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SHORT-RUN LINKAGES BETWEEN ASIAN "PAPER TIGERS": A VAR AND FUZZY CLUSTERING APPROACH

This study first implements vector autoregressive (VAR) technique on the index returns of major stock markets in East Asia, namely All Ordinaries Index (AOS), Bombay Stock Index (BOMSE), Hang Seng Stock Index (HSIND), Kuala Lumpur Composite Index (KLCI), Korea Stock Index (KOSPI), NIKKEI, Straits Times Exchange (STI), and Taiwan Weighted Index (TAIWII), in addition to Dow Jones Industry Average (DJIA), to obtain the coefficient estimates that quantify the between-market interactions. Following that, a fuzzy clustering analysis is deployed on the estimates to classify markets into subsets of markets with symmetrical degrees of interactions. Findings are compared across 4 periods, that is, the Asian crisis period, the stable period after the Asian crisis but before the global crisis, the global recession period, and the whole sample period. Whilst groupings of markets differ depending on period, it seems clear that extents of association with DJIA predominantly determine the pattern of linkages across Asian markets. In another respect, the paper demonstrates the usefulness of complementing conventional econometric methodology with cluster analysis, a comparatively rarely used approach in finance.

Keywords: *VAR; East Asia; fuzzy clustering; cluster analysis.*

JEL Classifications: *C5; C8; F36; G01; G15.*

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КОРОТКОСТРОКОВІ ЗВ'ЯЗКИ МІЖ АЗІАТСЬКИМИ "ПАПЕРОВИМИ ТИГРАМИ": VAR-АНАЛІЗ І ПІДХІД НЕЧІТКОЇ КЛАСТЕРИЗАЦІЇ

У статті вперше застосовано векторну авторегресію (VAR) до індексів прибутковості основних фондових ринків Східної Азії, а саме: індексу All Ordinaries (AOS), індексу Bombay Stock (BOMSE), індексу Hang Seng Stock (HSIND), індексу Kuala Lumpur Composite (KLCI), індексу Korea Stock (KOSPI), NIKKEI, Straits Times Exchange (STI) і індексу Taiwan Weighted (TAIWII), на додаток до Dow Jones Industry Average (DJIA), для отримання коефіцієнтної оцінки рівня міжринкової взаємодії. Потім до отриманих оцінок використано аналіз методом нечіткої кластеризації для класифікації ринків на групи із симетричною мірою взаємодії. Результати порівнюються по 4 періодах, тобто період азіатської кризи, стабільний період після азіатської кризи, але до світової кризи, період глобального занепаду і загальний аналізований період. Хоча групування ринків відрізняються залежно від періоду, представляється очевидним, що міра асоціації з DJIA переважно визначає характер зв'язків між азіатськими ринками. Продемонстровано корисність доповнення звичайних економетричних методик кластерним аналізом, який порівняно рідко використовується у фінансах.

Ключові слова: *VAR; Східна Азія; нечітка кластеризація; кластерний аналіз.*

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КРАТКОСРОЧНЫЕ СВЯЗИ МЕЖДУ АЗИАТСКИМИ "БУМАЖНЫМИ ТИГРАМИ": VAR-АНАЛИЗ И ПОДХОД НЕЧЕТКОЙ КЛАСТЕРИЗАЦИИ

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В статье впервые применена векторная авторегрессия (VAR) к индексам доходности основных фондовых рынков Восточной Азии, а именно: индексу All Ordinaries (AOS), индексу Bombay Stock (BOMSE), индексу Hang Seng Stock (HSIND), индексу Kuala Lumpur Composite (KLCI), индексу Korea Stock (KOSPI), NIKKEI, Straits Times Exchange (STI) и индексу Taiwan Weighted (TAIWII), в дополнение к Dow Jones Industry Average (DJIA), для получения коэффициентной оценки уровня междурыночного взаимодействия. Затем к полученным оценкам использован анализ методом нечеткой кластеризации для классификации рынков на группы рынков с симметричной степенью взаимодействия. Результаты сравниваются по 4 периодам, то есть период азиатского кризиса, стабильный период после азиатского кризиса, но до мирового кризиса, период глобального спада и общий анализируемый период. Хотя группировки рынков отличаются в зависимости от периода, представляется очевидным, что мера ассоциации с DJIA преимущественно определяет характер связей между азиатскими рынками. Продемонстрирована полезность дополнения обычных эконометрических методик кластерным анализом, сравнительно редко используемым подходом в области финансов.

Ключевые слова: *VAR; Восточная Азия; нечеткая кластеризация; кластерный анализ.*

1. Introduction. Amidst the recent global economic and financial crisis, advanced and emerging economies have behaved differently in relation to the catastrophe, and so have their stock markets. This is not surprising as stock markets in emerging economies practice a different regulation framework than their counterparts in advanced economies. In particular, regulations in emerging markets are more restrictive (Fuss, 2002). Specifically, Asian markets appear to have large and strong potentials on the surface but are actually fragile - loosely labeled as "Paper Tigers" (see Corsetti, Pesenti, and Roubini, 1998). Against this unique setting, scholars have attempted to explore the mystery of emerging financial markets within the context of portfolio diversification.

In this field, most studies have used vector autoregressive (VAR) model in examining short-term transmission interactions across stock market returns. Within the VAR estimation framework, Awokuse et. al (2009), for instance, found significantly greater integration across East Asian markets since their financial liberalizations in the 1990s, with hegemons of Japan and Singapore. At the same time, others have detected the interactions to be short-lived (see Janakiramanan and Lamba, 1998; Yang and Lim, 2002).

In another respect, Huyghebaert and Wang (2010) pointed out that Hong Kong and Japan exert an important influence in transmitting the volatility of the 2008 global crisis across the East Asian markets. The dominance of Japan was also shown earlier by Yang and Bessler (2008) who concluded that positive movements in Japan's stock markets tended to buffer the adverse effects from the late 1980s US recession. Despite the above, the influence of the US is still significant. Arshanapalli and Doukas (1993), Chowdhury (1994), and Awokuse et al. (2009), for instance, commonly suggested that US markets maintain strong short-term (but short-lived) interactions with major stock markets in the East Asian region.

While the above investigations have laid emphasis on correlations of coefficients estimated from VAR and other similar methods in identifying closely interrelated markets, this paper implements fuzzy cluster analysis, a statistical tool from the school of pattern recognition commonly applied in biological and computer sciences, on the VAR estimates. The objective is to classify major East Asian markets into symmetrical subsets in respect of their short-run interactions. The markets in question are AOS, BOMSE, HSIND, KLCI, KOSPI, NIKKEI, STI, and TAIWII. In addition, as the US is expected to exert dominant influence, DJIA is also included. Data period is segmented into 3 subperiods, namely, Asian crisis period, the "stable" period after the Asian crisis but before the global crisis, and the period of the recent recession since the global financial crisis. Findings for the whole sampled data are also examined.

