A single currency for Asia?

Evaluation and comparison using hierarchical and model-based cluster analysis

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Abstract

Today, there is increased speculation on the possibility of an Asian currency, as the region begins to show increased promise as a region of nascent economic activity. Any monetary integration scheme in East Asia would likely have to include both China and India though, so this paper attempts to assess the evolution of convergence among the East Asian countries, including China and India, according to the optimum currency area theory criteria, which is operationalized through the use of cluster analysis. In this paper we use both traditional "hierarchical" clustering as well as the more recently developed "model-based" clustering techniques and compare the outcome in each case. As the East Asian crisis of 1997-98 is likely to affect the results, the exercise is done for pre-crisis, crisis, and post-crisis periods. The results reveal some structure among the countries, an increase in the degree of subregional homogeneity, and a robust relationship between Malaysia and Singapore.

Keywords: optimum currency area; cluster analysis; business cycles; monetary union; Asia

JEL classification: C19, E32, F10, F15, F41, O53

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1 Introduction

In recent decades, studies on optimum currency areas (OCAs) have proliferated, with their focus shifting from being applied almost exclusively to the European region to being applied to nearly all other parts of the world. In East Asia, recent literature on potential monetary union includes a paper by Dutta (2000) which explicitly called for studies of "the economic rationale of an institutional Asia-Pacific Monetary Union" and another by Swofford (2008), who implicitly answered Dutta's call by examining the interrelationships amongst various Asian economies.

More than a decade ago, using vector autoregression (VAR) method, Bayoumi and Eichengreen (1994) concluded that East Asia came as close as the European Economic and Monetary Union (EMU) to being an OCA. They also discovered two subsets of East Asian countries of high potential: a Northeast Asian bloc of Japan-Korea-Taiwan, and a Southeast Asian bloc of Hong Kong-Indonesia-Malaysia-Singapore-Thailand. Recently, Kawai (2008) established that Japan-Korea, China-Hong Kong, and Singapore-Malaysia-Brunei may benefit by initiating subregional currency stabilization schemes. At the same time, Shirono (2008) suggested that certain regional currency arrangements in East Asia would stimulate regional trade and could generate economically significant welfare gains.

In practical terms, an initial step was taken to form closer cooperation between the East Asian countries when the ASEAN + 3 (ASEAN plus Japan, Korea, and China) or 'APT' in May 2007 agreed to the Chiang Mai Initiative, a network of bilateral swap agreements which allows East Asian countries to borrow funds from one another. The issuance of an Asian regional accounting currency (ACU) was also put forward at this time. In 2008, the APT leaders agreed to create an $80 billion fund in wake of the global financial and economic crisis. Essentially, monetary cooperation in this region is in part intended to ward off speculative attacks, given the success of currency blocs elsewhere in the world at re-buffing currency speculation (Ngiam and Yuen (2001)). Also behind this initiative was a strong aversion to real appreciation of exchange rates, a result of East Asia's long-standing reliance on export promotion (Kenen and Meade (2008)). Against this backdrop, it is not unreasonable to envisage a form of monetary integration in East Asia in the 21st century or indeed efforts to achieve such an objective.

This paper attempts to assess the evolution of convergence among the East Asian countries according to the criteria set by the OCA theory. It is operationalized through hierarchical cluster analysis. The results generated may assist in decision-making among the national authorities with respect to the critical areas for improvement and the sequence of country accession. The remainder of this paper is structured as follows. Section II presents some background on the existing monetary arrangements in East Asia and the relevant literature. Section III describes the methodology adopted in this paper. Section IV discusses the variables used in the empirical analysis. Section V presents the results and section VI concludes and compares the results obtained with those found in the existing literature.

2 Background

At one extreme, before the Asian financial crisis, Japan had a floating exchange rate, although it engaged in substantial intervention to influence the path and rate of change in the yen-dollar rate. At the other extreme, China had a rigid fixed rate vis-à-vis the U.S. dollar, while Hong Kong, Brunei, and Macau had even stricter currency-board regimes based on the U.S. dollar, the H.K. dollar, and the Singapore dollar, respectively. As for the other ASEAN countries and Korea, most of them described themselves officially as having flexible exchange rates, though numerous studies have shown that most of them pegged their currencies more or less firmly to the dollar, partaking of what McKinnon (2005) described as the "East Asian dollar standard".

During and after the Asian crisis, however, most of the ASEAN countries began to do what they had previously only claimed to do—let their exchange rates fluctuate more freely. Malaysia was the clear exception, as it switched to a strict dollar peg backed by the imposition of capital controls. In July 2005, however, Malaysia loosened its ties to the dollar and on the same day China revalued the renminbi by 2.1 percent vis-à-vis the dollar and announced that its money price would be guided by a multi-currency basket. Meanwhile, India has been found to have adopted de facto dollar peg since 1993 which continued after the crisis (Patnaik and Shah (2008)). Currently, the East Asian region is divided when it comes to exchange rate regimes with most of the exchange rate regimes categorized by the IMF as either managed floating or independently floating rate regimes.

Regionwide monetary cooperation in East Asia began in the 1990s when the Japanese government decided to promote the international use of yen. In September 1997, having taken the lead in mobilizing financial support for Thailand, the Japanese government proposed the creation of an Asian Monetary Fund (AMF). In 1998, the ASEAN governments agreed to study the feasibility of a common currency area whilst the Asia-Europe Meeting of finance ministers organized a very ambitious study, the Kobe Research Project, to study the feasibility and merits of an Asian monetary union. In 2000, Chiang Mai, Thailand, at the first annual meeting of the finance ministers of the APT countries, participants agreed to exchange data on capital flows whilst Japan proposed the bilateral credit arrangements now known as the Chiang Mai Initiative (CMI). At Chiang Mai, China, Japan, and Korea agreed in principle to negotiate bilateral swap agreements with each ASEAN country, as well as bilateral swap agreements among themselves. In 2005, at the Istanbul meeting of the Asian Development Bank (ADB), four cooperative objectives were agreed upon. These objectives pertain to surveillance, collective decision-making, and size and conditions of bilateral swaps.

There have been other efforts to foster cooperation throughout Asia, and some have already borne fruit. The Executives' Meeting of East Asia and Pacific Central Banks (EMEAP) has sponsored the creation of two bond funds. The first, created in 2003, was a $1 billion fund to be used for buying dollar-denominated bonds issued by Asian governments. The second, created in 2004, aims at financing a set of bond funds to invest and trade in local-currency bonds.

In spite of this, several observers have questioned the feasibility of the proposed Asian monetary union and the ability of member countries to adjust to external shocks in the absence of the exchange rate as a policy instrument. The standard tool used in economic literature to evaluate the adequacy of a monetary integration is the OCA theory, originated by Mundell (1961) and McKinnon (1963), with refinements by Kenen (1969) and Krugman (1990). The OCA theory compares the benefits and costs to countries participating in a currency area. Benefits include lower transaction costs, price stabilization, improved efficiency of resource allocation, and increased access to product, factor, and financial markets. The main cost, however, is the country's loss of sovereignty to maintain national monetary and exchange rate policies. Both costs and benefits depend on the nature of exogenous shocks affecting potential member countries and the speed with which they adjust to them. The costs tend to be lower (higher) if shocks are symmetric (asymmetric) and market mechanisms are quick (slow) to restore equilibrium after the shock. Nonetheless, the existence of heterogeneities across countries does not necessarily imply that monetary integration cannot be achieved. This follows from the endogeneity argument—originally proposed by Frankel and Rose (1998), which suggests that countries become similar when they form a monetary union.

Much of the research hinges on the symmetry or asymmetry of shocks. For instance, Chow and Kim (2003) investigated the symmetry of shocks and found that East Asian countries are structurally different from each other and thus are likely to be subject to asymmetric shocks. On the other hand, Eichengreen and Bayoumi (1999), Bayoumi and Eichengreen (2001), and Kawai and Motonishi (2005) were able to conclude that East Asia is nearly as good a candidate as the European Union for an internationally harmonized monetary policy. More recently, Huang and Guo (2006) found several East Asian subgroups of which one is more synchronized and might form a currency union ahead of the other subgroups.

While shock symmetry is important, other criteria come into play as well. Thus, Nguyen (2007) attempted fuzzy clustering to examine the degree of homogeneity in East Asia on the basis of macroeconomic characteristics stemming from the OCA theory. Using data for the period 1990–2003, he found that East Asia has not been homogenous but instead can be classified into about four groups with significant degrees of fuzziness.

In this paper, we compare results for different economic periods and include more countries . Our analysis differs from Nguyen (2007) in that we use both hierarchical and model-based clustering analysis to examine the convergence pattern of the countries.

3 Methodology

3.1 Hierarchical Cluster Analysis

Cluster analysis refers to methods used to organize multivariate data into groups (clusters) according to homogeneities among the objects such that features in the same group are as similar as possible. The resulting data partition improves our understanding of the data by revealing its internal structure. The use of cluster analysis as an exploratory tool is well-established in disciplines such as geology, paleontology, archeology, and even in biology and developmental psychology. In this paper, both hierarchical clustering and model-based clustering methods are used, and comparisons made between the two approaches. There are other clustering methods which are available such as fuzzy clustering which was used by Artis and Zhang (2002) and Nguyen (2007).

In general, cluster analysis possesses a number of desirable features. First, by allowing the analysis to account for a number of variables simultaneously, it enables us to investigate synchronization in terms of the symmetry of business cycles as well as the symmetry of various other relevant variables. Second, cluster analysis needs less stringent data requirements in terms of time dimension than other methodologies, and so works well for variables (e.g., data on labor) and countries (e.g., less-developed Asian economies) with limited time-series data or differing frequency data. Third, by exploring group patterns in the data, this methodology identifies the areas in which each country needs to improve in order to achieve convergence.

