ISSN 1518-3548

BANCO CENTRAL DO BRASIL

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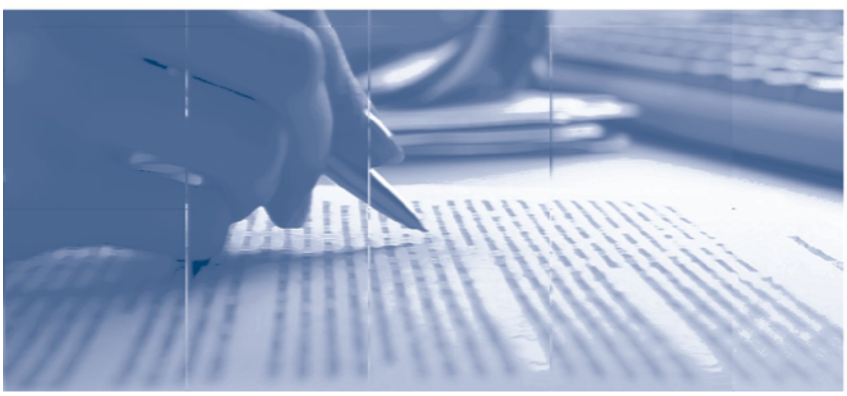
Ahmet Sensoy and Benjamin M. Tabak

Março, 2014

Working Papers



351

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	n. 351	Março	2014	p. 1-30

Working Paper Series

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Dynamic spanning trees in stock market networks: The case of Asia-Pacific*

Ahmet Sensoy**

Benjamin M. Tabak***

Abstract

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This article proposes a new procedure to evaluate Asia Pacific stock market interconnections using a dynamic setting. Dynamic Spanning Trees (DST) are constructed using an ARMA-FIEGARCH-cDCC process. The main results show that: 1. The DST significantly shrinks over time; 2. Hong Kong is found to be the key financial market; 3. The DST has a significantly increased stability in the last few years; 4. The removal of the key player has two effects: there is no clear key market any longer and the stability of the DST significantly decreases. These results are important for the design of policies that help develop stock markets and for academics and practitioners.

Keywords: Asia-Pacific financial markets; Dynamic Spanning Tree - DST; centrality measures; survival rate.

JEL Classification: G21, G28

*Benjamin M. Tabak gratefully acknowledges financial support from CNPQ Foundation.

**Borsa Istanbul, Research Department, Istanbul, Turkey and Bilkent University, Department of Mathematics, Ankara, Turkey.

***Departamento de Estudos e Pesquisa, Banco Central do Brasil, e-mail: benjaminm.tabak@gmail.com.

1 Introduction

Financial markets around the world can be regarded as a complex system. This forces us to focus on a global-level description to analyze the interaction structure among markets which can be achieved by representing the system as a network. Correlation between stock markets play a central role in investment theory and risk management, and also are key elements for the optimization problem in the Markowitz (1952) portfolio theory. Thus, a correlation based network could be very useful in analyzing the interactions between financial markets and building optimal investment strategy.

During recent years, networks have proven to be a very efficient way to characterize and investigate a wide range of complex financial systems including stock, bond, commodity and foreign exchange markets.[1] In this study, we are interested in analyzing the connection structure of Asia-Pacific stock market network formed with correlations of returns in the last two decades. In order to do that, we construct the minimal spanning tree (MST) by the metric introduced by (Mantegna, 1999). However, it is a well known fact that correlations tend to vary over time. To capture this fact, we use the consistent dynamic conditional correlation model of Aielli (2013). By this way, we also consider the problem of the stability associated with the minimal spanning tree (MST) obtained from price returns.

Although similar analysis have been performed on several stock markets in the Econophysics literature, surprisingly Asia-Pacific received no attention considering the importance of the region in the world financial system.[2] Moreover, such an analysis is particularly interesting in understanding the interaction of different type of economies since the region covers a variety of them: It includes developed economies such as Australia and Japan, the export-led growth Asian tigers of Hong Kong, South Korea, Singapore and Taiwan as well as emerging economies such as India and Thailand. The countries within the region also display varying degrees of barriers to capital flows with Hong Kong displaying virtually none and China and Malaysia some formal capital controls. In this paper, we intend to fill the existing gap in the literature.[3]

The analysis shows that the DST shrinks significantly over time (in particular, in times of the 1997 Asian financial crisis and the 2008 global financial crisis) suggesting an increase in the interdependence among the Asia-Pacific markets over the past two

[1]For the frontier studies, see Mantegna (1999); Bonanno et al. (2000, 2001a,b, 2003); Onnela et al. (2003b,a); Micciche et al. (2003a,b); Onnela et al. (2004); Bonanno et al. (2004); Di Matteo et al. (2004, 2005); Tumminello et al. (2005, 2007a); Borghesi et al. (2007); Tumminello et al. (2007b); Cajueiro and Tabak (2008); Tola et al. (2008); Tabak et al. (2009); Schweitzer et al. (2009); Tumminello et al. (2010); Di Matteo et al. (2010); Tabak et al. (2010); Papadimitriou et al. (2013).

[2]However, there are some studies partly covering many of the indexes investigated in this manuscript. For example, see Song et al. (2011).

[3]For recent studies analyzing the interconnectivity and transmission mechanisms among the region's stock markets without using network theory, see Wong and Fong (2011) and Abbas et al. (2013).

decades. Using several tools from network theory, we reveal that Hong Kong is clearly the key market in the region for almost all the time. Moreover, in the last few years the network is stabilized and importance of Hong Kong increases in the region. We ask the question “what happens to the network if the key element was not present?” and repeat the analysis omitting this important market. In this case, the key market in the network varies widely over time and the stability is significantly lower compared to the original network.

In the rest of this paper, Section 2 presents the data and the methodology of our study. Section 3 discusses the results of the analysis and finally, Section 4 concludes.

2 Data and methodology

We analyze the Asia-Pacific stock market interactions from June 5, 1992 to June 28, 2013. The data set (in local currencies) which covers more than 20 years helps us to see the effects (if any) of major events such as the 1997 Asian crisis, 1998 Russian debt crisis, 2001 dot-com bubble, 2008 global financial crisis and the recent eurozone debt crisis. The list includes all major stock markets in the region: Japan (NIKKEI225), India (SENSEX), Hong Kong (HSI), China (Shanghai Composite), Taiwan (TWSE), Thailand (SET), Malaysia (FTSE Bursa), Indonesia (Jakarta Composite), Philippines (PSEi), Australia (S&P/ASX 200), South Korea (KOSPI 200) and Singapore (Straits Times). Moreover, instead of daily, we use weekly log-returns so that the adverse effects of belonging to different time zones and having different operating days are minimized, yet we do not lose the dynamics of the correlations.

2.1 Time-varying correlations

Unlike the common approach of rolling window Pearson correlations[4], the dynamic correlations between Asia-Pacific stock markets will be obtained by the cDCC model[5] of Aielli (2013) which is based on the DCC modeling approach of Engle (2002).[6] The motivation comes from the fact that there is a heteroskedasticity problem when measuring correlations, caused by volatility increases during the crisis.[7] This is overcomed by the cDCC model since it estimates correlation coefficients of the standardized returns and thus accounts for heteroskedasticity directly.

For each individual return series, standardized returns are obtained from ARMA(p, q)-

[4]Which are heavily autocorrelated due to the overlapping windows and the choice of the window length and the rolling step can be controversial. The problem of overlapping can be overcomed by using non-overlapping windows. However, in this case the problem of window size is still a big problem and moreover another problem also arises. For example, in our analysis, we use more than 21 years of weekly data. In total, we have 1101 weeks of price series for each stock market, thus 1100 returns i.e. 1100 data points. Now, to have a statistically significant correlation between the time series, how many data points do we need? For example, if we take 52 points as the window size (which corresponds to a year in our analysis) then the number of non-overlapping windows is going to be 21, which is very small and really meaningless in our case. To have more time varying correlation data, we need to shorten the window size: For example, for 25 points (6 months) the number of non-overlapping windows is 44, which again is a very small number for our analysis. And, for shorter window sizes, Pearson correlations will start to be meaningless. In the cDCC case, every week (from the beginning to the end) is associated with a correlation level without consuming any initial data. For comparison purposes, we present all correlations obtained from both approaches in Figure 1 and Figure 2. In Pearson correlations, we use non-overlapping windows of length 25 data points. The significant differences are clearly visualized.

[5]See A for details.

[6]As far as we know, the only other study in the literature that uses DCC in constructing MST belongs to Lyocsa et al. (2012).

[7]That is, if a crisis hits country A with increasing volatility in its stock market, it will be transmitted to Country B with a rise in volatility and, in turn, the correlation of stock returns in both Country A and B.

