Stock Market Linkages: Implications for Chinese Mainland Investors

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Major Paper presented to the

Department of Economics of the University of Ottawa

in partial fulfilment of the requirements of the M.A. Degree

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Ottawa, Ontario

September, 2003

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Abstract

This paper examines long-run relationship and short-run dynamics among US, Japan, Singapore, Hong Kong, Taiwan, and South Korea stock market indices by using Johansen's FIML methodology and estimating a first-differenced VAR model. Because of the nonstationarity of the stock index of Singapore, we drop off it in both long-run and short run analysis after the unit root test. We find first from the cointegration analysis that common trend does present in the long-run relationship of some sub-groups of markets, but some countries do not enter the common trend and some countries do not react to the movement in the common trend. We find from the examination of the first-differenced VAR model that short-run linkages between US and Asian markets are very close and varying degrees of linkage are also found among four Asian markets including Japan, South Korea, Taiwan, and Hong Kong. Our empirical results have implications for international portfolio diversification from the perspective of Chinese mainland investors

1. Introduction

International portfolio diversification has become a popular research topic in the field of financial and monetary economics. In order to realize the potential gain from international diversification, investors must be able to predict the future comovements of international stock markets because a low level of correlation among international markets always means a high level of gains from international diversification (Meric and Meric 1989). This paper provides an investigation into the long run as well as short run relationships between five Asian stock market indices and the United States stock market index. Stock price indices from the US, Japan, Singapore, Hong Kong, Taiwan, and South Korea over the period of July 9, 1999 to May 02, 2003 are used in the empirical investigation. As we will mention in the following section, the Asian stock market became increasingly integrated after the Asian currency crisis. The currency crisis period was assumed to last from June 1, 1997 to February 26, 1999. Thereafter the post-crisis period followed. So it will be sensible to just examine the post-crisis indices of the above mentioned stock markets in order to find more convincing evidence of integration.

It also makes sense to select the above mentioned six stock markets for our analysis at least from the point of view of investors from mainland China. Although China has not undergone equity-market liberalization as yet, it does plan to eventually relax the controls imposed on the outflow of domestic capital in an attempt to ease the pressure for appreciation of the RMB (Chinese Yen). Considering the close relationship between Mainland China and the above six countries (regions) either economically or culturally, we can anticipate that a substantial portion of the out-flow of capital investment from mainland China will go to the above six markets after deregulation comes into being in the foreseeable future. One natural concern of mainland investors will then be the question of whether or not there exist common trends among the above five capital markets and how big the impact of common trends on the benefits from diversifying a portfolio internationally is. If the stock markets of the six countries are cointegrated, they share at least one common stochastic trend such that they will tend to drift together over time. The implication of this is that any benefits from portfolio diversification will be diminishing over the long run and therefore investors with long horizons may not actually benefit from diversifying their portfolios internationally. On the other hand, if the above mentioned six markets show degrees of interlinkage in the short-run, the benefits from investment diversification can not be achieved even over a short period as well.

Our work in this paper contributes to the existing literature in the following way: First, we choose a special group of countries to study, which differs from those examined by previous studies. The relationships between the six stock markets in this special group of countries have important implications for investors from mainland China who are considering diversifying their investment portfolio among the six markets. Secondly, we choose a sample period that ranges from the end of the Asian currency crisis to the most recent date. Studies of this sample period can capture the most recent movements of the six stock markets and thus offer the most updated information for the investors from mainland China.

This paper is organized in the following manner. Section 2 is a literature review of the articles relevant to the topic of our paper. Section 3 contains a brief introduction to the data. Section 4 focuses on Johansen's Full Information Maximum Likelihood (FIML) methodology in cointegration analysis and further investigates the long-run relationship between the stock markets of Japan, Hong Kong, Taiwan, South Korea, and the US on the basis of empirical findings from multivariate cointegration analysis. Section 5 discusses the first-differenced vector autoregression (VAR) approach in short run dynamic analysis and examines the outcome of the impulse response analysis and variance decomposition as well as causality tests for the above five stock markets. We do not incorporate Singaporean stock index into our comprehensive analysis because unit root test shows that it is nonstationary. Finally, a conclusion appears in Section 6.

2. Literature Review

In recent years the linkages or interdependence between international markets has been the focus of large body of research. As early as the 1980s, Hogan and Sharpe (1984) investigated the mechanism of transmission of innovations across foreign exchange markets. They studied the relationships between the Reserve Bank of Australia's official US$/$ Australian exchange rate and the New York Closing Spot

US$/$ Australian exchange rate by examining daily data for the 1981-1982 period. They hypothesised that the official spot exchange rate is linearly related to the difference between the overnight New York rate and the lagged official rate. They estimate the linear relationship by conducting simple OLS regressions and concluded at the end of their study that the official exchange rate is predictable from overnight movements in the New York closing exchange rate. Hamao, Masulis and Ng (1990) employ an Autoregressive Conditional Heteroskedastic (ARCH) family of statistical models to examine the so-called "spillover" effect among the three major international stock markets of New York, Tokyo, and London. They show that financial markets should become increasingly integrated when short term news in one market spills over into other markets, and in their empirical study they find that price volatility spills over from New York to Tokyo, London to Tokyo, and New York to London. Eun and Shim (1989) construct a VAR model and conduct impulse response analysis to examine the speed and strength of the intertemporal transmission of innovations across nine major international stock exchanges. Since no prior restrictions are imposed on the VAR model, they are able to locate all possible main channels of transmission within the system. Their findings indicate a significant amount of interdependence among the nine major stock markets.

An increasing proportion of empirical studies on long-run market relationships are now employing either bivariate or multivariate cointegration methods and examining the number of common stochastic trends. Taylor and Tonks (1989) use simple correlation analysis to capture the short run relationships among the returns of six matured stock markets -- the UK, the US, the Netherlands, West Germany, and Japan -- and find no significant increase in the correlation of short-run stock market returns after the abolition of exchange controls. However, most importantly, they were the first to apply bivariate cointegration analysis to the UK and the other four markets to test how important the performance of other markets is to the UK's after the abolition of foreign exchange controls in 1979. They use monthly data for the six matured stock markets from January 1973 to June 1986 and then conduct pairwise cointegration analysis. They find that the UK market is cointegrated well with the other four leading markets in the long-run.

Kasa (1992) was the first to apply the multivariate cointegration method to estimate the permanent as well as transitory components of stock price series. In part of his analysis, he uses monthly stock market index data from January 1974 to August 1990 to examine if there exist common stochastic trends as drivers of a cointegrated system including five well-established financial markets. The test results indicate one cointegrating relationship among those markets in long-run.

Chudder (1997) focused on stock markets in Latin America. Long-run relationships between six major Latin American stock markets and the US market are investigated by means of multivariate cointegration analysis using weekly data from January 1989 to December 1993. The analysis is applied to a group that merely includes the six Latin American stock markets and to another group that includes the six Latin American markets and the US market. He found at least one cointegrating relationship among stock markets in both groups. He also estimates a vector error correction model (VECM) including all the seven market indices and applies an F test to examine the causality relationship among the seven markets. The findings of his causality analysis reveal that in the short-run, the US market is not greatly affected by the other six regional markets, while the US market can Granger cause all the other six regional markets.

Leachman and Francis (1995) conduct a multivariate cointegration analysis using monthly data for G-7 countries as well as a sub-group of five countries in the G-7 group from January 1975 to May 1993. In order to investigate in depth the long-run effect of the Plaza and Louvre Accords, which introduced a flexible exchange rate system among G-7 countries, the sample period is separated into two sub-periods in an attempt to determine whether the change of a major macroeconomic policy affects the interdependence of each individual market in the G-7 group. They find an increasingly more integrated long-run relationship among both the G-7 and G-5 countries after the major event happened.

Although most of the recent studies employ the cointegration method to capture the long-run relationship among different groups of international financial markets, some authors follow different approaches in their market integration analysis. Pan et al. (1999) use a modified cointegration test to detect the possible long-run relationships among a group of Asian-Pacific stock markets. They address the problem of common time-varying variance across the national stock market indices by taking into consideration the generalized autoregressive conditional heteroskedasticity (GARCH) effects exhibited by the time series. This means that they examine long-run market integration through the analysis of the second moments of the data. Tan and Tse (2002) use Geweke measures to investigate the long-run linkages among a group of East and South-East Asian (ESEA) stock markets. Geweke measures of feedback can not only capture the same-day relationship by calculating contemporaneous correlations across the error terms from two seemingly unrelated regressions, but also can allow us to compare contemporaneous feedback across a long period so that we are able to trace the changes of the daily comovement over a long time for a pair of markets. They found there is a long-run relationship among the group of markets examined.