In the terminology of cluster analysis, there are N objects (countries) and p variables (features) in a data set (with N=17 and p=7 or 8 in this study), which are denoted as $X_1, ..., X_N$, ($X_j = (x_{j1}, ..., x_{jp})$ for $j = 1, 2, ..., N$). We take the dissimilarity coefficient or distance, $d(j, k)$, between two objects, X_j and X_k, to be defined by the Euclidean distance:

$$d(j,k) = \sqrt{\sum_{l=1}^{p}(x_{jl} - x_{kl})^2} \tag{1}$$

The definition of the dissimilarity coefficient between two clusters is important in determining the shape of the homogenous groups. There exist a few agglomerative algorithms which differ only in the definition of dissimilarity between clusters. Here, we adopt two of the most popular approaches: the group-average clustering and centroid clustering algorithms. Both of these algorithms produce ball-shaped clusters. The dissimilarity coefficient, $d(\omega_j, \omega_k)$, of two clusters ω_j and ω_k, defined by the group-average clustering algorithm can be expressed as:

$$d(\omega_j, \omega_k) = \frac{1}{|\omega_j|\,|\omega_k|} \sum_{j \in \omega_j} \sum_{k \in \omega_k} d(j,k) \tag{2}$$

where $|\omega_j|$ and $|\omega_k|$ denote the number of objects in the cluster, ω_j and ω_k respectively. For the centroid clustering method, a cluster, ω_j, once formed is represented by its centroid, $\overline{x}(\omega_j)$, which, together with its coordinates $\overline{x_k}(\omega_j)$ (for k=1,2, … p), may be expressed as:

$$\overline{x}(\omega_j) = (\overline{x_1}(\omega_j), \overline{x_2}(\omega_j), ..., \overline{x_p}(\omega_j)) \tag{3}$$

where

$$\overline{x_f}(\omega_j) = \frac{1}{|\omega_j|} \sum_{k \in \omega_j} x_{kf} \tag{4}$$

for $f = 1, 2, ..., p$. The dissimilarity coefficient, $d(\omega_j, \omega_k)$, between two clusters, ω_j and ω_k, is then defined as the Euclidean distance between two centroids.

Both algorithms start from a classification denoted $\Omega_0 = [\omega_1^0, \omega_2^0, ..., \omega_N^0]$ with N clusters in it, and each cluster containing only one object. The algorithms proceed by successively merging two clusters into one at each stage until a single cluster is obtained. The merging criterion at each stage is to choose two clusters which have the least dissimilarity between them. A new classification at stage i, $\Omega_i = \left[\omega_1^i, \omega_2^i, ..., \omega_{N-i}^i\right]$, is identified after two clusters have been merged and the dissimilarities between clusters updated.

Since the clustering algorithms differ in their definition of distance or dissimilarity between objects we use a measure of cophenetic correlation to determine the best way to represent the data. This is a measure which determines how well the generated clusters represent dissimilarities between objects, with values close to one representing better clustering.

The outcome of hierarchical clustering is presented in the form of a tree known as dendrogram. The heights of the links of the dendrogram represent the distance at which each fusion is made such that greater dissimilarity between objects is reflected by larger distances and taller links. Although the dendrogram is a natural guide to cluster divisions, where large changes in fusion levels indicate the best cut for forming clusters, various more 'formal' rules have also been proposed to determine the appropriate number of clusters. As suggested by Calinski and Harabasz (1974), here the pseudo-F (CH) index is used to determine the optimal number of clusters. It is defined as:

$$CH = \frac{\frac{S_b}{k-1}}{\frac{S_w}{N-k}} \tag{5}$$

where S_b is the between clusters sum of squares, S_w is the within clusters sum of squares, k is the number of clusters, and N is the number of objects. Higher values of the index indicate more distinct partitioning and therefore better clustering.

3.2 Model-based cluster analysis

3.2.1 Model parameterization

Model-based clustering was first used in single currency area studies by Crowley (2008). One of the drawbacks of the hierarchical clustering method is that it does not directly address the issue of how many clusters there should be, so instead various strategies are used to choose the number of clusters, but none of these methods has been entirely satisfactory from a computational or methodological standpoint. The most recently developed alternative as presented by Fraley and Raftery (2002a) and Fraley and Raftery (2002b) is computationally relatively straightforward, and is also intuitively appealing, so we augment the hierarchical approach by using the model-based approach as a robustness check.

In probability based clustering, each observation is assumed to be generated by a mixture of underlying probability distributions where each component in the mixture represents a different cluster. Given a set of data $\mathbf{x} = (\mathbf{x}_1, ...\mathbf{x}_n)$, then the likelihood function for a mixture model with G components is:

$$\mathcal{L}_{MIX}\left(\theta_1, \theta_2, ..., \theta_G; \tau_1, ..., \tau_G|\mathbf{x}\right) = \prod_{i=1}^{n}\sum_{k=1}^{G}\tau_k f_k(\mathbf{x}_i|\theta_k) \tag{6}$$

where f_k and θ_k are the density and parameters of the kth component in the mixture and τ_k is the probability that an observation belongs to the kth component (- the mixing proportion). Generally f_k is the multivariate normal (Gaussian) density which has parameters μ_k and covariance matrix Σ_k. Data generated by multivariate normal densities are then characterized by groups or clusters centred at their means with increasing density at points near to the mean. These clusters will be ellipsoidal with geometric features (shape, volume, orientation) determined by the covariances Σ_k.

Banfield and Raftery (1993) propose a general framework for geometric cross-cluster constraints by parametrizing covariance matrices through an eigenvalue decomposition of the form:

$$\Sigma_k = \lambda_k D_k A_k D_k^T \tag{7}$$

where D_k is an orthogonal matrix of eigenvectors, A_k is a diagonal matrix whose elements are proportional to the eigenvalues, and λ_k is a constant scalar. This leads to a geometric interpretation of the ellipsoidal clusters - D_k determines the orientation, A_k determines the shape of the density contours and λ_k specifies the volume. These characteristics can then be allowed to vary between clusters, or constrained to be the same for all clusters. This approach actually subsumes many previous approaches at model-based clustering - more details can be located in Fraley and Raftery (2002b). The range of models used has now been expanded from the original 1998 software, and the new 2002 MCLUST library uses a more extensive set of models within the same framework following Celeux and Govaert (1995). In the approach taken here, the parameterizations of the covariance matrix are detailed in table 1 below:

Given the different model parameterizations above, agglomerative hierarchical clustering can be used by merging clusters so as to maximize the resulting likelihood as specified in equation (1) above.

Identifier	Model	Distribution	Volume	Shape	Orientation
EII	λI	Spherical	equal	equal	NA
VII	$\lambda_k I$	Spherical	variable	equal	NA
EEI	λA	Diagonal	equal	equal	coordinate axes
VEI	$\lambda_k A$	Diagonal	variable	equal	coordinate axes
EVI	λA_k	Diagonal	equal	variable	coordinate axes
VVI	$\lambda_k A_k$	Diagonal	variable	variable	coordinate axes
EEE	λDAD^T	Ellipsoidal	equal	equal	equal
VVV	$\lambda_k D_k A_k D_k^T$	Ellipsoidal	variable	variable	variable
EEV	$\lambda D_k A D_k^T$	Ellipsoidal	equal	equal	varialbe
VEV	$\lambda_k D_k A D_k^T$	Ellipsoidal	variable	equal	variable

Table 1: Parameterizations of the Covariance matrix for Model-based Clustering

3.2.2 Clustering algorithms

The algorithm used for maximizing the likelihood function here is the EM (Expectation-Maximization) algorithm (see McLachlan and Krishnan (1997)). The EM algorithm was designed for maximum likelihood estimation with n multivariate observations $\mathbf{y}_i$ recoverable from $(\mathbf{x}_{i,}\mathbf{z}_i)$, in which $\mathbf{x}_i$ is observed and $\mathbf{z}_i$ is unobserved. If the $\mathbf{x}_i$ are iid according to a probability distribution f with parameters θ then the complete-data likelihood is given by:

$$\mathcal{L}_C(\mathbf{x}_i|\theta) = \prod_{i=1}^{n} f(\mathbf{x}_i|\theta) \tag{8}$$

If we assume that the unobserved variable depends only on the observed data $\mathbf{x}$, and not on $\mathbf{z}$, then we can integrate out the unobserved variable from the likelihood to get the observed-data likelihood, or $\mathcal{L}_O$:

$$\mathcal{L}_O(\mathbf{x}_i|\theta) = \int \mathcal{L}_C(\mathbf{x}_i|\theta)d\mathbf{z} \tag{9}$$

The EM algorithm iterates between an "E" step, which computes a matrix $\mathbf{z}$ such that $\mathbf{z}_{ik}$ is an estimate of the conditional probability that observation i belongs to group k given the current parameter estimates, and an "M" step, which computes maximum likelihood parameter estimates given $\mathbf{z}$. In mixture models, the complete data are considered to be $\mathbf{y} = (\mathbf{x}, \mathbf{z})$ where $\mathbf{z} = (\mathbf{z}_{i1}, \mathbf{z}_{i2}, ..., \mathbf{z}_{iG})$ represents the unobserved portion of the data, which in turn refers to cluster membership. In the limit, under certain regularity conditions the parameters usually converge to the maximum likelihood values for the Gaussian mixture model and the sums of the columns of $\mathbf{z}$ converge to n times the mixing proportions $\blacksquare k$, where n is the number of observations (i.e. the numbers of clusters, **G**.should reflect the number of distributions in the mixture model.

The EM algorithm is not without its problems though. Fraley and Raftery (2002b) detail several problems notably i) a slow rate of convergence, ii) the number of conditional probabilities associated with each observation equals the number of components in the mixture, so that the EM algorithm may not be suitable for large datasets and iii) when the covariance matrix becomes singular or nearly singular (otherwise known as "ill-conditioned") the EM algorithm breaks down. The latter problem was evident but not a decisive issue in this study - it usually relates to clusters which only contain a few observations where the observations contained are co-linear.