FIEGARCH$(1, d, 1)$ process[8] where the lags p and q are determined according to sample-partial autocorrelation analysis and Bayesian information criterion.[9] The AR(p) and MA(q) parts are used to account for the autocorrelation of market returns and lingering effects of random shocks respectively, which are found in almost all the markets under investigation. FIEGARCH model is used to model volatility clustering (as in the ARCH and GARCH models), to capture asymmetric response of the volatility (as in the EGARCH models) and to take into account the characteristic of long memory in the volatility (as in the FIGARCH models, with the advantage of being weakly stationary if $d < 0.5$).[10]

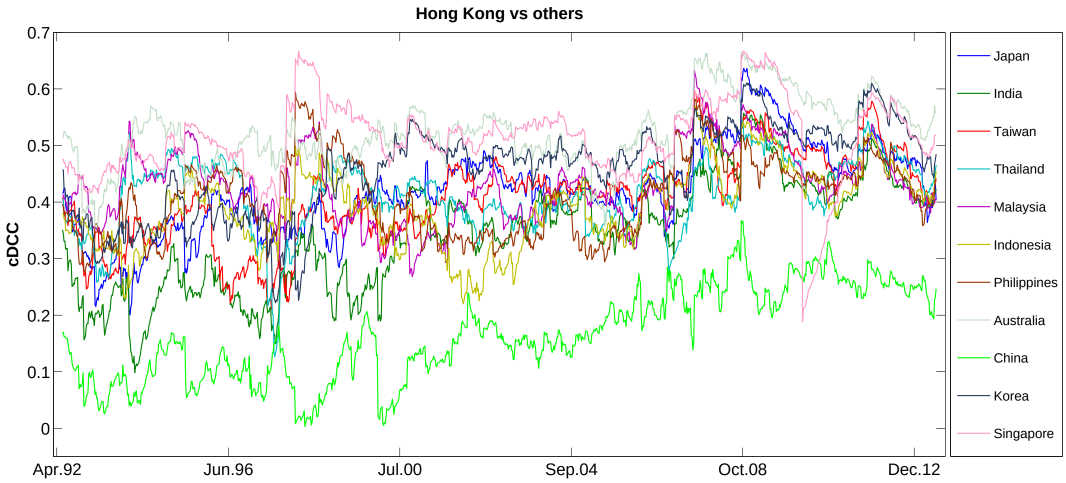

Figure 1: Dynamic correlations between Hong Kong and other Asia-Pacific stock markets revealing the decreased diversification benefits across the region due to the increased correlations.

[8]ARMA and FIEGARCH are abbreviations for autoregressive moving average and fractionally integrated exponential generalized autoregressive conditional heteroskedasticity respectively.

[9]Descriptive statistics and the estimated parameters are presented in B.

[10]For more information on FIEGARCH processes, refer to Bollerslev and Mikkelsen (1996).

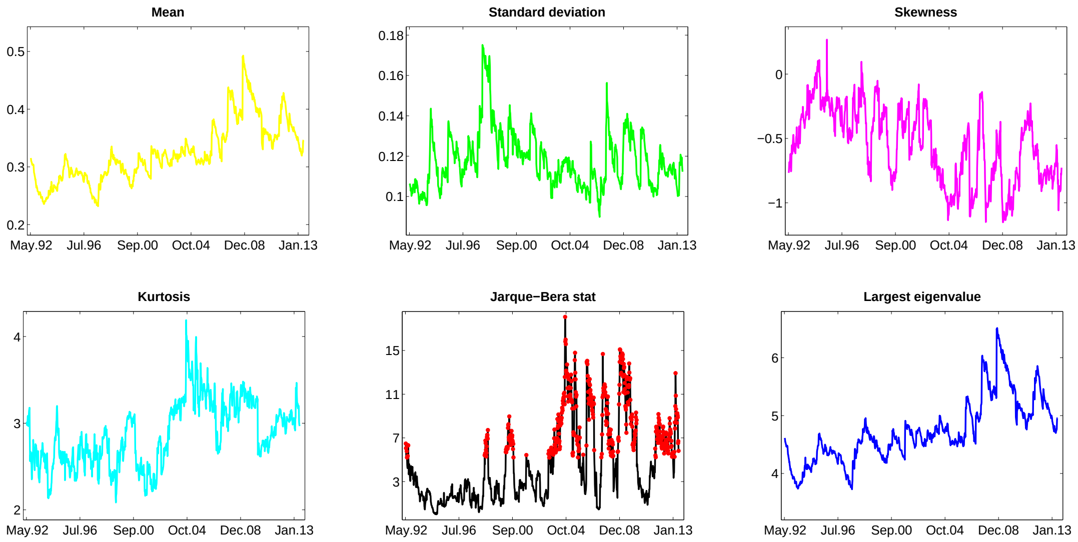

Figure 2: Time-varying fundamental statistics of the dynamic correlation matrix (red points in the Jarque-Bera stats denote the rejection of normality at 5% significance level).

2.2 Constructing the network

To create a dynamic network based on return correlations, we use the metric defined by Mantegna (1999),

$$d_{ij}(t) = \sqrt{2(1 - \rho_{ij}(t))} \tag{1}$$

It is a valid Euclidean metric since it satisfies the necessary properties; (i) $d_{ij} \geq 0$, (ii) $d_{ij} \Leftrightarrow i = j$, (iii) $d_{ij} = d_{ji}$ and (iv) $d_{ij} \leq d_{ik} + d_{kj}$. This transformation creates a $N \times N$ distance matrix from $N \times N$ correlation matrix. For any time t, distance $d_{ij}(t)$ varies from 0 to 2 with small distances correspond to high correlations and vice versa.

Then we construct the MST as the following: we start with the pair of elements with the shortest distance and connect them, then the second smallest distance is identified and added to the MST. The procedure continues until there is no element left, with the condition that no closed loops are created. Finally we obtain a simply connected network that connects all N elements with $N-1$ edges such that sum of all distances is minimum. This can be seen as way to find the $N-1$ most relevant connections among a total of $N(N-1)/2$ connections which is especially appropriate for extracting the most important information concerning connections when a large number of markets is under consideration. In terms of stock markets, MST can also be considered as filtered networks enabling us to identify the most probable and the shortest path for the transmission of a crisis.

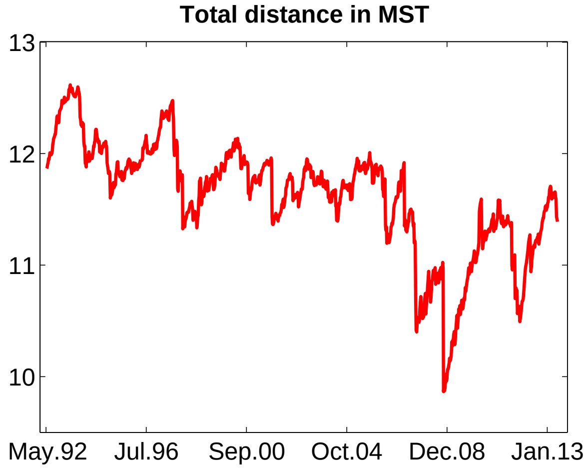

Figure 3: Time-varying total distance in the MST.

2.2.1 Centrality measures and survival rate

In network theory, the centrality of a node determines the relative importance of that node within a network. In this paper, we perform a detailed analysis on the time-varying MST using different quantitative definitions of centrality. The definitions are given below;

Node degree is the number of nodes that is adjacent to it in a network.

Node strength is the sum of correlations of the given node with all other nodes to which it is connected.

Eigenvector centrality is a measure that takes into account of how important the neighbors of a node are. It is useful in particular when a node has low degree but connected to nodes with high degrees thus the given node may be influent on others indirectly. It is defined as the i^{th} component of eigenvector $\mathbf{v}$, where $\mathbf{v}$ corresponds to the largest eigenvalue λ of the *adjacency matrix* $\mathbf{A}$.

Betweenness centrality measures the importance of a node as an intermediate part between other nodes. For a given node k, it is defined as

$$B(k) = \sum_{i,j} \frac{n_{ij}(k)}{m_{ij}} \tag{2}$$

where $n_{ij}(k)$ is the number of shortest geodesic paths between nodes i and j passing through k, and m_{ij} is the total number of shortest geodesic paths between i and j.[11]

Closeness centrality is a measure of the average geodesic distance from one node to all others. This measure is high for strongly connected central nodes and large for poorly

[11] MST is a fully-connected network so $m_{ij} \neq 0$.

connected ones. For node i in a network with N nodes, it is defined as

$$C(i) = \frac{1}{\sum_{j=1}^{N} d(i, j)} \tag{3}$$

where $d(i, j)$ is the minimum geodesic path distance between nodes i and j.

In general the larger these centrality measures, the more important the node is. Time-varying highest centrality measures and the corresponding market(s) having these measures are presented in Fig. 4.