Since a substantial proportion of international capital flows to Asian emerging markets -- for example, in 1996, forty eight percent of net private capital flows to all emerging market economies was directed to Asian capital markets -- Asian-Pacific economies have attracted much interest recently. Sewell et al. (1996) use several very sophisticated econometric techniques to measure the relationships within a special group of national stock market indices including the US, Japan, Hong Kong, Singapore, Taiwan, and South Korea, all of which will be included in our study. They find evidence of varying degrees of market co-movement among the indices by means of cross-spectral analysis, which differs from the cointegration approach we will use in the following sections of our paper.

Janakiramana and Lamba (1998) include indices of nine Australasian stock markets and the US stock market from 1988 to 1996 in their study. They used the daily returns of the ten indices to estimate an unrestricted VAR and then conduct impulse response and variance decomposition analysis. They found through their analysis that the US market takes a dominant role over the other nine regional markets, while the other nine markets do not affect US market much. They also found that when the US market is excluded from the group of markets, none of the remaining nine markets takes a leading role over the other eight markets. However, markets closing earlier exert a stronger influence on markets that close later in the day.

Phylaktis (1999) uses both monthly and quarterly data on real interest rates as well as stock market indices from seven Pacific-Basin countries – the US, Japan, Malaysia, Hong Kong, Singapore, Taiwan, and South Korea – in a multivariate cointegration analysis. The sample period covers the early 1970s to September 1993. She uses the Johansen trace statistic, corrected for small sample bias (Reimers 1992), to test for cointegrating relationships. The lag length is chosen by applying the Schwarz Information Criterion (SIC) to the undifferenced VAR model. Evidence of the existence of long-run comovements is found among the seven countries' capital markets. Furthermore, she conducts impulse response analysis to examine the speed of adjustment of real interest rates to long-run equilibrium, which is an alternative measure of the degree of market integration. Based on the findings obtained in her study, she concludes that in the short-run the six Asian markets are closely linked with world financial markets and the linkages are stronger with Japan than with the US.

Garrett and Spyros (1999) use monthly data for six emerging Asian stock markets from January 1985 to December 1994 to conduct cointegration analysis. Even though they find at least one cointegrating vector among the six markets, they still conclude that only the markets of Thailand and South Korea actually enter the long-run relationship.

Recently, Darrat and Zhong (2002) use multivariate cointegration analysis to examine the long-run comovement between eleven emerging Asia-Pacific stock markets and two mature markets -- the US and Japan. After analyzing weekly data from November 1987 through May 1999, they argue that the effect of the movements in the Japanese market on the Asia-Pacific region is only transitory, while the US market is the main permanent force driving the equilibrium relations across all the Asian-Pacific markets. We note that in contrast to most other studies, they choose the lag length to conduct cointegration analysis using non-AIC criteria. They argue in their paper that "lag-selection criteria like the AIC only satisfy necessary conditions for optimality" (Darrat and Zhong 2002, 32).

Most recently, researchers have shown great interest in studying the Asian currency crisis that happened at the end of last century, which is said to have had a great influence on the relationships between financial markets in Asian-Pacific region. Moon (2001) conducts a comprehensive investigation of the relationships among a group of Asian-Pacific markets from 4 January, 1995 to 30 June, 2000 using daily stock markets indices. The stock markets he chooses to study are markets of the US, Japan, Singapore, Taiwan, Hong Kong, South Korea, and other four South-East Asian countries. He first separated the sample period into three sub-periods: pre-crisis, during crisis, and post-crisis and then applied methods of simple correlation, cointegration, causality, impulse response analysis, and variance decomposition to examine long-run as well as short run relationships during each of the three sub-periods for this group of markets. In his cointegration analysis, he chooses the number of legs included in the VECM model according to the AIC criterion. He finds that both the long run relationships and the short run dynamics between Asian and U.S markets on the one hand and between Asian markets themselves on the other hand became increasingly integrated after the Asian currency crisis. The crisis also increases the dominance of the US stock market over the other Asian markets.

Finally, Hashmi and Liu (2001) concentrate their short-run dynamic studies on a group of seven South-East Asian stock markets plus the markets of Japan and the US. They use daily stock market indices and separate the entire sample period into two sub-periods: the pre-crisis period which covers from March 1, 1994 to July 31, 1997 and the post crisis period which covers from August 1, 1997 to December 29, 2000. The latter period includes the crisis period itself. Results similar to those of Moon (2001) were obtained after several conventional econometric methods were applied to the data. They find first that South-East Asian stock markets are more interdependent after the crisis, and second that it is the Singaporean market, not those of Japan and the US, which dominates the other markets in this region.

After this introduction to the past studies which are relevant to our work, we can briefly summarize what we have learned from the analysis conducted by other researchers. First, most authors, especially recently, employ cointegration analysis, either bivariate or multivariate, to investigate the long-run relationship among a group of national markets. They collect high frequency data, from weekly or monthly to quarterly, to carry out their long-run comovement analysis. Meanwhile, in order to examine the short-run dynamics among stock market indices, most empirical studies employ at least one of the following three approaches: causality analysis, impulse response analysis, and variance decomposition. The data frequency in short-run stock market analysis is generally higher than that used in long-run analysis. In most studies, researchers choose daily data, but sometimes weekly data is also used for short-run analysis by some researchers, such as Chudder (1997) and Darrat and Zhong (2002) mentioned in our literature review. The method of choosing the optimal lag length is also crucial for all the analyses based on VAR and VEC models: most researchers employ the AIC criterion to select lag length.

Second, there are two areas which have drawn great attention from lots of researchers. They are (1) the relationship, either long-run or short run, between emerging markets and mature markets or among emerging markets themselves; and (2) how big is the effect of a major macroeconomic event on the already existing long-run relationship among a specific group of markets?

Third, most of the studies document market linkages among markets in the Asia-Pacific region either in the long-run or in the short-run, and the results also show that US market is, most of the time, the main driver of the long-run common trend defined by a group of countries including the US. In the short-run, the US also exerts the strongest influence over the other markets in the same group.

3. Data

The data used in our analysis are the natural logarithms of the weekly closing values (Friday) of national stock market indices at the end date of every week in terms of local currency over the period from July 9, 1999 to May 02, 2003, which constitutes 200 observations for each individual time series. These indices include the Nikkei 225 (Japan), the Straits Times (Singapore), the KOSPI (Korea), the Hang Seng (Hong Kong), the TWSE (Taiwan), and the S&P 500 (United States), and come from ECONSTATS.[1] We take the natural log of the data because we need to transform the possible exponential trends in the data into linear ones. Since New York is located in a time zone which is twelve hours later than the time zone where the other Asian markets lie in, we prefer weekly data to daily data because "when daily indices are used, the problem of nonsynchronous trading become serious and leads to an erroneous representation of the true relationships among these markets. However, this bias could be reduced if a weekly interval of indices is used" (Hung and Cheung 1995, 282).

For other economic variables, such as macroeconomic variables, analyses of long-run relationships are usually not carried out using such high-frequency data or such a short span of years. However stock market indices are very volatile and likely adjust back to long-run equilibrium very quickly, so we can use high frequency weekly data to carry out our long-run time series analysis. In fact, as mentioned in our

[1] ECONSTATS is a website with the link: http://www.econstats.com/.

literature review, most researchers use weekly or monthly data to investigate long-run relationships between stock market time series..

In all the figures and tables attached to this paper, we define the above five variables after taking logarithms in the following way: LUS for the US index, LJA for the Japanese index, LSI for the Singaporean index, LHK for the Hong Kong index, LTW for the Taiwanese index, and LSK for the South Korean index. Also we define the first-differenced variables of LUS, LJA, LSI, LHK, LTW, and LSK as DUS, DJA, DSI, DHK, DTW, and DSK respectively. As mentioned earlier, the reason why we choose a sample period beginning in mid-1999 is that the Asian stock markets are believed to be interlinked more closely after the Asian currency crisis. As shown in Panel A of Figure 1, we see obvious trends in all six time series in levels because they all seem to be trending downward over the sample period, except for the index of South Korea which was trending downward first and then trending upward from September, 2001 to March, 2002 and finally trending downward again thereafter. We also note that all the indices show a sharp drop simultaneously in September 2001 when the 9/11 terrorism attack happened in New York City and caused a temporary turmoil in world-wide stock markets. However, in Panel B of Figure 1, we see that the five time series all appear to achieve stationarity after first differencing. We also see from the graphs that considerable correlations exist among these five stock market indices.