The rest of the paper is structured as follows. The second section describes the data and the methodology used, concentrating on VAR methodology and fuzzy cluster analysis. Section 3 details the findings. Section 4 concludes.

2. Data and Methodology. For the data, we use daily indices of 9 major stock markets, namely All Ordinary Index of Australia, Bombay Stock Index, Dow Jones Index Average, Heng Seng Index, KLSE Stock Composite Index, Korean Stock Index, NIKKEI, Strait Index and Taiwan Weighted Index. The whole sampled period is from July 1, 1997 till May 31, 2011 while the subperiods are Jan 1, 1997 — Dec 31, 1998 (the Asian crisis period), Jan 1, 1999 — Dec 31, 2006 (the stable period), and Jan 1, 2007 — May 31, 2011 (the global recession period).

The daily indices are transformed into natural log stock return using the following method:

$$\text{Return} = 100 \times [\ln(P_{t+1} / P_t)], \tag{1}$$

where P_{t+1} is the closing index for the respective equity market for the period t+1, while P_t refers to that for the period t.

The ensuing subsections introduce the VAR estimation technique and the fuzzy clustering method. In a nutshell, VAR analysis quantifies short-term interactions between returns of markets. Then, using the estimated coefficients generated from the VAR analysis, we perform fuzzy cluster analysis to classify the markets.

2.1. Vector Autoregressive (VAR) Estimation. Sims (1980) introduced vector autoregressive model as an alternative technique that allows a researcher to simulate huge range of equations in the context of structural models. Using VAR framework, we model the returns of 9 markets including lagged returns to recognize short-term associations between them, as follows:

$$r_{1t} = \alpha_0 + \sum_{i=1}^{k} \alpha_1 r_{1,t-i} + \sum_{i=1}^{k} \alpha_2 r_{2,t-i} \ldots\ldots + \sum_{i=1}^{k} \alpha_9 r_{9,t-i} + \varepsilon_t, \tag{2}$$

where α_0 denotes the constant term, α_1, α_2,..... and α_9 are the parameters to be estimated. ε_t represents the residuals which are independently identically distributed, while r_{1t}, r_{2t}, ..., r_{9t}, are the index returns of 9 stock markets.

In comparison to conventional structural models, a VAR model provides better forecasting and estimation results (Sims, 1980). Furthermore, it allows checking the dependency of variable against its own lagged terms, other independent variables, and its error term. Another advantage is the simplification of assuming all the variables as endogenous.

The VAR approach is not without its limitations though. According to Brook (2002), when numerous variables are included simultaneously, a large number of estimated parameters will be generated, and it is a formidable task for researchers to interpret them. Moreover, the VAR model specifies that all the tested variables must be stationary so that it can jointly or singly test the interrelation between these variables. Another drawback is the determination of the correct number of lag lengths (Phylaktis and Ravazzolo, 2005). This issue, however, can be addressed by performing the lag length criterion test, as implemented for the present analysis.

2.2. Fuzzy Cluster Analysis. In brief, cluster analysis examines similarities and dissimilarities of structure in the data and thereby uncovers homogenous subsets of objects, given a set of objects. Broadly, there are two variants of cluster analysis, hard and fuzzy clustering. While hard clustering (e.g. Quah and Crowley, 2010) attempts to assign each object to one and only one cluster, fuzzy clustering (e.g. Artis and Zhang, 2002) allows some ambiguity in the data by assigning each object to a cluster with a membership coefficient signifying the degree of belongingness of the object to that cluster. To an extent, it has more power in approximating the situation involving incomplete and uncertain information, which is often the case in the real world. An object (estimated coefficient from VAR, in our case) is most likely belonging to the cluster with which it has the largest membership coefficient.

The algorithm of fuzzy analysis employed here is the widely used fuzzy C-means (FCM) technique proposed by Dunn (1973) and Bezdek (1973). In the terminology of cluster analysis, there are n objects (market returns) and p variables (the coefficients of the lagged regressors) in a dataset with each object being denoted by a vector x_i ($x_i = (x_{i1}, x_{i2},..., x_{ip})$ for $i = 1, 2,..., n$). Each variable is standardized with a mean and standard deviation being equal to zero and unity respectively so that the variables are treated as having equal importance in determining the partition structure.

The dissimilarity coefficient, or distance d_{ij} between two objects x_i and x_j is defined by the Euclidean distance:

$$d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}. \quad (3)$$

The fuzzy C-means technique is based on the minimization of the following objective function:

$$\sum_{k=1}^{m} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} u_{ik}^2 u_{jk}^2 d_{ij}^2}{2\sum_{j=1}^{n} u_{jk}^2} \quad (4)$$

subject to the following constraints:

$$u_{ik} \geq 0, \sum_{k=1}^{m} u_{ik} = 1 \text{ for } i = 1,2,..,n, k = 1,2,..m \quad (5)$$

in which u_{ik} stands for the membership coefficients of object x_i belonging to cluster k and m is the number of clusters. In fuzzy clustering, the membership coefficients of each object are non-negative with their sum over all clusters being equal to one. On

[1]With respect to the present paper, unlike other measures, XBI has provided unique solutions, that is, only one minimum value for every exercise.

the contrary, in hard clustering, membership coefficients are effectively forced to take the value of either one or zero.

The above algorithm is based on the assumption that the number of clusters is known in advance. In reality, however, researchers have to choose the number of clusters to ensure that the clusters are as "crisp" as possible. Hence, to determine the optimal number of clusters Xie and Beni's index (XBI) is used:

$$XBI = \frac{1}{n}\frac{\sum_{i=1}^{n}\sum_{k=1}^{m}(u_{ik})^2 d_{ik}^2}{\min_{i,k} d_{ik}^2}, \quad (6)$$

where d_{ik} is the Euclidean distance between x_i and the center of the cluster k,

$$\sum_{i=1}^{n} u_{ik}^2 x_i / \sum_{i=1}^{n} u_{ik}^2.$$

Low indices indicate less (greater) variations within (between) clusters. Hence, smaller index values represent more compact and separated clusters[1].