The *survival rate* is a measure of the robustness of the edges in the network. The k-step survival rate $s_t(k)$ is the fraction of links found in k consecutive MST at times $t - k + 1, t - k + 2, ..., t - 1$ and t.

$$s_t(k) = \frac{1}{N - 1} \times |E_t \cap E_{t-1} \cap ... \cap E_{t-k+1}| \tag{4}$$

where $N - 1$ is the number of links and E_t is the set of edges in the MST at time t. For small and large values of k, $s_t(k)$ measures the short and long term stability of the network respectively where higher the survival rate, more stable the network is. Time-varying survival rates for different number of steps are presented in Fig. 5.

3 Results and discussions

Fig. 2 shows that the mean of the lower triangular correlation matrix increases over time suggesting an increased interdependence in the region. However, the distribution of the pair-wise correlations seems to be normal around regular times and the normality is rejected mostly during the high volatile periods. The significantly increased correlations around the 1997 Asian crisis and the 2008 global financial crisis can be regarded as evidence of existence of contagion effects. Another interesting observation is the behavior of the largest eigenvalue (generally accepted to carry the useful information) of the correlation matrix. It follows almost the same pattern as the mean of the correlation matrix and similarly peaks during the crisis periods.[12]

According to the Fig. 3, the MST shrinks over time suggesting an increased interdependence (as expected due to the behavior of the mean correlation) and this shrinkage is most significant around 1997 and 2008, however, one should also notice the wild fluctuations in the total length of the MST.

Considering the centrality measures, Hong Kong is, no doubt, the most important element in the MST for almost all the time. Other than Hong Kong; Singapore, Australia and occasionally South Korea play a significant role in the network. The values of the highest centrality measures significantly increase in the last few years. Observing the fact that Hong Kong is the (only) most important member in the network during the same time period (see Fig. 4), this picture is an evidence for the increased importance of Hong Kong in the region. On the other hand, considering the market size and the liquidity, an unexpected result of the analysis is the insignificant role of Japan in the network as it one of the world most important financial markets. This result may first seem to contradict with the findings of Chuang et al. (2007): According to authors, the Japanese market, while being the most exogenous and the least susceptible to volatility stimuli from other markets, is the most influential in transmitting volatility to the other East Asian markets. However, the fact that Japan in our investigation seems to have "insignificant role" may not be contradicting with respect to the fact that Japan might transmit volatility. Our investigation regards price returns, however, volatility (risk) and returns might well behave in a different way.

In the last few years, the survival rates also present interesting results: For each 1, 10, 50 and 100 steps, there is a significant increase in the survival rates revealing an increased stability of the dependence structure of the Asia-Pacific stock markets (For example, even the 100-step survival rate takes values around 50%. See Fig. 5). This high stability, in particular, increases the applicability of MST in policy making analysis as it

[12] Which coincides with the findings of Podobnik et al. (2010): The authors study 1340 time series with 9 year daily data and investigate how the maximum singular value λ changes over (time lags) for different years and find that it is greatest in times of crises.

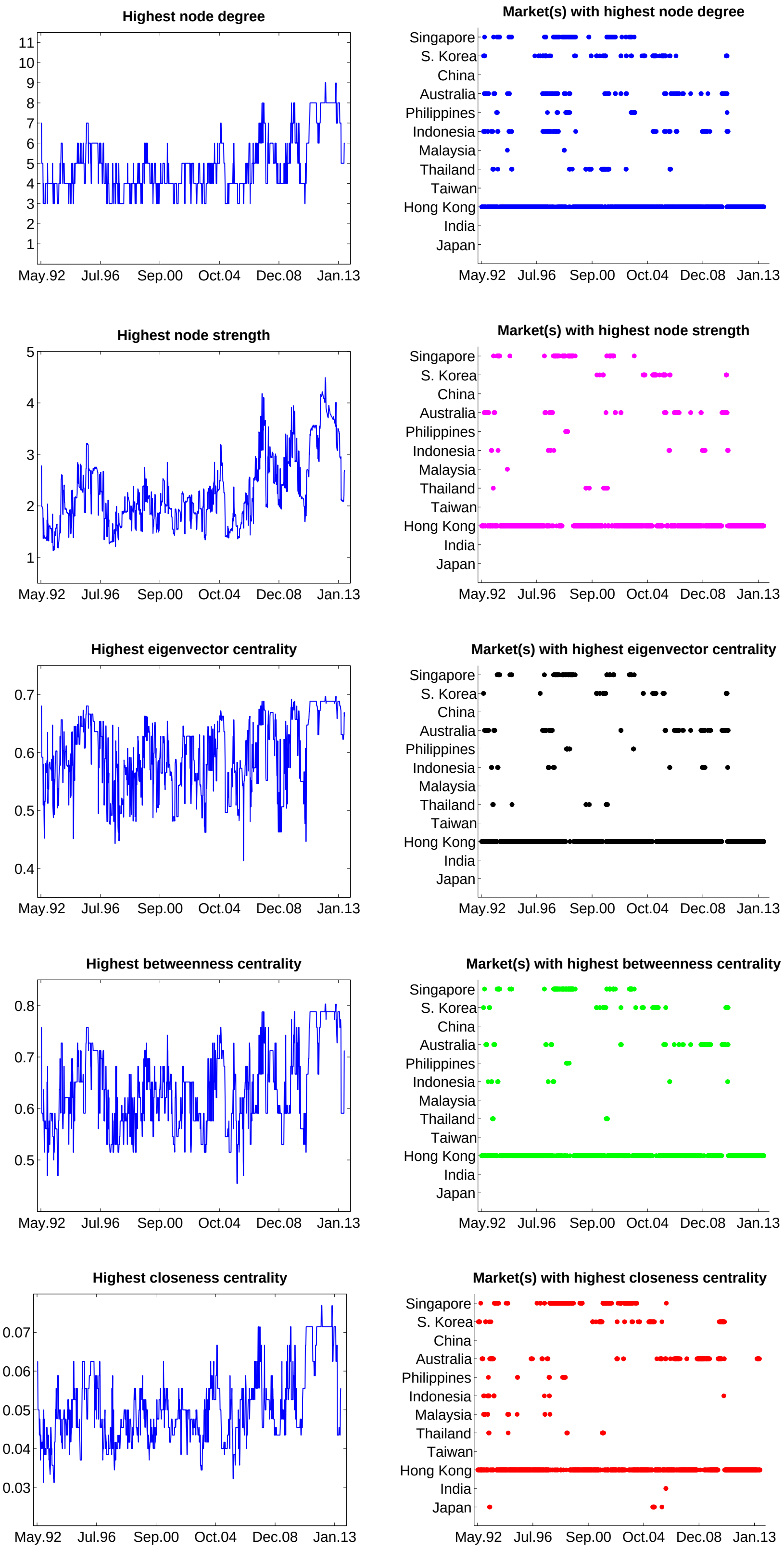

Figure 4: Time-varying highest centrality measures and the corresponding market(s) in the MST.

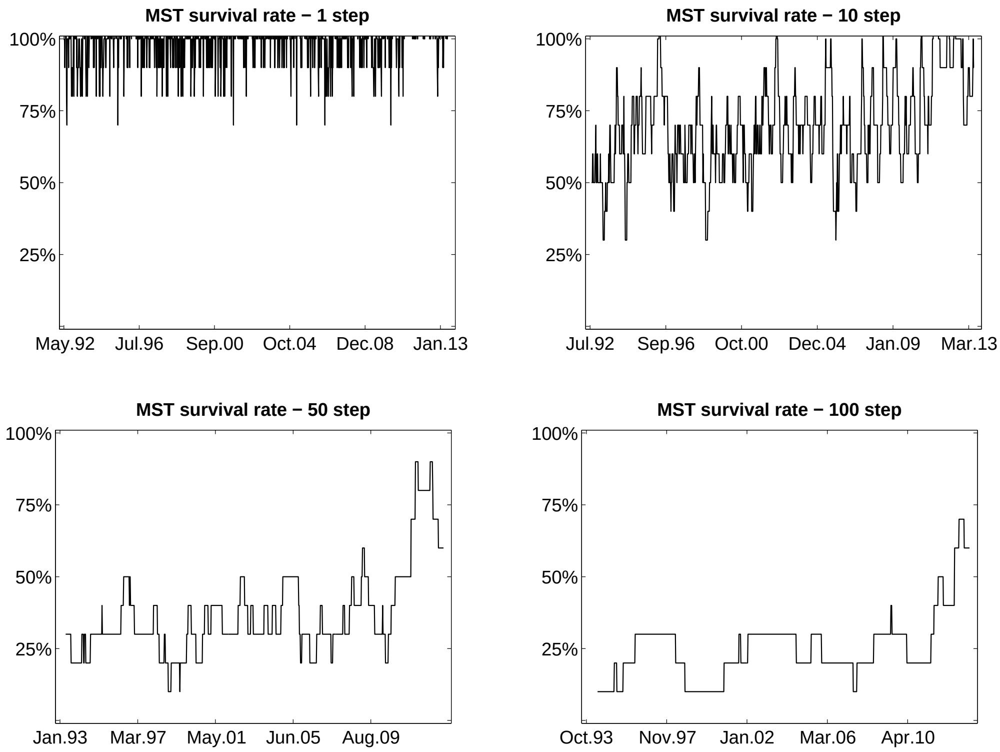

Figure 5: Survival rates of the MST for different number of steps.

will provide results with long term reliability. This result also shows that finding of Flavin et al. (2008), which states that the linkages between equity markets in the region do not appear to be stable, is no longer valid after the global financial crisis.