3.2.3 Model selection

The mixture model approach allows the use of approximate Bayes factors and posterior model probabilities to compare models (see Kass and Raftery (1995)). If there are several different contender models, $M_1, M_2, ..., M_K$ with prior probabilities $p(M_k); k = 1, ..., K$ then by Bayes's theorem the posterior probability of model M_k given data D is proportional to the probability of the data given model M_k times the model's prior probability:

$$p(M_k|D) \propto p(D|M_k)p(M_k) \tag{10}$$

When there are unknown parameters, by the law of total probability, we integrate over the parameters:

$$p(D|M_k) = \int p(D|\theta_k, M_k)p(\theta_k|M_k)d\theta_k \tag{11}$$

where $p(\theta_k|M_k)$ is the prior distribution of θ_k, and $p(D|M_k)$ is known as the integrated likelihood of model M_k. The Bayes factor is then defined as the ratio of the integrated likelihood between two models:

$$B_{12} = \frac{p(D|M_1)}{p(D|M_2)} \tag{12}$$

with the comparison favoring M_1 if $B_{12} > 1$.

The main problem in calculating the Bayes factor is the numerical evaluation of the integral in equation 11. But this can be approximated as:

$$2\ln p(D|M_k) \approx 2\ln p(D|\widehat{\theta}_k, M_k) - \upsilon_k \ln(n) = BIC \tag{13}$$

where υ_k is the number of independent parameters to be estimated and model M_k Thus we can now determine which is the most appropriate model by taking differences in BIC values:

$$2\ln(B_{12}) = 2\ln p(D|\widehat{\theta}_1, M_1) - 2\ln p(D|\widehat{\theta}_2, M_2) = BIC_1 - BIC_2 \tag{14}$$

A standard convention for calibrating BIC differences is that differences of less than 2 correspond to weak evidence, differences between 2 and 6 to positive evidence, differences between 6 and 10 to strong evidence, and differences greater than 10 to very strong evidence.

3.2.4 Clustering strategy

The general strategy adopted here is similar to that of Fraley and Raftery (2002b) The strategy comprises 3 core elements:

i) initialization using model-based hierarchical agglomerative clustering,

ii) then maximum likelihood estimation using the EM algorithm, and lastly

iii) selection of the model and the number of clusters via the approximate Bayes factors using the BIC

Model-based agglomerative hierarchical clustering proceeds by successively merging pairs of clusters corresponding to the greatest increase in the classification likelihood, where the classification likelihood is defined as:

$$\mathcal{L}_{CL}(\theta_1, ..., \theta_G; \ell_1, ..., \ell_n|\mathbf{x}) = \prod_{i=1}^{n} f_i(\mathbf{x}_i|\theta_i) \tag{15}$$

where $\ell_i = k$ indicates a unique classification of each observation if x_i belongs to the kth component. Note that if the probability model in equation 15 is λI then the selection criterion reverts to a sum-of-squares.

The estimation process thus consists of the following steps:

a) determine a maximum number of clusters to consider, and a set of candidate parameterizations of the model to use.

b) use agglomerative hierarchical clustering for the unconstrained Gaussian model, to obtain classifications for up to M groups.

c) do EM for each parameterization and each number of clusters, starting with the classification from hierarchical clustering.

d) compute the BIC for the one cluster model for each parameterization and for the mixture likelihood with optimal parameters from EM for other clusters.

e) plot the BIC - this should hopefully indicate a local maximum and a specific model.

f) determine cluster membership and the uncertainty relating to cluster membership for all the data.

4 Data

4.1 Variables

We explore the feasibility of currency areas in East Asia by examining whether the economic structures of candidate countries are similar enough to support fixation of exchange rates. Therefore, our choice of variables is based on the OCA literature for establishing a monetary union. Because of the dominance of the U.S. dollar in international financial and economic transactions, we nominate the U.S. dollar a priori as the anchor currency and measure our chosen variables relative to the United States. The groups we subsequently identify will then be similar in respect to their characteristics vis-à-vis the U.S. Hence, a form of a dollar bloc is proposed.

The U.S. dollar is chosen as the anchor currency primarily because soft pegs against the dollar are still strong and prevalent in East Asia despite the Asian financial crisis (McKinnon (2005)). As noted by McKinnon and Schnabl (2004), the dollar is widely used as the invoice currency for most of East Asian trade even though Japanese trade in the region is as large as that of the U.S. Besides, Mundell (2003) has explicitly called for fixation of the yen-dollar rate to achieve a regionwide monetary stability in Asia. We now turn to the variables used in the analysis.

1. **Trade openness (TRA)**

   The OCA theory suggests that countries which trade a great deal with each other are good candidates for monetary integration since the benefits of transaction costs saving will be enhanced (McKinnon (1963)). Accordingly, Bayoumi and Eichengreen (1997) found that the European countries which witnessed the greatest increase in bilateral trade have also experienced the greatest increase in their readiness for monetary union. As suggested by Edison and Melvin (1990), in choosing which currency to peg to, a country should consider a bilateral trade criterion. The bilateral trade intensity measure, as used by Artis and Zhang (2001) and Boreiko (2003), is adopted here to measure trade openness with the reference country; for any country i, trade openness is measured by $(x_{i,US} + m_{i,US})/(x_i + m_i)$ where $x_i$and $m_i$are the total exports and imports of goods and services and subscript US indicates destination to or sourced from U.S., the reference country. The ratios are averaged over each period

2. **Synchronization in the business cycle phase (BUS)**

   It is clearly understood that when business cycles are synchronized between two economies, the argument for flexible exchange rates that serve as a shock absorber to resolve asymmetric recessionary or inflationary pressures between them becomes irrelevant. In light of this, the higher the business cycle association of an East Asian country with the U.S., the stronger the argument for this country to fix its exchange rate against the dollar. In terms of measurement, it has become popular to implement the OCA criterion related to symmetry of output shocks by studying the cross-correlation of the cyclical components of output. In accordance, the method of Gerlach (1988) and Baxter and Stockman (1989), is adopted. In this paper, symmetry in output shocks is identified with cross-correlation with a displacement of zero in the cyclical components of annual GDP series, detrended by applying Hodrick-Prescott (H-P) filter.

3. **Export diversification (EXP).**

   For a diversified economy, even if each of its export sectors might be subject to shocks, if the shocks are independent and the country produces a sufficiently large variety of different goods, the law of large numbers will come into play and total production will not suffer much Kenen (1969). Thus, it is easier to fix the currency value in a diversified economy than that of a specialized economy. In this paper, as in Nguyen (2007), the degree of export diversification is measured by the inverse of the period average of the annual Herfindahl indices, a popular indicator of the degree of specialization. The Herfindahl index is computed as where is share of the export of product i, and is the number of products exported. Since data of individual export products are unavailable, annual export data according to the first-digit sub-industries of the United Nation's Standard International Trade Classification (SITC) Revision

2 are used.

3. **Inflation convergence (INF)**

   The traditional OCA literature was generated during the era of 'fix-price' economies, so introducing inflation convergence as a criterion could just be regarded as an appropriate normalization Artis and Zhang (2002). Since similar inflation rates result from similarities in monetary and fiscal stance and the country's economic structure, the cost of joining a currency area is presumably low when inflation rates are similar across countries (Nguyen (2007)). Moreover, convergence in inflation performance, both actual and political, is of course the central theme of the Maastricht Treaty criteria. This criterion is measured by the absolute inflation differential, where and is the rate of inflation in country and the U.S. respectively. Absolute value is used since the magnitude of the difference is of concern here. Differentials are averaged over period; the smaller the differential, the higher the inflation convergence.

4. **Volatility in the real exchange rate (RER)**

   Real exchange rate variability is a good indicator of synchronicity in terms of economic forces between countries (Vaubel (1978)). These economic forces pertain to inflation rates, openness, economy size, price, wage flexibility, factor mobility, commodity diversification, goods market integration, and fiscal integration (Tavlas (1993)). Artis and Zhang (1997) too, suggested that lower real exchange rate volatility might indicate an absence of asymmetric shocks and greater business cycle conformity, and thus a stronger case for monetary union. We measure volatility in real exchange rate as the standard deviation of the log-difference of monthly real exchange rates against the dollar, where deflation is accomplished using relative consumer prices.

5. **Synchronization in the real interest rate cycle (INT)**

   Though not listed as one of the criteria based on traditional OCA theory (Tavlas (1993)), this factor is indicated by a 'revealed preference' argument. It states that if the monetary policy of an OCA candidate country historically has differed little from that in the anchor country, the cost of relinquishing monetary independence is accordingly low. Thus, it is assumed here that synchronization in real interest rate may be interpreted as an indicator of coordination in monetary policy with the U.S.

4.2 Regimes

The analysis is undertaken for three separate periods; 1981-1996, 1997-2000, 2001-2007 (see e.g. Font-Vilalta and Costa-Font (2006)). With separate analysis for each period, comparisons can be made between the 'growth' period of 1981-1996, the 'crisis' period of 1997-2000, and the 'post-crisis' period of 2001-2007. 1981-1996 is part of the period prior to the Asian financial crisis when the region experienced high economic growth—coined by World Bank as the "East Asian Miracle" (Calomiris and Beim (2000)). This period also takes into account the structural change after the petroleum crises in 1979. The 'crisis' period, 1997-2000 is studied to determine whether the results are significantly different during times of distress. The final period, 2001-2007 is analyzed separately since many believe that the regional crisis has driven East Asia toward greater regional integration and bilateral cooperation (see e.g. Plummer (2007)). This multi-period approach with natural 'breakpoints' is a similar approach to that used by Crowley (2008).

The features of the data across the pre-crisis, crisis, and post-crisis periods, are summarized in Figures 1-3 for each variable. In Figure 1, the pre-crisis period data for all variables are plotted using a hatch-plot. Immediately it is apparent that for nearly all of the variables there are no obvious groupings of the countries. The exception here is the INT variable, the synchronization of real interest rate cycle where there are apparently three clear groupings with a highly positively correlated group of countries, a highly negatively correlated group of countries and a few countries that appear to have neither highly positive or negative correlations to the U.S. real interest rate cycle.

Figure 2 shows a hatch-plot for the values of the variables used in the clustering exercise for the crisis period. Once again, in Figure 2 there are no obvious groupings for most of the variables, except perhaps for INF, the inflation differential with the U.S. Here there are clearly three countries that are outliers, while all the other countries maintain relatively small inflation differentials with the U.S.