Other than that, it may also be useful to introduce one diagnostic statistic in fuzzy analysis, namely Dunn's Partition Coefficient (DPC) which measures the degree of fuzziness in the partitions. DPC is defined as the sum of squares of all the membership coefficients divided by the number of objects and may be normalized as in the following formula:

$$DPC = \frac{m\sum_{i=1}^{n}\sum_{k=1}^{m}\frac{u_{ik}^2}{n} - 1}{m-1}. \quad (7)$$

The normalized DPC, varying from 1 to 0, is a useful indicator of the data structure where a value close to 1 indicates no fuzziness in the data, whilst a value close to 0 indicates complete fuzziness.

3. Results.

3.1. Preliminary Findings. Table 1 presents some vital statistics of 9 stock market returns. Based on the descriptive statistics, DJIA, HSIND, and NIKKEI exhibit the highest mean returns (respectively greater than 9%), while KLCI and KOSPI maintain the lowest mean returns (each less than 7%). In terms of variability from mean, DJIA shows the smallest deviation at only 0.14. Meanwhile, BOMSE portrays the largest deviation at 0.66. Generally, the second moment statistics is less than 1% for each return series.

Table 1. **Descriptive Statistics**

	LAOS	LBOMSE	LDJIA	LHSIND	LKLCI	LKOSPI	LNIKKEI	LSTI	LTAIWII
Mean	8.238	8.830	9.230	9.598	6.772	6.859	9.448	7.635	8.806
Std. Dev.	0.261	0.659	0.143	0.314	0.315	0.480	0.253	0.307	0.226
Skewness	0.412	0.293	-0.193	0.081	-0.203	-0.191	-0.038	-0.137	-0.394
Kurtosis	2.012	1.530	2.674	2.188	2.955	2.216	1.821	2.507	2.399
Jarque-Bera	237.141	358.755	36.607	98.259	23.883	108.898	200.113	45.569	140.944
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

On distribution, the skewness statistics indicates that the distributions of the returns of AOS, BOMSE and HSIND are positively skewed whilst the remaining 6 market return series are negatively skewed. Meantime, kurtosis shows that only KLCI is normally distributed while other series are characterized by platykurtic distribution. Based on the more formal Jarque-Bera test statistics, all 9 return series have not appeared to be significantly normally distributed. On the assumption of stationarity, the Augmented Dickey-Fuller (ADF) test results suggest the non-existence of unit root problem for these market return series. For all the cases, the null hypothesis of presence of unit root can be significantly rejected.

3.2. VAR estimation results.

This section reveals the VAR estimation results for the 9 models. The number of lag was determined by the lead lag criterion test results. Based on the lag length test, we estimated the VAR model with two lagged periods and the results are displayed in Table 2 for the whole sample period of July 1, 1997 till May 31, 2011.

Interestingly, the coefficients indicate that AOS is inversely related to BOMSE, KOSPI, NIKKEI and TAIWII and positively related to DJIA and STI. It is also of interest to find NIKKEI having significant positive relations with BOMSE, DJIA and STI and negative relations with AOS, HSIND and KLCI in addition to its own lagged terms. This implies that Japanese market moves in parallel with Indian, the US and Singapore one but move disparately with Australian, Hong Kong, and Malaysian ones.

Remarkably, STI maintains somewhat substantial short-term interactions with all other markets except KOSPI. Also interesting are the significant positive associations between KLCI and DJIA, HSIND, KOSPI, STI and TAIWII. KLCI is also significantly associated with its past returns.

The rest of the findings are self-explanatory but it may be worthy to note that DJIA exhibits significant short-run linkages with all other markets, especially HSIND, KOSPI, NIKKEI, STI and TAIWII. This is consistent with the relatively liberal environment and large trading volume found at these markets.

On top of the above, as mentioned earlier, we have also segregated the data period into 3 subperiods, namely, the Asian crisis period, the stable period and the global recession period. The results by subperiods for AOS are presented in Table 3.

The estimated coefficients will be used for the clustering analysis.

3.3. Fuzzy Clustering Findings.

Upon obtaining the coefficients from VAR estimations (Table 3), the analysis proceeds with fuzzy cluster analysis to draw out symmetrical groupings of market returns according to the coefficients of the lagged regressors (the first and the second lagged returns). Every variable is standardized to mean of 0 and standard deviation of 1, as shown in Table 4, so that each variable is given equal weight in the cluster analysis. This exercise is repeated for each of the sample periods.

Table 2. **VAR estimation results for 9 stock index returns, whole sample period**

	α_{RAOS-1}	α_{RAOS-2}	$\alpha_{RBOMSE-1}$	$\alpha_{RBOMSE-2}$	$\alpha_{RDJIA-1}$	$\alpha_{RDJIA-2}$	$\alpha_{RHSIND-1}$	$\alpha_{RHSIND-2}$	$\alpha_{RKLCI-1}$	$\alpha_{RKLCI-2}$
RAOS	-0.148[a]		0.042[a]		0.461[a]	0.102[a]				
RBOMSE		0.082[b]		-0.034[b]	0.242[a]	0.138[a]	-0.034[c]			
RDJIA					-0.074[a]	-0.05[a]	-0.023[c]			
RHSIND	-0.140[a]	0.086[b]	0.047[a]		0.588[a]	0.179[a]	-0.213[a]	-0.062[a]	0.035[b]	
RKLCI					0.257[a]		0.0418[b]		-0.060[a]	0.036[b]
RKOSPI	-0.108[b]	0.105[a]	0.043[b]		0.477[a]	0.112[a]		0.035[c]		-0.056[a]
RNIKKEI	-0.065[b]		0.067[a]		0.557[a]	0.123[a]	-0.042[b]			-0.025[c]
RSTI	-0.097[a]			0.020[c]	0.401[a]	0.116[a]		0.038[b]	0.048[a]	0.051[a]
RTAIWII	-0.076[b]		0.069[a]		0.356[a]	0.076[a]			0.036[b]	0.044[a]
	$\alpha_{RKOSPI-1}$	$\alpha_{RKOSPI-2}$	$\alpha_{RNIKKEI-1}$	$\alpha_{RNIKKEI-2}$	α_{RSTI-1}	α_{RSTI-2}	$\alpha_{RTAIWII-1}$	$\alpha_{1RTAIWII-2}$	α_0	R-squared
RAOS		-0.015[b]	-0.045[a]			0.022[c]	-0.024[a]			0.327
RBOMSE	0.027[c]	-0.023[c]	-0.078[a]							0.04
RDJIA		-0.044[c]	-0.037[b]		0.037[b]		0.022[c]	0.032[b]		0.017
RHSIND	0.067[a]		-0.084[a]	-0.052[b]	0.116[a]		-0.047[b]			0.174
RKLCI		0.032[b]			0.080[a]			0.039[b]		0.07
RKOSPI		-0.051[a]	-0.070[b]	-0.045[c]	0.106[a]					0.099
RNIKKEI			-0.139[a]	-0.048[a]	0.066[a]				-0.0004[c]	0.207
RSTI			-0.064[a]		0.046[b]	-0.064[c]	-0.035[b]	0.026[c]		0.129
RTAIWII					0.046[b]		-0.058[a]	0.035[b]		0.108