In the stock market complex network framework the most important market is the one that is highly correlated to other markets. In this case such market can either influence other markets and in the event of a crisis would spread shocks through the network. On the other hand shocks in other markets would also influence this market which would propagate the shocks through the network. Therefore, these markets have an important influence in the network. Our results are in line to some extent with Huyghebaert and Wang (2010) which find evidence that Hong Kong is an influential stock market in the region using a different methodology. However, these authors also pinpoint the importance of Singapore.

Markets with low centrality and lower strength are markets that can be seen as more resilient to external shocks and may depend more on domestic conditions. This is the case of Japan that has a lower importance in the network according to network measures and to its position in the MST.

In terms of investment decisions these results can provide useful insights as to which countries could be included in a portfolio to improve its performance. If the main objective is to diversify the portfolio choosing stock markets that are in different clusters (far

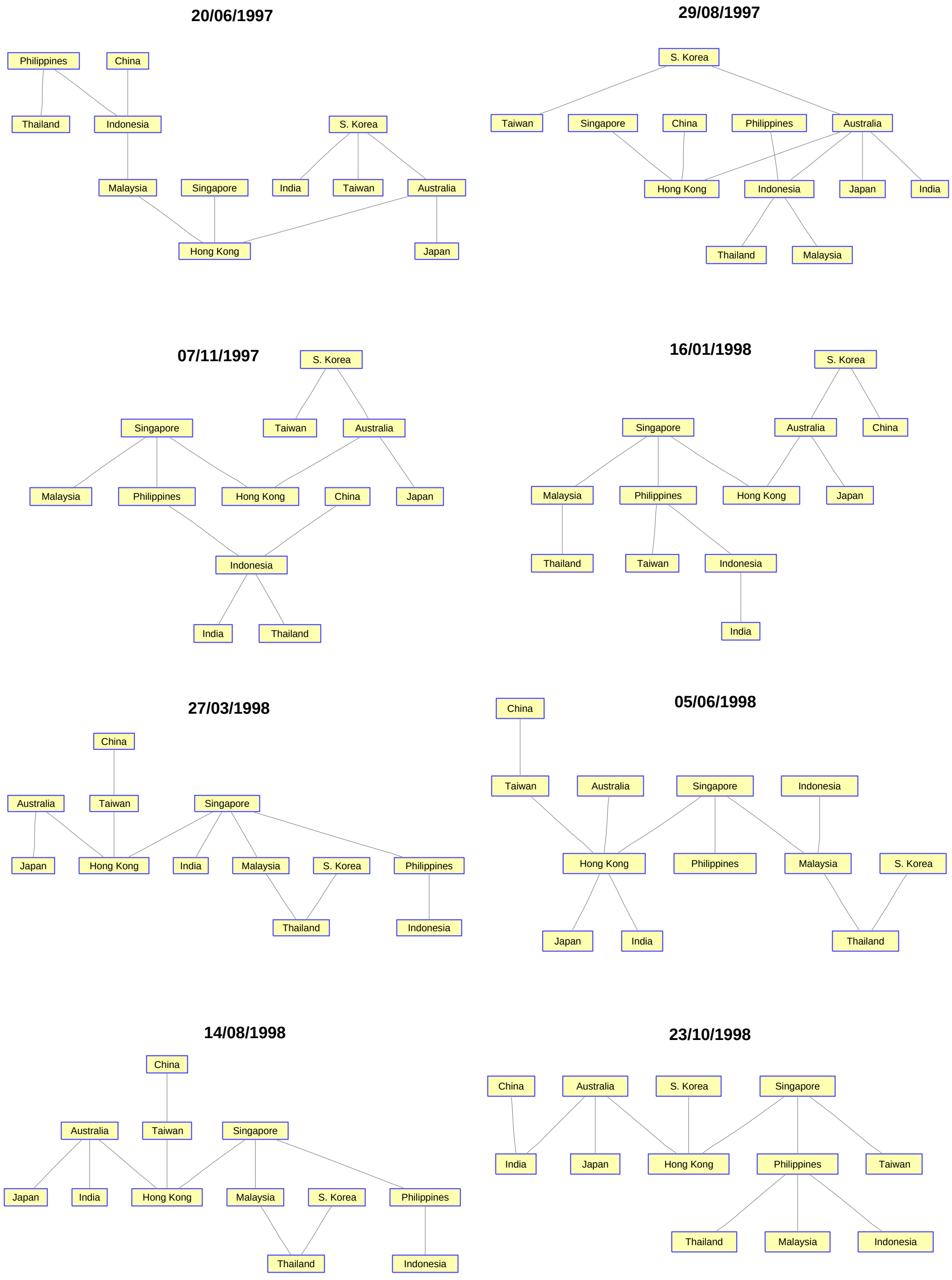

Figure 6: Time-varying MST during the 1997-1998 Asian financial crisis.

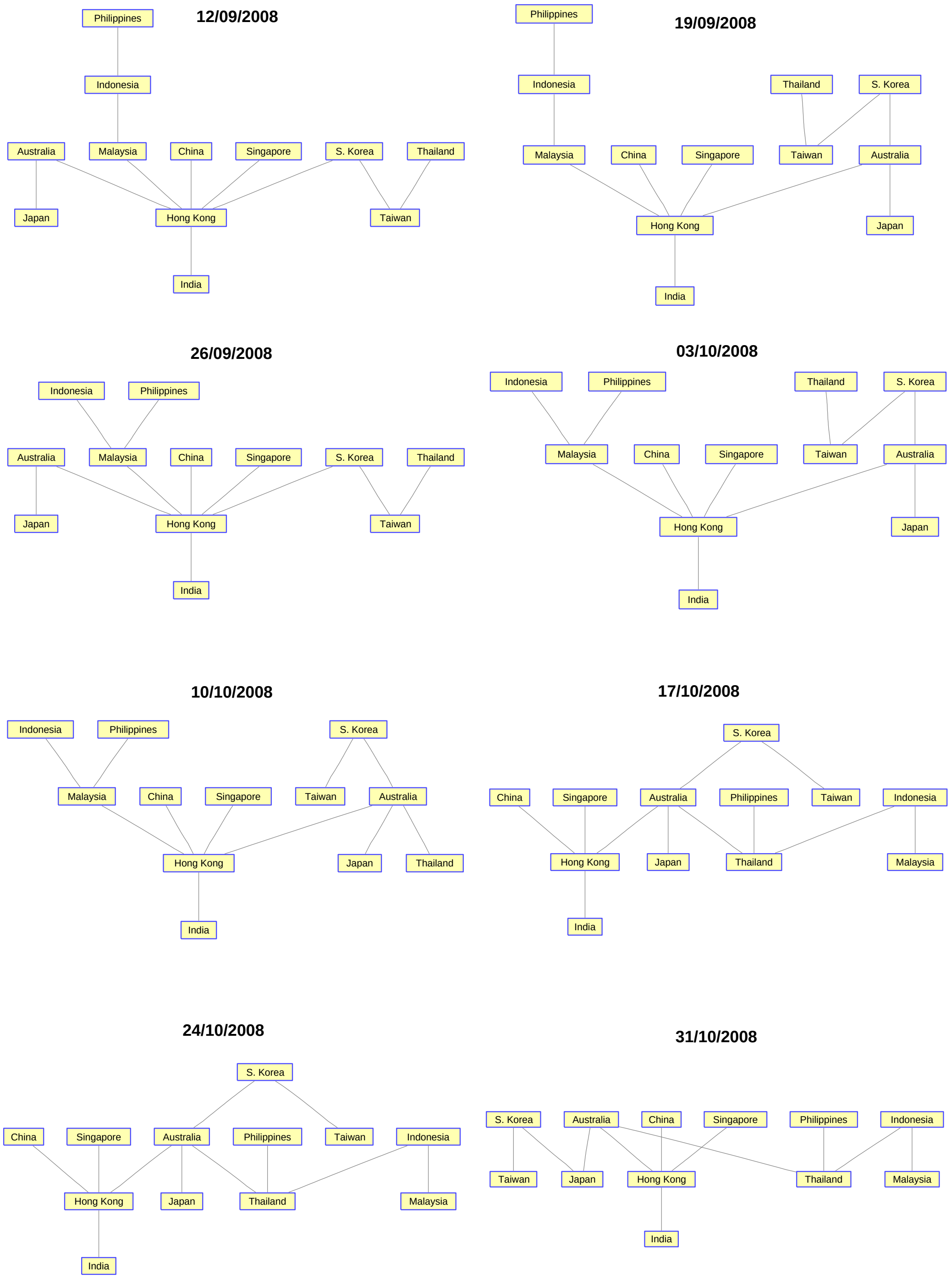

Figure 7: Time-varying MST during the financial turmoil of 2008.

away from each other) would be beneficial. This analysis is also relevant in crisis periods. In crisis periods investors prefer to have a large and well diversified portfolio. One can use the methods presented in the paper to construct a portfolio that would likely have a lower risk in the event of crisis.

