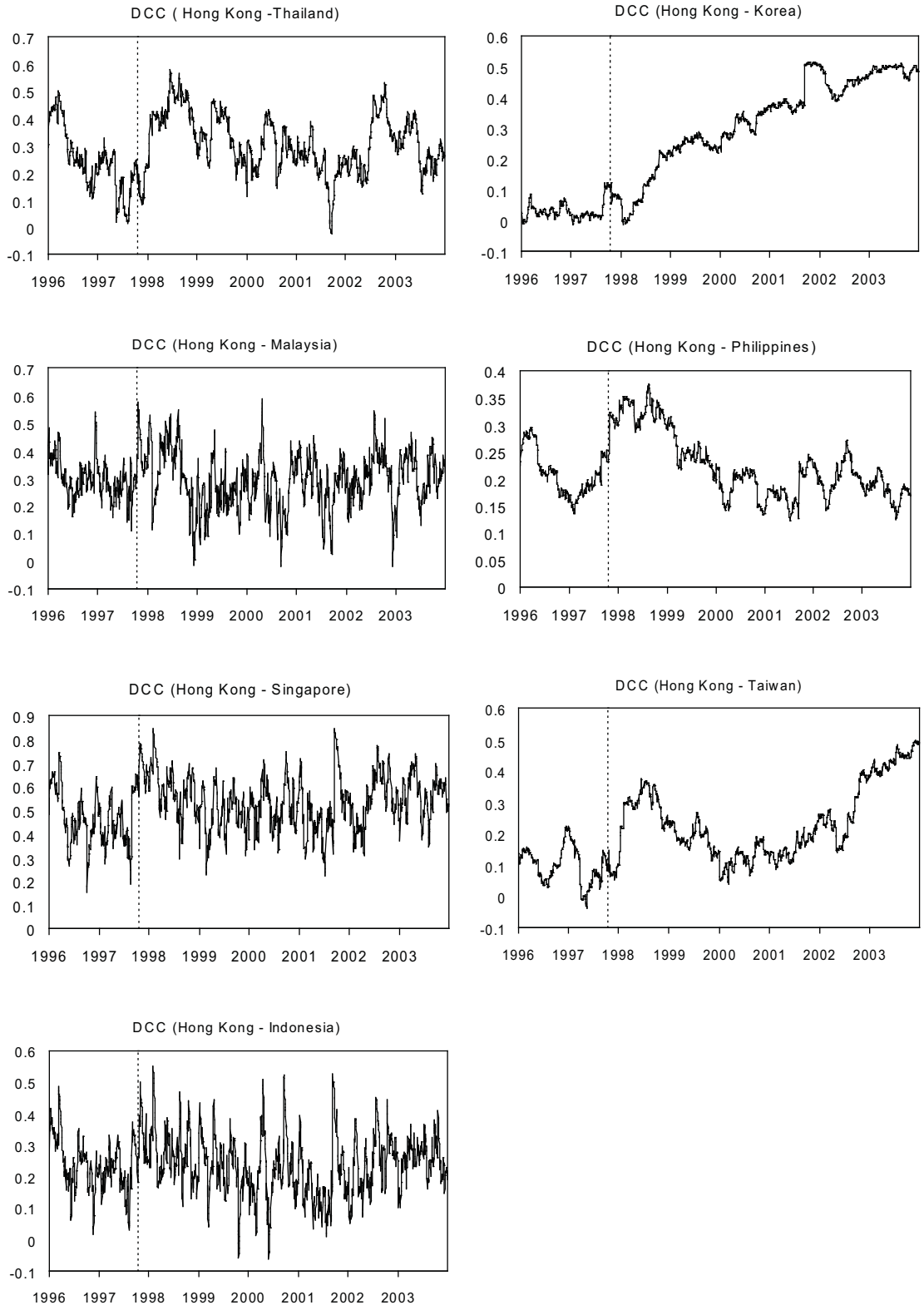

Figure 2: The Estimated dynamic correlation coefficients (Contagion source: Hong Kong)

This figure shows the estimated dynamic correlation coefficients (DCC) for each pair of the contagion source (Hong Kong) and target country. The vertical dash line in each plot indicates October 17, 1997.