4. Common Stochastic Trends in International Stock Markets

4.1 Methodology

We use the cointegration technique, introduced by Granger (1981) and developed by Engle and Granger (1987), to analyze long run relationships among the time-series data on stock indices, taking into account the problem of non-stationarity. When there are unit roots in the series, cointegration analysis is the most popular method of characterizing the long-run relationships among series with unit roots, or in other words, among the non-stationary series without differencing the data. Cheung and Lai (1993) and Gonzalo (1994) suggest that the Johansen-Juselius (1990) maximum likelihood approach is robust and considerably more efficient than the other approaches. The Johansen-Juselius test is particularly appropriate for multivariate models that exhibit several significant cointegrating vectors. A brief outline of the procedure follows.

The first step is to test whether the data are difference-stationary or not. We will briefly discuss the methods used to test unit roots in the series in section 4.2. If all the series are found to be I(1), we are in a position to apply Johansen's approach. Johansen's procedure requires first specifying a K order vector autoregression (VAR) model for an n x1 vector of I (1) variables, X_t:

$$X_t = \mu + A_1 X_{t-1} + \ldots + A_k X_{t-k} + \varepsilon_t, \qquad (1)$$

where each of the A_i matrices is an nxn matrix of parameters, μ is an nx1 vector containing deterministic terms, and ε_t is a vector of residuals assumed to be an i.i.d. Gaussian process. This system of equations can be rewritten in the following error correction form (VECM):

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-i} \Delta X_{t-k+1} + \Pi X_{t-k} + \varepsilon_t , \qquad (2)$$

where

$$\Pi = - I + A_1 + \ldots + A_k \qquad (3)$$

and

$$\Gamma_i = -I + A_1 + \ldots + A_i , \qquad i = 1, \ldots., k-1. \qquad (4)$$

The Γ_i represent the matrices of the traditional first-difference coefficients which capture the short-run dynamics. However, the most important is the matrix of coefficients Π which contains the information about the long-run relationships between the n variables in the data. We denote the rank of the matrix Π as r. It is the rank r of Π which indicates the number of cointegrating vectors. If $r = n$, all the time series are themselves stationary and a conventional estimation method can be applied to this equation system. On the other hand, if Π has a rank of zero ($r = 0$), equation (2) is reduced to a VAR in first differences and no stationary long-run relationships are present. If Π has rank r, $0 < r < n$, it can be factored as $\Pi = \alpha\beta'$, where α and β are both nxr matrices. The r columns of β are the cointegrating vectors such that βX_t is stationary, while $n - r$ represents the number of common stochastic trends. The individual values α_{ir} represent the speed with which the ith series adjusts to the rth cointegrating vector, larger values of α_{ir} indicating a more rapid speed of adjustment.

Thus we can not only determine the presence of a cointegrating relationship, but also estimate the relative speed of adjustment of each series to this long-run equilibrium.

As shown in Johansen and Juselius (1990), the estimation procedure is simplified by conducting two OLS regressions separately; that is regressing each of the scalars Δx_{it} in the vector ΔX_t on a constant and all the elements of the vectors ΔX_t, ..., ΔX_{t-k+1}, and also regressing each of the scalar $x_{i,t-1}$ in the vector X_{t-1} on a constant and all the elements of the vectors ΔX_t, ... , ΔX_{t-k+1}. Let u_t denote an nx1 vector of OLS residuals from the first set of regressions and let v_t denote the nx1 vector of residuals from this second battery of regressions. Then we can calculate the sample variance-covariance matrices of the OLS residuals u_t and v_t in the following way:

$$\sum vv \equiv (1/T) \sum v_t v_t' \tag{5}$$

$$\sum uu \equiv (1/T) \sum u_t u_t' \tag{6}$$

$$\sum uv \equiv (1/T) \sum u_t v_t' \tag{7}$$

$$\sum vu \equiv (\sum uv)' \tag{8}$$

From equations (5) to (8), we can find the eigenvalues of the matrix $\sum(vv)^{-1}\sum(uu)\sum(uv)^{-1}\sum(vu)$ and order them such that $\lambda_1 > \lambda_2 >, ..., > \lambda_n$. The Johansen likelihood ratio statistic for testing the null hypothesis that there are at most r cointegrating vectors, $0 < r < n$, and thus $(n - r)$ common stochastic trends, is the Trace statistic: $\lambda_{trace} = -T\sum_{i=r+1}^{n}\ln(1-\lambda_i)$. Another approach would be to test the null hypothesis of r cointegrating relations against the alternative of $r + 1$ cointegrating relations. The Maximum eigenvalue statistic for testing this hypothesis is given by

$\lambda_{max} = -T\ln(1-\lambda_{r+1})$.

There are four important issues we should pay attention to before applying Johansen's method to actual data. First, typically the cointegrating relations could include non-zero intercepts. If we have included constants in the above auxiliary regressions, the asymptotic distribution in this case depends on whether or not any of the series exhibit deterministic time trends. If all trends are stochastic, we just need to include a constant and no trend in the cointegrating vector. If some of the series are trend stationary, we need to include both a constant and a trend in the cointegrating vector. The asymptotic distributions for the different cases were tabulated and presented in Osterwald-Lenum (1992). Second, because of differences in the specification of the alternative hypothesis, the critical values associated with the λ_{max} and λ_{trace} statistics often lead to different conclusions. The inconsistency is usually the result of the low power of the tests when the cointegrating relationship is quite close to the non-stationary boundary. Third, we apply to the λ_{trace} statistics a correction for degrees of freedom recommended by Reimers (1992).[2] He suggests that we should first multiply the λ_{trace} statistic by (T-nk)/T, where T is the number of observations, n is the number of variables in the VECM, and k is the number of lags in the VAR model

[2] In his paper, he examined the small sample bias of the λ_{trace} statistic only.

and then compares the adjusted λ_{trace} statistic value with the critical value to make a decision. No adjustment was made to the λ_{max} statistic. Lastly, it is very important to determine the appropriate number of lags to construct our VECM since the results of cointegration tests can be sensitive to the choice of lag length for the VECM. We apply several different criteria to the undifferenced VAR model in choosing the optimal lag order: the sequential modified LR test statistic, the final prediction error, the Akaike information criterion, the Schwarz information criterion, and the Hannan-Quinn information criterion. When the criteria differ in their choice of lag length, we make a decision based on the AIC criterion since it is recommended by most researchers and is most commonly used in their studies.

4.2 Long-run relationship between series[3]

The first step for our analysis is to detect whether each time series possesses a unit root. It is necessary to determine the order of integration of the six stock market indices before we can proceed to the next step of testing for cointegration. First, we use the traditional ADF method to test for the presence of a unit root in each series. Dickey and Fuller (1979) showed that the distribution under the null hypothesis is nonstandard, and simulated the critical values for selected sample sizes. MacKinnon (1991) provides estimates of response surfaces that can be used to generate critical values for any sample size; EViews reports these MacKinnon critical values for the ADF unit root test (EViews 4.1 Help). The ADF approach handles higher-order

[3] All empirical work in this section is carried out in EViews 4.1.

correlation of the residuals by adding lagged difference terms of the dependent variable to the right-hand side of the regression. The usual practice is to include lags sufficient to remove any serial correlation in the residuals. In addition, we also adopt the Elliott-Rothenberg-Stock DF-GLS approach to test for unit roots in the five series (Elliott et al, 1996). The test has been shown to be more powerful than the ADF test. The lag structure for each series in both the ADF and DF-GLS test is selected automatically by EViews according to the Modified AIC (MAIC) proposed by Ng and Perron (2001).

We also need to make assumptions with respect to the deterministic terms included in the test regression before implementing the ADF test because the asymptotic distribution of the t-statistic under the null hypothesis depends on our assumptions regarding these deterministic terms. In practice, if the series seems to contain a trend (whether deterministic or stochastic), we should include both a constant and trend in the test regression. If the series does not exhibit any trend and has a nonzero mean, we should only include a constant in the regression, while if the series seems to be fluctuating around a zero mean, we should include neither a constant nor a trend in the test regression (Hamilton 1994, 501). As mentioned earlier in section 2, all the six series under investigation exhibit trends in levels and appear to achieve stationarity in first difference around a zero mean.