The relative importance of Hong Kong is not surprising. It is one of the world's largest trading centers. It also serves as a trading entrepot with a large amount of re-exports providing a commercial bridge between important neighbors such as China. Besides it has one of the largest stock markets around the world and in Asia.

3.1 Removing the key element from the network

Several centrality measures suggest that Hong Kong is, without a doubt, the key financial market in the Asia-Pacific region. One of the possible questions that comes to our mind is that what would be the case if such a key element did not exist in the network? In particular, would a new key element arise and would the new network be more stable? To answer these questions, we repeat our analysis omitting Hong Kong. For the new case, the time-varying centrality measures and the survival rates are presented in the Fig. 8 and Fig. 9 respectively.

According to the new case, there is not a clear winner in terms of centrality measures. Singapore, South Korea, Australia, Indonesia, Thailand and occasionally Philippines play a key role in the network (sometimes simultaneously. See Fig. 8). Moreover, in contrast to the previous case, the highest values of the centrality measure do not significantly increase in the last few years.

The stability of the MST also decreases significantly compared to the previous case. Furthermore, a significant increase in the survival rates of the MST is not observed in the last few years (see Fig. 9).

Combining the above results reveals that for the Asia-Pacific stock markets, removing the (only) most important element from the network produces several new key members, however, destabilizes the dependence structure.[13]

[13]The immediate question to be asked here is that if this kind of behavior is valid in general? We will not address this question in this paper, however it is an important issue and will be considered in the forthcoming studies.

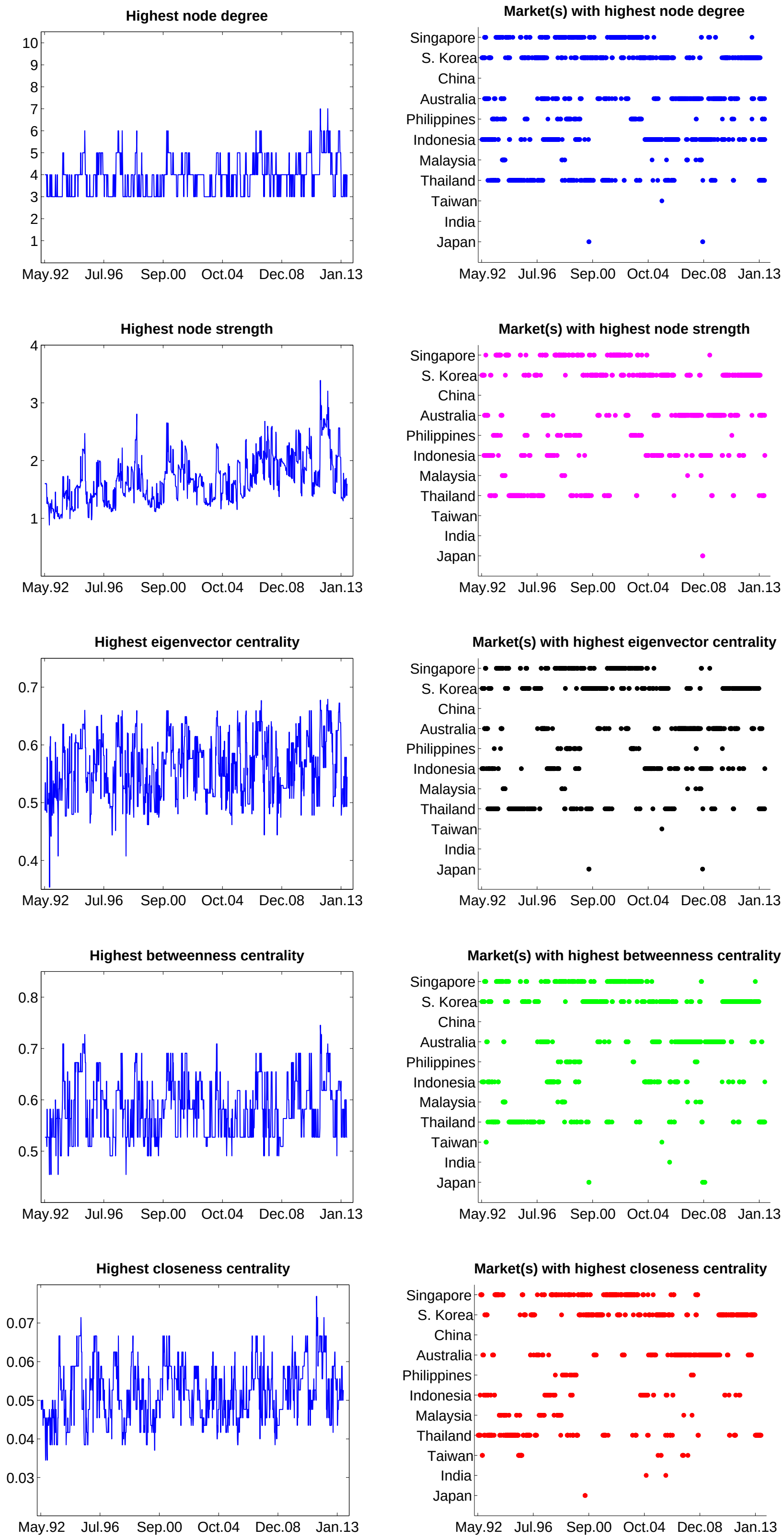

Figure 8: Time-varying highest centrality measures and the corresponding market(s) in the MST (reconstructed by excluding Hong Kong).

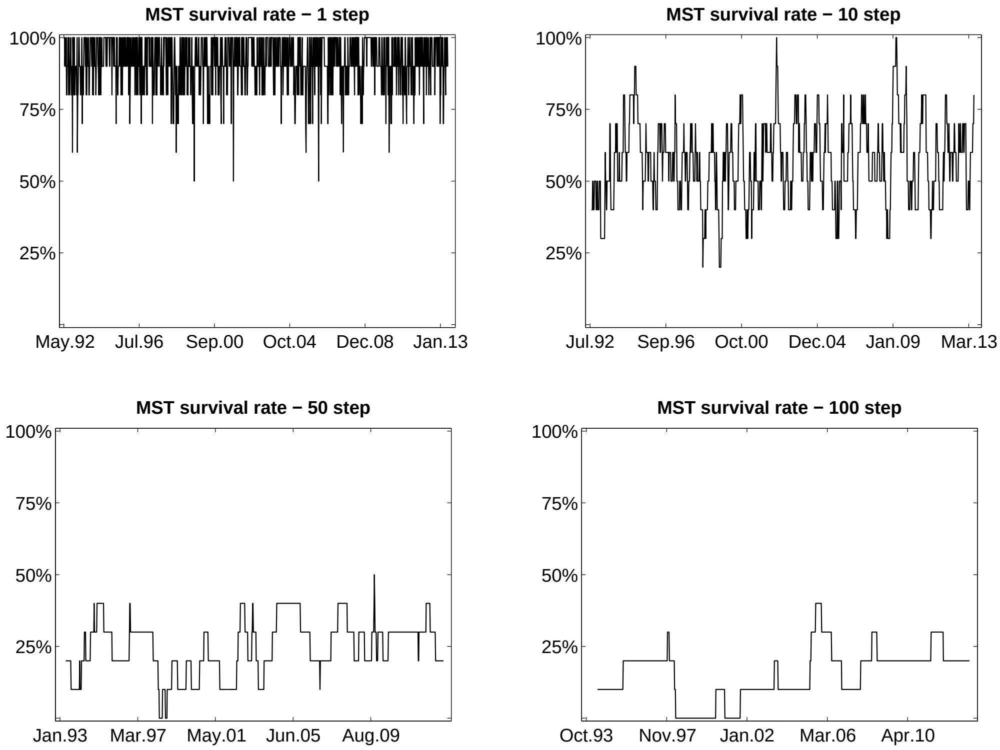

Figure 9: Survival rates of the MST for different number of steps (for the reconstructed MST excluding Hong Kong).

4 Conclusion

In this paper, we studied the time-varying dependence structure of Asia-Pacific stock markets using dynamic minimal spanning tree constructed by distances obtained from consistent dynamic conditional correlation process. The dynamic minimal spanning tree is analyzed using several centrality measures (node degree, node strength, closeness centrality, betweenness centrality and eigenvector centrality) and k-step survival rates.