Table 3. **VAR estimation results for 9 stock index returns, by periods**

	αRAOS	αRAOS	αRBOMSE	αRDJIA	αRDJIA	αRHSIND	αRHSIND	αRKLCI	αRKLCI
	-1	-2	-1	-1	-2	-1	-2	-1	-2
Asian Crisis Period			0.048[b]	0.508[a]		-0.046[b]	-0.042[b]	0.044[a]	
Stable Period	-0.131[a]		0.024[a]	0.325[a]	0.047[a]				0.025[b]
Global Recession Period	-0.198[a]		0.039[b]	0.602[a]	0.225[a]	-0.049[b]			
	αRKOSPI	αRKOSPI	αRNIKKEI	αRSTI	αRSTI	αRTAIWII	αRTAIWII	α0	R-squared
	-1	-2	-1	-1	-2	-1	-2		
Asian Crisis Period									0.389
Stable Period			-0.035[a]					0.0003[b]	0.254
Global Recession Period		-0.097[a]	-0.0818[a]		0.066[b]				0.417

Notes: [a] represents 1 %level of significance; [b] represents 5 %level of significance; [c] represents 10 %level of significance

Table 4. **Coefficients of lagged regressors, whole sample period, standardized.**

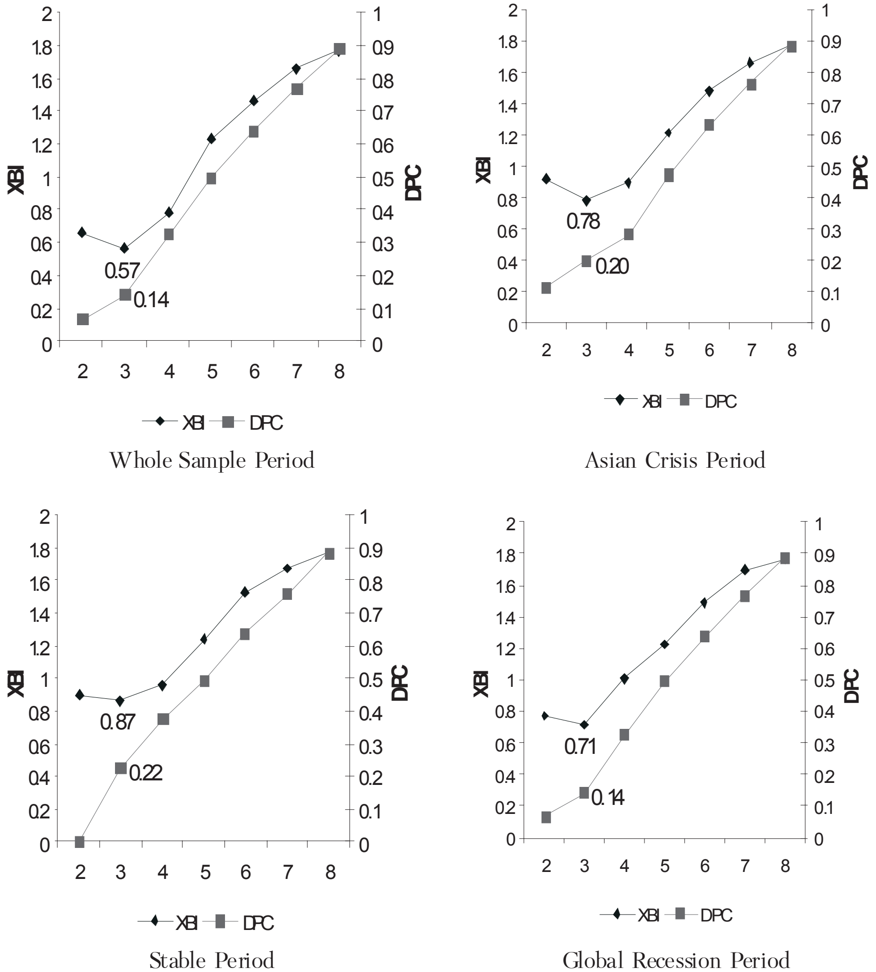
	α_{RAOS-1}	α_{RAOS-2}	$\alpha_{RBOMSE-1}$	$\alpha_{RBOMSE-2}$	$\alpha_{RDJIA-1}$	$\alpha_{RDJIA-2}$	$\alpha_{RHSIND-1}$	$\alpha_{RHSIND-2}$	$\alpha_{RKLCI-1}$
RAOS	-1.38	-0.35	0.30	-0.39	0.48	0.22	0.29	-0.18	0.07
RBOMSE	0.51	1.02	-0.93	-2.33	-0.60	0.70	-0.01	-0.15	0.11
RDJIA	1.47	-1.15	-1.14	0.02	-2.15	-1.92	0.14	0.30	-0.37
RHSIND	-1.22	1.15	0.50	0.55	1.11	1.22	-2.46	-2.34	0.77
RKLCI	1.28	-0.63	-0.65	-0.10	-0.52	-1.33	1.03	0.30	-2.24
RKOSPI	-0.59	1.61	0.34	0.6α	0.56	0.34	0.10	1.02	-0.40
RNIKKEI	0.26	-0.63	1.32	-0.22	0.96	0.49	-0.12	-0.05	0.07
RSTI	-0.37	-0.12	-1.14	0.96	0.19	0.39	0.18	1.12	1.19
RTAIWII	0.04	-0.89	1.40	0.84	-0.03	-0.12	0.85	-0.01	0.80
Mean	0	0	0	0	0	0	0	0	0
SD	1	1	1	1	1	1	1	1	1
	$\alpha_{RKLCI-2}$	$\alpha_{RKOSPI-1}$	$\alpha_{RKOSPI-2}$	$\alpha_{RNIKKEI-1}$	$\alpha_{RNIKKEI-2}$	α_{RSTI-1}	α_{RSTI-2}	$\alpha_{RTAIWII-1}$	$\alpha_{RTAIWII-2}$
RAOS	0.01	-0.75	-0.04	0.41	0.63	-1.49	0.67	-0.22	-1.35
RBOMSE	0.04	0.57	-0.36	-0.44	1.28	-0.73	-0.30	1.11	-0.36
RDJIA	-0.29	-0.25	-1.21	0.59	0.52	-0.62	0.09	1.53	0.74
RHSIND	-0.58	2.35	0.08	-0.59	-1.30	1.57	1.19	-1.10	0.28
RKLCI	0.19	-0.07	1.93	1.03	-0.39	0.56	-0.43	0.50	1.15
RKOSPI	-1.62	-1.16	-1.45	-0.23	-1.04	1.32	0.44	0.24	-0.01
RNIKKEI	-0.70	-0.20	0.69	-2.01	-1.15	0.19	0.93	0.12	-1.76
RSTI	1.59	-0.25	0.28	-0.10	0.30	-0.40	-2.15	-0.64	0.39
RTAIWII	1.38	-0.25	0.08	1.34	1.17	-0.40	-0.43	-1.56	0.92
Mean	0	0	0	0	0	0	0	0	0
SD	1	1	1	1	1	1	1	1	1

