An Alternative Perspective on the Stock Markets Integration: Multilateral Measure of the Degree of Integration

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Abstracts

This paper analyzes the degree of integration among 22 stock markets from Asia Pacific, Europe, and America during period of 2000 – 2010. Unlike in previous literatures in capital market integration study, the author uses minimum spanning tree technique to measure the degree of integration of those samples simultaneously or on multilateral basis (on a set of markets), instead of on bilateral basis (relationship between one market to another). The technique enables author to observe the dynamism of the degree of integration and provides graphical analysis. The findings show that the degree of integration is volatile but tend to increase (markets become more integrated). However, the stock markets integration is incomplete, market segments based on geographic proximity are detected.

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1. Introduction

Financial market integration between two countries takes place when the countries let capitals flow in and out freely; participants (investors) can buy and sell assets on both markets. As a result, comparable assets traded on both markets would be at the same price level and the comovements of returns exist.

European Union and their use of single currency (Euro), the forming of free trade area such as ASEAN Free Trade Area (AFTA) that recently elaborated to ASEAN+China Free Trade Area (AC-FTA), and North American Free Trade Agreement (NAFTA) are examples of efforts made to ascertain integrated markets that expectedly fostering intertrades and capital flow. However, as an impact of more integrated financial market, a market shock in a market (country) may affect the others, and they were not necessarily crises, even a bad news or negative signal indicated by a worsening economic variable in a market might trigger negative comovements of stocks prices or returns in different markets. The effect of high degree of integration among capital markets has changed the way investors should price the risk in estimating stocks' expected returns on a particular market. This is because there is covariance between country-specific risk factors and common world factors such that they cannot just relying on domestic and company's fundamental information.

If markets were completely integrated there would be no differences in expected returns and prices of assets at the same level of risk, regardless the market in which the assets are traded. Whereas, in segmented market, a common world factors of risk may have no explanatory power on the asset pricing model that used to estimate the expected returns. The disequilibrium in risk pricing across segmented markets leads to formation of internationally diversified portfolios. The portfolios are intended to reduce country-specific systematic risks that domestically would never be reduced by diversifying the holding assets. In segmented emerging capital markets that usually characterized by significant excess returns during stable condition compared to those in developed markets, would experience hot money (short-term) inflows from developed markets investors. The high mobility of hot money would destabilize the segmented market once negative signal exposed and raising the volatility (risk) of assets returns even to the higher level. However, the growing regional economic integrations, the formation of free trade areas (not only for labor and commodities, but

also capitals), markets liberalization, and economic policy harmonizations that intensively took place in 1990s until recently have changed the degree of integration among the world capital markets.

In previous researches of financial market integration, the degree of integration is measured by bilateral-based measure rather than multilateral-based measure. The former measure usually studies the relationship or comovements of returns between two markets or one market to "*world market*" that represented by a synthetic internationally diversified portfolio (world market index). The potential problem with this measure in measuring the degree of integration of a market to the world is that the world index may not represent the world preference. For example, investor who wants to form an internationally diversified portfolio prefers maximizing her expected return (while retaining her risk target) to minimizing the risk (while maintaining her expected return target). She might put more weigh on emerging markets stocks that offer relatively higher returns but with higher volatility than those on developed markets in her portfolio. In this case, the world equally weighted index is not her benchmark index. When cross-countries freer capital movements are realized, there would be many international investors who not only come from developed markets but also from emerging markets that both of them might have different risk preferences. Thus, measuring the degree of market integration using bilateral-based measure might be sensitive to how the world index is selected or formed.

This paper offers an alternative measure of the degree of integration using multilateral-based measure that measures how stock markets in the world are interrelated. There would be a single indicator that reflects how close are the markets in forming a world markets network. Based on this measure, some research questions would be addressed: Are the markets become more integrated? Are there market clusters (market segmentation) or markets are fully integrated (no clusters)? How strong is developed and emerging markets relationship and inter-regional relationship? And at last, what are factors that drive the degree of integration?

The measure of degree of integration proposed in this paper is an application of graph theory, especially minimum spanning tree (MST) method. I added a numerical graph

analysis to address questions of cluster or segmentation and proposed an indicator for measuring stability (robustness) of relationship structure in MST graphs.

2. Literature Review

Studies on financial market integration have utilized various parametric and non-parametric models to measure the degree of integration, but most of them relying on bilateral relationship of the markets being studied.

Market integration measured in parametric model is stemmed from equilibrium model such as Arbitrage Pricing Theory (APT), International-Capital Asset Pricing Model (some literatures also named it as World Capital Asset Pricing Model) and or its variations. For example, Mittoo (1992) found evidences of Canadian stock market integration with US stock market using CAPM and APT frameworks. Bekaert and Harvey (1995) proposed a measure of capital market integration arising from a conditional regime-switching model. The model that they proposed is the modification of World CAPM by allowing the model in the state where markets are integrated or segmented. The model proposed by Bekaert and Harvey is a critic on the use of World CAPM or any other asset pricing models in which the models are used to test a joint hypotheses, but particular assumptions on whether markets are fully integrated, semi-integrated, or segmented have to be set prior to draw a conclusion. The rejection of the hypothesis in such models hence has multi-interpretation, i.e. whether the rejection is caused by the use of one factor model (World CAPM is a one factor model, where a world index represent a world market), market inefficiency, or as a result of imposing full integration assumption.

Stemming from similar critic on the use of asset pricing model in this topic, Basak (1996) developed a mean-variance intertemporal model to investigate the equilibrium asset prices and allocation, the risk-free interest rate, and the intertemporal consumption behavior and welfares of two countries, under circumstances of segmentation or integration. He found that the equilibrium interest rate is increased on integration, and that the integrating markets may be significantly welfare decreasing for one of the countries.

Efforts have been made to develop an indicator of degree of integration. Korajczyk (1996) developed time-varying market integration index (MII) as the extension of World CAPM, followed by Levine and Zervos (1998) who makes some adjustment to the pricing errors. The time-varying MII is recursively estimated from time series rolling regression of World CAPM, Korajczyk defined the MII as the absolute value of pricing errors (the intercept term) in the asset-pricing model.

More recent papers that used asset-pricing models as the base model to investigate markets integration includes de Jong and de Roon (2005) who studied the diminishing segmentation of emerging markets; and Lin (2005) and Chi, Li, and Young (2006) for examining market integration in Asian markets.

Other bilateral parametric models used to investigate stock market integration include Laurenceson (2003) who carried out the test under real interest parity (RIP) and uncovered interest parity (UIP) frameworks and found that financial markets integration among China and ASEAN-5 countries remains significantly incomplete; Fauver, Houston, and Naranjo (2003) who included company diversification, financial, legal, and regulatory environment as factors that explain the degree of integration; and Clark, Zenaidi, and Trabelsi (2008) that investigate the impact of currency crises and exchange rate regimes on capital market integration.

Vector Autoregression (VAR), Cointegration (ECM), VECM, and other multivariate time series analysis are often used as tools to identify the relationship among markets returns. However, the analysis resulted from those tools are still in bilateral mode; the degree of integration is measured from analyzing pairs of stock markets relationship. To name a few of papers that used those tools, following are the examples: Bhatacharayya and Banerjee (2004) who used VECM and Granger Causality Tests; Yang, Khan, and Pointer (2003) and Jeyanthi and Pandian (2008) who used cointegration tests; and Ibrahim (2006) who used VAR model to study integration or segmentation of Malaysian equity market.

The non-parametric measures in market integration study measure the degree of integration based on comovements of returns or prices, and therefore coefficient of correlation between a pair of markets is frequently used. Cross-correlation

coefficients then become the main indicator of integration. One of indicators of markets integration is the presence of contagion effect that narrowly defined as a significant increase in cross-market linkages after a shock to one country (or group of countries). Forbes and Rigobon (2002) provides a detailed analysis of effect of the volatility burst during a period of crisis on the robustness of conditional and unconditional coefficient of correlation in detecting contagion effect and interdependence between two stock markets. They argued that conditional cross-correlation coefficient is subject to volatility bias; the coefficient would increase in the period of high volatility (during a crisis or shock), and as a consequence may lead to wrong conclusion that there is contagion effect during a crisis yet in fact it is just as an effect of volatility burst (when the coefficient after a shock is as high as before the shock, it is called interdependence relationship). The unconditional correlation thus relatively less affected by the volatility and provides a better measure. However, the conditional correlation still can be applied but with some adjustment that they proposed.

Apart from the methods used in measuring the degree of integration, most studies show that the capital markets in the world really become more integrated as results of economic liberalization, monetary and market union, harmonization of regulation of international trades for both goods and services, and also several crises or market shocks.

The relationship between economic policies harmonization and the degree of capital market integration has long been studied, see for example the study of financial market integration in Europe by Altman (1965), Mandelson (1972), Forbes (1993), Buch (2000), Oh (2003), Guiso, Jappelli, Padula, and Pagano (2004), Askari and Chatterjee (2005), Birg and Lucey (2006), Christiansen (2007), Sifakis-Kapetanakis (2007), Alhorr, Moore, and Payne (2008), Claudia (2008), and recently the study of Kučerová (2009).

The rapid economic growth and regional economic harmonization in Asia also play an important role in fostering emerging capital markets to be more integrated to major developed capital markets. Study on emerging capital markets and or Asian capital markets integration with developed capital markets are Laurenceson (2003), Yang,

Khan, and Pointer (2003), Lin (2005), Plummer and Click (2005), Genberg (2006), Jing and Young (2006), Ibrahim (2006), Ying and Feng (2006), Hatemi and Morgan (2007), Leijonhufvud (2007), Jeyanthi and Pandian (2008), Mukherjee and Bose (2008), Purfield, Kramer, and Jobst (2008), Bensidoun and Unal (2009), Mahmood, Wan Mansor and Dinniah (2009), Oh (2009), Raj and Dhal (2009).