First, we show that the time-varying pair-wise correlations are normally distributed in regular times (introducing the possibility of idiosyncratic diversity) and the rejection of normality occurs, in general, in high volatile periods. The MST, constructed by the distances obtained from dynamic correlations, is shown to shrink over time and this shrinkage is observed significantly around the 1997 Asian financial crisis and the 2008 global financial crisis. This picture reveals an increased interdependence between Asia-Pacific stock markets over the last two decades and is an evidence for a contagion effect during the 1997 and the 2008 financial crises.

The time-varying centrality measures show that Hong Kong is the key member of the dynamic MST for the majority of the time, which is in parallel to the high importance of this market in the global financial system. Moreover, considering its significantly improved centrality measure values, its importance in the region is increased in the last few years. An unexpected outcome is the insignificance of the Japanese stock market in the MST, as it is one of the most important financial markets in the world.

The stability (robustness) of the MST characteristics has been investigated using survival rates with different steps. The analysis shows that MST is highly stable over the last decade, furthermore the stability significantly increases in the last few years. This situation favors the usage of MST in policy making for the markets in the region as it tends to produce long term reliable results.

Then, we ask "what would be the case if the key member of the network did not exist?". In order to do that, we remove Hong Kong from the network and redo the previous analysis. In the new case, the system does not have a unique key member as it varies widely between Singapore, South Korea, Australia, Indonesia, Thailand and Philippines over time, and simultaneous key members are observed frequently. Moreover, the stability of the new MST is significantly lower compared to the original one, and we do not observe an improved stability in the last few years unlike the original MST. Such an outcome brings the question if this would be the case, in general, for regional financial market interactions which will be investigated in the forthcoming studies.

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A cDCC modeling

We will analyze the dynamic relationship between the changes in major Asia-Pacific stock market indexes. For any stock market i, the weekly changes will be taken as the log-returns i.e. $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$ where $P_{i,t}$ is the value of the index i on week t.

Furthermore, we apply an ARMA(P, Q) filtering for individual returns to account for the serial correlation and lingering effects of random shocks i.e.

$$r_{i,t} = \mu_i + \varepsilon_{i,t} + \sum_{p=1}^{P} \varphi_{i,p} r_{i,t-p} + \sum_{q=1}^{Q} \delta_{i,q} \varepsilon_{i,t-q} \tag{5}$$

where AR and/or MA parts are optional and used when necessary.

Let $\varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]'$ be the vector of residuals. In the next step, we obtain the conditional volatilities $h_{i,t}$ from univariate FIEGARCH(1,d,1) model of Bollerslev and Mikkelsen (1996). In particular, we estimate the following

$$\begin{aligned} \ln h_{i,t} &= \omega + (1 - \beta L)^{-1}(1 - \alpha L)(1 - L)^{-d} g(\varepsilon_{i,t-1}) \\ g(\varepsilon_{i,t}) &= \theta \varepsilon_{i,t} + \gamma(|\varepsilon_{i,t}| - E[|\varepsilon_{i,t}|]) \end{aligned} \tag{6}$$

where L is the backwards shift operator i.e. $L^k(X_t) = X_{t-k}$ and $(1-L)^d$ is the financial differencing operator defined by the Maclaurin series expansion as,

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k - d)}{\Gamma(k + 1)\Gamma(-d)} \tag{7}$$

with $\Gamma(.)$ is the gamma function.

In Eq.(6), ω, β, d, α respectively denote the location, autoregressive, differencing and moving average parameters of $\ln h_{i,t}$. The i.i.d. residuals $g(\varepsilon_{i,t})$ depend on a symmetric response parameter γ and an asymmetric response parameter θ that enables the conditional variances to depend on the signs of the terms $\varepsilon_{i,t}$.

Next, the dynamic correlations between the analyzed variables will be obtained by the cDCC model of Aielli (2013). To consider cDCC modeling, we start by reviewing the DCC model of Engle (2002). Assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, ...$ The asset conditional covariance matrix H_t can be written as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{8}$$

where $R_t = [\rho_{ij,t}]$ is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by $D_t = diag(h_{1,t}, ..., h_{n,t})$. Engle (2002) models the right hand side of Eq.(8) rather than H_t directly and proposes the dynamic correlation structure

$$R_t = \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2},$$
$$Q_t = (1 - a - b)S + a u_{t-1} u'_{t-1} + b Q_{t-1}, \tag{9}$$

where $Q_t \equiv [q_{ij,t}]$, $u_t = [u_{1,t}, ..., u_{n,t}]'$ and $u_{i,t}$ is the transformed residuals i.e. $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$, $S \equiv [s_{ij}] = E[u_t u_t']$ is the $n \times n$ unconditional covariance matrix of u_t, $Q_t^* = diag\{Q_t\}$ and a, b are non-negative scalars satisfying $a + b < 1$. The resulting model is called DCC.

However, Aielli (2013) shows that the estimation of Q by this way is inconsistent since $E[R_t] \neq E[Q_t]$ and he proposes the following consistent model with the correlation driving process

$$Q_t = (1 - a - b)S + a\{Q_{t-1}^{*1/2} u_{t-1} u'_{t-1} Q_{t-1}^{*1/2}\} + b Q_{t-1} \tag{10}$$

where S is the unconditional covariance matrix of $Q_t^{*1/2} u_t$.

B Supplementary materials

Table 1: Descriptive statistics of the raw returns

	Japan	India	Hong Kong	China	Taiwan	S. Korea
Mean	-0.00027	0.00169	0.00112	0.00043	0.00053	0.00124
Median	0.00116	0.00271	0.00239	0.00007	0.00303	0.00287
Max	0.11450	0.13171	0.13917	0.71565	0.18318	0.17945
Min	-0.27884	-0.17381	-0.19921	-0.22629	-0.16408	-0.21645
Std. Dev.	0.03068	0.03575	0.03552	0.05162	0.03448	0.04151
Kurtosis	9.74977	4.61674	5.72374	45.80656	5.32744	5.38617
Skewness	-0.75535	-0.20791	-0.36921	3.45582	-0.20962	-0.18144
Jarque-Bera	2192.7	127.7	365.0	86174.6	256.3	267.0

	Thailand	Malaysia	Indonesia	Philippines	Australia	Singapore
Mean	0.00068	0.00100	0.00253	0.00138	0.00094	0.00066
Median	0.00311	0.00172	0.00355	0.00251	0.00254	0.00108
Max	0.21838	0.24579	0.18803	0.16185	0.09114	0.48572
Min	-0.26661	-0.19027	-0.23297	-0.21985	-0.17016	-0.46337
Std. Dev.	0.03762	0.02955	0.03746	0.03456	0.02041	0.03606
Kurtosis	7.39440	12.22223	8.11481	7.63881	8.74011	60.68066
Skewness	-0.23761	0.10157	-0.42665	-0.48605	-0.84608	0.00266
Jarque-Bera	895.4	3900.0	1232.4	1029.6	1641.4	152490.2

Table 2: Parameter estimates for ARMA(P, Q) process

	μ	φ_1	φ_2	δ_1	δ_2
Japan	0.000	-0.648***	-	0.603***	-
	(0.77)	(0.00)	(-)	(0.00)	(-)
India	0.002	0.519**	-	-0.463*	-
	(0.16)	(0.03)	(-)	(0.07)	(-)
Hong Kong	0.001	0.701**	-	-0.671**	-
	(0.35)	(0.02)	(-)	(0.03)	(-)
China	0.000	-0.444**	-	0.519**	-
	(0.80)	(0.04)	(-)	(0.01)	(-)
Taiwan	0.001	0.565***	0.100***	-0.590***	-
	(0.67)	(0.00)	(0.00)	(0.00)	(-)
S. Korea	0.001	0.628***	0.108***	-0.703***	-
	(0.38)	(0.00)	(0.00)	(0.00)	(-)
Thailand	0.001	0.096	-0.311**	-0.071	0.472***
	(0.59)	(0.58)	(0.03)	(0.66)	(0.00)
Malaysia	0.001	0.847***	-	-0.783***	-
	(0.42)	(0.00)	(-)	(0.00)	(-)
Indonesia	0.003*	1.374***	-0.630***	-1.411***	0.738***
	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Philippines	0.001	-	-	0.018	0.120***
	(0.23)	(-)	(-)	(0.55)	(0.00)
Australia	0.001	-	-	-	-
	(0.13)	(-)	(-)	(-)	(-)
Singapore	0.001	-0.114***	-	-	-
	(0.50)	(0.00)	(-)	(-)	(-)

1. For the ARMA process, refer to Eq. (5).
2. The values in the parenthesis are p-values obtained from robust standard errors.
3. *,** and *** denote significance levels at 10%, 5% and 1% respectively.