We report the results of the ADF tests in the Panel A Table 1. We first test for the presence of a unit root in levels including both a constant and trend in the regression. Second, we report the results from the ADF test using data in first difference, including in the regression neither a constant term nor a trend. On the one hand we find that the null hypothesis of a unit root in levels can not be rejected for all series at the 10% level. On the other hand, the null hypothesis of a unit root in first differences was rejected for all six series at 1% level except LTW, for which the null hypothesis is rejected at the 5% level.

We also report the results of the DF-GLS test in Panel B of Table 1. The results from this test differ from those of traditional ADF test only when a constant or both a constant and a trend appear in the test equation. Because we assume that the first difference of each series under investigation is stationary around a zero mean, we need not report the DF-GLS test results for the first-differenced data in Panel B of Table 1 since they will be the same as those in Panel A. We find from the DF-GLS test results that the null hypothesis of a unit root in levels can not be rejected at the 10% level, except in the case of Singapore, where it can be rejected at the 5% level. Thus, based on results from both the traditional ADF and the DF-GLS unit root tests, we can conclude that all six stock indices except that of Singapore follow an I(1) process; that is, five of the series are stationary after first differencing and non-stationary in levels, but the Singaporean market index in levels is stationary around a deterministic trend according to the DF-GLS test. Since the nature of the series of Singaporean stock index differs from those of the other five market indices and all the variables in the

VECM should be of the same order of integration, we will exclude it from both our long-run and short-run analysis.[4]

Next, we employ Johansen's method to test for the presence of a cointegrating relationship among the remaining five series. The maximum lag length we specify in our test for optimal lag order is set to be eight[5]. The results are reported in Panel A of Table 2 and all of the criteria indicate the optimal lag order is between one and two. We choose two as the lag length for all the equations in the undifferenced VAR system based on the AIC result. However, since we will use first differenced data to construct a VECM model, the lag length in the VECM system should be one less than that of the corresponding VAR. This means we can only include one lag in our VECM.

As mentioned earlier in section 4.1, the asymptotic distribution of the λ_{max} and λ_{trace} statistics depends on whether or not any of the series exhibit deterministic time trends. Most researchers who have carried out cointegration tests for sets of stock market indices include a constant but no trend in the cointegrating equation. Given the evidence of trends in the levels of all five stock indices, we include a constant in the cointegrating equation as well as in the estimation of the auxiliary regressions (Hamilton 1994, 646-647). Since the unit root tests indicated the presence of stochastic

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[4] The exclusion of Singapore may affect the short-run dynamics among the remaining five stock indices. This is a limitation of this paper.

[5] When the maximum lag is set less than twenty, the optimal lag length chosen by all criteria other than the LR criterion remains unchanged. When the maximum lag is set to twenty or more, the optimal lag length chosen by the criteria othan than the LR criterion always equals the maximum lag. The LR criterion indicates a longer optimal lag length as the maximum lag length is increased.

trends in all five stock market indices in levels, a time trend is not included in the cointegrating equation.

We report the results from both the λ_{max} and modified λ_{trace} tests in Panel A of Table 3.[6] Both tests indicate no cointegrating relationship in the entire group of five markets[7]. In other words, we are unable to find a stationary long-run relationship among the five markets. In order to investigate in depth the possible long-run relationships governing the sub-groups of markets, we separate the five markets into several sub-groups. Three sub-groups are formed such that Group One includes the markets of Hong Kong, Taiwan, and South Korea; Group Two includes the markets of the US, Hong Kong, Taiwan, and South Korea; and Group Three includes the markets of Japan, Hong Kong, Taiwan, and South Korea. Group One is used to examine the long-run relationship among the three Asian markets. Group Two and Group Three are used to analyze whether it is the markets of the US or Japan which drives the other three Asian markets in the long-run.

First, we need again to determine the VECM lag structure for each sub-group using the same method we have employed in selecting the lag length for the entire group of five variables. Those results are reported in Panel B of Table 2 for Group One, Panel C of Table 2 for Group Two and Panel D of Table 2 for Group Three.

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[6] The critical values reported in EViews are taken from Osterwald-Lenum (1992) and differ slightly from those reported in Johansen and Juselius (1990).

[7] Since the values of λ_{max} statistics are smaller than the critical value, had a small-sample correction been applied to the λ_{max} statistic, it would have made it even smaller and would not change the results.

According to the AIC criterion, we choose one lag to construct the VECM model for all the three sub-groups.

We report the results from both the λ_{max} and λ_{trace} tests for Group One, Group Two, and Group Three in Panel B, Panel C, and Panel D of Table 3 respectively. The λ_{trace} test indicates one cointegrating equation at the 5% level among the markets in Group One as well as those in Group Two and no cointegrating relationship among markets of Group Three, while the λ_{max} test indicates no cointegrating relationship in any of the sub-groups. In other words, we are able to find stationary long-run relationships among the markets only in Group One and Group Two. This suggests that there is one common stochastic trend driving the markets of Taiwan, Hong Kong, and South Korea, and the markets of the US, Taiwan, Hong Kong, and South Korea. Meanwhile, Japan shares no long-run relationship with the other three Asian markets. Therefore, in the following long-run relationship analysis, we can just focus our investigation on the markets in Group One and Group Two.[8]

Next, we report the cointegrating vector β for Group One as well as the corresponding adjustment coefficients α for Group One in Panel A of Table 4 and those for Group Two in Panel B of Table 4. We normalize the cointegrating equation on the log of the Hong Kong index in Group One and the log of the US index in Group Two. Normalization may have been done on the stock index of any market in the group, but the implications of the results would be the same; the US and Hong Kong

[8] When we include a time trend in the cointegrating vector, the results of both cointegration tests change slightly. No cointegrating relationships are found in all three sub-groups.

were chosen arbitrarily. As mentioned before, the normalized vector represents the implied long-run effects imposed by the variables in each sub-group and the adjustment coefficients represent the relative speeds at which each national market in each sub-group adjusts to the long-run equilibrium governing this group.

The interesting issue now is how to actually interpret the finding that there is one common stochastic trend driving the markets in each sub-group. From the discussion earlier in the paper, it is tempting to argue that since all of these markets in each sub-group move together in the long run, any benefits from diversifying portfolios across this group of markets will disappear. However, the finding of cointegration does not in itself mean that benefits from portfolio diversification will eventually disappear in the long run. For instance, as Kasa (1992) notes,

> The economic relevance of any long-term comovement hinges on the speed of adjustment towards the common trend. If transitory deviations from the common trend have persistence measured in decades, then to an investor with a finite horizon the existence of a common trend is of little significance. (Kasa 1992, 97)

In other words, the presence of a common stochastic trend may actually have little significance to the benefits from diversification if each national stock market index does not react significantly to the common trend. A second point worthy of mention is that the finding of a cointegrating vector among a group of countries is often explained as meaning that all countries in this group participate in the driving force of the common trend, more or less. However, it may be the case that some countries do not enter the common stochastic trend. Therefore, even though a common trend is present, further formal statistical investigation is necessary before any conclusions on the benefits from portfolio diversification can be drawn.

We use a LR test to test for the statistical significance of each market's relationship with the common trend. In our case, the LR statistic has a Chi-Square distribution with one degree of freedom. Panel A of Table 5 presents test results from imposing these zero restrictions on the composition of the cointegrating vector found in Group One and Panel B of Table 5 for Group Two. The results of tests for zero restrictions on the reaction of each individual market to the common trend are reported as well. The first set of tests test whether each country enters the cointegrating vector and the second set of tests test whether the stock index from each country reacts to the common stochastic trend.