Previous studies documented that there were significant increases in mobility of capital after market liberalization and free trade area formation. The benefits and costs of financial market integration in the perspective of countries initiating the process of integration were outlined by Agénor (2003). Recent studies of capital market integration benefits in the form of capital mobility, income convergence, and growth opportunity are Abiad, Leigh and Mody (2009) that support the findings of Bekaert, Harvey, Lundblad, and Siegel (2007).

3. Methodology

3.1. Minimum Spanning Tree

A tree is a set of acyclic edges that connect all nodes in the undirected graph. If the number of nodes is N and the distance between node i and j is $d_{ij,}$ then the number of edges in the tree is $N-1$ and we can compute the total distance of edges that connect all nodes as D. The number of possible trees from N nodes is N^{N-2}. In this paper, the nodes represent stock exchanges with $N=22$, while the distance d_{ij} a transformed measure of coefficient of correlation, ρ_{ij}, between market returns of stock market i and j. There are two coefficients of correlation that are used in this paper; (i) conditional correlation, estimated from multivariate GARCH model (Diagonal BEKK method) and (ii) unconditional correlation. The methods of correlation coefficient estimation are discussed in the next section. At time t, the coefficient of correlation ρ_{ij} is transformed to pseudo distance measure as follows:

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

Since $-1 < \rho_{t,ij} < 1$ for $i \neq j$ and $\rho_{t,ij} = 1$ for $i=j$, and $\rho_{t,ij} = \rho_{t,ji}$, the number of d_{ij} needs to be estimated is only $N(N-1)/2$ since the matrix of distance as well as matrix of correlation is a symmetric matrix where the distances or correlation coefficients are

lying on the off-diagonal of the matrix. The transformation fulfills the axiom of a metric: (i) $d_{t,ij} = 0$ if $i=j$ or if $\rho_{t,ij} = 1$ when $i \neq j$; (ii) $d_{t,ij} = d_{t,ji}$ and (iii) $d_{t,ij} = d_{t,ik} + d_{t,kj}$.

The aim of using spanning tree is to find tree that has the least total distance of edges that connect all nodes. In the context of this paper, the objectives are how to describe the strongest (closest) structure of relationship among stock markets and define the degree of integration (strength of relationship) as *D,* the total distance of edges of the tree. D_t is the minimum total distance of edges of a tree observed at time *t*. By observing D_t over time ($t=1, 2, 3, \ldots T$), we will be able to observe the dynamics of the degree of integration among the stock markets. Since the number of stock markets used in this paper is 22, there are approximately 7.054 x 10^{26} (22^{20}) possible trees produced at time *t* and from that number of trees we have to find only one tree that has the least D_t.

Fortunately, there is an efficient algorithm in which only requires a few steps of iteration to find the least D_t developed by Kruskal (1956) and known as *minimum spanning tree* (MST) algorithm or *greedy* algorithm. Started by the graph of forest *F* that graphs edges of all possible connections among nodes, the algorithm is stated as follows:

sort the edges of F in increasing order by length
keep a subgraph S of F, initially empty
for each edge e in sorted order if the endpoints of e are disconnected in S
add e to S
return S

The iteration is stopped when all nodes in subgraph *S* are all connected by edge(s). The MST algorithm is vastly available in many mathematical computer programs that make the computation become faster and efficient[1]. The algorithm to find MST using Kruskal's method has been applied in many studies in economics or finance, for example Hill (1999, 2001 and 2004) that used MST for comparing price indexes

[1] The author gratefully thanks Paul A. Jensen who developed ORMM Excel Add-in for running the MST algorithm. The Excel Add-in is available and downloaded from http://www.me.utexas.edu/~jensen/ORMM/

among countries, and Bonanno et al. (2001) who investigating the effect of time horizon in cross-correlation coefficient estimation on the stability of hierarchical structure of stocks returns relationship in NYSE using intraday data. But so far, MST has not been used in investigating the degree of stock market integration, that makes this paper is unique compare with other literatures in the field.

The MST offers advantages in measuring the degree of stock markets integration: (i) Provides ability to assess the degree of integration of a set of stock markets (multilateral/multivariate) simultaneously. Most of previous studies in this field measure only bilateral degree of integration by utilizing parametric model (such as International Capital Asset Pricing Model/I-CAPM) or non-parametric model (conditional/unconditional cross-correlations). (ii) By observing D_t over a period of time, one can perform further analysis using parametric models to find factors contributing to the dynamics of stock market integration in a lesser number of parameters to be estimated, this shall make the models become more parsimonious. (iii) Provides graphical analysis to identify the structure of relationship of stock markets. The analysis shall provide answers to such questions as: Are there stock markets clusters? Do the clusters attributable to regional area (geographical proximity) or to stock market class (emerging versus developed stock market)? What is the likelihood of connection or relationship? (For example, whether Asian stock markets tend to have stronger returns comovements/correlations with other stock markets within the region or with European stock markets).

To be able to utilize the latter MST advantage (graphical analysis), it is important to understand the following properties of MST:

a. If the number of nodes is N, the number of acyclic edges (E) in MST is N-1

$$E = N - 1 \tag{2}$$

   The types of possible connection in a tree are presented in Figure 1 (a).

b. If nodes are associated with some attributes (i.e. region or market class), we can group the nodes according to the attributes. But group in MST graph is defined as at least two connected nodes with the same attribute. The maximum

number of edges ($E_{gg'}^{max}$) that connect nodes between the group g and g' *(non-group g nodes/g complements)* must be *max*(N_g, $N_{g'}$), where N_g and $N_{g'}$ is number of nodes in group g and g' respectively. See Figure 1 (b) for the example.

$$E_{gg'}^{max} = \max\,(N_g, N_{g'}) \tag{3}$$

c. If the number of groups in a tree is G (a sub-set of a group is treated as if it is a group) and when members of each group form a tree within the group as in Figure 1 (c), number of edges connecting all groups is $G - 1$, and hence the number of nodes in the tree, E, can be restated as:

$$E = (\textstyle\sum_g^G N_g) - 1 \tag{4}$$

and the number of edges that form a sub tree of full connections within group g, E_g, following (1) is $N_g - 1$, therefore (4) can also be stated as:

$$E = (\textstyle\sum_g^G E_g) + (G - 1) \tag{5}$$

However, if a pair of groups, let say group g and h is connected by more than one edges (nodes in one or both groups do not form sub trees that all of its edges connect with other nodes within the groups, in other words, the groups may comprise of sub groups as in Figure 1 (d)), then

$$E = (\textstyle\sum_{g,h}^G \tilde{E}_{gh}^{max}) + (G - 1)\,, for\ g \neq h \tag{6}$$

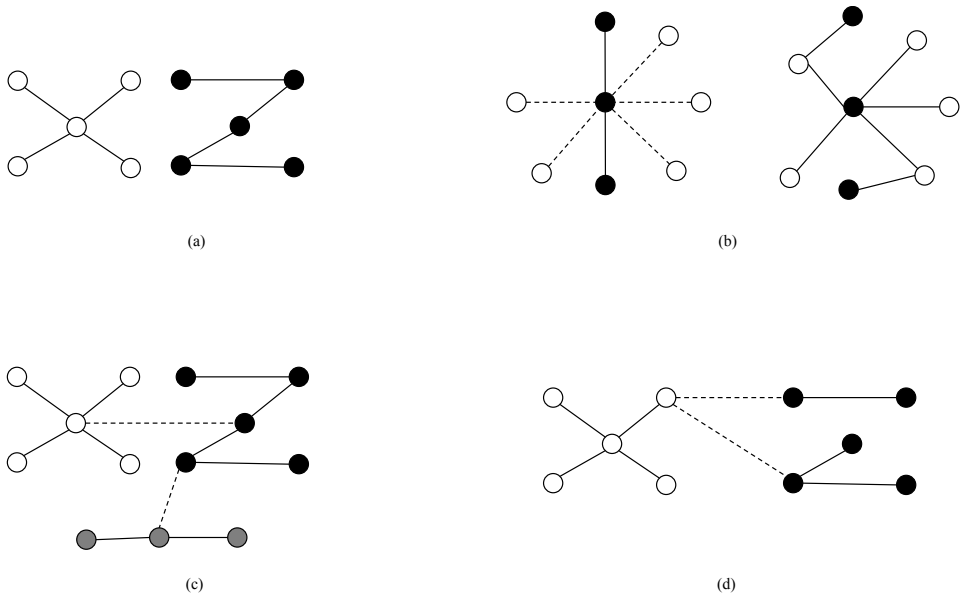
where $\tilde{E}_{gh}^{max}$ is E_{gh}^{max} that has unique value from pairs of groups combination formed by G groups.

Following is an example of the case of property (c) to illustrate equation (5) and (6). If we have four groups *(G=4)* of let say *g1, g2, g3* and *g4*, in which has N_g nodes on each group (the subscript denotes group name) and within the group the nodes form a tree, then there are $G - 1$ edges that connect those four groups by one edge on each pair of groups, this explains the last term *(G – 1)* on equation (5) and (6). The first

term in equation (5), $\sum_{g}^{G} E_g$, is the sum of number of edges within each group. However, if there are more than one edges that connect nodes between groups, then we have six possible connections of nodes between groups (computed from the formula of combination *G!/2!(G-2)!),* those pairs are g_1g_2, g_1g_3, g_1g_4, g_2g_3, g_2g_4, and g_3g_4.