Lastly, Figure 3 shows a hatch-plot for the values of the variables used for the post-crisis period. Again, there are no clear groupings of countries according to the plots. The same variable, INF, separates one to three countries from the rest of the pack, depending on which other variables we look at.

The cursory evaluation of the data for clustering has two implications for the clustering approach presented here. First, the grouping of data varies for each variable, so there is no easy way to classify the data according to a simple classification using high/medium/low categories across all variables. This directly justifies using an optimization based clustering

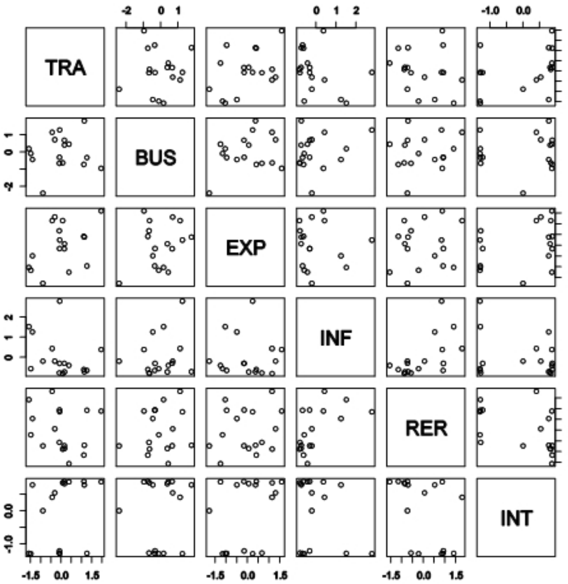

Figure 1: Hatch plot for pre-crisis period

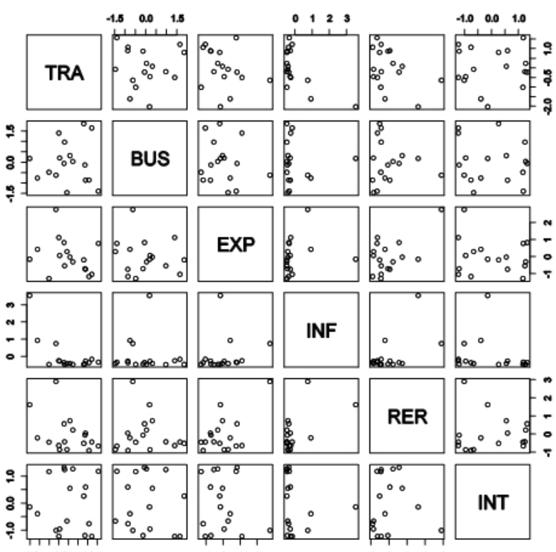

Figure 2: Hatch plot for crisis period

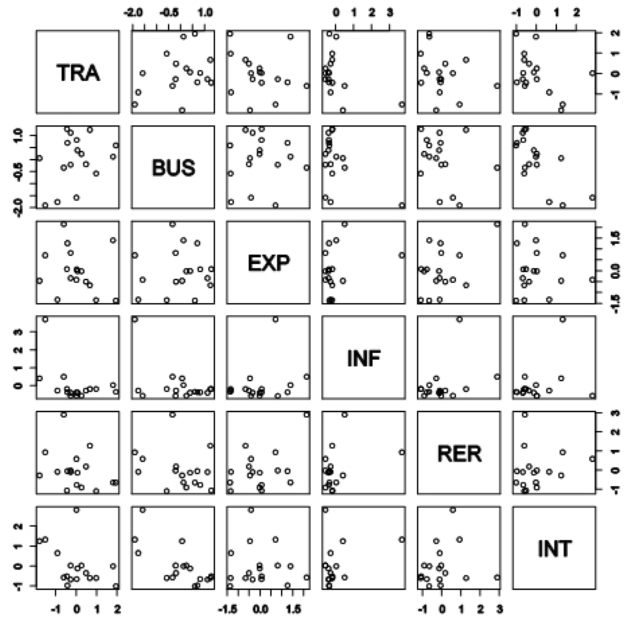

Figure 3: Hatch plot for post-crisis period

technique to analyze the data. Second, the distribution of the data clearly varies across variables with some very close groupings in certain cases with a small number of outliers, so for all the analyses conducted using cluster analysis and principal component analysis presented below, all data are normalized.

5 Hierarchical clustering results

5.1 Empirics

We shall now turn to hierarchical analysis and organize countries into discreet groups based on the variables discussed above for the three economic periods in question: pre-crisis, crisis, and post-crisis periods. Figures 4, 5, and 6 present the results of hierarchical clustering for the pre-crisis, the crisis, and the post-crisis period, respectively. In each figure, the horizontal axis represents countries included, and the vertical axis indicates distances (or dissimilarities) between them. The cophenetic correlation coefficient reported with the dendrograms has a reasonably high value in all cases, indicating that the cluster information generated by the dendrograms is a good representation of dissimilarities in the data. Each dendrogram is followed by a table showing the mean of each variable for each grouping.

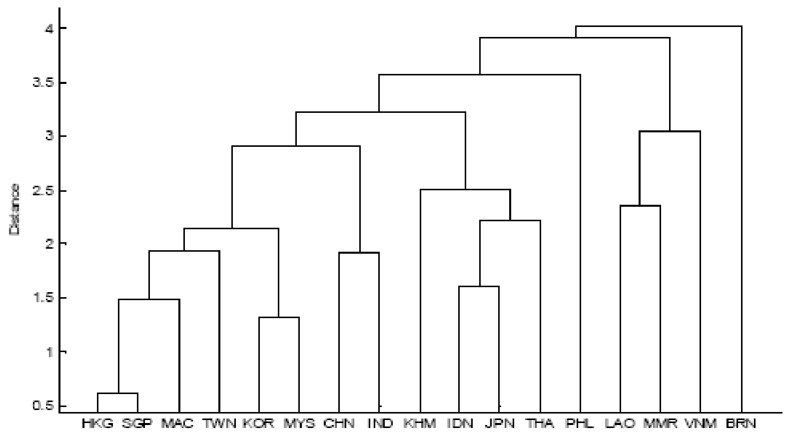

Figure 4: Merging process by group-average clustering for the pre-crisis period

Comparing the means across the groupings allows us to characterize each grouping.

Cluster	Members
1	HKG,KOR,TWN, MYS, SGP,MAC
2	CHN, IND
3	KHM
4	IDN, THA, JAP
5	PHL
6	LAO, MMR
7	VHM
8	BRN

Table 2: Clusters for Pre-Crisis Period

For the pre-crisis period, the CHI value indicates eight clusters. In Figure 4, clusters can be identified where countries are linked to each other at relatively small distances. The first group comprises Hong Kong, Singapore, Macau, Taiwan, Korea and Malaysia, displays the lowest inflation differential, the most stable (real) exchange rate, and very high monetary policy synchronization. These attributes are highly desirable for a dollar bloc. The second group, the China-India pair, is recognized for its relatively high (real) business cycle correlation and export diversification. The third group, the Indonesia-Japan-Thailand trio, displays relatively low inflation differential and very low interest rate cycle correlation. The fourth group, the Laos-Myanmar pair, sticks out with the highest inflation differential and exchange rate volatility. The rest appear as singletons. The Philippines has the largest trade linkage, the most diversified exports, and the highest monetary policy synchronization.

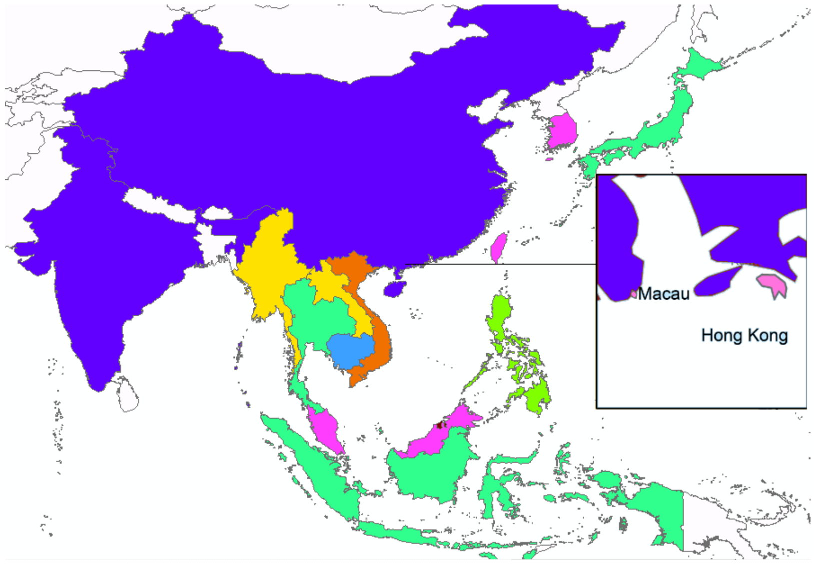

Figure 5: Map of clusters for pre-crisis period using hierarchical clustering

Vietnam is isolated by its high inflation differential and the highest business cycle correlation while Cambodia is separated by its low coordination in monetary policy. Meanwhile, Brunei is singled out by the lowest low business cycle synchronization and export diversification.

Hitherto, some points are worth mentioning. From Figure 4, we can see that the Asian Tigers (Korea, Taiwan, Hong Kong, Singapore), Macau, and Malaysia are at the forefront of convergence. This could indicate that their association with the U.S. is highly homogenous before the Asian crisis. In fact, their highly coordinated monetary policies, stable exchange rates, and similar inflation rates with the U.S. are evidence to the prevalent dollar pegs in the region (see McKinnon and Schnabl (2004)). In another respect, whilst it is understandable that the Indo-China countries are dissociated from the rest of the East Asian countries, Brunei's location at the end of the convergence process is rather surprising.