Based on the results in Panel A of Table 5, we can reject the null hypothesis of a zero contribution to the common trend at the 1% level for South Korea. For Hong Kong and Taiwan, even though the null hypotheses can not be rejected at the 10% level, the values of both test statistics are all very close to the 10% critical value. That means the null hypothesis for the Hong Kong and Taiwan markets can probably be rejected at a level a little bit higher than 10%. Examining Panel B of Table 5, not only we can not reject the null hypothesis for the US market at the 10% level, but also the value of the test statistic is quite small in comparison with the 10% critical value. This means that the US most likely is not involved in the common market trend driven by the four markets. For Hong Kong market, even though the null hypotheses can not be rejected at the 10% level, the value of the test statistic is again very close to the 10% critical value. That means the null hypothesis for Hong Kong market can be rejected at a level a little bit higher than 10%. It clearly shows that the finding of cointegration and hence the presence of common stochastic trends is no guarantee that all countries actually have an influence on the common trend in the long run. Moreover, in the case of testing the adjustment coefficients, we find that only the South Korean market reacts significantly to the comovement driven by the three markets of Group One and in Group Two, both the South Korean and US markets react significantly to the common trend. In other words, Hong Kong and Taiwan appear to be weakly exogenous in both Group One and Group Two. Our findings would suggest that the cointegrating relationship is limited to the markets just including three Asian countries and indicates lack of linkages among the entire group of markets consisting of the US, Japan, Hong Kong, Taiwan and South Korea. Hence, any gains from diversification over the above five markets should persist, even in the long run.

The results we have found from our long-run relationship analysis are not consistent with the conclusions drawn by some of the other authors, who base their conclusions on their own empirical findings. The most striking difference is that the US market is found in our study to be unable to exert significant influence on the other Asian markets in the long-run, while some of the authors mentioned in our literature review conclude that US market is always the main driver of the long-run comovement in whatever group of markets. In the Asia-Pacific region, for example, Darrat and Zhong (2002) and Moon (2001) found the US market to be the major force driving the long-run comovements defined by varying groups of Asian-pacific countries. However, we should note the fact that we conduct our analysis using a group of countries and a sample period which differ from those of other studies. We use the US and four other major markets in East Asia in our empirical work and use a sample period which ranges from June 1999 to the most recent date. However, many of the studies covered in our literature review include a more broad range of markets, often including markets throughout the entire Asian region. In fact, none of the studies reported in our literature review includes the same markets in one group as we do.

Another possible source of the inconsistency in test results could be the selection of a different frequency of data. As the data frequency changes, even the same group of series over the same sample period will generate different results using same statistical methods. Some researchers prefer to examine monthly or even annual data in their long-run relationship analysis. We should also pay more attention to the Johansen method of cointegration analysis itself. The results from the Johansen method are quite sensitive to the choice of the lag structure for the estimated model. However, the way to select the optimal lag length in constructing a VAR varies among researchers, although most of them prefer the AIC criterion. It is also worthwhile to mention the nonsynchronous trading problem here again. In section 3, we point out that in order to reduce the bias caused by nonsynchronous trading in a group of stock markets, we use weekly data rather than daily data in our studies. However, the nonsynchronous trading problem still may have an undesirable effect on our study because it was just reduced, not eradicated, even though we have choose the weekly data. To check the robustness of the result, the analysis was repeated using Thursday's closing price for the US stock market, instead of Friday's closing price. We find that all of the conclusions regarding the long-run relationship between the US index and the other four indices are the same as those derived from the original analysis. Therefore, we can conclude with some confidence that the nonsynchronous trading problem is not one of the factors that renders our conclusions inconsistent with those of others.

5. Short-run dynamics among the series

5.1 Methodology

In our analysis of short-run dynamics, we do not divide the five markets into sub-groups as we did in the analysis of long-run relationship. Although a short-run analysis could be based on the VECM models for Group One and Group Two, we are interested in the short-run dynamic relationships between entire group of five countries.

As all five series under investigation have been found to be I(1) processes and no cointegration has been found among them, a VAR in first differences instead of a VAR in levels should be applied to the entire group of series so as to capture the short-run dynamic adjustment of these five nonstationary variables (Hamilton 1994, 652). A VAR is a non-structural approach used for forecasting systems of interrelated time series and for analyzing the dynamic impacts of random shocks on the system of interrelated variables. It bypasses the need to pre-specify which variables are endogenous and which variables are exogenous, a procedure necessary in structural modeling. It simply defines every endogenous variable in the system as a function of the lagged values of all the endogenous variables in the system. In the present context the following representation is implied:

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-i} \Delta X_{t-k+1} + \varepsilon_t, \tag{9}$$

where μ = a vector of constant terms;

Γ_i = matrices of first-difference coefficients;

ΔX= vector of first difference of the logs of all stock indices.

Equation (9) assumes a vector process where the first-differenced index of each stock market is a function of a constant term, its own lagged values, the lagged first-differenced values of all other variables in the system, and an i.i.d Gaussian error process which is serially uncorrelated but can be contemporaneously correlated. In other words, the present performance of a market incorporates not only its own past information, but also the past information of other markets. To identify the short-term dynamics of the system, the VAR model in equation (9) can be transformed into a vector MA representation expressed as

$$\Delta X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{10}$$

so that the present value of the index of a stock market can be expressed in terms of its own past shocks plus the shocks from other markets. The a_{ij} are called the impulse response functions, which show the response of the ith market s-periods after a unit random shock in the jth market provided other things remain constant.

The innovations in equation (9) may be contemporaneously correlated such that the covariance matrix of innovations is not diagonal. Such contemporaneous correlation implies that a shock in one market may be transmitted to other markets through the innovations. It is customary to transform these correlations by orthogonalzing the innovations in the system by Cholesky decomposition according to a pre-specified causal ordering so that the covariance matrix of the resulting innovations is diagonal. The results of this approach are, however, not invariant to the ordering of the variables in the system. In our paper we adopt the generalized impulse response proposed by Pesaran and Shin (1998), which is invariant to the ordering of the variables in the VAR in first difference. As described by Pesaran and Shin (1998), the generalized impulse responses from an innovation to the j-th variable are derived by applying a variable-specific Cholesky factor computed with the j-th variable at the top of the Cholesky ordering.

The VAR model also makes it possible to analyze the decomposition of forecast error variance. While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, decomposition of the forecast error variance separates the variation in an endogenous variable into the component shocks to the VAR. In our case, the decomposition provides a measure of the overall relative importance of an individual market in generating variations in its own first-differenced stock index and in the other market stock indices in first difference. This method is known as variance decomposition and provides an alternative method of describing the system dynamics.

An unrestricted VAR for all five series in first differences will be constructed to carry out impulse response as well as variance decomposition analysis in the following sections. As mentioned earlier, since the unrestricted VAR sidesteps the need to pre-specify which variables are endogenous and which variables are exogenous, we will not put any restrictions on the first-differenced VAR model used in our analysis.

The lag structure of our VAR model in first differences is determined by the criteria we have employed in testing for cointegration relationship by Johansen's FIML method and the results of varying criteria are reported in Panel E of Table 2. We choose the number of lags according to the AIC criterion. Thus, one lag for each first-differenced series will be included in our first-differenced VAR model.

5.2 VAR Pairwise Granger Causality/ MWALD Test

Before moving on to the impulse response and variance decomposition analysis, we first look at the short run dynamics of the levels of the five stock indices by performing multivariate Granger-Causality tests. We will use the results of this analysis in a later section of our paper.

We implement the MWALD test proposed by Toda and Yamamoto (1995) to investigate the Granger Causality relationship between the groups of five non-stationary variables. The most attractive merit of this test is that we need not know beforehand whether or not the series under study are actually cointegrated. This allows us only to construct an unrestricted VAR in levels without differencing the data to carry out the MWALD test. Toda and Yamamoto proved that the Wald statistics for zero restrictions on the coefficients of a K-order VAR have an asymptotic Chi-Square distribution with K degrees of freedom when a VAR model with a lag order of $K+D$ is estimated, where D is the maximum order of integration in the system. In our study, because the optimal order for our unrestricted VAR in levels is two for each variable (see Table 2 Panel A) and all the series are I(1) processes, we need to first estimate a VAR with a lag order of three. Then Wald statistics can be calculated for each equation in the VAR to test for the joint significance of each of the lagged variables on the right-hand side in the equation. In our case, the Wald statistic for each variable appearing on the right-hand side of the equation has a Chi-Square distribution with two degrees of freedom.

The results of the test are present in Table 6.[9] The null hypothesis that the coefficients of the lagged values of the US stock index appearing in the equations of all the other four stock indices are zero can be rejected even at the 1% level. In contrast, the null hypotheses that the coefficients of the lagged values of the four Asian market indices appearing in the US equation are zero can not be rejected even at a level of 10%. Thus, we find that the US stock index Granger causes stock indices in the other four markets, but there is no causality from the four Asian markets to the US.