On each pair, the maximum possible number of edges is defined in (3) and suppose the number of nodes on each group is ordered such that $N_1>N_2>N_3>N_4$, as the results, only three unique $\tilde{E}_{gh}^{max}$ are available, those are $\tilde{E}_{12}^{max} = \tilde{E}_{13}^{max} = \tilde{E}_{14}^{max}$, $\tilde{E}_{23}^{max} = \tilde{E}_{24}^{max}$, and $\tilde{E}_{34}^{max}$. Moreover, the number of edges that connect all of these four groups is at least three *(G – 1)*. In total, the number of edges in the MST would be as defined in (5).

Figure 1
Hypothetical Spanning Tree



(a) *Connection types: star (white nodes) and chain (black nodes). Number of edges on each tree is equal to number of nodes – 1.*
(b) *Left: black nodes have full within groups connection, white nodes do not form a group, the dashed lines represent group to non-group connection. Right: Black and White nodes are not two different groups, color is not a group attribute. Both left and right graphs show no inter-group connection.*
(c) *White nodes, black nodes and grey nodes are three distinctive groups, the maximum inter-groups connections is equal to the number of groups – 1.*
(d) *White nodes form full within group connection, while black nodes consist of two sub-set groups. Number of inter-groups connections (sub-groups are treated as if they separate groups) is equal to the number of groups – 1.*

As one of objectives of this paper is to investigate the dynamic of the degree of integration among the sample stock markets, MST algorithm was run for each observation period during the period of analysis sample and then observed the D_t.

In addition, graphical analysis was performed to find whether clusters were found and the likelihood of connection or relationship between groups (based on class of stock market or based on regional area) could be identified. As shown in the properties of MST above, especially with regard to property (c), we cannot draw a conclusion about the tendency or likelihood of relationship between a pair of groups only from the frequency of edges that connect nodes in those two groups during the observation period. This is because the number of nodes in each group determines the maximum number of possible edges on each observation time. Using the frequency alone will produce a bias measure when we try to compare it with the frequency of the other pairs of groups' connection, unless the number of nodes on each group is set to be equal. To overcome this problem, I propose a measure of connection likelihood (CL_{gh}) between group g and h as follows:

$$CL_{gh} = \frac{\sum_{t=1}^{T} E_{t,gh}}{T E_{gh}^{max}} \tag{7}$$

where T is number of observation period. The value of CL_{gh} must be within a range of zero to one, the higher the value, the more likely that group g and h have strong relationship (in this case, strong comovements of returns).

In addition, the graphed structure of relationship in MST might be sensitive to the method to determine the pseudo distance measure, D_t. The structure of relationship is identified by a list of edges connecting nodes produced by MST algorithm for each observation at time t. Lists of edges are produced over the observation period T. I denote $c_{i,t} = j$ if node i at time t is connected to node j. For each node, I count the frequency of connection changes in T observations, I denote this by F_i for node i. The average of frequency of connection changes for all nodes is simply $\bar{F} = \frac{\sum_{i=1}^{N-1} F_i}{(N-1)T}$. The measure of MST structure stability S is then defined by:

$$S = \sqrt{\frac{\sum_{i=1}^{N-1} \frac{F_i}{N-1} (\frac{F_i}{N-1} - \bar{F})^2}{N-1}} \tag{8}$$

where $F_i = \sum_{t=1}^{T} \Delta c_{i,t}$, $\Delta c_{i,t} = 0$ for $c_{i,t} = c_{i,t-1}$ and , $\Delta c_{i,t} = 1$ for $c_{i,t} \neq c_{i,t-1}$.

Equation (8) is similar to standard deviation formula, except that I put more weight on nodes that are more frequently connected with different nodes. If the structures of connection in the MSTs are stable, then we expect that *S* would be approaching to zero. The value of *S* can be interpreted as percentage of changes in MST structure relative to number of observations. For example, if *T=100* and *S=0.1* means that MST structure has changed equivalent to 10 times in 100 observations.

3.2. Cross-Correlation Coefficient

Following the previous explanation, the degree of integration of a set of stock markets is measured by a multivariate coefficient, which is the total length of acyclic arcs connecting stock markets produced by MST algorithm. Before running the algorithm, the matrix of correlation coefficients for all possible pairs of stock market returns must be identified and then transform them into the pseudo distance measure as defined in equation (1). There are two kinds of correlation coefficient we shall consider, the first is conditional correlation coefficient and the second one is unconditional correlation. These two correlation coefficients will be used to obtain MST graphs, and then the two graphs will be compared with one to another to test whether the relationship structure in MST graphs is sensitive to the way the pseudo distance is measured. This step is performed considering the caveat proposed by Forbes and Rigobon (2002) that the conditional correlation may be biased to volatility burst during periods of crises.

The matrix of cross-correlation coefficients is estimated on each observation period for the conditional one, and estimated on each rolling window with fixed window size of 60 weeks (about one year) for the unconditional one.

Conditional correlation is obtained from conditional variance-covariance matrix, which one-step ahead estimation based on any past information is thought relevant.

The conditional variance-covariance matrix is obtained by running multivariate GARCH, Diagonal BEKK model as specified in the following equations.

The mean equations for the continuously compounding returns are regressed against a constant and stated in vector form as follow:

$$R_t = C_t + u_t \tag{9}$$

where R_t, C_t, and u_t is a column vector of N elements that represent markets returns, column vector of constants where $C_t = [c_{1,t}\ c_{2,t}\ \dots\ c_{i,t}\ \dots c_{N,t}]'$, and column vector of innovations on each market where $u_t = [u_{1,t}\ u_{2,t}\ \dots\ u_{i,t}\ \dots u_{N,t}]'$ respectively. Vector u_t is assumed to be normally distributed with mean zero and covariance H_t. The market return of stock market i as element of R_t is defines as $r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, so that $R_t = [r_{1,t}\ r_{2,t}\ \dots r_{i,t}\ \dots\ r_{N,t}]'$.

The conditional variance-covariance matrix H_t is specified according to Engle and Kroner (1995) Diagonal BEKK model:

$$H_t = \Omega\Omega' + Au_{t-1}u'_{t-1} + BH_{t-1}B' \tag{10}$$

where Ω, A, and B are symmetric diagonal rank one matrices with NxN elements. The terms in the right-hand-side of equation (10) are set in quadratic forms to ensure that the conditional variance-covariance matrix H_t is positive semidefinite (PSD). Equation (10) yields the conditional variance of stock market i and the conditional covariance between stock market i and j stated in equation (11) and (12) respectively.

$$h_{ii,t} = \Omega_{ii}^2 + a_{ii}^2 u_{ii,t-1}^2 + b_{ii}^2 h_{ii,t-1} \tag{11}$$

$$h_{ij,t} = \Omega_{ij}^2 + a_{ij}^2 u_{ii,t-1} u_{jj,t-1} + b_{ij}^2 h_{ii,t-1} h_{jj,t-1} \tag{12}$$

where $h_{ij,t}$, Ω_{ij}, a_{ij}, and b_{ij} is element of matrix Ω, A, and B, the subscript i and j represent the row and column for respective matrices. The conditional correlation between stock market returns i and j, ρ'_{ij} is then computed as

$$\rho'_{ij,t} = \frac{h_{ij,t}}{h_{ii}^{1/2} h_{jj}^{1/2}} \tag{13}$$

The coefficient matrices are obtained by maximizing the log likelihood equation l_t as follows:

$$l_t = -\frac{1}{2} N \log(2\pi) - \frac{1}{2} \log(|H_t|) - \frac{1}{2} u_t{}' H_t^{-1} u_t \tag{14}$$

where N is the number of mean equations which is equal to the number of stock markets as sample in this paper.

The unconditional correlation coefficient between stock market i and j, $\rho_{ij,t}$, is estimated from historical data from $t–60$ until t. The unconditional variance covariance matrix at time t is defined as

$$E_t[(R_t - \mu_t)(R_t - \mu_t)'] = \begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} & \cdots & \sigma_{1N,t} \\ \sigma_{21,t} & \sigma_{22,t} & \cdots & \sigma_{2N,t} \\ \vdots & \vdots & & \vdots \\ \sigma_{N1,t} & \sigma_{N2,t} & \cdots & \sigma_{NN,t} \end{bmatrix} = E_t[R_t R_t{}'] - \mu_t \mu_t{}' \tag{15}$$

where $\mu_t = \begin{bmatrix} \mu_{1,t} \\ \mu_{2,t} \\ \vdots \\ \mu_{n,t} \end{bmatrix} = \begin{bmatrix} E[R_{1,t}] \\ E[R_{2,t}] \\ \vdots \\ E[R_{2,t}] \end{bmatrix} = E[R_t]$

By dividing $\sigma_{ij,t}$ by $\sigma_{i,t}\sigma_{j,t}$, we obtain the unconditional correlation matrix:

$$Corr_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1N,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{2N,t} \\ \vdots & \vdots & & \vdots \\ \rho_{N1,t} & \rho_{N2,t} & \cdots & 1 \end{bmatrix} \tag{16}$$

4. Data and Samples

Weekly stock market indices from the beginning of 2000 until the end of 2010 are used as sample and are collected from Yahoo Finance. All stock market indices are converted into US Dollars before computing the markets returns. There are 22 stock markets comprise of both emerging and developed stock markets from three

continents: Europe, Asia Pacific and America. All seven European stock markets are categorized as developed stock market and members of European Union (except Switzerland and Israel) and only United Kingdom that is EU member but not using the Euro currency. Asia Pacific stock markets comprise of four developed stock market and six emerging markets. Meanwhile, stock markets in America are represented by five stock markets (two developed markets, and three emerging markets). The representative indices and the statistical figures of those markets are shown in Table 1.