Cluster	Members
1	KOR, MYS, SGP, THA, BRN
2	CHN, PHL, VHM, MAC, JAP
3	HKG
4	MMR
5	TWN, KHM
6	IDN, IND
7	LAO

Table 3: Clusters for Crisis Period

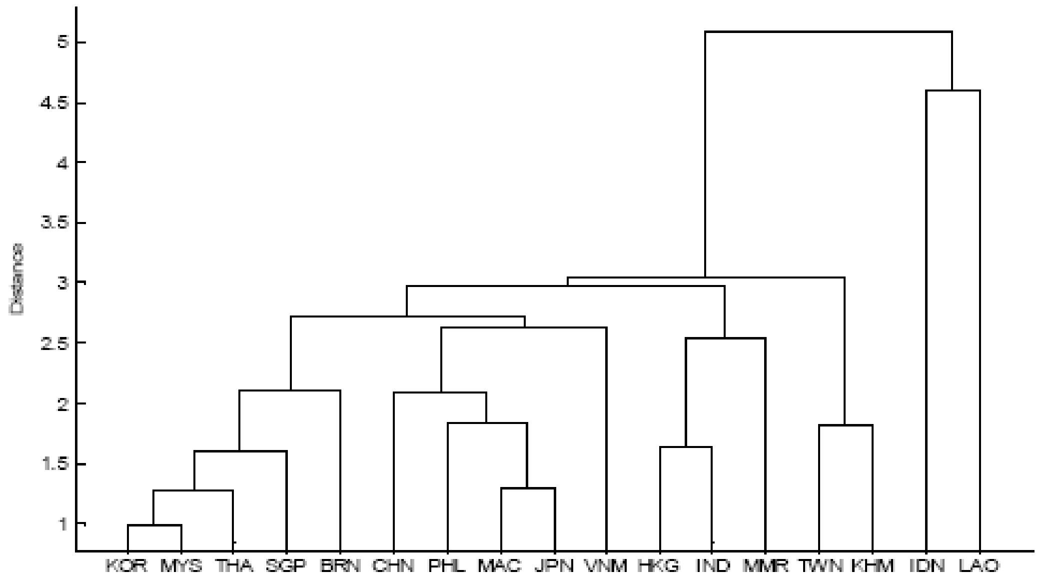

Figure 6: Merging process by group-average clustering for the crisis period

Figure 5 shows the merging process for the crisis period. The CHI suggests that seven is the optimal number of clusters. Unlike that of the pre-crisis period, the grouping structure of the crisis period has changed considerably. Visibly, Indonesia and Laos are distanced from the rest. The first group, made up of Korea, Malaysia, Thailand, Singapore, and Brunei, displays the lowest inflation differential and the highest monetary policy coordination with the U.S. Its relatively high exchange rate volatility is most probably due to the variability brought about by the crisis. The second group, consisting China, the Philippines, Macau, Japan, and Vietnam, exhibits high trade linkage but the most dissimilar business cycle from the U.S. The third group, the Hong Kong-India pair, possesses the most stable exchange rate against the dollar but the most different monetary policy from the U.S. policy. The fourth group, the Taiwan-Cambodia pair, demonstrates the largest trade linkage, the highest business cycle association, and the lowest export diversification. The singletons, Myanmar, Indonesia, and Laos, are all characterized by high inflation differential. Indonesia also has the most diversified exports.

The merging pattern for post-crisis period is exhibited in Figure 5. The CHI indicates four groups only. From Table 4, we can see that China and Hong Kong lead 10 other economies in the first group. This dominant group is actually built upon the earlier mergers of China-Hong Kong-Singapore, and Taiwan-Malaysia-Philippines-Thailand. India, Japan, and the Cambodia-Macau pair joined later. This group possesses some of the most desirable

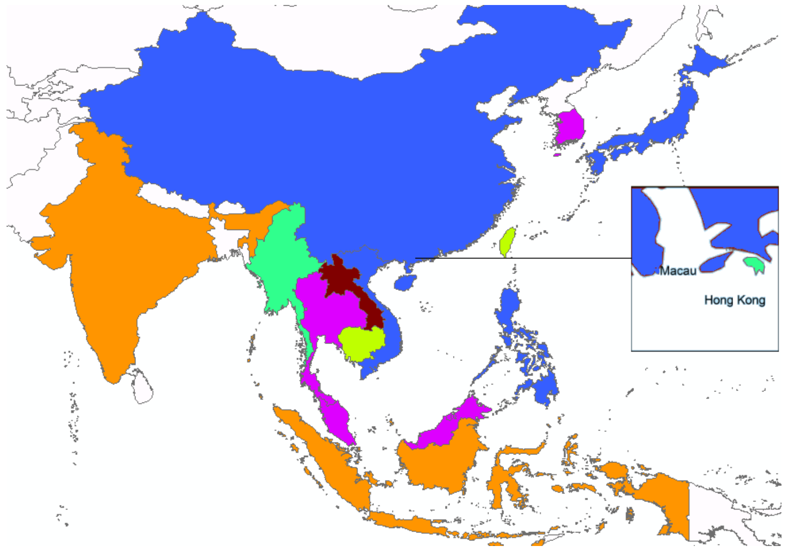

Figure 7: Map of clusters for crisis period using hierarchical clustering

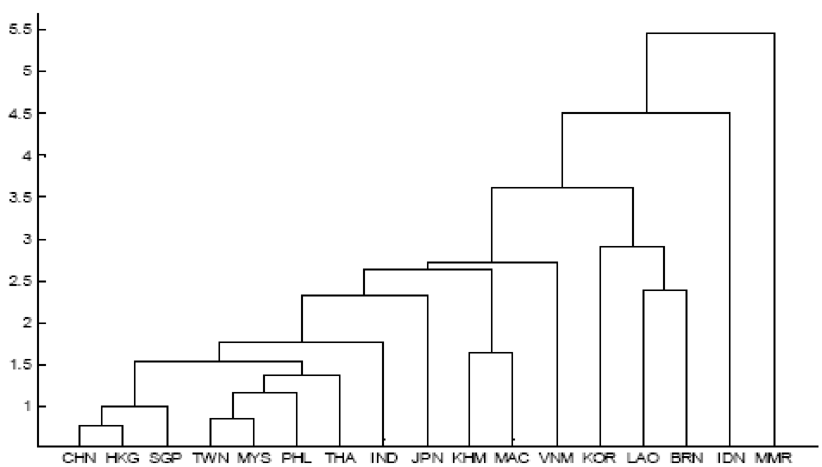

Figure 8: Merging process by group-average clustering for the post-crisis period

Cluster	Members
1	CHN, HKG, TWN, KHM, IDN, MYS, PHL, SNG, THA, VHM, MAC, JPN
2	KOR, LAO, BRN
3	IND
4	MMR

Table 4: Clusters for Post-Crisis Period

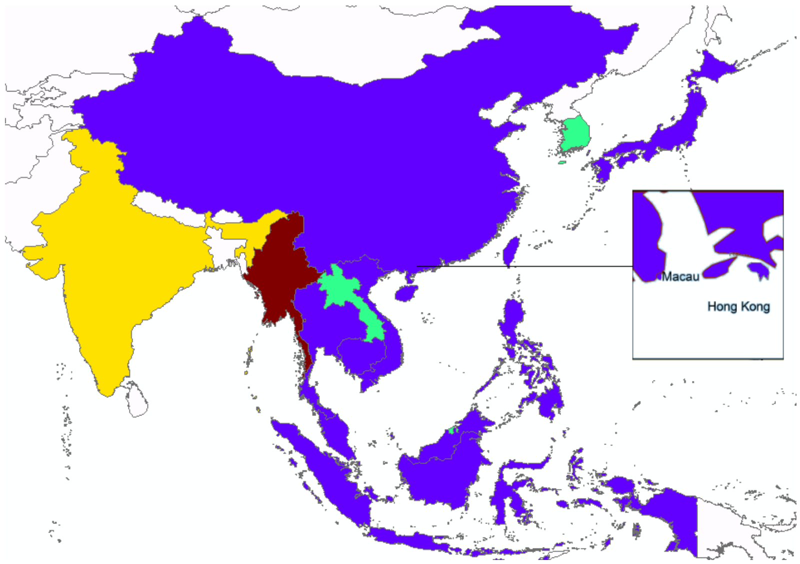

Figure 9: Map of clusters for post-crisis period using hierarchical clustering

attributes for a dollar bloc. It has the largest trade linkage, the highest business cycle correlation, the highest inflation convergence, and the lowest exchange rate variability. The first group is joined later by the Korea-Laos-Brunei trio, put together primarily by the least diversified exports and the most different interest rate cycle from the U.S. cycle. The remaining two groups are the Indonesia and Myanmar singletons. Indonesia is distinguished by the largest inflation differential, the most volatile exchange rate, and the lowest interest rate cycle correlation. Myanmar does not join any group until the final stage. This indicates that Myanmar has the least similar economic structure and has distinct features of the least bilateral trade linkage, the least synchronized business cycle, and the most divergent inflation, vis-à-vis the U.S.

5.2 Discussion

Some noteworthy findings can be observed from the results. First, we could label the countries which form the first group as the 'core' whereas the singletons or groups which congregate at a later stage as the 'periphery'. Unlike those in the periphery, the economies in the core are more homogeneous relative to U.S. Though the composition of the core is dynamic, it can be seen that Singapore and Malaysia are consistently in the core. On the contrary, Laos, and Myanmar are constantly two of the last four countries in the periphery—which is not surprising since their economic structures are very different from the rest in the region. In a related aspect, the state of economic development does not seem to be associated with whether a country is placed in the core or not. The more advanced economies, Japan, Taiwan, and Korea, are not in the core for the pre-crisis, crisis, and post-crisis periods, respectively.

Second, contrasting the results across the periods, some significant changes can be seen. Whilst the Philippines and Vietnam have 'progressed' steadily to be in the core for the post-crisis period, Korea has actually 'regressed' from the core to the periphery. This may indicate an increase in the degree of similarity with the core countries for the Philippines and Vietnam, and an increase in dissimilarity for Korea. Other than these positional changes, the number of groups has also decreased. Plus, in the post-crisis period more countries are at the forefront of convergence and the distances among them, shown by the vertical axis of the dendrogram (Figure 6), have also reduced substantially. This change indicates increased homogeneity within the region which might imply greater preparedness for a dollar bloc.