[9] The MWALD test is carried out using SHAZAM 9.1 following the procedure proposed by Rambaldi and Doran (1996).

In the equations for Taiwan and South Korea, all the coefficients other than those on the US and the countries' own lagged values are found to be insignificant. This suggests that no other markets with exception of the US and a market's own past history can Granger cause the above two markets.

Looking at the equation for Hong Kong, we find that, at the 5% level of significance, we can reject the null hypothesis that there is no Granger causality from the Japanese market to the Hong Kong market. Therefore, with the exception of Taiwan and South Korea, there are at least three markets, including itself, which can Granger cause the Hong Kong market.

In the equation of Japan, we find that besides the markets of itself and the US, the South Korean market can Granger cause the Japanese market at 10% level.

In general these results indicate that there is evidence of causality between indices. The US does Granger cause all the other four markets and there is causality from two outside markets to the Hong Kong as well as Japanese markets. We can conclude that the US market is the dominant power driving the short-run movements of all the other four Asian markets. The Hong Kong market is easily affected by the movements from outside markets. The other three markets are relatively independent of the influence of outside markets except the US in the short run.

5.3 Impulse responses[10]

We now move to an investigation of the speed of the transmission of information across the five markets under consideration, using impulse response analysis. As mentioned earlier, our first-differenced VAR model includes only one lag for all five first-differenced variables (Table 2 Panel E). We report in Table 7 as well as Figure 2 the 10-week time horizon impulse responses of the first-differenced stock index in each national market to a shock in their own and other market innovations. By examining the graphs reported in Figure 2, we conclude that all the transmissions within the system are nearly completed within three weeks (at the end of 4th week) because the response of each individual variable to one unit shock of their own and other markets all converges to a stable level of zero after three weeks. Figure 2 also displays the confidence band for each individual variable's impulse response to the others' shocks. The confidence bands are based on asymptotic standard errors. We notice that generally the impulse responses include zero as early as the second week after the shock, suggesting that a complete adjustment to the shocks may in fact occur in less than three weeks. Since we use weekly data, we can not identify more precisely how many days the transmission will take to converge in each market. However we still can obtain some useful information from the impulse response function to outline the dynamic relationship among the five indices. We briefly comment on it below by looking at the Table 7.

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[10] The impulse response analysis is carried out by EViews 4.1

The biggest shock to all the five markets comes from their own innovations. The innovations from the markets of Japan and Taiwan affect the US market at a negligible level which is less than 0.01 in period one. However the other two Asian markets – Hong Kong and South Korea – do have an effect on the US market which exceeds 0.01 in period one. No innovations from markets outside Japan seem to affect the Japanese market at a relatively high level because they are all less than 0.01 in period one.

In the cases of Hong Kong, Taiwan, and South Korea, we notice that these three markets are affected substantially by shocks from outside. The magnitude of the effects are all greater than 0.01. Although the US market affects every market at a considerable level, it is not the most influential one for every individual market. Innovations from Japanese market have the weakest effect on all the other four markets.

In general, the results show that the national stock markets of the four Asian countries respond to shocks from the US market with a moderate sensitivity. Hong Kong, Taiwan, and South Korea exert a significant influence over each other. Japan seems to stand a little bit outside the short-run dynamic relationship which governs the group of countries.

5.4 Variance Decomposition[11]

The problem with the impulse responses is that they show the effect in each period separately. If we are interested in some kind of cumulative effect, the variance decomposition is a better tool.

We can not apply the method of generalized impulse to the variance decomposition analysis since non-orthogonal factorization will yield decompositions that do not satisfy an adding up property. Our choice of factorization is limited to orthogonal factorizations. We adopt the Cholesky decomposition to orthogonalize the innovations in the system. As mentioned earlier, the result of Cholesky decomposition is sensitive to the change of the order of variables. The most popular way is to order markets starting from the most exogenous one to the most endogenous one. This ordering is crucial when we want to decompose the variance of the forecast error of a particular group of market. We use the results from the VAR Pairwise Granger Causality analysis conducted in section 5.2 and the results from impulse response analysis as a rough guideline for variable ordering. These results suggest the following ordering: US, Taiwan, Korea, Japan, and Hong Kong. We call this particular ordering UTKJH (using first letter of each market's name). The results of the variance decomposition are present in Table 8. All the following discussion is based on it.

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[11] The variance decomposition analysis is carried out by EViews 4.1

Starting with the US, we see that most of the forecast error variance is explained by movements in its own index. The movements of the other four Asian markets do not greatly affect US market movement at all.

When we look at the Japanese market, we find that the US explains about 14% of its variance, the second lowest contribution of the US market to the four Asian markets. The other Asian markets explain only a small fraction of its variance.

The US market affects the Taiwanese market in a moderate way, explaining about 13% of the market movement of Taiwan, which in turn explains 86% of its own variance. US market disturbances cause about 18% of the variance in South Korean market movements. Taiwanese markets also have a considerable effect on the South Korean market, explaining 14% of the variance of its market movement.

Hong Kong appears to be affected by all the markets at various levels. The US explains 29% of the forecast error variance, while South Korea and Taiwan account for 11% and 6% of the variance of the market movements of Hong Kong, respectively.

Before we draw any general conclusions from our analysis of the variance decomposition it is worthwhile to summarize our variance decomposition results using the UTKJH ordering. The conclusion that the US is the leader in the short run relationship among the five markets is unquestionable. We also notice that, rather than Japan, it is South Korea that has a relatively strong effect on the other East Asian markets. However, it is too early to conclude that South Korea is the regional leader because the conclusion may be sensitive to the ordering of variables. The markets that appear high in our ordering tend to have a strong effect on the markets that appear low.

We need to try another ordering to see if the conclusion remains the same. As an alternative, we order the variables in the following way: US, Japan, Taiwan, South Korea, and Hong Kong (UJTKH)[12]. The results of this ordering indicate that we should change the conclusion that South Korea plays the most important role among East Asian markets. In fact, we tried several orderings and the results show that Hong Kong, Taiwan, South Korea, and Japan exert a significant influence over each other and none of them is able to take a dominant role among others.

The results from the short-run dynamic analysis are generally consistent with the conclusions drawn by the other researchers, such as Phylaktis (1999), Janakiramana (1998), and Moon (2001). The US market can Granger cause other Asian markets, while it is hard for other markets to exert an influence on the US market. The US market takes an unquestionable dominant role over Asian markets in the short-run. Based on the results from the variance decomposition analysis, the US market affects the other Asian markets in a relatively strong way. Unlike some studies we discuss in our literature review, such as Hashmi and Liu (2001), we can not identify which Asian market is emerging as the market leader in the Asian region. The reason behind this inconsistency may be again due to the use of a different group of markets over a different sample period. Further more, as mentioned before, different ways of ordering variables to achieve orthogonalization of the innovations will lead to different outcomes from our variance decomposition analysis.

[12] These results are not reported in the paper.

6. Conclusion

In this paper, we have focused on the implications of finding a long-run common stochastic trend as well as short-run closely linked dynamics among a specific group of six stock market indices. The issue of whether the six markets follow common trends and whether they have a close inter-linkage is an important one in terms of the benefits of international portfolio diversification for the investor in mainland China. Many studies argue that close linkages in the short run and common trends in the long-run imply that markets will move together nearly perfectly with the consequence that benefits to diversification will be eradicated.

Since the Singaporean market index follows an I(0) process, we have to exclude it from our later analysis. For the remaining five markets, we examined whether common stochastic trends are present by performing Johansen's FIML analysis. We found no cointegrating relationship existing among the entire group of five stock markets under investigation, but found at least one cointegrating vector existed among two sub-groups of markets. For each of the two sub-groups, we also conducted LR tests to determine which markets actually have an influence on the common trend the markets follow and which markets actually react to the common trend, in which case they converge to the long run equilibrium defined by the common trend. A closer examination of the nature of the common stochastic trend and the reaction of different markets to it reveals that the composition of the common trend is limited to the sub-group of three Asian markets including Hong Kong, South Korea, and Taiwan and only the South Korean market actually reacts to the common trend. The US and Japanese markets do not actually get involved in the common stochastic trend formed by these three Asian markets. Thus, the evidence presented here suggests that in the long run there will be limited erosion of any benefits to diversification due to these markets being highly correlated.