Table 1: Estimation parameters of mean, variance, and correlation models

This table provides the estimation results for the mean, variance, and correlation model as introduced in the methodology section. They are as follows.

$$r_t = a_0 + a_1 r_{t-1} + a_2 r_{t-1}^{S\&P} + \varepsilon_t$$

$$h_t = b_0 + b_1 \varepsilon_{1t}^2 + b_2 h_{1t-1}^2$$

$$Q_t = \bar{Q}\left(1 - \alpha - \beta\right) + \alpha v_{t-1} v_{t-1}' + \beta Q_{t-1}$$

The correlation model is run for each pair of the contagion source (Thailand and Hong Kong) and target countries. P-values are given in parentheses. ρ represents the unconditional correlation coefficient in the matrix $\bar{Q}$.

Parameter	a_0	a_1	A_2	b_0 ρ10 ^{4}	b_1	b_2	Thailand			Hong Kong		
							ρ	α	β	ρ	α	β
Thailand	0.000	0.118	0.340	0.045	0.106	0.879				0.2923	0.019	0.966
	(0.628)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				(0.000)	(0.000)	(0.000)
Hong Kong	0.000	-0.015	0.586	0.043	0.079	0.901	0.2923	0.019	0.966			
	(0.367)	(0.346)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Korea	0.000	0.026	0.460	0.025	0.086	0.904	0.2035	0.005	0.992	0.2002	0.005	0.995
	(0.578)	(0.110)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.171)	(0.000)	(0.000)	(0.000)	(0.000)
Malaysia	0.000	0.072	0.360	0.079	0.101	0.889	0.3103	0.037	0.888	0.2918	0.038	0.900
	(0.944)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Philippines	0.000	0.182	0.307	0.058	0.105	0.864	0.2251	0.015	0.968	0.1943	0.005	0.991
	(0.925)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.023)	(0.000)
Singapore	0.000	0.105	0.422	0.058	0.130	0.835	0.5457	0.016	0.973	0.3628	0.045	0.910
	(0.879)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Taiwan	0.000	0.033	0.361	0.054	0.065	0.919)	0.1479	0.024	0.948	0.128	0.009	0.991
	(0.446)	(0.042)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.004)	(0.000)
Indonesia	0.000	0.191	0.260	0.016	0.115	0.891)	0.2463	0.009	0.985	0.221	0.034	0.902
	(0.869)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2: Tests of the mean and the median differences of the estimated dynamic correlation coefficients between the stable and turmoil periods

This table shows the test results of the statistical differences of the means and the medians. The contagion source countries are Thailand (panel A) and Hong Kong (panel B). The break points between the stable and turmoil periods are July 2, 1997, and October 17, 1997, respectively. The P-values of the t-tests show the statistical significance of the mean differences. The P- values of Wilcoxson z-tests represent the statistical significance of the median differences.