Third, the results do serve as a helpful reference for policymakers. By looking at the characteristics which describe the groups, areas that need to be improved can be identified by national authorities to achieve structural convergence. This is especially true for the post-crisis era, the most relevant period for today. For instance, the Indonesia monetary authority may want to stabilize the real value of the rupiah since the real exchange rates of the rest of the region are relatively much more stable against the dollar. In another aspect, Indonesia and Myanmar may need to control their inflation, a factor repeatedly stressed by Robert Mundell (see e.g. Mundell, 2000) as a crucial convergence dimension. In addition, policymakers may also want to use the convergence process illustrated in the dendrogram as an aid for sequencing the accession among aspiring countries.

Lastly, let us examine the post-crisis results in greater detail. Suppose the sequencing indicated by the post-crisis dendrogram is valid, a reasonably firm progression to a regional dollar bloc can actually be inferred. If the distance at which two countries are joined represents the time elapsed before convergence, China's participation is the earliest. With China's leadership, its huge dollar reserves would definitely enhance the credibility and the potentiality of a wider union. It is not too difficult to envisage a voluntary cooperation from China which has 70 percent of its national assets denominated in dollar. As duly labeled by Krugman (2008), China is said to have fallen into a dollar trap and could hardly move out of it even in the wake of the American made global financial crisis.

Similarly, India and Japan's accession in the middle of the process also implies a relatively easy transition. Given their economic dominance in the region, the timing of their accession can be considered early. The formation process toward a dollar bloc might not be that promising should China, Japan, or India, is located at the very end of the sequence.

Despite these findings, one question is left to be answered. The question is, "Are some variables more important than the others?" The variables used here are not expressed on a common scale, and although they are standardized and equally weighted, in a sense it is not obvious how important each criterion is relative to another. To answer this question, we explore a weighting scheme as in Artis and Zhang (2001). Since the post-crisis period is the most relevant period for today, this exercise is only carried out for this period. This issue is dealt with in Appendix B. In that result, the core-periphery structure remains intact as it appears in the main analysis. The structure, however, has become more distributed.

6 Model-based clustering results

6.1 Empirics

In model-based clustering, hierarchical clustering is used as a starting point, and then the orientation, distribution and volume of the clusters is allowed to vary. This permits a more generalized clustering strategy, with more flexible configurations possible. The exercise above with the identical dataset is repeated here but using a Bayesian criteria for choosing the optimal configuration of clusters, and the results are quite different from those using conventional hierarchical cluster analysis. In table 5 the cluster membership for the pre-crisis period is displayed, and in figure **??** the BIC profile by number of clusters is plotted for each "model" specified above in table 1. The cluster configuration that maximizes the BIC is 2 clusters with a diagonal distribution with variable volume and shape (VVI). Indeed the figure suggests that although 8 cluster components is a local maximum if 8 is considered to be the maximum number of components, 10 clusters could also be considered a second choice if an equal volume and shape model (EEE) is used. Figure **??** then projects

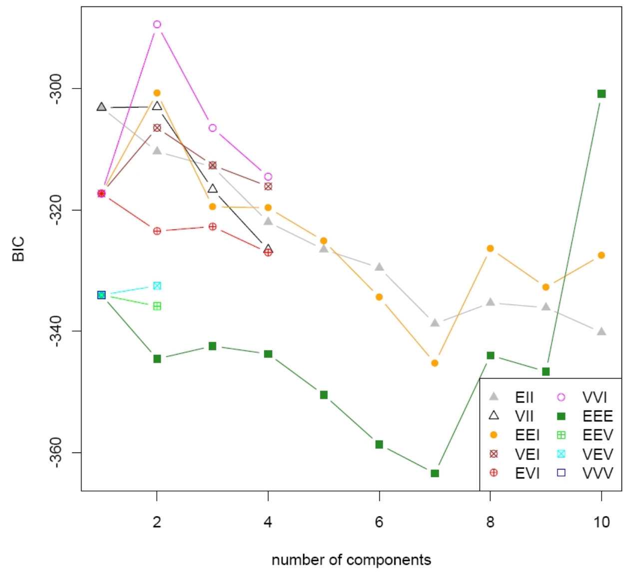

Figure 10: BIC for pre-crisis period

the clusters in two-dimensional space for two of the variables used. The circular shapes represent the clusters and denote one standard deviation from the cluster centers. Lastly figure 12 shows the geographic interpretation of the clusters. It is notable that the two clusters are just a different configuration of what was found with the hierarchical clustering exercise for this period. Cluster 2 here corresponds to cluster 1 in table 2, whereas cluster 1 here is the aggregation of all the 7 clusters in table 2.

Cluster	Members
1	CHN, KHM, IDN, LAO, MMR, PHL, THA, VHM, IND, BRN, JPN
2	HKG, KOR, TWN, MYS, SGP, MAC

Table 5: Clusters for pre-crisis period

During the crisis period model-based clustering once again provides different cluster configurations from hierarchical clustering. model-based clustering suggests there are only 2 clusters, with most countries falling into one large cluster shown by table 6, with only Indonesia, Laos and Myanmar remaining outside this large cluster. Figure **??** shows the BIC profiles for the different models used, with once again only the "EEE" equal volume and shaped clusters approaching the BIC value of both the VVI and EVI models (- variable volume and shapes, and equal volume but variable shapes cluster models) at higher

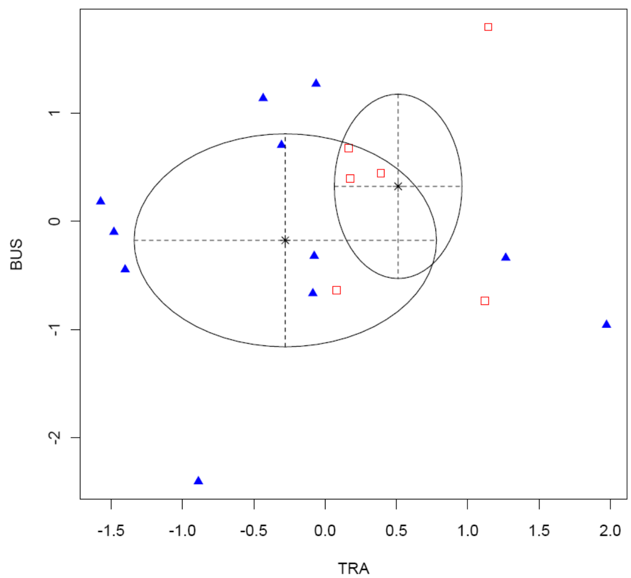

Figure 11: Cluster configuration for pre-crisis period

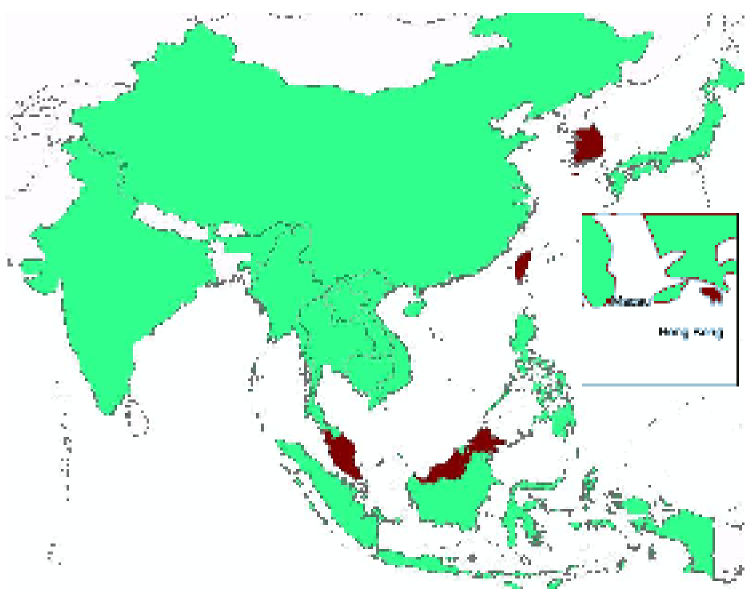

Figure 12: Cluster map for pre-crisis period using MBC

numbers of components. In figure **??** it is clear that separation of the clusters is more distinct (using the TRA variable) than in the pre-crisis period, and that the larger cluster clearly contains a wide variety of experiences during the crisis period. When viewed from a geographical perspective in figure 15, it is clear that although Laos and Myanmar are contiguous, Indonesia is not, so maybe became a part of this group because of its well-known "exceptional" response during the crisis period.

When comparing to the configuration obtained using hierarchical clustering there are less obvious cluster overlaps, but taking cluster 4, 6 and 7 from table 3 then includes all of cluster 2 in 6 except that India is not included here. Further investigation reveals relatively high levels of uncertainty associated with India's clustering here in cluster 1, so then if India is reclassified into cluster 2 here, cluster 1 would roughly correspond to clusters 1, 2, 3 and 5 from table 3 using hierarchical clustering. It should also be noted that with model-bsed clustering, if greater than 10 clusters is permitted, the optimal number of clusters is at 12 groupings, which rather than the suggestion of a homogeneous response to the Asian financial crisis, suggests a much more heterogeneous response.

Cluster	Country
1	CHN, HKG, KOR, TWN, KHM, MYS, PHL, SGP, THA, VHM, IND, MAC, BRN, JPN
2	IDN, LAO, MMR

Table 6: Clusters for crisis period

In the post-crisis period, model-based clustering suggests 4 clusters represent the economic behavior of the main Asian countries. Table 7 shows this configuration, while figure **??** shows the BIC plots for the different models. It is clear that an equal volume equal shape but variable orientation (EEV) achieves the highest BIC with 4 clusters, and this matches the number of clusters that is chosen using hierarchical clustering for this period. Figure **??** then shows the configuration of clusters, with clusters 2 and 4 bunched in the bottom left hand corner of the figure, cluster 1 clearly identifiable towards the top of the figure and cluster 3 on the right hand side of the figure. Figure 18 then shows the geographical interpretation of the clusters, with a major grouping definitely apparent and then other diverse groupings apparent.