Second, the short-run inter-linkages among weekly indices from the US, Japan and the other three Asian markets were examined by first conducting Granger causality analysis on an undifferenced VAR model and then by means of impulse response and variance decomposition analysis on a unrestricted first-differenced VAR model. We found that the US market exerts a strong influence on all four markets in the short run, but is not much affected by them. The markets of Taiwan, Hong Kong and South Korea are not only closely linked with the US market but also present significant linkages with each other. No Asian market emerges as a leader in the Asian region.

The analysis in the paper of stock market linkages in these five markets has indicated that Chinese mainland investors have opportunities for portfolio diversification by investing in some of the five markets. However, in drawing such a general conclusion, we should keep in mind the limitations of the statistical method used. First, the results from the Johansen method are quite sensitive to the choice of the lag structure for the estimated model. Second, the results also vary when different assumptions are made regarding the specification of dynamic terms included in the cointegrating as equations as well as the regression equations. Finally, we should pay more attention to the choice of data frequency, since even the same group of series over the same sample period may generate different results using same statistical methods when the frequency of the data is changed. On the one hand, the results from the common trend analysis show that although the linkages have increased in recent years, there is still room for long-term gains by investing in these markets. On the other hand, the results from short-run dynamics show that although long-term diversification benefits from exposure to these markets might be feasible, short-run benefits might be limited due to a close relationship between Asian and US markets and between Asian markets themselves.