We begin by looking at the values of Xie-Beni's index (XBI) and Dunn's partition coefficient (DPC). To reiterate, the former statistics is used to indicate the appropriate number of clusters, whilst the latter is used to signify the degree of fuzziness in the partitions. Their values for the sample periods are plotted against *k*th number of clusters in Figure 1.

For each period, the XBIs are smallest at 3 clusters; hence the configurations of 3 clusters are used. The corresponding DPCs are 0.14, 0.20, 0.22, and 0.14 for the whole, crisis, stable, and recession periods, signifying a relatively well-defined partition when stable period data are used. Based on these small values of DPCs, the partition structures are highly fuzzy; which is not unexpected given only 9 objects in the analysis.

Table 5 shows the membership coefficients of the markets (market returns) for belongingness to the corresponding clusters. By and large, the partitions for all periods are clear-cut as the membership coefficients are significantly large for belongingness to only one cluster.

Accordingly, we can also examine the relative belongingness of a market to its grouping by weighting its membership coefficients as such so that the total weighted memberships to a cluster sum to 100%, as shown in Table 6. To illustrate, for the whole sample period there are 3 clusters, whereby for the first cluster, DJIA with a weighted membership of 42.2% is the group member most closely linked to the group, followed by KLCI (34.6%), and BOMSE (23.2%). This shows that the degrees of belongingness to the group are asymmetric amongst its members.



Source: Fuzzy cluster analysis.

Figure 1. **XBIs, DPCs, and number of clusters**

Table 5. **Membership coefficients (%)**

	Whole Period			Asian Crisis Period			Stable Period			Global Recession Period		
	I	II	III	I	II	III	I	II	III	I	II	III
RAOS		46.6			71.3			50.8		47.5		
RBOMSE	38.9				58.4			43.2			64.3	
RDJIA	70.7				59.5		57.1				45	
RHSIND			54.7			46.7			96.9			59.8
RKLCI	58			88.5			46.3			43.4		
RKOSPI			50.1			38.6		40.6		54.9		
RNIKKEI			64.9		60.3		50					73.7
RSTI		61.4				49.1		70.9			54.9	
RTAIWII		62.1				57		55.8		78		

Source: Fuzzy cluster analysis.

Table 6. **Weighted memberships for each cluster (%)**

		Whole Period			Asian Crisis Period			Stable Period			Global Recession Period		
		I	II	III	I	II	III	I	II	III	I	II	III
1	RAOS		27.4			28.6			19.4		21.2		
2	RBOMSE	23.2				23.4			16.5			39.2	
3	RDJIA	42.2				23.8		37.2				27.4	
4	RHSIND			32.2			24.4			100			44.8
5	RKLCI	34.6			100			30.2			19.4		
6	RKOSPI			29.5			20.2		15.5		24.5		
7	RNIKKEI			38.2		24.2		32.6					55.2
8	RSTI		36.1				25.7		27.1			33.4	
9	RTAIWII		36.5				29.8		21.4		34.9		
		100	100	100	100	100	100	100	100	100	100	100	100

Source: Fuzzy cluster analysis.

One of the objectives of the present work is to compare the grouping configurations over the economic periods. For this purpose, Table 7 puts together the compositions of the 4 sample periods. First of all, it is apparent that the findings of the subperiods are rather different from that of the whole period. This justifies a multiperiod analysis and is consistent with any possible structural changes following the Asian crisis and the global turmoil.

Secondly, it is notable to find the standalone KLCI in the Asian crisis period, which is unique when compared to its grouping in other subperiods. This indicates that KLCI has responded differently to the past returns of all the markets during the Asian crisis period. One reason for this could be the drastic capital control measures implemented by Malaysian authorities that were not found elsewhere during that episode. Meanwhile, for the stable period, HSIND is a singleton, not in linkage with any other market. This might possibly be due to its proximity and privileged access to China and its relatively advanced capital market which distinguish HSIND from the others.

Thirdly, we can find the Asian Tigers, namely Hong Kong, Korea, Singapore and Taiwan, sharing the same grouping in the Asian crisis period finding. This is in line with the Asian nature of the crisis during the Asian turmoil in contrast to that during the global recession. Differently, for the global recession period, BOMSE and STI are linked with DJIA, signifying a convergence between Asian and the US markets in that episode.

Fourthly, it may be of interest to find KOSPI and TAIWII (in bold) consistently placed together across the subperiods, indicating a stable degree of homogeneity shared by the two markets across the subperiods. Nonetheless, they are not placed together when the whole sample period is used.

Lastly, the stable period seems to record a slightly more convergent configuration in the sense that the largest cluster contains 5 cases, namely AOS, BOMSE, KOSPI, STI and TAIWII, in contrast to the Asian and the global crisis period where the biggest cluster at most includes only 4 markets.

We now turn to examining the coefficients of the lagged regressors by grouping as depicted in Figures 2 to 5. The codes representing the coefficients in the charts are shown in Table 8. First of all, some general observations can be seen across the findings.

At a glance, it is apparent that all current returns are to an extent positively associated with the two preceding returns of DJIA. This is in line with our general economic knowledge of the US dominance at the capital markets. In addition, it is also obvious to note the exceptional positive influences of DJIA in both the Asian and global crisis periods. This seems to indicate a much greater integration with the US market during times of turbulence, that once again coincides with our general economic knowledge. Quite on the opposite, during the stable period, all the coefficients including those of DJIA are remarkably smaller, signifying lower degrees of interconnectedness in that period.