When compared with hierarchical clustering, the results are definitely different in terms of cluster membership. Only cluster 2, that of Korea, Loas and Brunei are the same between the two configurations. Nevertheless, there is a grouping which consists of China, Hong Kong, Taiwan, Malaysia, Singapore and Thailand that appears to be common between the

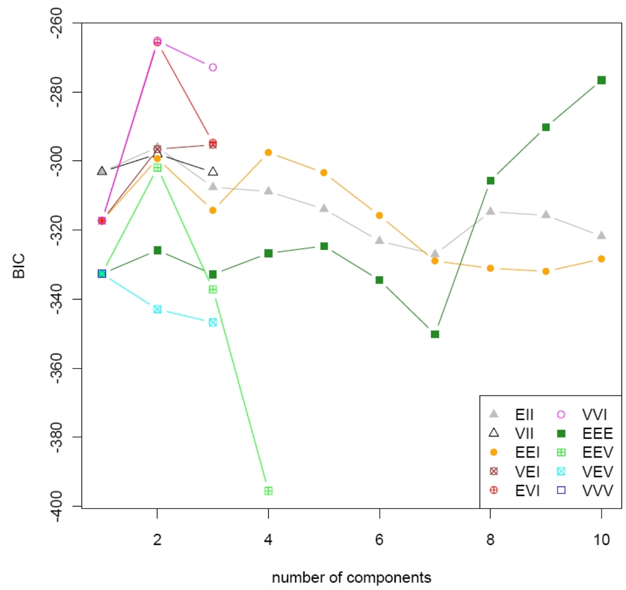

Figure 13: BIC for crisis period

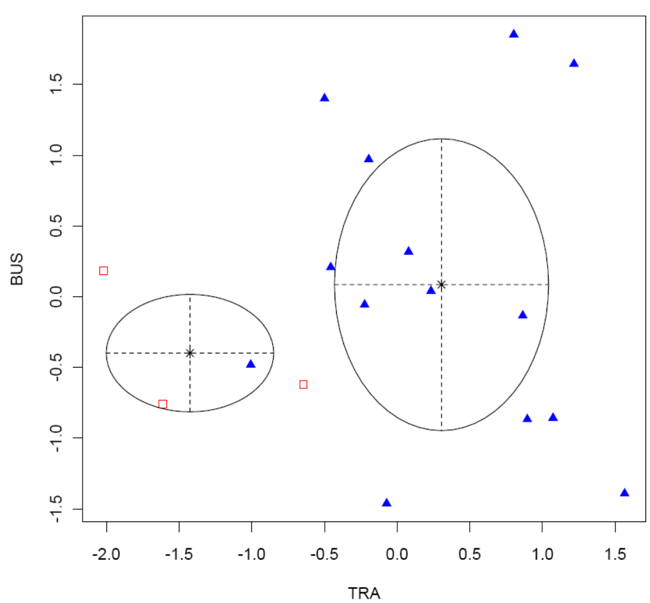

Figure 14: Cluster configuration for crisis period

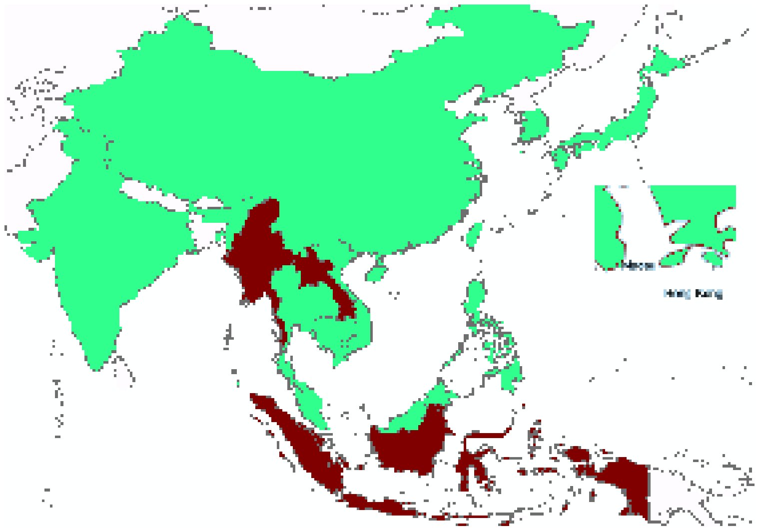

Figure 15: Map for crisis period using MBC

two methods, and compared with the large cluster obtained with hierarchical clustering in table 4 table 7 appears to suggest that Cambodia, Phillipines, Vietnam, Macau and Japan appears to form another cluster. Interestingly India slots in here with the larger cluster, but in hierarchical clustering it forms its own cluster. When looking at the observations where significant uncertainty exists, only Thailand has a high degree of uncertainty attached to its classification.

Cluster	Countries
1	CHN, TWN, HKG, MYS, SGP, THA, IND
2	KOR, LAO, BRN
3	KHM, PHL, VHM, MAC, JPN
4	IDN, MMR

Table 7: Clusters for post-crisis period

6.2 Discussion

Several things are apparent from the model-based clustering exercise, and contrast with that of the hierarchical cluster based exercise.

First, in contrast to the hierarchical clustering exercise, the number of clusters appears to increase after the crisis period. This suggests that although some convergence may have occurred given that some of the cluster memberships are common to both methods

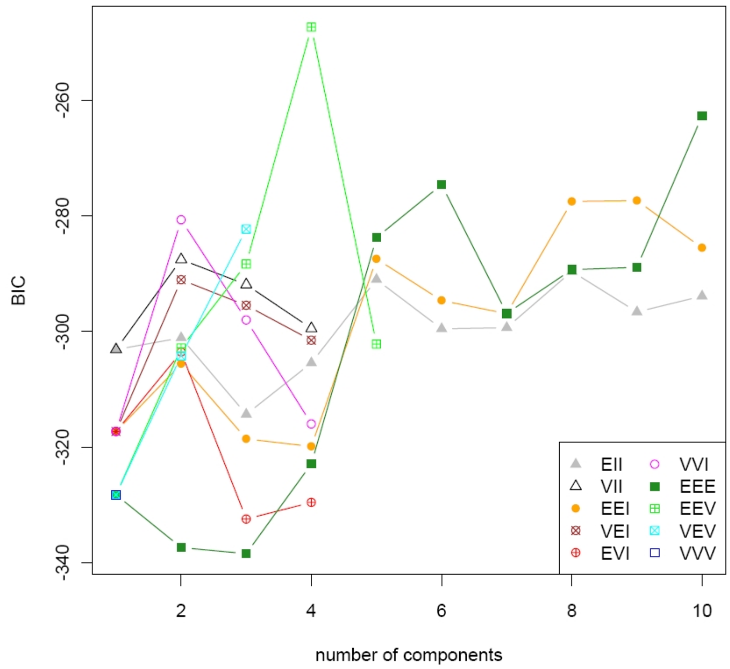

Figure 16: BIC for post-crisis period

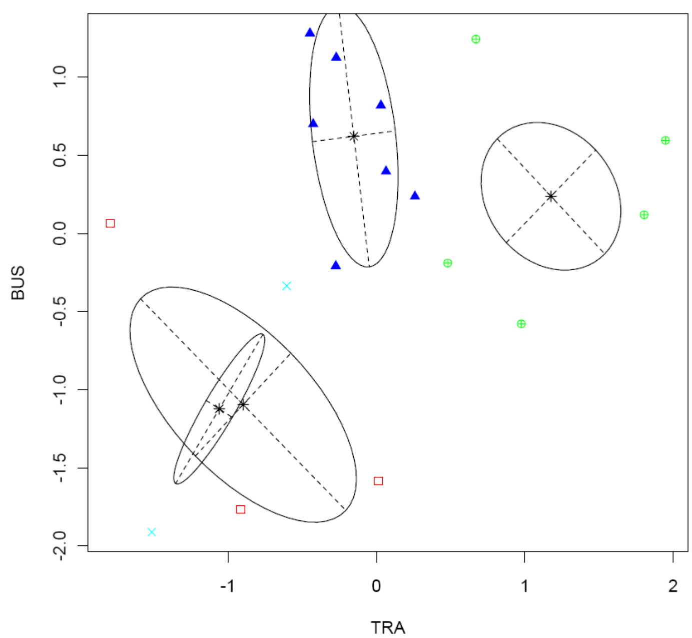

Figure 17: Cluster configuration for the post-crisis period

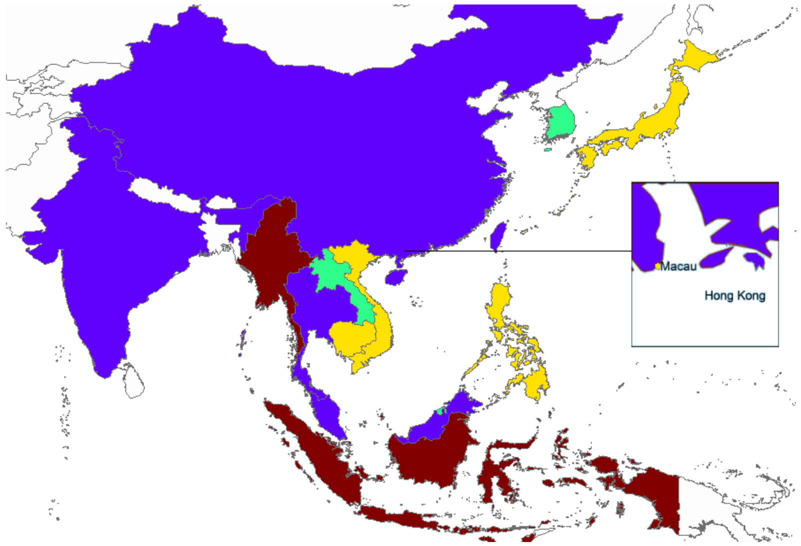

Figure 18: Map for post-crisis period using MBC

particularly in the pre-crisis period, there is still a significant amount of heterogeneity in business cycles in Asia.