The emerging markets are characterized by higher average returns compared with those in developed markets, yet the risks are also higher. In addition, developed markets tend to be more informationally efficient than the emerging ones, with Asian developed stock markets are ones of the most efficient markets as shown by no significant autocorrelations. The statistical figures indicate that there are still distinctive characteristics between emerging and developed stock markets, as well as different characteristics among regional markets. Therefore, suspicion on regional clustering or segmentation based on market class (developed or emerging market) is relevant to be further investigated.

The significant autocorrelations found in several stock markets indicate that the time series of returns could be predicted by the past returns (AR). Therefore, mean equations in equation (9) may be better estimated by adding AR terms. However, I have tested equation (9) by adding AR terms and without AR terms and found that the value of maximum likelihood function of model without AR terms is larger than the other one. All markets returns time series are also stationary, both based on individual unit root test (Augmented Dickey-Fuller and Phillips-Perron test) and panel unit root test (Levin, Lin, and Chu t-statistic) that the null hypotheses (that time series have unit root) are rejected at 1% level.

Table 1
Sample Descriptive Statistic of 2000 – 2010

			Annualized Arithmetic		Annualized Geometric		Autocorrelation at lag:						
Country	Index Name and Code		Mean	Std. Dev.	Mean	Std. Dev.	1	2	3	4	5	15	30
EUROPE			0.030	0.245	-0.003	0.035							
EUROLAND			*0.022*	*0.262*	*-0.015*	*0.038*							
Netherland	AEX General	AEX	-0.033	0.256	-0.067	0.037	0.060	0.029	-0.057	0.010	0.015	**0.057**	-0.028
Austria	ATX	ATX	0.107	0.281	0.064	0.041	0.038	0.037	0.020	0.103	0.048	**0.046**	-0.063
France	CAC40	FCHI	-0.014	0.245	-0.047	0.035	-0.009	0.024	-0.048	-0.008	0.003	**0.050**	-0.019
Germany	DAX	GDAXI	0.028	0.265	-0.011	0.038	0.013	0.049	**-0.116**	**0.033**	-0.001	**0.037**	-0.025
NON-EURO			*0.040*	*0.223*	*0.013*	*0.032*							
United Kingdom	FTSE100	FTSE	-0.014	0.219	-0.040	0.032	-0.077	0.025	**-0.085**	0.035	0.029	**0.071**	**-0.034**
Switzerland	Swiss Market	SSMI	0.037	0.206	0.014	0.030	**-0.184**	**0.107**	**-0.116**	**0.052**	**-0.007**	**0.041**	**-0.022**
Israel	TA-100	TA100	0.096	0.244	0.065	0.035	**-0.093**	**0.117**	**0.100**	**-0.012**	**-0.011**	**-0.015**	**-0.073**
ASIA PACIFIC			0.059	0.252	0.024	0.036							
DEVELOPED			*0.029*	*0.233*	*-0.001*	*0.034*							
Australia	All Ordinaries	AORD	0.080	0.248	0.046	0.036	-0.016	0.065	-0.037	0.002	0.028	**0.039**	-0.005
Hong Kong	Hang Seng	HSI	0.026	0.238	-0.005	0.034	-0.024	0.053	-0.023	0.076	0.002	-0.005	-0.016
Japan	Nikkei225	N225	-0.034	0.222	-0.059	0.032	-0.044	0.069	-0.045	0.008	-0.002	0.012	0.022
Singapore	Straits Times	STI	0.043	0.225	0.015	0.032	0.022	0.032	-0.010	0.061	0.040	0.026	0.017
EMERGING			*0.079*	*0.264*	*0.041*	*0.038*							
India	BSE30	BSESN	0.119	0.279	0.079	0.040	0.070	0.107	**-0.011**	**0.042**	-0.002	**0.081**	**-0.049**
Indonesia	IDX Comp.	IDX	0.129	0.293	0.085	0.042	**0.082**	**0.090**	**0.201**	**0.056**	**0.081**	**0.085**	**0.069**
Malaysia	KLSE Comp.	KLSE	0.074	0.168	0.061	0.024	**0.105**	**0.095**	**0.012**	**-0.012**	**0.088**	**0.053**	0.043
South Korea	KOSPI	KS11	0.062	0.338	-0.002	0.049	-0.064	-0.014	0.016	0.021	0.011	**-0.002**	**0.026**
China	Shanghai Comp.	SSEC	0.083	0.246	0.052	0.035	0.040	0.059	**0.103**	0.019	**0.033**	**-0.008**	**0.015**
Taiwan	Taiwan Weighted	TWII	0.009	0.262	-0.028	0.038	-0.016	0.051	0.078	0.033	0.057	-0.021	**0.073**
AMERICA			0.074	0.305	0.019	0.044							
DEVELOPED			*0.031*	*0.217*	*0.005*	*0.031*							
United States	S&P500	GSPC	-0.014	0.189	-0.033	0.027	-0.043	0.063	**-0.100**	**-0.024**	**0.054**	**0.095**	**-0.011**
Canada	S&P TSX	GSPTSE	0.076	0.245	0.044	0.035	-0.064	0.066	-0.057	0.025	0.043	**0.076**	**0.026**
EMERGING			*0.103*	*0.363*	*0.028*	*0.052*							
Brazil	IBOVESPA	BVSP	0.136	0.414	0.041	0.060	**-0.108**	**0.093**	**0.050**	0.029	**-0.036**	**0.003**	**-0.072**
Argentina	MERVAL	MERV	0.043	0.380	-0.040	0.055	0.003	0.071	0.011	0.078	-0.061	0.078	**-0.006**
Mexico	IPC	MXX	0.130	0.297	0.084	0.043	-0.034	0.024	-0.007	0.008	-0.010	0.071	0.047

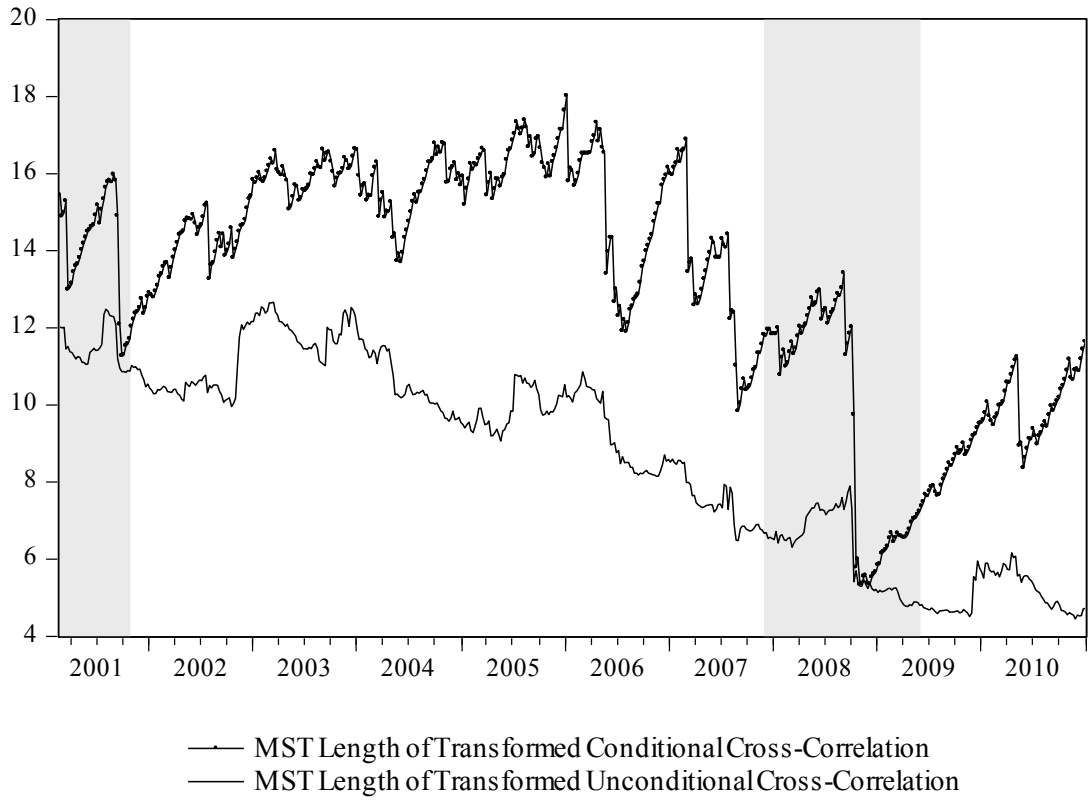
**Bold face indicates autocorrelation is significant at 5% level. Source: Yahoo Finance and author computation. The stock markets returns are based on US Dollar prices.*

5. Findings

5.1. The World Stock Markets Integration Dynamics

Time-varying degree of integration or MST length based on conditional and unconditional correlations are presented on Figure 2. It is apparent for unconditional one that the degree of integration is dynamic but it shows a negative trend, meaning that the markets are more integrated. Meanwhile, the MST length estimated from conditional correlation is more erratic compared with the unconditional one. Nevertheless, both measures show that the comovement of markets returns are very volatile and tend to have negative trend (for conditional correlation-based MST, the negative trend can be observed after 2005). The significant drop of MST length occurs during high volatility period, i.e. during recession period in the end of 2001 and 2008. This is happened not only on conditional correlation-based MST but also on the unconditional one; it indicates that shocks in US market were contagious or transmitted to other markets around the world. However, we can observe that MST length drop in 2008 recession is deeper than the 2001 recession; this is because the nature of the two recessions is different. The 2001 recession period was triggered by the burst of dot-com bubbles when many internet or high-tech companies were in financial distress, which is more likely happened in developed stock markets than in emerging ones. In addition, the deepest drop of MST length in 2001 was a coincident with 9-11 event, which had greater impact to US itself. Meanwhile, the 2008 recession although many believed that it was triggered by the US subprime mortgage crises or housing bubble, but eventually it had greater effect to the disruption in financial system not only in US but also almost in all countries. The US financial institutions are known as among the largest institutions in the world, and invested in companies or sovereign bonds in many countries, and therefore the impact of the collapse of US financial institutions were very contagious to other countries. The largest drop of MST length in 2008 occurred at the same time as the bankruptcy of Lehman Brothers.