Table 7. **Cluster configurations compared**

	Whole Period	Asian Crisis Period	Stable Period	Global Recession Period
1	RBOMSE, RDJIA, RKLCI	RKLCI	RDJIA, RKLCI, RNIKKEI	RAOS, RKLCI, **RKOSPI**, **RTAIWII**
2	RAOS, RSTI, RTAIWII	RAOS, RBOMSE, RDJIA, RNIKKEI	RAOS, RBOMSE, **RKOSPI**, RSTI, **RTAIWII**	RBOMSE, RDJIA, RSTI
3	RHSIND, RKOSPI, RNIKKEI	RHSIND, **RKOSPI**, RSTI, **RTAIWII**	RHSIND	RHSIND, RNIKKEI

Source: Fuzzy cluster analysis.

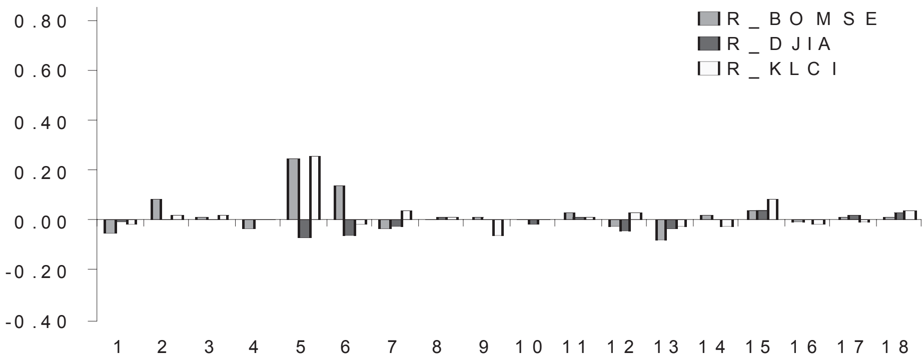
Table 8. **Codes for coefficients**

α_{RAOS-1}	α_{RAOS-2}	$\alpha_{RBOMSE-1}$	$\alpha_{RBOMSE-2}$	$\alpha_{RDJIA-1}$	$\alpha_{RDJIA-2}$	$\alpha_{RHSIND-1}$	$\alpha_{RHSIND-2}$	$\alpha_{RKLCI-1}$
1	2	3	4	5	6	7	8	9
$\alpha_{RKLCI-2}$	$\alpha_{RKOSPI-1}$	$\alpha_{RKOSPI-2}$	$\alpha_{RNIKKEI-1}$	$\alpha_{RNIKKEI-2}$	α_{RSTI-1}	α_{RSTI-2}	$\alpha_{RTAIWII-1}$	$\alpha_{RTAIWII-2}$
10	11	12	13	14	15	16	17	18

Looking at each specific period, for the whole period, Figure 2 shows that for the 3 clusters, the first lag return of DJIA is more substantive than the second lag return. Nevertheless, to DJIA itself, its current return is somewhat negatively related with its past returns. Another common observation across the clusters is the relatively substantive negative associations with the first lag return of AOS and of NIKKEI, and the slightly positive linkages with the first lag return of STI. Along this line, it appears that the relationships with DJIA, AOS, NIKKEI and STI are more predominant.

In particular, the cluster of BOMSE, DJIA and KLCI can be defined as maintaining the smallest degrees of association with the first lag returns of DJIA and AOS, and low extents of linkage with the past returns of NIKKEI and STI. The group of AOS, STI and TAIWII in turn can be described as having greater relationships with DJIA and AOS but low associations with NIKKEI and STI. Finally, the cluster of HSIND, KOSPI and NIKKEI can be regarded as displaying the greatest linkages with DJIA and STI and fairly large relations with AOS and NIKKEI.