Second, from an economics perspective, the formation of clusters only serves to indicate similarity in correlations between different countries, but not neccessarily similarity with US business cycles. So, for example, just because a group of countries forms a cluster first in the clustering process does not necessarily mean that these groups of countries have cycles that are most similar to that of the US - it might only means that they possess the same degree of dissimilarity.

Third, Hong Kong is the one territory in Asia that has consistently fixed its currency to the US dollar by means of a currency board arrangement. So it is likely that any countries that are placed in the same cluster as Hong Kong are more likely to be appropriate candidates for adopting the US dollar if Asia chose to adopt the US currency. It is interesting that in the post-crisis period the largest group of countries contained Hong Kong, but in the pre-crisis period the largest group of countries did not contain Hong Kong. Even though the evidence for convergence seems much weaker using model-based cluster analysis, this larger cluster of countries which includes Hong Kong tends to suggest that there is convergence on similar business cycles to that of Hong Kong, and by extension to that of the US.

Why should there be such a discrepancy between the results of hierarchical and model-based cluster analysis? There are two obvious reasons:

i) hierarchical clustering only allows clusters with one type of distribution and identical orientation, although with obviously different volumes, whereas model-based clustering allows many more variations of these parameters, which leads to different configurations of clusters being identified in the data. Of course this is still not foolproof, as there are limits to the number of models that can be included in model-based cluster analysis; and

ii) hierarchical clustering has no obvious optimizing method for determining the number of clusters - there are various different methodologies which could all lead to different results dependent on the empirical data distribution. Model based clustering.does have a Bayesian methodology to determine the optimum number of clusters although this is not foolproof either, as clearly a separation of BIC values of greater than 10 is required to yield a clear optimal cluster configuration.

7 Conclusion

The two clustering methods used in this paper have different approaches to classifying observations into groupings/clusters, and although there was some commonality between the two methods, there was also significant differences, particularly in the crisis and post-crisis periods. For each period studied, there exists at least two groupings. Some countries are consistently in certain groupings irrespective of economic conditions while others appear to be more dynamic. Results also suggest that the leading countries in the convergence process have become more homogenous. The countries that appear to be consistently in a grouping that is relatively synchronous with the US includes Hong Kong, Taiwan, Malaysia, Singapore and Thailand. Interestingly, these countries almost make up a single north-south geographical bloc. It is also notable that for the post-crisis period using a model-based clustering approach, China and India appear to have joined a group of more convergent countries, which is undoubtedly more significant than the loss of some small countries from this "core" grouping.

Still, how would our identifications from clustering compare with those made by others using different criteria (and methods)? Comparison would only be logical if results from equal time periods are compared. Our pre-crisis core grouping is consistent with the Hong Kong-Singapore grouping identified in Yuen's (2000) clustering study with convergence theory. Besides, our pre-crisis Korea-Singapore grouping has also been indicated by Font-Vilalta and Costa-Font's (2006) correlational analysis as potential members of a monetary bloc. Meanwhile, the post-crisis core countries identified in our analysis do have some overlap with the potential economies of Hong Kong, Malaysia, Singapore, and Thailand found by Huang and Guo's (2006) structural VAR exercise. In addition, the stable Malaysia-Singapore grouping found here has actually been identified earlier by Bacha (2008) using a VAR exercise and Nguyen (2007) using fuzzy clustering analysis.

If we compare our results to empirical arrangement in practice, the Hong Kong pre-crisis and post-crisis groupings seem to support the convergence of business cycles in the region, particularly as i) there are more members of the cluster and ii) these new members include both China and India.

The study is limited in the sense that the criteria considered here cannot guarantee a successful monetary union akin to the EMU since other factors including political and institutional factors are needed prior to monetary union formation. Further analysis to assess the merits and demerits of the proposed integration as well as of the possible alternatives to a dollar area, needs to be undertaken.

Appendices

A Cluster variable means

Table A1 Variable means of each cluster for pre-crisis period

	Cluster	TRA (%)	BUS	EXP	INF (%)	RER[1]	INT
	All cases	15.829	0.019	3.076	6.570	2.309	0.187
1	Hong Kong, Singapore, Macau, Taiwan, Korea, Malaysia	20.418	0.106	3.187	**2.777**	**1.154**	**0.959**
2	China, India	12.513	**0.266**	**4.449**	7.292	3.407	0.617
3	Cambodia	2.562	-0.007	1.782	2.928	2.051	**-1.000**
4	Indonesia, Japan, Thailand	19.126	-0.099	2.912	**2.869**	2.816	**-0.963**
5	Philippines	**33.506**	-0.237	**4.854**	8.930	3.353	**0.982**
6	Laos, Myanmar	4.994	-0.032	4.457	**30.558**	**6.916**	-0.092
7	Vietnam	15.261	**0.360**	3.346	**24.109**	3.310	-0.998
8	Brunei	7.867	**-0.624**	**1.099**	5.303	1.444	n.a.

Notes:
[1] Standard deviation (x10^2) of the log difference in bilateral real exchange rate against the dollar.
[2] 'n.a.' for data not available.

Table A2 Variable means of each cluster for crisis period

	Cluster	TRA (%)	BUS	EXP	INF (%)	RER[1]	INT
	All cases	15.981	-0.132	2.878	9.414	4.274	-0.051
1	Korea, Malaysia, Thailand, Singapore, Brunei	14.330	-0.042	2.529	**2.258**	4.801	**0.799**
2	China, Philippines, Macau, Japan, Vietnam	**22.396**	**-0.664**	2.477	3.363	2.205	-0.181
3	Hong Kong, India	12.437	0.323	3.623	5.050	**1.090**	**-0.888**
4	Myanmar	4.034	-0.560	3.412	**24.586**	3.340	-0.353
5	Taiwan, Cambodia	**23.468**	**0.857**	**2.088**	4.185	2.247	-0.421
6	Indonesia	11.197	-0.482	**6.390**	**21.576**	16.519	-0.826
7	Laos	1.013	-0.028	2.674	**67.298**	11.101	-0.159

Notes:
[1] Standard deviation (x10^2) of the log difference in bilateral real exchange rate against the dollar.

Table A3 Variable means of each cluster for post-crisis period

	Cluster	TRA (%)	BUS	EXP	INF (%)	RER[1]	INT
	All cases	14.787	0.277	3.102	3.971	1.541	-0.403
1	China, Hong Kong, Singapore, Taiwan, Malaysia, Philippines, Thailand, India, Japan, Cambodia, Macau, Vietnam	**17.932**	**0.519**	3.026	**2.293**	**1.264**	-0.627
2	Korea, Laos, Brunei	7.743	-0.300	**2.049**	3.216	1.597	**0.372**
3	Indonesia	10.045	0.100	**6.159**	6.663	**3.931**	**-0.685**
4	Myanmar	**2.913**	**-0.729**	4.119	**23.681**	2.307	0.251

Notes:
[1] Standard deviation (x10^2) of the log difference in bilateral real exchange rate against the dollar.

B Data sources

DATA DEFINITIONS AND SOURCES[1]

Table A
Data definitions and sources

Country	Trade[2]	GDP[3], GDP deflator	Exchange rate[4], CPI[5]	Interest rate	Period[6]
Brunei	81Q1-07Q4	81-04	83:1-08:3[7]	Lending rate	98:1-08:3
Cambodia	81Q1-07Q4	88-07	94:10-07:12	Lending rate	95:10-07:12
China	81Q1-07Q4	81-06	87:1-08:4	Discount rate	92:6-08:3
Hong Kong	81Q1-07Q4	81-06	81:1-08:3	Discount rate	92:6-08:3
India	81Q1-07Q4	81-07	81:1-08:3	Discount rate	92:6-08:3
Indonesia	81Q1-07Q4	81-07	81:1-08:4	Discount rate	92:6-08:3
Japan	81Q1-07Q4	81-07	81:1-08:4	Discount rate	92:6-08:3
Korea	81Q1-07Q4	81-07	81:1-08:4	Discount rate	92:6-08:2
Laos	81Q1-07Q4	82-07	87:12-01:12, 03:5-08:3	Discount rate	92:6-08:3
Macau	81Q1-07Q4	82-07	88:1-08:3	Interbank rate	92:6-08:4
Malaysia	81Q1-07Q4	81-07	81:1-08:3	Interbank rate	92:6-08:4
Myanmar	81Q1-07Q4	81-03	81:1-07:12	Discount rate	92:6-07:12
Philippines	81Q1-07Q4	81-05	81:1-08:4	Discount rate	92:6-08:4
Singapore	81Q1-07Q4	81-06	81:1-08:3	Interbank rate	92:6-08:4
Taiwan[8]	81-88, 89:1-07:12	81-07	81:1-08:4	Discount rate	92:6-08:6
Thailand	81Q1-07Q4	81-07	81:1-08:4	Discount rate	92:6-08:4
United States	n.a.[9]	81-07	81:1-08:4	Discount rate	92:6-08:3
Vietnam	81Q1-07Q4	90-07	90:1-08:4	Discount rate	96:1-06:12

Notes:
[1] Series are from IMF-IFS database except stated otherwise.
[2] Trade data are from IMF-DOTS database.
[3] GDP for gross domestic product.
[4] Data range of exchange rate is tied to the data range of CPI since CPI is needed to compute real exchange rate.
[5] CPI for consumer prices index. For China, Vietnam and Brunei, CPIs are sourced from ILO-LABORSTA database whenever not available in IMF-DOTS database. Cross-validation shows that both sources are equal.
[6] The following starting point is selected to cover most of the countries with the most similar range possible.
[7] CPI data after 2005 are sourced from Department of Economic Planning and Development (DEPD) website, retrieved July 17, 2008, from http://www.depd.gov.bn/archive.html. Data should be consistent since data from IFS are sourced from DEPD as well.
[8] Taiwan data are sourced from Bureau of Foreign Trade, Directorate-General of Budget, Accounting and Statistics (DGBAS) and central bank databases.
[9] 'n.a.' for not applicable.

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