Figure 2
The Degree of Integration Measured by the Length of
Conditional Correlation-based MST and Unconditional Correlation-based MST



MST length represents the measure of the degree of integration among stock markets being studied, that its value is derived from correlation coefficients of connected markets in the MST graph and therefore the length is an inverse function of the coefficient, the shorter the length ("distance"), the more correlated the markets are. Both estimations of cross-correlation coefficients were estimated using weekly US Dollars value markets returns during sample period of 2000-2010. The unconditional cross-correlation coefficients were estimated using rolling window estimation with windows size of 60 observations (about one year). The shaded areas represent US recession periods based on NBER's Business Cycle Dating Committee report.

The unit root tests were performed to test whether the stock markets really become more integrated over the observation period. The idea behind unit root test is to identify whether the degree of integration measure is either stationary or random walks, and since the MST graphs in Figure 2 also show an indication of stochastic trend, hence the unit root test performed in the following model is based on assumption that the time series D_t (MST length) is a random walk with drift around a stochastic trend, and the unit root test is specified following the Augmented Dickey-Fuller (ADF) test:

$$\Delta D_t = \beta_1 + \beta_2 t + \delta D_{t-1} + \sum_{l=1}^{L} \gamma_l . \Delta D_{t-l} + \epsilon_t \qquad (17)$$

The null hypothesis is that $\delta = 0$, that is, the D_t is nonstationary. The number of lag for ΔD_{t-1} is determined by Akaike Information Criterion (AIC). To test the null

hypothesis, the *student t-distribution* is replaced by *tau-statistic (τ)* developed by Dickey and Fuller. The negative value β_2 is expected, to indicate that the degree of integration is diminishing or the stock markets become more integrated. The results are presented on Table 2. The results confirmed that both the two measures of integration degree are nonstationary and have negative trend to indicate that the degrees of integration are dynamics and the stock markets are really become more integrated in the last ten years of observation.

Table 2
Unit Root Test of Dt

	β_1	β_2	δ	Prob.(τ)
MST ConCor	0.4159	-0.0003	-0.0239	
t-stat.	***3.2656***	***-2.4132***	*-3.1225*	0.1020
MST UnCor	0.3399	-0.0004	-0.0256	
t-stat.	***2.5822***	***-2.5769***	*-2.6809*	0.2450

MST ConCor and MST UnCor is D_t based on conditional correlation and unconditional correlation respectively. Bold face on t-statistic value indicates that the coefficient is significant different from zero at 5% level.

On average, D_t based on conditional and unconditional correlations is 13.177 and 8.734 respectively. Transforming back the average D_t to correlation coefficient, the average conditional and unconditional correlation in each spanning tree is 0.556 and 0.706 respectively, which is quiet strong. To identify which stock market that has significant influence to the comovements of stock markets returns, I performed VAR (vector autoregression) analysis and estimated the impulse response function and variance decomposition. Since the time series of D_t and stock market indices are nonstationary, the VAR analysis used the first difference of D_t and markets returns of respective sample. Based on MST graphs produced in each observation period or sample window (for rolling window unconditional correlation), the prominent stock markets that frequently in the position as a hub market are France/Germany, United Kingdom, Singapore, and United States. These stock markets are also representing their regional area. By choosing only the representative markets, we can avoid multicollinearity in the VAR model. As a control variable, world oil prices were included in the model. The lag selection is based on information criterion (Akaike Information Criterion). The results of VAR analysis are presented on the following tables.

Table 3
VAR Analysis of Conditional Correlation-Based MST Length

	D_MST_C	RX_FTSE	RX_GDAXI	RX_GSPC	RX_STI	RX_OIL
D_MST_C(-1)	-0.049469	0.000987	-0.002040	-0.000251	**0.006875**	**0.006799**
	(0.04175)	(0.00297)	(0.00361)	(0.00260)	(0.00295)	(0.00384)
	[-1.18491]	[0.33278]	[-0.56583]	[-0.09637]	[2.33236]	[1.76897]
D_MST_C(-2)	-0.014731	-0.004041	-0.004595	-0.001778	0.002094	0.003062
	(0.04009)	(0.00285)	(0.00346)	(0.00250)	(0.00283)	(0.00369)
	[-0.36749]	[-1.41868]	[-1.32741]	[-0.71178]	[0.73990]	[0.82967]
RX_FTSE(-1)	**3.010351**	**-0.262530**	**-0.218710**	0.034162	-0.053608	0.192915
	(1.23571)	(0.08781)	(0.10671)	(0.07701)	(0.08725)	(0.11375)
	[2.43614]	[-2.98963]	[-2.04963]	[0.44361]	[-0.61443]	[1.69590]
RX_FTSE(-2)	-1.341625	-0.093991	0.035492	0.047607	0.087730	-0.105149
	(1.25529)	(0.08921)	(0.10840)	(0.07823)	(0.08863)	(0.11556)
	[-1.06878]	[-1.05365]	[0.32743]	[0.60855]	[0.98982]	[-0.90993]
RX_GDAXI(-1)	0.848889	-0.000490	0.006419	-0.016516	0.086746	-0.081441
	(1.03465)	(0.07353)	(0.08934)	(0.06448)	(0.07305)	(0.09525)
	[0.82046]	[-0.00666]	[0.07184]	[-0.25615]	[1.18744]	[-0.85507]
RX_GDAXI(-2)	-0.764575	-0.063743	-0.108644	-0.086705	-0.091165	0.021173
	(1.03128)	(0.07329)	(0.08905)	(0.06427)	(0.07282)	(0.09493)
	[-0.74139]	[-0.86978]	[-1.21998]	[-1.34910]	[-1.25200]	[0.22303]
RX_GSPC(-1)	0.854334	**0.257940**	**0.274723**	-0.014445	**0.307076**	0.018704
	(1.22374)	(0.08696)	(0.10567)	(0.07626)	(0.08640)	(0.11265)
	[0.69813]	[2.96608]	[2.59973]	[-0.18940]	[3.55393]	[0.16603]
RX_GSPC(-2)	**3.290848**	**0.223819**	**0.269603**	**0.141439**	**0.231733**	-0.027133
	(1.22049)	(0.08673)	(0.10539)	(0.07606)	(0.08618)	(0.11235)
	[2.69633]	[2.58058]	[2.55807]	[1.85954]	[2.68909]	[-0.24150]
RX_STI(-1)	0.779846	0.000306	-0.005835	-0.055375	**-0.185812**	**0.221766**
	(0.80645)	(0.05731)	(0.06964)	(0.05026)	(0.05694)	(0.07424)
	[0.96702]	[0.00534]	[-0.08379]	[-1.10181]	[-3.26325]	[2.98724]
RX_STI(-2)	**2.228570**	0.042625	0.002808	-0.004232	-0.039438	0.095284
	(0.77932)	(0.05538)	(0.06730)	(0.04857)	(0.05503)	(0.07174)
	[2.85963]	[0.76966]	[0.04173]	[-0.08713]	[-0.71673]	[1.32816]
RX_OIL(-1)	0.664060	-0.006373	-0.027781	-0.020626	0.004560	**0.202935**
	(0.46844)	(0.03329)	(0.04045)	(0.02919)	(0.03307)	(0.04312)
	[1.41761]	[-0.19145]	[-0.68678]	[-0.70656]	[0.13787]	[4.70606]
RX_OIL(-2)	-0.000158	**-0.056333**	-0.033320	-0.020773	-0.045527	-0.011531
	(0.45424)	(0.03228)	(0.03922)	(0.02831)	(0.03207)	(0.04182)
	[-0.00035]	[-1.74516]	[-0.84946]	[-0.73381]	[-1.41952]	[-0.27576]
C	0.002752	-4.72E-05	0.000793	2.63E-05	0.001475	0.001477
	(0.01853)	(0.00132)	(0.00160)	(0.00115)	(0.00131)	(0.00171)
	[0.14856]	[-0.03587]	[0.49584]	[0.02275]	[1.12757]	[0.86605]
R-squared	0.165349	0.045373	0.038329	0.017042	0.097484	0.125395
Adj. R-squared	0.147400	0.024844	0.017648	-0.004097	0.078075	0.106586
Sum sq. resids	108.0330	0.545566	0.805585	0.419579	0.538580	0.915497
S.E. equation	0.440009	0.031268	0.037996	0.027421	0.031068	0.040505
F-statistic	9.211911	2.210144	1.853322	0.806179	5.022645	6.666855

Standard errors in () and t-statistics in []. Bold face indicates that the parameter is significant at 5% level.