Table 3: Parameter estimates for FIEGARCH(1,d,1) and cDCC(1,1) processes

	ω	d	α	β	θ	γ
Japan	-7.048***	0.377***	0.101	-0.033	-0.229***	0.270*
	(0.00)	(0.00)	(0.64)	(0.83)	(0.00)	(0.07)
India	-6.301	0.686***	0.507	-0.161	-0.077*	0.231*
	(0.15)	(0.00)	(0.24)	(0.60)	(0.09)	(0.08)
Hong Kong	-6.399	0.747***	0.545	-0.117	-0.076	0.226*
	(0.35)	(0.00)	(0.38)	(0.78)	(0.21)	(0.09)
China	-4.767**	0.562***	0.539	0.331	-0.066**	0.268***
	(0.01)	(0.00)	(0.23)	(0.46)	(0.04)	(0.00)
Taiwan	-6.524***	0.648***	2.034	-0.139	-0.020	0.118*
	(0.00)	(0.00)	(0.21)	(0.20)	(0.36)	(0.07)
S. Korea	-6.561***	0.661***	0.266	-0.212**	-0.117***	0.310***
	(0.00)	(0.00)	(0.42)	(0.03)	(0.00)	(0.00)
Thailand	-6.506***	0.616***	-0.163	-0.005	-0.121	0.281**
	(0.00)	(0.00)	(0.56)	(0.97)	(0.15)	(0.01)
Malaysia	-7.531**	0.749***	1.671	0.254	-0.010	0.098
	(0.01)	(0.00)	(0.53)	(0.46)	(0.70)	(0.37)
Indonesia	-6.622**	0.459***	-0.059	0.562***	-0.077*	0.294**
	(0.03)	(0.00)	(0.82)	(0.00)	(0.06)	(0.04)
Philippines	-6.508***	0.507***	0.750	0.274*	-0.056*	0.154**
	(0.00)	(0.00)	(0.45)	(0.08)	(0.09)	(0.02)
Australia	-7.796***	0.618**	0.040	-0.128	-0.116	0.302**
	(0.00)	(0.02)	(0.93)	(0.55)	(0.27)	(0.01)
Singapore	-6.166***	0.227	1.433	0.496**	0.015	0.277**
	(0.00)	(0.42)	(0.43)	(0.03)	(0.87)	(0.01)

cDCC parameters	
a	b
0.013***	0.960***
(0.00)	(0.00)

1. For the FIEGARCH and cDCC processes, refer to Eq. (6) and Eq. (10) respectively.
2. The values in the parentheses are p-values obtained from robust standard errors.
3. *,** and *** denote significance levels at 10%, 5% and 1% respectively.

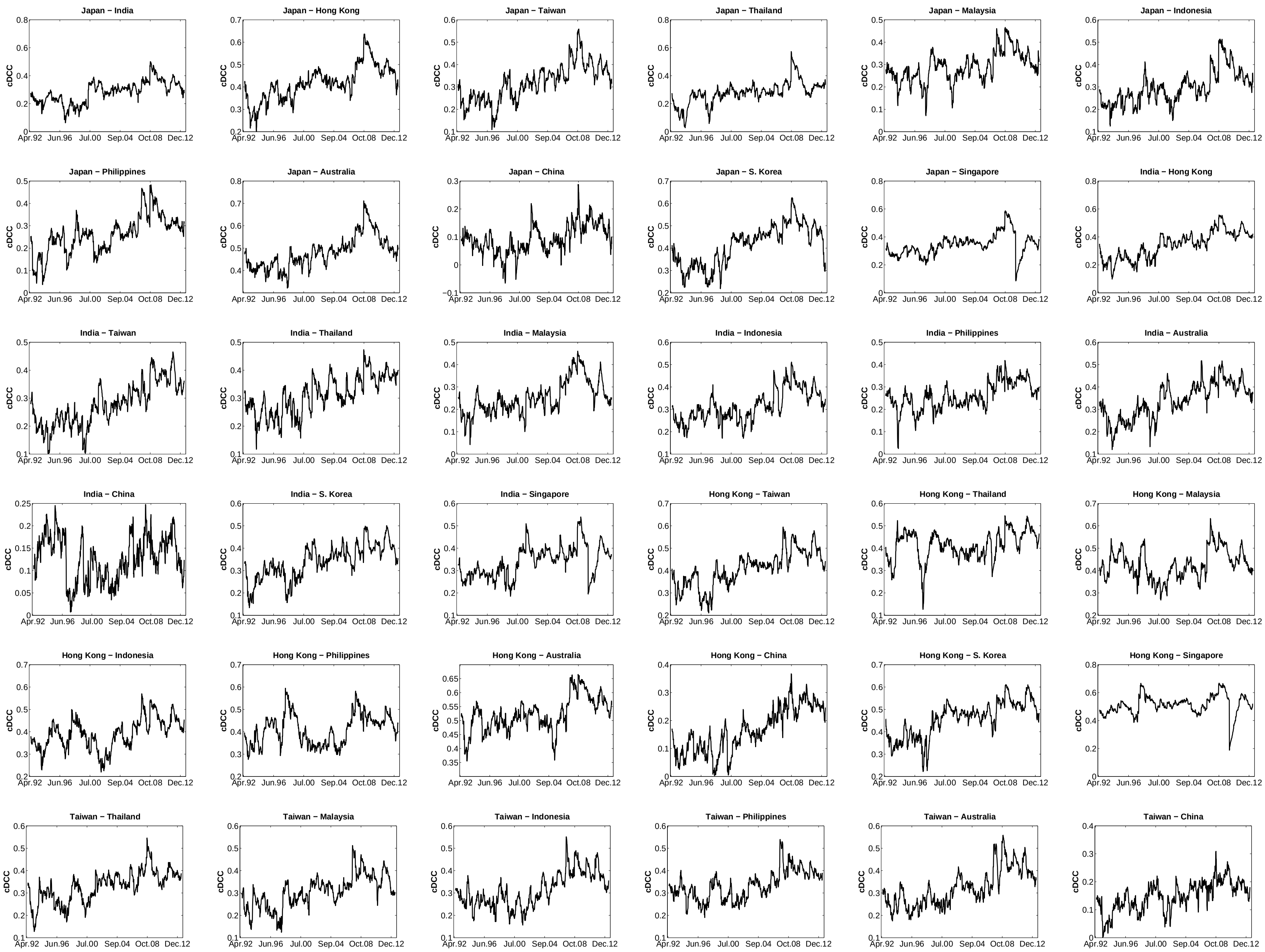

Figure 1: Dynamic conditional correlations between Asia-Pacific stock markets.

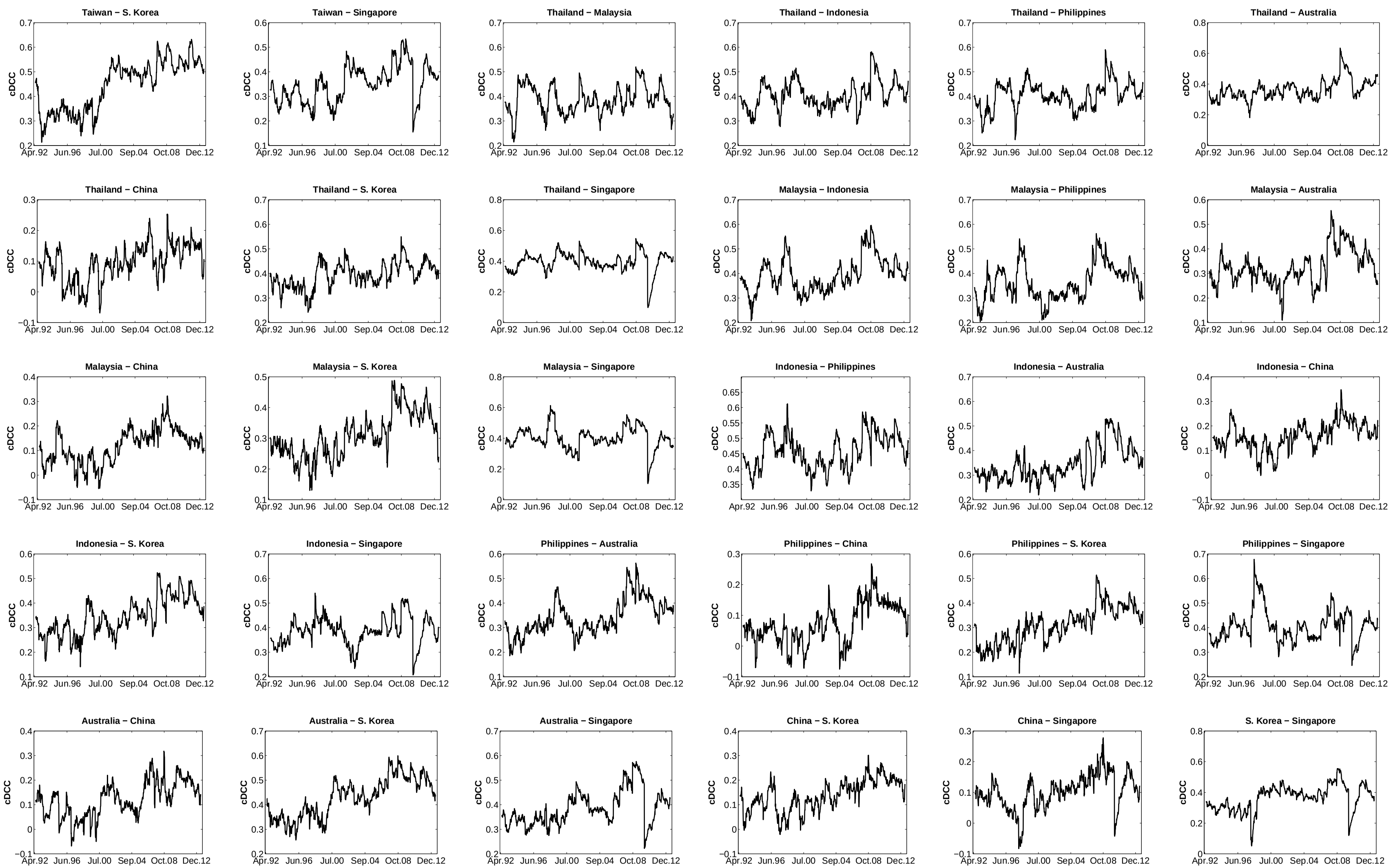

Figure 1: continued.