Similar but different patterns can also be found for the subperiods, as illustrated in Figures 3, 4, and 5. A summary of the main features are listed in Table 9. To sum up, the predominant criterion utilized by the cluster analysis to determine whether a market belongs to a grouping with one another is the extent of association with DJIA, that is, markets with higher relations with DJIA are usually grouped together and vice versa.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R _ K L C I
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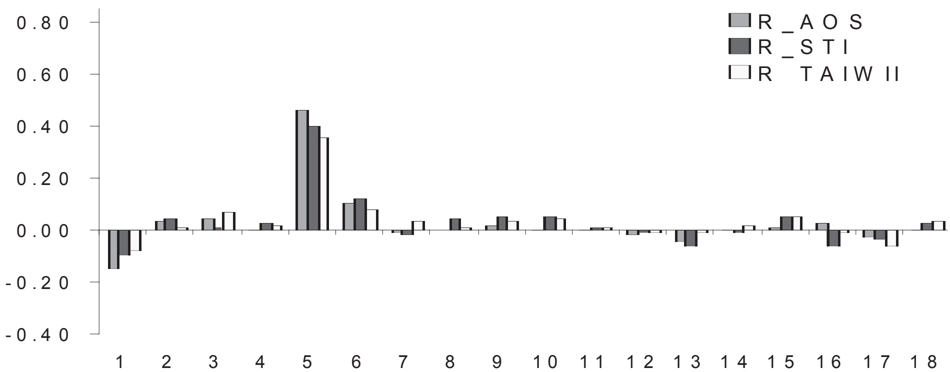
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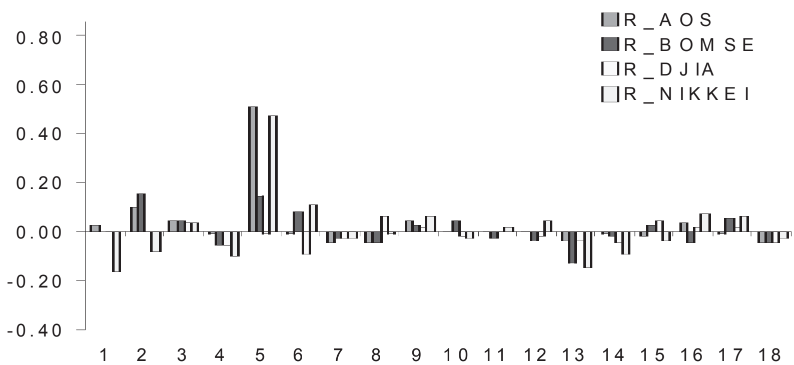
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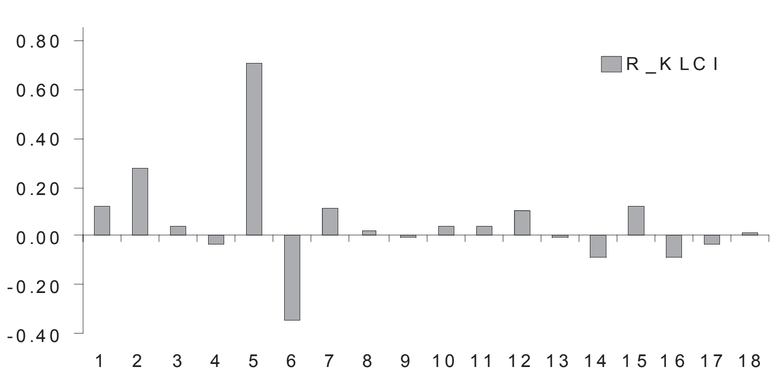
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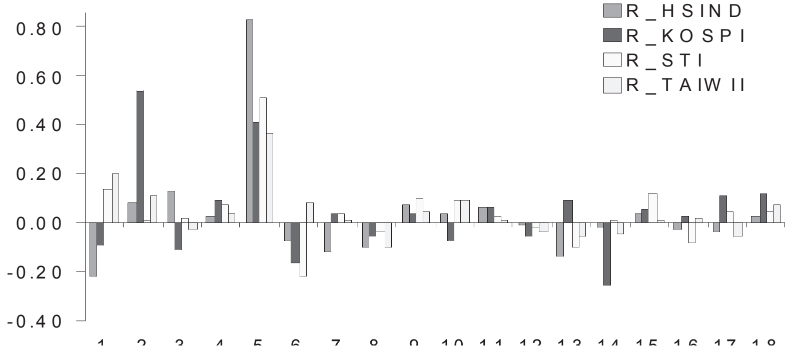
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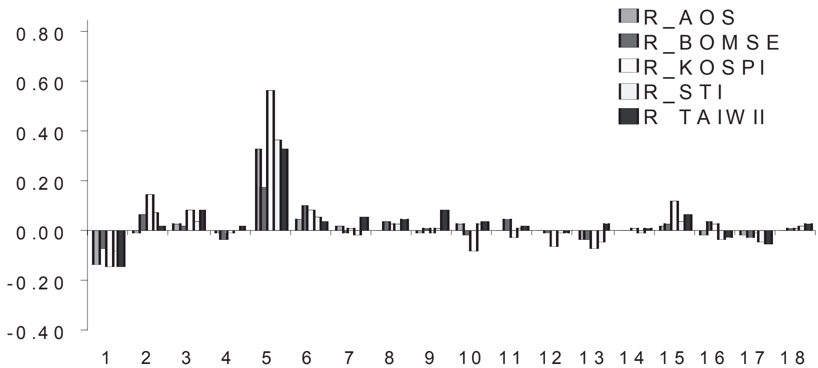
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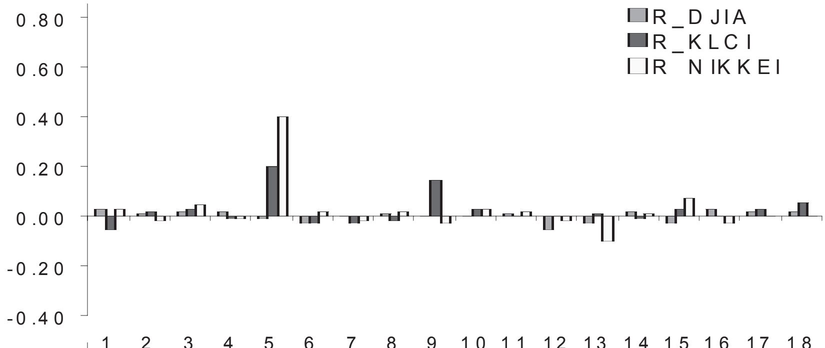
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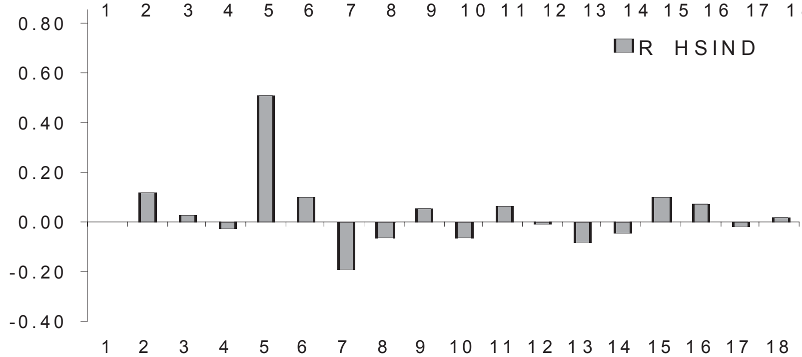
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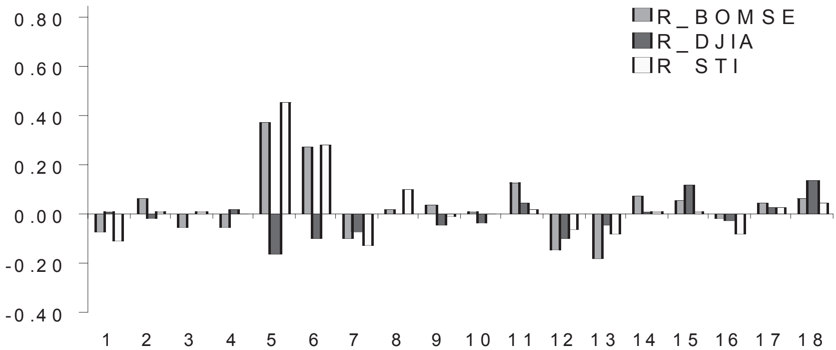
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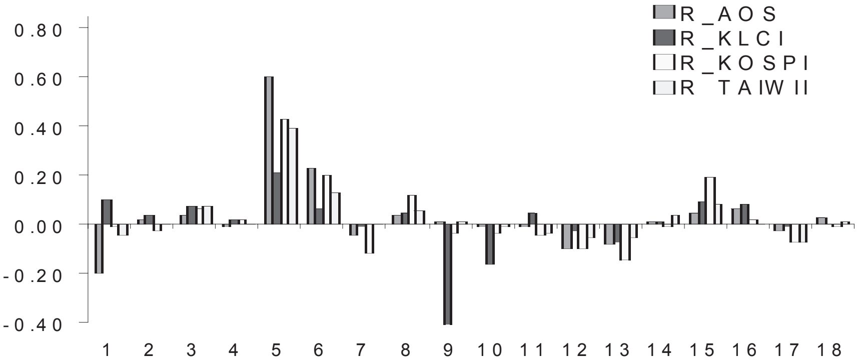
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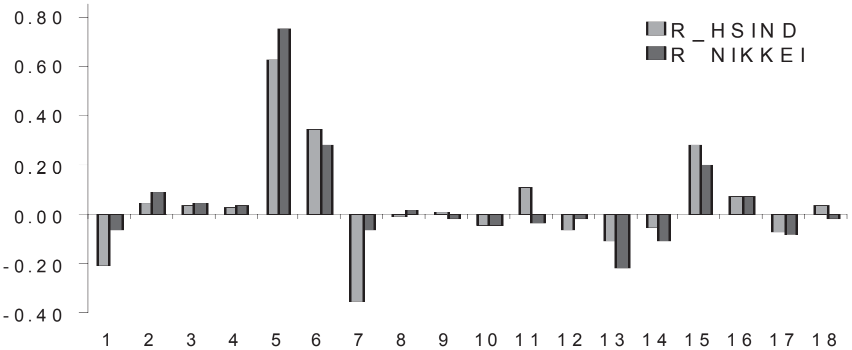
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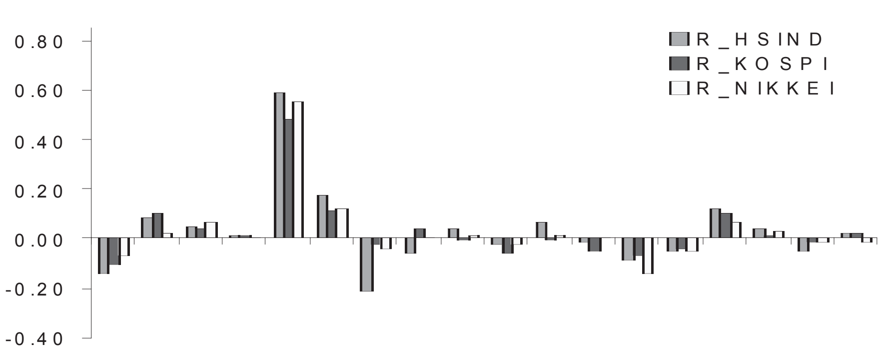
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R_NIKKEI
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1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