Table 4
VAR Analysis of Unconditional Correlation-Based MST Length

	D_MST_U	RX_FTSE	RX_GDAXI	RX_GSPC	RX_STI	RX_OIL
D_MST_U(-1)	0.049334	-0.006358	-0.003926	-0.001535	-0.005622	-0.007297
	(0.04650)	(0.00716)	(0.00862)	(0.00608)	(0.00700)	(0.00891)
	[1.06104]	[-0.88839]	[-0.45519]	[-0.25244]	[-0.80345]	[-0.81914]
D_MST_U(-2)	0.008423	0.003476	0.002168	6.38E-05	**0.014633**	**0.019419**
	(0.04641)	(0.00714)	(0.00861)	(0.00607)	(0.00698)	(0.00889)
	[0.18149]	[0.48654]	[0.25190]	[0.01051]	[2.09518]	[2.18406]
RX_FTSE(-1)	-0.724656	**-0.285030**	**-0.253056**	-0.020724	**-0.164980**	**0.274918**
	(0.64792)	(0.09973)	(0.12018)	(0.08476)	(0.09751)	(0.12414)
	[-1.11843]	[-2.85789]	[-2.10569]	[-0.24451]	[-1.69191]	[2.21459]
RX_FTSE(-2)	0.253604	-0.108160	0.007100	0.038770	0.021807	-0.117358
	(0.65348)	(0.10059)	(0.12121)	(0.08549)	(0.09835)	(0.12520)
	[0.38808]	[-1.07525]	[0.05858]	[0.45352]	[0.22174]	[-0.93733]
RX_GDAXI(-1)	-0.274576	-0.038069	-0.043379	-0.050198	0.120233	-0.110552
	(0.53980)	(0.08309)	(0.10012)	(0.07062)	(0.08124)	(0.10342)
	[-0.50866]	[-0.45816]	[-0.43326]	[-0.71086]	[1.47999]	[-1.06892]
RX_GDAXI(-2)	-0.542162	-0.086818	-0.140479	-0.088268	-0.070520	-0.016015
	(0.53845)	(0.08288)	(0.09987)	(0.07044)	(0.08104)	(0.10317)
	[-1.00689]	[-1.04747]	[-1.40658]	[-1.25310]	[-0.87022]	[-0.15523]
RX_GSPC(-1)	**1.442529**	**0.327682**	**0.383956**	0.089358	**0.331615**	-0.000959
	(0.66299)	(0.10205)	(0.12297)	(0.08673)	(0.09978)	(0.12703)
	[2.17578]	[3.21086]	[3.12228]	[1.03028]	[3.32348]	[-0.00755]
RX_GSPC(-2)	0.478704	**0.293416**	**0.358748**	0.174075	0.327554	0.024835
	(0.66225)	(0.10194)	(0.12284)	(0.08663)	(0.09967)	(0.12689)
	[0.72285]	[2.87832]	[2.92057]	[2.00930]	[3.28646]	[0.19573]
RX_STI(-1)	0.253434	0.026799	0.011161	-0.028482	**-0.138125**	**0.213957**
	(0.41183)	(0.06339)	(0.07639)	(0.05387)	(0.06198)	(0.07890)
	[0.61539]	[0.42275]	[0.14611]	[-0.52867]	[-2.22857]	[2.71159]
RX_STI(-2)	0.652477	0.030985	0.011887	-0.017934	-0.052963	0.129146
	(0.40425)	(0.06223)	(0.07498)	(0.05288)	(0.06084)	(0.07745)
	[1.61405]	[0.49794]	[0.15853]	[-0.33912]	[-0.87055]	[1.66742]
RX_OIL(-1)	-0.226452	0.007405	-0.033139	-0.032652	0.014929	**0.188244**
	(0.24059)	(0.03703)	(0.04463)	(0.03147)	(0.03621)	(0.04610)
	[-0.94123]	[0.19994]	[-0.74260]	[-1.03744]	[0.41230]	[4.08368]
RX_OIL(-2)	-0.271870	**-0.065159**	-0.043166	-0.027987	-0.025299	-0.024099
	(0.22988)	(0.03539)	(0.04264)	(0.03007)	(0.03460)	(0.04405)
	[-1.18263]	[-1.84138]	[-1.01235]	[-0.93062]	[-0.73124]	[-0.54714]
C	-0.012710	0.000291	0.001257	0.000373	0.002050	0.001890
	(0.00927)	(0.00143)	(0.00172)	(0.00121)	(0.00139)	(0.00178)
	[-1.37159]	[0.20422]	[0.73106]	[0.30747]	[1.46958]	[1.06477]
R-squared	0.029650	0.052275	0.049805	0.020577	0.100078	0.132549
Adj. R-squared	0.006315	0.029484	0.026955	-0.002976	0.078437	0.111688
Sum sq. resids	21.33071	0.505416	0.733849	0.365042	0.483136	0.783039
S.E. equation	0.206753	0.031825	0.038349	0.027047	0.031116	0.039613
F-statistic	1.270636	2.293647	2.179616	0.873654	4.624385	6.354054

Standard errors in () and t-statistics in [].Bold face indicates that the parameter is significant at 5% level.

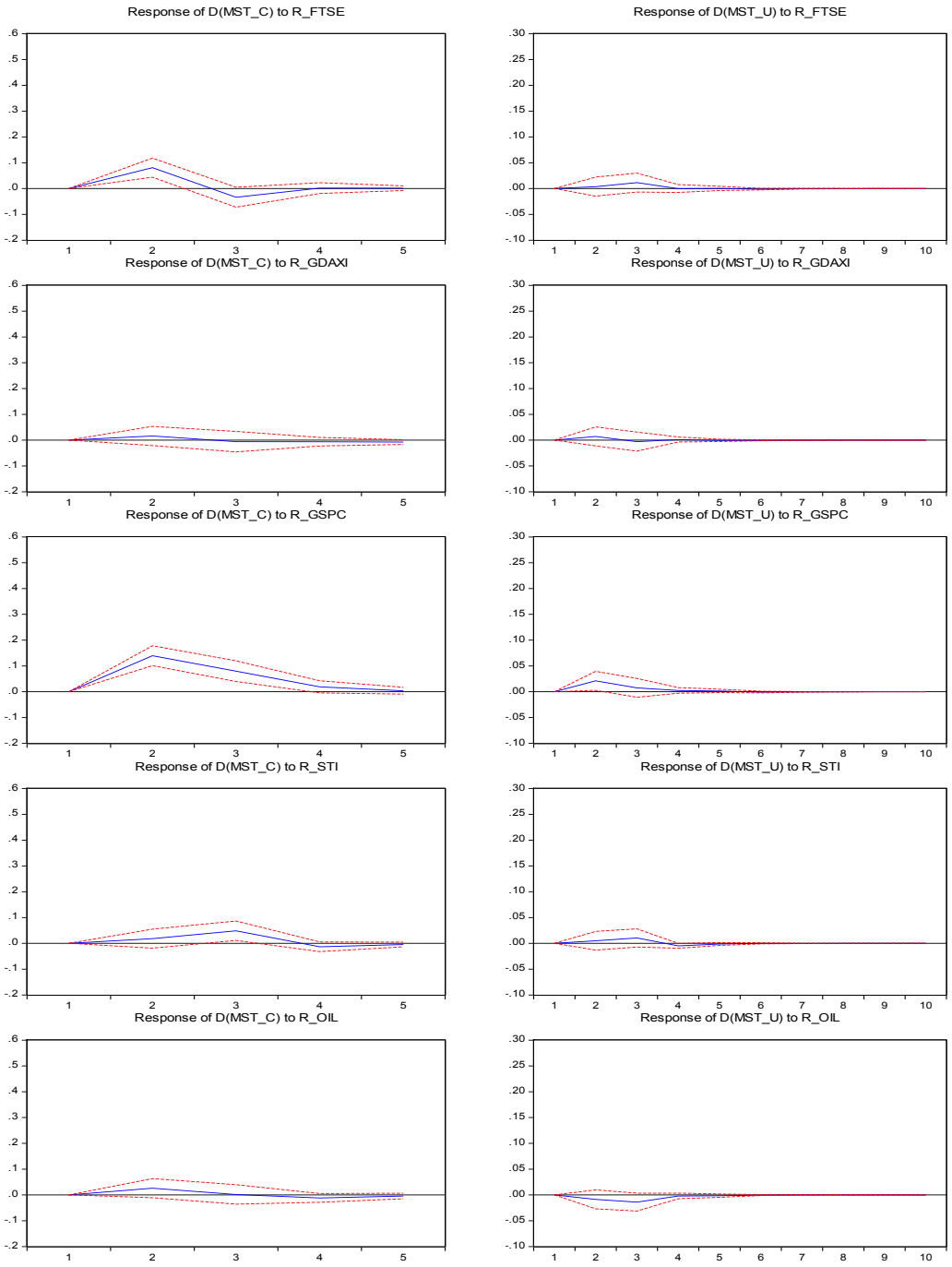
On Table 3, the variations of conditional correlation-based MST length can be explained by variations in stock returns of UK (FTSE), US (GSPC) and Singapore (STI). The US stock market is also the most influential one as its lagged returns able to explain the variations of returns in European stock markets (UK and Germany[2]), and Asian stock market (Singapore). Meanwhile, Singaporean stock market (STI), which is the hub of Asian emerging markets, as well as Japanese stock market is highly affected by the variations of other markets (as shown by the significant coefficient of lagged MST length on STI returns). As previously discussed, the conditional correlation-based MST is more volatile and also more sensitive to volatility bias, therefore we can detect more markets returns explaining the MST length. In contrast, the unconditional correlation-based MST is only explained by the variations of US stock market returns (Table 4). Moreover, the results on Table 3 and Table 4 both show that oil price shock is not an eminent factor that drove the integration of world stock markets. The results of impulse response function (Figure 3) and variance decomposition (Figure 4) are in line with the above analysis. The US stock market shocks contributed to about 11% of the changes in the degree of integration (unconditional correlation-based MST), while the others only 3% or lower.