Panel A: Contagion source is Thailand (Turmoil breakpoint: July 2, 1997)											
	Stable period				Turmoil period				Mean	t test	z test
Target	N	Mean	Median	Std Dev	N	Mean	Median	Std Dev	Increase (%)	p Value	p Value
Hong Kong	392	0.2664	0.2458	0.1052	391	0.3316	0.3953	0.1543	24.5	0.0000	0.0000
Korea	392	0.1153	0.1214	0.0334	391	0.1988	0.1929	0.0523	72.4	0.0000	0.0000
Malaysia	392	0.2755	0.2708	0.0788	391	0.3018	0.3049	0.1041	9.5	0.0000	0.0000
Philippines	392	0.1710	0.1696	0.0732	391	0.2385	0.2712	0.1213	39.5	0.0000	0.0000
Singapore	392	0.3464	0.3385	0.0927	391	0.3673	0.4263	0.1526	6.0	0.0206	0.0000
Taiwan	392	0.0655	0.0603	0.0492	391	0.1593	0.1603	0.0988	143.2	0.0000	0.0000
Indonesia	392	0.2066	0.1897	0.0766	391	0.2780	0.2948	0.0827	34.6	0.0000	0.0000
Panel B: Contagion source is Hong Kong (Turmoil breakpoint: October 17, 1997)											
Thailand	491	0.2390	0.2286	0.1133	292	0.3998	0.4158	0.1086	67.3	0.0000	0.0000
Korea	491	0.0326	0.0227	0.0307	292	0.1044	0.0828	0.0732	220.2	0.0000	0.0000
Malaysia	491	0.3047	0.2947	0.0798	292	0.3320	0.339	0.1171	9.0	0.0000	0.0000
Philippines	491	0.2139	0.2089	0.0451	292	0.3257	0.3262	0.0201	52.3	0.0005	0.0000
Singapore	491	0.4793	0.4569	0.1235	292	0.5919	0.6014	0.0912	23.5	0.0000	0.0000
Taiwan	491	0.0987	0.0996	0.0566	292	0.2692	0.2959	0.0829	172.7	0.0000	0.0000
Indonesia	491	0.2418	0.2309	0.0855	292	0.2752	0.2666	0.0794	13.8	0.0000	0.0000