Table 9. **Summary of group features**

	Whole period	Notable common features amongst group constituents in comparison to other groups within the same period
1	RBOMSE, RDJIA, RKLCI	Low (+, -)$\alpha_{RDJIA-1}$, low coefficients with past returns of all markets.
2	RAOS, RSTI, RTAIWII	High (+)$\alpha_{RDJIA-1}$, high (+)$\alpha_{RDJIA-2}$; high (-)a_{RAOS-1}, low associations with the rest.
3	RHSIND, RKOSPI, RNIKKEI	Very high (+)$\alpha_{RDJIA-1,}$ very high (+)$\alpha_{RDJIA-2}$, high (-)α_{RAOS-1}, high (+)$\alpha_{RAOS-2;}$ lag, high associations with other markets especially NIKKEI and STI.
	Asian Crisis Period	
1	RKLCI	High (+)$\alpha_{RDJIA-1}$, very high (-)$\alpha_{RDJIA-2}$, high (+)α_{RAOS-2}
2	RAOS, RBOMSE, RDJIA, RNIKKEI	Low (+)$\alpha_{RDJIA-1}$, low (+)$\alpha_{RAOS-2,}$ high (-)$\alpha_{RNIKKEI-1}$
3	RHSIND, RKOSPI, RSTI, RTAIWI	Very High(+)$\alpha_{RDJIA-1,}$ low (-)$\alpha_{RDJIA-2;,}$ high (+)$\alpha_{RAOS-2,}$ high (-)$\alpha_{RNIKKEI-1}$, high (-)$\alpha_{RNIKKEI-2}$
	Stable Period	
1	RDJIA, RKLCI, RNIKKEI	Low (+)$\alpha_{RDJIA-1,}$ for KLCI high (+)$\alpha_{RKLCI-1}$
2	RAOS, RBOMSE, RKOSPI, RSTI, RTAIWII	Very high (+)$\alpha_{RDJIA-1}$, high (-)α_{RAOS-1}
3	RHSIND	High (+)$\alpha_{RDJIA-1}$, and high (-)$\alpha_{RHSIND-1}$
	Global Recession Period	
1	RAOS, RKLCI, RKOSPI, RTAIWII	High (+)$\alpha_{RDJIA-1}$ and high (+)$\alpha_{RDJIA-2}$, high (+)α_{RSTI-1}
2	RBOMSE, RDJIA, RSTI	Low (+)$\alpha_{RDJIA-1}$ and low (+)$\alpha_{RDJIA-2}$, very high (+)α_{RSTI-1}
3	RHSIND, RNIKKEI	Very high (+)$\alpha_{RDJIA-1}$ and very high (+)$\alpha_{RDJIA-2}$, low (+)α_{RSTI-1}

4. Conclusion. This study has first implemented VAR technique on the index returns of major stock markets in East Asia, namely AOS, BOMSE, HSIND, KLCI, KOSPI, NIKKEI, STI and TAIWII, in addition to DJIA, to obtain the coefficient estimates that quantify the between-market interactions. Following this, a fuzzy clustering analysis is deployed to classify markets with homogenous degrees of interactions between the markets. The findings are compared across 4 periods, that is, the Asian crisis period, the stable period, the global recession period, and the whole sample period. The following findings may be worth emphasizing.

First of all, the groupings of the subperiods are substantially different from that of the whole period. Secondly, KLCI is distinctive in the Asian crisis period. Thirdly, the Asian Tigers share the same grouping in the Asian crisis period. Fourthly, Korean and Taiwanese markets are consistently placed together across the subperiods. Fifthly, the stable period has shown a more convergent configuration. Finally, the groupings of the markets appear to be largely determined by the degrees of association with DJIA.

The above findings corroborate many of those in the literature which indicate that interactions across major share markets are highly dynamic and variable. Accordingly, this paper adds to the pool of knowledge by confirming the existing findings using a clustering technique which is comparatively rarely applied in finance and economics. The work also demonstrates the usefulness of fuzzy cluster analysis in identifying symmetrical clusters of stock markets, which could serve as a vital reference for practitioners in the financial sector to consider cluster analysis as an alternative approach to conventional econometric methods.

Despite the above, the empirical evidence has highlighted the tendency of interactions between stock markets to converge in the long run. Using the VAR framework, the paper only focuses on short-run interactions. Future research could enrich the present work by incorporating long-run relationships into the clustering exercise.

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