5.2. The Structure of Relationship of the World Stock Markets

Minimum spanning tree graphs were produced on both conditional and unconditional correlation bases. There are 574 conditional correlation-based MST graphs and 515 unconditional correlation-based ones. List of stock markets connections and some MST graphs on important events during period from 2000 until 2010 are provided in the appendix. However, MST graphs produced using whole observation period based on constant conditional correlation (CCC) and unconditional correlation are not significantly different to each MST graph produced using conditional correlation and rolling window unconditional correlation estimations.

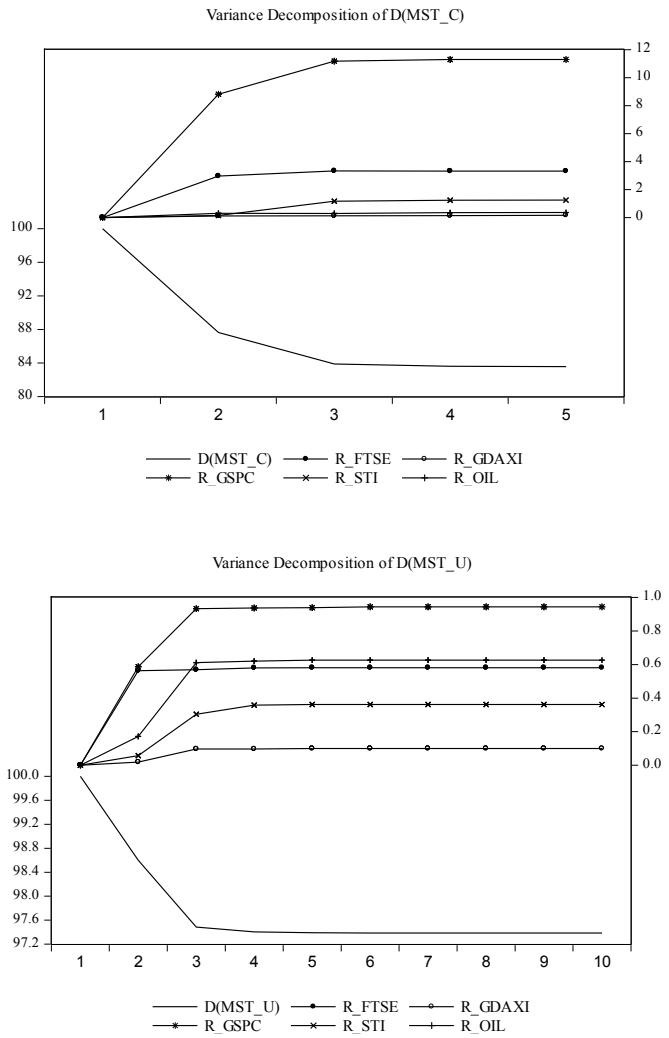
[2] Replacing Germany stock market with France stock market did not significantly change the results, since both Germany and France stock markets are highly correlated. UK is selected to represent non-euro European market.

Figure 3
Impulse Response Function of Conditional Correlation-Based and
Unconditional Correlation-Based MST Length to Markets Returns and Oil Price Shocks



The responses are in Cholesky one standard deviation innovation, the dashed line represent ± 2 S.E. D(MST_C) and D(MST_U) is the first difference of conditional and unconditional correlation-based MST length respectively. Markets returns (with R_ prefix) are computed based on US Dollars markets indices.

Figure 4
Variance Decomposition (%) of Conditional Correlation-Based and
Unconditional Correlation-Based MST Length to Markets Returns and Oil Price Shocks



D(MST_C) and D(MST_U) is the first difference of conditional and unconditional correlation-based MST length respectively. Markets returns (with R_ prefix) are computed based on US Dollars markets indices and use the right axis.

Figure 5 and Figure 6 show that there are apparent clusters based on regional proximity. The most consistent cluster is Asian stock market with Singaporean stock market as the market hub, and the next eminent cluster is European stock market, with exception of Israeli stock markets (although it might not be appropriate to include Israeli stock market as part of European market, but geographically that is the closest approximate grouping for Israel among the samples). The American stock markets are also clearly clustered in CCC-based MST, but rather scattered in unconditional correlation-based MST.

Figure 5
MST Graph Based on Conditional Constant Correlations
2000 – 2010

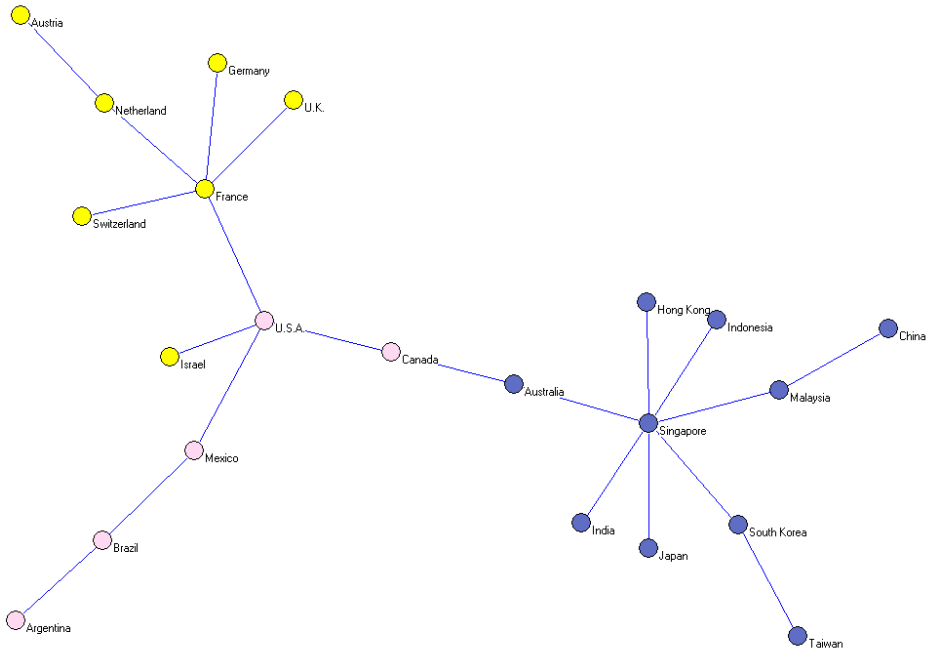
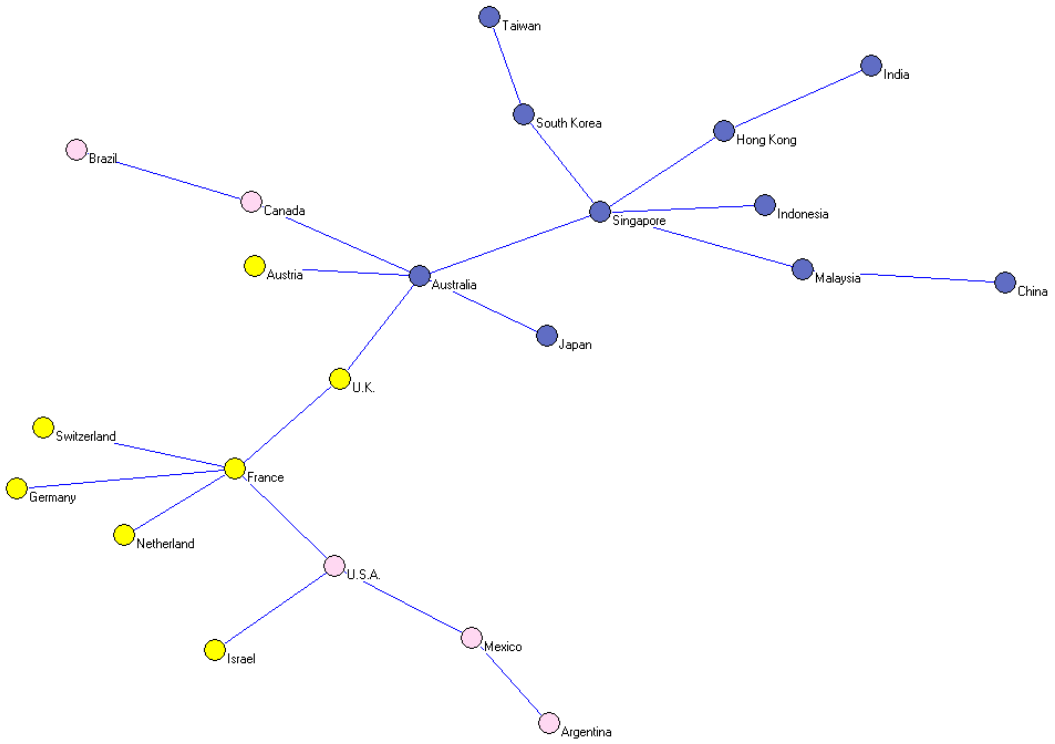


Figure 6
MST Graph Based on Unconditional Correlations
2000 – 2010



The structure of relationship of the stock markets identified by MST graphs is relatively stable. As shown on Table 5, on average, conditional correlation-based MST produced 7.84 percent variation of the relationship structure among 574 trees, while the unconditional one only produced 4.31 percent variations of the relationship structure among 515 trees. It means that unconditional correlation-based MST produced more consistent structure of relationship than the conditional one; it might be attributed by the volatility bias where conditional correlations are more affected to that. Therefore unconditional correlation-based MST is more appropriate to be used for analyzing the interdependence structure of the stock markets. However, both types of MSTs are almost similar in its connections structure that leads to similar general conclusions.