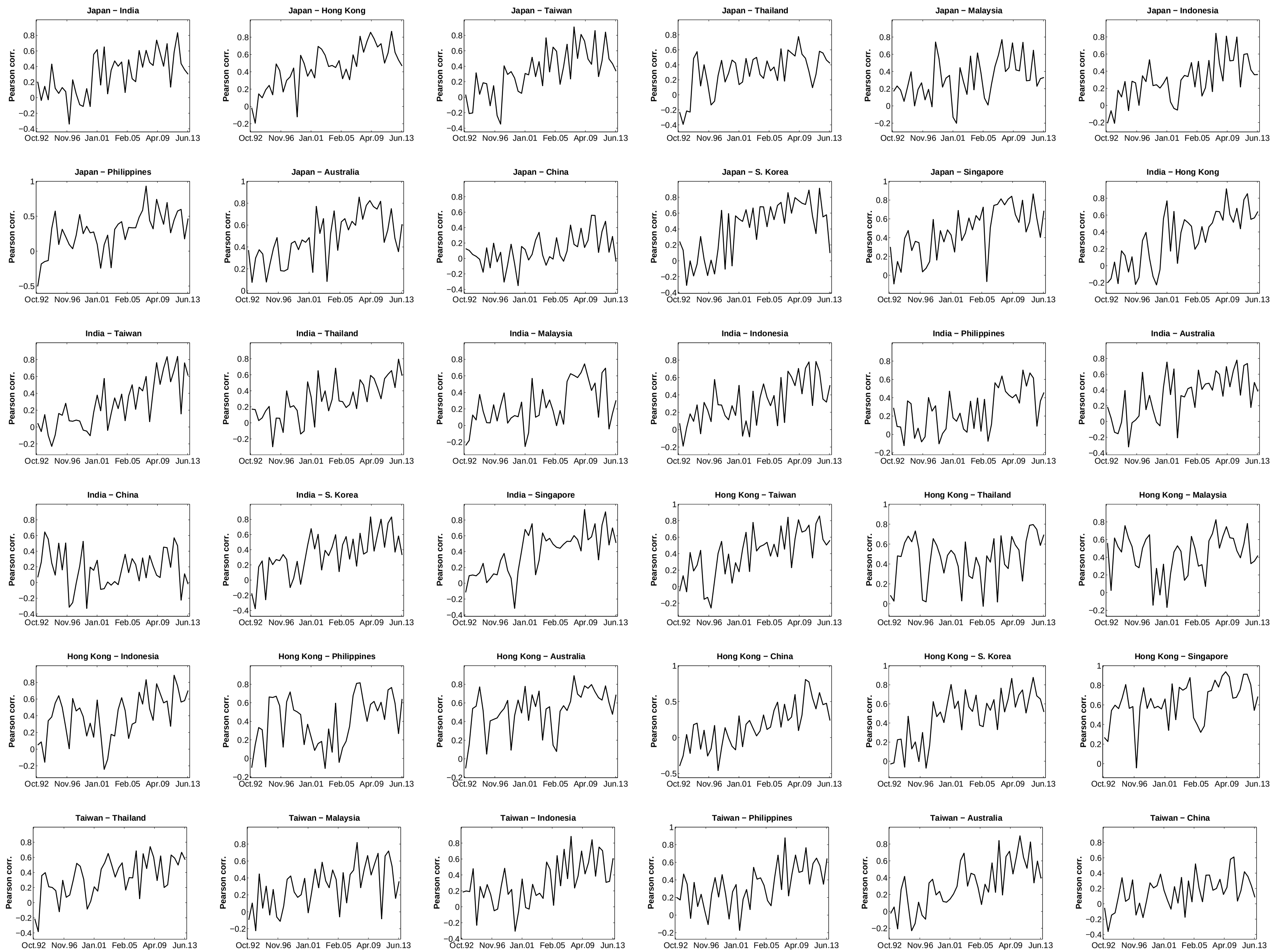

Figure 2: Time-varying Pearson correlations between Asia-Pacific stock markets.

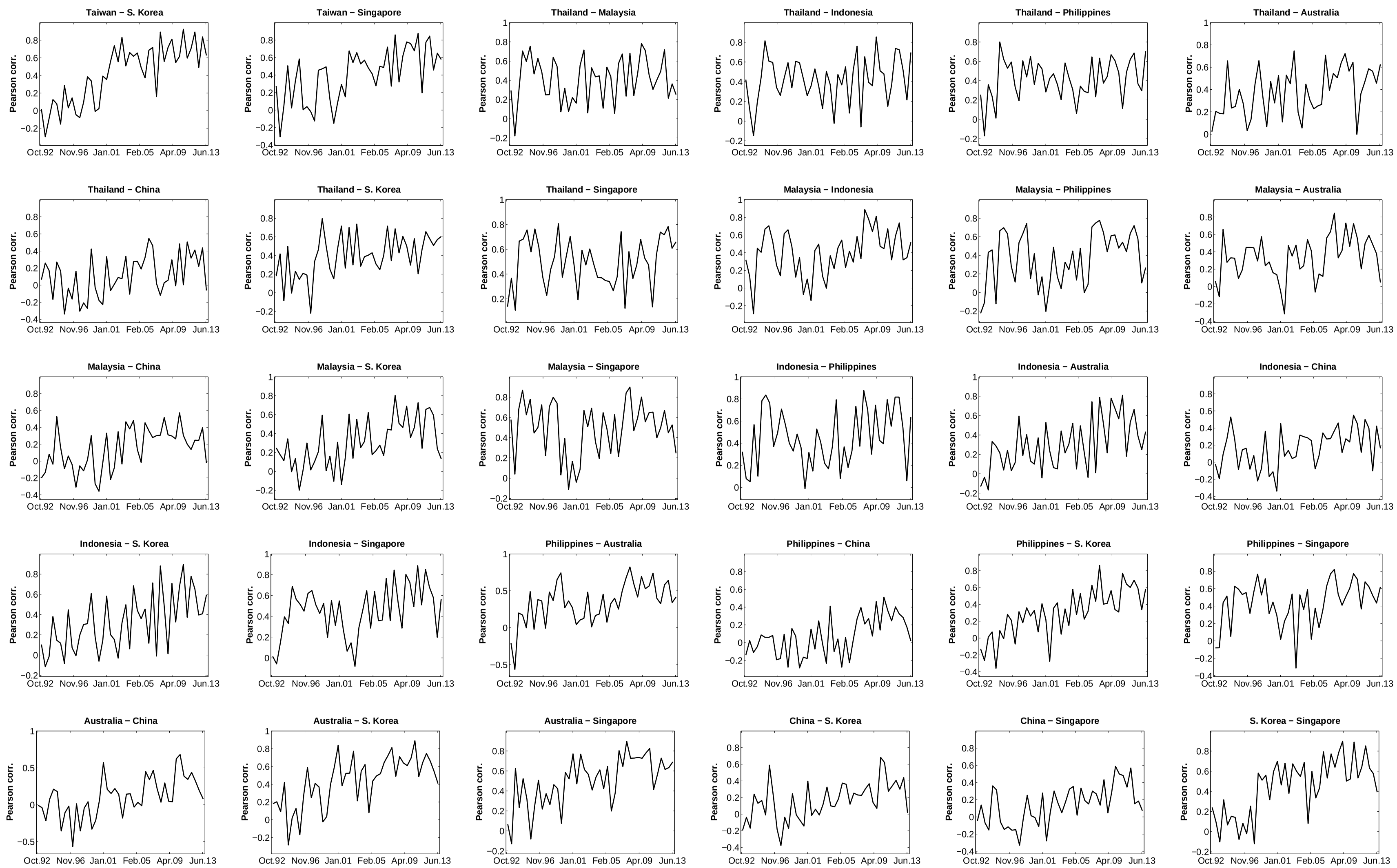

Figure 2: continued.