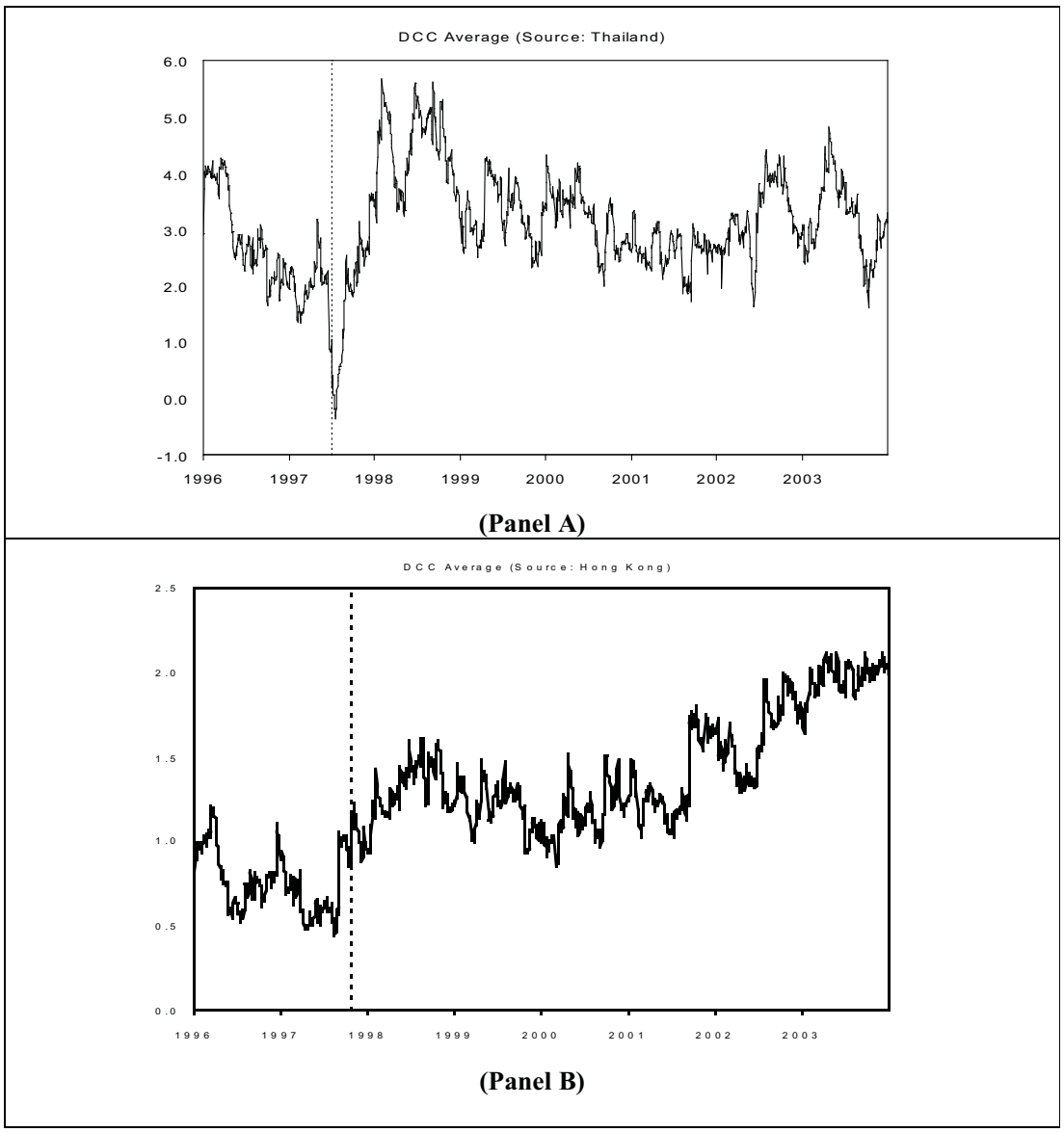

Figure 3: Averages of the estimated dynamic correlation coefficients

This figure plots the averages of the estimated dynamic correlation coefficients for all the pair-wise countries. In Panel A, the contagion source is Thailand and in Panel B it is Hong Kong. Prior to averaging, each pair-wise DCC is normalized by dividing it by its value on the day prior to the crisis break point. The break-point dates are indicated by vertical dash lines. These dates are July 1, 1997, if the contagion source is Thailand, and October 17, 1997, if the contagion source is Hong Kong.

To check the existence of contagion, we employ t-tests for the mean difference and Wilcoxon z-tests for the median difference. Our test results on the contagion effects are shown in Table 2. All the t-tests and the z-tests in the last two columns of this table are statistically significant at the one percent or below, thus rejecting the null hypothesis of no contagion. As represented by the significance of the p-values, the tests demonstrate the presence of contagion effects arising from the financial crisis. Based on the increase in the DCC mean

values in percentage term (see column 10 of Table 2), the two countries that are most influenced by the contagion effects are Taiwan if the contagion source country is Thailand, and Korea if the contagion source country is Hong Kong.

6. Summary and Conclusions

Consistent with prior literature, we have chosen two dates for financial distress in the East Asian financial markets: July 2, 1997, the devaluation of Thailand baht, and October 17, 1997, the Hong Kong stock market crash. We have provided a set of uniform results that suggest, overwhelmingly, contagion in the 1997 Asian equity markets.

Our approach and findings contribute to the existing literature by addressing a few contentious points on contagion. First, our findings indicate the existence of contagion in the 1997 East Asian financial markets as measured by the returns in the equity exchanges. Second, our approach is less cumbersome and is statistically simpler in terms of procedure and data requirements. For example, there is no need to resort to other measures including dummy variables, nor is there a need to run further regressions to show the existence of contagion.

Third, we have provided a simple methodology to assist us in measuring and identifying contagion. This is done without resort to other measures, including dummy variables. Under some conditions, it has been shown that dummy variables could be persistent and, thus, their interpretation could be subject to statistical shortcomings (see Ferson et al., 2003). We have avoided this potential problem. Obviously, consideration of other measures to add insight to the ***cause*** of contagion is highly warranted, but we do not recommend such consideration for the detection of contagion.

Finally, notwithstanding all of the above, what could still be the subject of further inquiry is the definition of contagion. We have opted for a statistically powerful and straightforward definition, i.e., statistical break in dynamic conditional correlation as measured by the shifts in the mean and the median of the computed DCCs. Further refinements and research along this line of analysis could be the subject of future research.

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