Table 5
Stability of MST Structure

Nodes:	Panel A: MST Structure - Conditional Cross-Correlation				Panel B: MST Structure - Unconditional Cross-Correlation			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
AORD	115	20.034	4.621	0.043	76	13.240	2.588	0.009
ATX	77	13.415	-1.999	0.005	55	9.582	-1.070	0.001
BSESN	121	21.080	5.666	0.068	79	13.763	3.111	0.013
BVSP	119	20.732	5.318	0.059	68	11.847	1.195	0.002
FCHI	26	4.530	-10.884	0.054	22	3.833	-6.819	0.018
FTSE	57	9.930	-5.484	0.030	35	6.098	-4.555	0.013
GDAXI	34	5.923	-9.491	0.053	30	5.226	-5.426	0.015
GSPC	88	15.331	-0.083	0.000	68	11.847	1.195	0.002
GSPTSE	83	14.460	-0.954	0.001	71	12.369	1.717	0.004
HSI	99	17.247	1.833	0.006	61	10.627	-0.025	0.000
IDX	86	14.983	-0.431	0.000	65	11.324	0.672	0.001
KLSE	75	13.066	-2.348	0.007	67	11.672	1.020	0.001
KS11	82	14.286	-1.128	0.002	74	12.892	2.240	0.006
MERV	123	21.429	6.015	0.078	66	11.498	0.846	0.001
MXX	78	13.589	-1.825	0.005	58	10.105	-0.548	0.000
N225	94	16.376	0.962	0.002	60	10.453	-0.199	0.000
SSEC	129	22.474	7.060	0.112	85	14.808	4.156	0.026
SSMI	73	12.718	-2.696	0.009	26	4.530	-6.122	0.017
STI	111	19.338	3.924	0.030	94	16.376	5.724	0.054
TA100	115	20.035	4.621	0.043	70	12.195	1.543	0.003
TWII	73	12.718	-2.696	0.009	54	9.408	-1.244	0.001
$\bar{F}$	15.414				10.652			
Structure Stability (S)	7.838				4.314			

All numbers are stated in percent, except for numbers in column (1). Number of nodes presented in this table are equal to number of edges = 21 (N-1). Column (1), (2), (3), and (4) are frequency of connection changes (F_i), Weight (W_i=F_i/N-1), deviation $(W_i - \bar{F_i})$, and $W_i(W_i - \bar{F_i})^2$ respectively. The average of frequency of connection changes is $\bar{F} = \frac{\sum_{i=1}^{N-1} F_i}{(N-1)T}$ where $F_i = \sum_{t=1}^{T} \Delta c_{i,t}$, $\Delta c_{i,t} = 0$ for $c_{i,t} = c_{i,t-1}$ and , $\Delta c_{i,t} = 1$ for $c_{i,t} \neq c_{i,t-1}$.

The MST Structure stability is defined as in equation (7): $S = \sqrt{\frac{\sum_{i=1}^{N-1} \frac{F_i}{N-1} (\frac{F_i}{N-1} - \bar{F})^2}{N-1}}$

Table 6
MST Structure: Inter-Groups Connection Likelihood

Group Connection	Conditional Cross-Correlation			Unconditional Cross-Correlation		
	Edges/Total Edges (1)	Max Number of Possible Edges (2)	Connection Likelihood (3)	Edges/Total Edges (1)	Max Number of Possible Edges (2)	Connection Likelihood (3)
Based on Market Class						
Developed-Developed	52.36	61.90	84.59	49.17	61.90	79.43
Emerging-Developed	37.47	61.90	60.53	35.18	61.90	56.83
Emerging-Emerging	10.16	38.10	26.68	15.64	38.10	41.07
Based on Region						
Asia Pacific-Asia Pacific	28.28	42.86	65.99	35.73	42.86	83.37
Europe-Europe	24.39	28.57	85.37	23.80	28.57	83.30
North America-North America	1.37	4.76	28.75	1.28	4.76	26.80
South America-South America	1.97	9.52	20.64	4.52	9.52	47.48
Asia Pacific-South America	1.94	42.86	4.53	2.48	42.86	5.78
Asia Pacific-Europe	17.50	42.86	40.82	10.17	42.86	23.73
Europe-South America	8.61	28.57	30.14	5.71	28.57	19.97
North America-Asia Pacific	2.65	42.86	6.17	3.17	42.86	7.40
North America-Europe	9.02	28.57	31.56	7.40	28.57	25.89
North America-South America	4.28	9.52	44.95	5.75	9.52	60.39

All numbers are in percent. Connection between a group and itself (e.g. Europe-Europe connection) is a kind of tree in which the nodes in the groups form full within group connection as in Figure 1 (c). Therefore the sum of maximum number of possible edges (as percentage of total edges) of a set of connections: Europe-Europe, Asia Pacific-Asia Pacific, North America-North America, and South America-South America added by (G-1)T/ET is equal to one, which is the application of equation (4) where it's both sides are multiplied by T and divided by ET. Equation (4) can also be applied for the case of group connection of developed-developed and emerging-emerging. Meanwhile, the sum of maximum number of possible edges as percentage of total edges of group connections: Asia Pacific-South America (or Asia Pacific Europe), Europe-South America (or North America Europe) and, North America-South America added by (G-1)T/ET is equal to one, which is the application of equation (5) where it's both sides are multiplied by T and divided by ET. This is similar to an example presented on Figure 1 (d). Connection likelihood is computed by dividing column (1) by column (2). This is the application of equation (6).

Attention must be put on Asian markets to further analyze the results. Combining the visual analysis of Figure 5 and 6 with numerical analysis derived from the graphs (Table 6), the structure of relationship among the stock markets can be identified. From Figure 5 and 6, one can deduct the interesting findings about Asian markets as follow. First, Asian stock markets are relatively more diverse compare with the European ones, but the markets formed a solid relationship structure as Europeans. Asian markets consist of both Emerging and Developed markets with different markets sizes. This indicates that Asian economies as reflected by their capital markets move at relatively coherent paces. Economic harmonization that takes place in Asia is without forcing political integration as it does in Europeans, but it is based on common economic and socio cultural objectives. This makes the economic cooperation among them become easier and faster to be implemented. ASEAN free trade area (AFTA) is an example of how ASEAN economies harmonize the regulations and integrate the markets to foster their growth, and even the agreement

has been enlarged by including China. The areas to be harmonized including the stock market regulations by forming ASEAN Capital Markets Forum (ACMF) which focuses on harmonization of rules and regulations before shifting towards more strategic issues to achieve greater integration of the region's capital markets under the ASEAN Economic Community (AEC) Blueprint 2015. The findings show that the initiative of forming ACMF and the efforts made has paved the way for ASEAN capital markets to move toward an integrated market. In addition, while Japan's economy is still uncertain but Asian economies are still growing driven by newly industrialized countries such as China, South Korea, India, Indonesia, and Australia which are the members of G20. Second, the hub for Asian markets is not Japan or China (both of them competing each other to sit on the second largest economy in the world recently), but Singapore. It shows that it is not the size of economy that matters, but the degree of economic openness that plays more important role to be international investment destination, especially through capital market. China's economy is undoubtedly the most growing one in the world, but its capital market become relatively more open in 2000s, relatively new compared with other Asian markets. While Japan for long known as having heavy regulated capital market, but it started to build alliance with London Stock Exchange in mid-2008, and since then Japanese stock market (Tokyo Stock Exchange) become more integrated to other markets. However, Japan's economy in the last decade is still depressed; it makes Japan less attractive for foreign investors.

Table 6 shows that stock market clusters are more apparent on the basis of geographical proximity rather than stock market class (developed or emerging market). This is consistent with the visual graphic analysis above. Strong interdependence based on market class is only detected for developed markets, while the emerging markets tend to have more relationship with developed markets. Meanwhile, clustering based on geographical proximity can be detected in Asian and European markets where the connections within the same region are more likely than between markets in the region and the other. For inter-regional connection, Asian stock markets tend to be more connected with European markets than North American markets. It is similar to the relationship structure depicted in Figure 6 where European stock markets are in the middle part of the network connecting Asian and American markets.

6. Conclusion

The findings can be summarized as follow:

1. The world stock markets indeed become more integrated during the last ten years.
2. The degree of integration is dynamics, but it is higher during high volatility periods. Both conditional and unconditional correlation-based MSTs show large drops as response to US stock market shocks, indicate that recession or market shock drove the markets to be more integrated.
3. Regarding the finding above (2), it also shows that there were contagion effects (not just interdependence) of US shocks to other markets in the world. This also proofed that US stock market is still the most influential market in the world.
4. The world stock markets integration is not complete; there are regional clusters. This finding indicates that the world stock markets are regionally segmented, but regarding the finding in number one above, these regional segments are getting closer and closer.
5. Although Asian economies are not integrated politically as Europeans, but the economic harmonization and market liberalization in Asia had shown the result that the markets become more integrated. This finding shows that such harmonization and liberalization really have effect to the economies.

Implication to these findings are: First, for investors who look for internationally diversified portfolio with long-term investment horizon would gain diminishing effect by investing in many foreign stocks in different stock markets. This is because markets become more integrated that the returns are covaried so that the expected risk diversification effect is diminished. However, ones can invest in stocks from different market segments (clusters) to gain maximum risk diversification. Second, since the stock markets become more and more integrated, one should be more cautious on shocks that occur in other markets. The contagion effect is much easier to be transmitted to other markets, especially when the source of shock is from influential market. The MST graph can be used as guidance to minimize the contagion effect by investing in markets that are indirectly connected. Third, for markets regulators, as they open up the market and let the capital movements easier than before, such precautionary system to anticipate the contagion effect needs to be established.

Collaboration among markets regulators is needed not only during harmonization of rules and regulations, but also when facing a crisis by releasing a common set of actions.

Finally, the use of minimum spanning tree can be extended to further examine economic and financial market integration, including the bond markets and banking systems. Other alternatives of pseudo distance measures can be applied to see whether the relationship structure is affected by such measures.

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