Figure 1 Panel A: Series in Levels

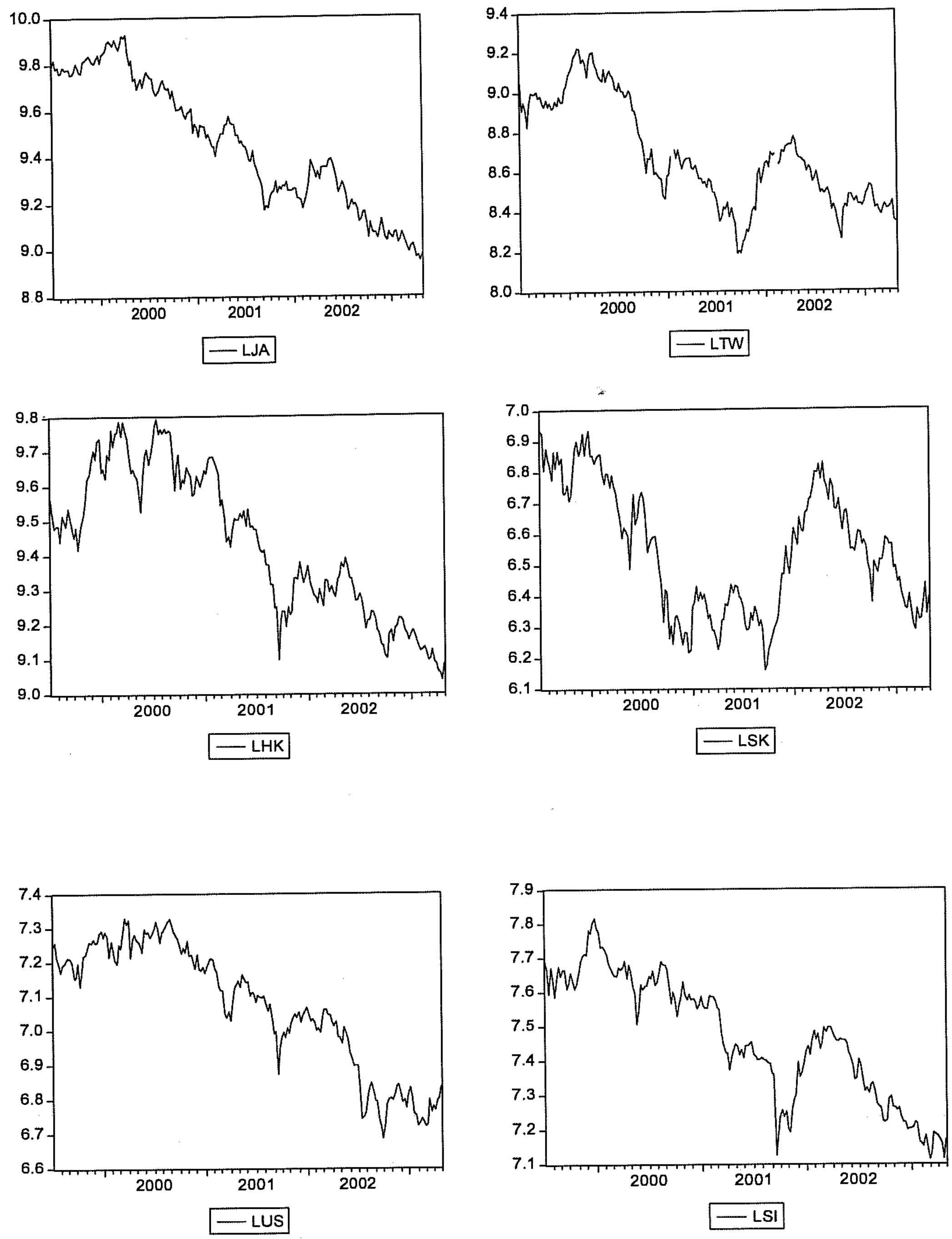

Figure 1 Panel B: Series in First Difference

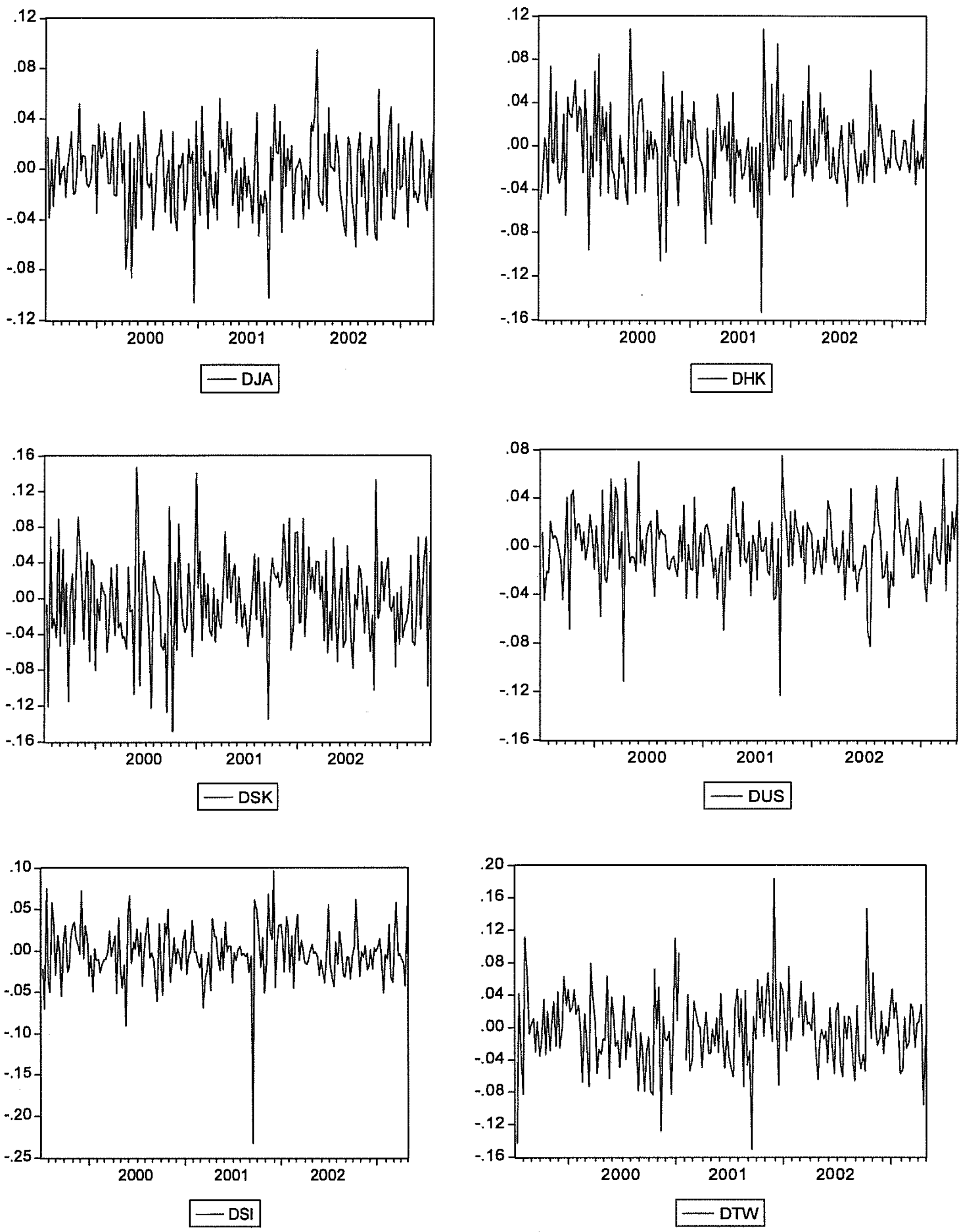

Figure 2: Impulse Response

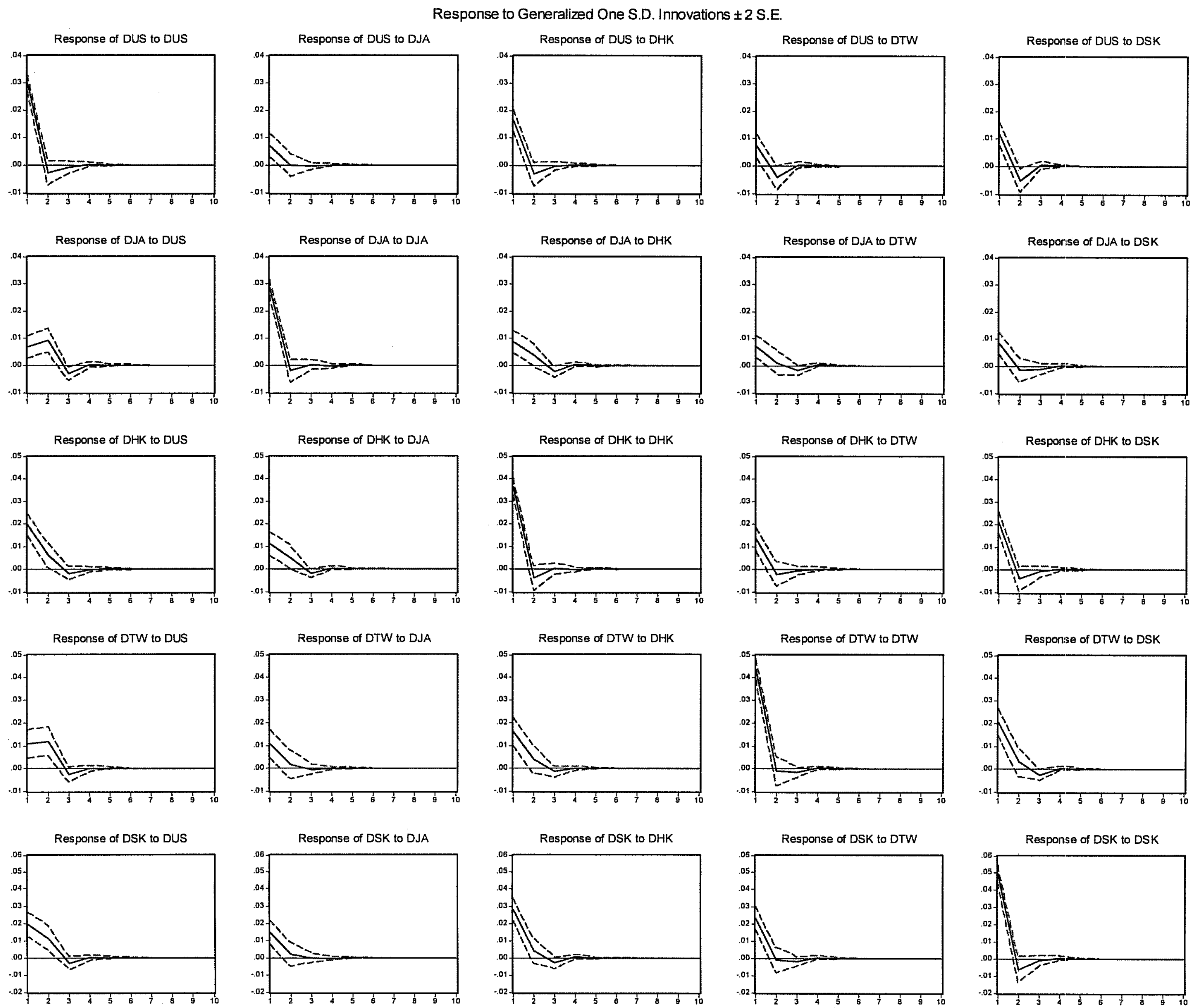

Table 1 Panel A: Augmented Dickey-Fuller Test Results

Log of Stock Indices	Null : Single Unit Roots	Null: Two Unit Roots
	Linear Trend and Constant	No Constant and Linear Trend
LUS	-2.928427	-9.992079*
LJA	-3.108864	-2.880651*
LHK	-2.622220	-4.891160*
LTW	-1.876555	-2.331404**
LSK	-1.644783	-5.759757*
LSI	-3.185528	-15.09642*

*(**) denotes rejection of the hypothesis at the 1 %(5%) level
Maximum lag length: 15
Actual lag length chosen: 1 for HK in levels, 0 for US in levels, 0 for JA in levels, 0 for SI in levels, 0 for TW in levels, 2 for LSK in levels, 1 for US in first difference, 12 for JA in first difference, 0 for SI in first difference, 5 for HK in first difference, 10 for TW in first difference, 4 for SK in first difference.

Table 1 Panel B: Elliott-Rothenberg-Stock DF-GLS test Results

Log of Stock Indices	Null : Single Unit Roots
	Linear Trend and Constant
LUS	-2.395193
LJA	-2.352234
LHK	-1.282044
LTW	-1.911690
LSK	-1.351493
LSI	-3.007288**

* (**) denotes rejection of the hypothesis at the 1 %(5%) level
Maximum lag length: 15
Actual lag length chosen: 15 for Hong Kong in levels, 2 for South Korea for levels, 0 for all the other series in levels

Table 2 Panel A: VAR Lag Order Selection Criteria for All Five Series in Levels

Lag	LogL	LR	FPE	AIC	SC	HQ
0	671.7482	NA	3.23E-10	-7.663772	-7.572995	-7.626947
1	1759.762	2100.992	1.60E-15	-19.88232	-19.33765*	-19.66137*
2	1793.580	63.36048*	1.44E-15*	-19.98368*	-18.98513	-19.57860
3	1807.954	26.10549	1.63E-15	-19.86155	-18.40911	-19.27235
4	1823.467	27.28094	1.83E-15	-19.75250	-17.84617	-18.97917
5	1842.879	33.02169	1.96E-15	-19.68826	-17.32805	-18.73081
6	1857.402	23.87122	2.23E-15	-19.56783	-16.75373	-18.42626
7	1875.580	28.83547	2.44E-15	-19.48943	-16.22144	-18.16373
8	1890.809	23.28104	2.77E-15	-19.37712	-15.65524	-17.86730

Table 2 Panel B: VAR Lag Order Selection Criteria for Group One

Lag	LogL	LR	FPE	AIC	SC	HQ
0	219.8515	NA	1.66E-05	-2.492546	-2.438080	-2.470451
1	973.3827	1472.417	3.19E-09	-11.05038	-10.83251*	-10.96200*
2	983.8938	20.17641*	3.13E-09*	-11.06774*	-10.68648	-10.91308
3	988.8286	9.302353	3.28E-09	-11.02102	-10.47635	-10.80007
4	992.9108	7.554465	3.48E-09	-10.96449	-10.25643	-10.67726
5	997.4155	8.180925	3.66E-09	-10.91282	-10.04136	-10.55930
6	1001.581	7.421837	3.88E-09	-10.85726	-9.822394	-10.43745
7	1010.198	15.05455	3.90E-09	-10.85285	-9.654589	-10.36676
8	1013.232	5.196660	4.18E-09	-10.78428	-9.422618	-10.23191

Table 2 Panel C: VAR Lag Order Selection Criteria for Group Two

Lag	LogL	LR	FPE	AIC	SC	HQ
0	465.3441	NA	5.85E-08	-5.302806	-5.230184	-5.273346
1	1372.752	1762.666	2.08E-12	-15.54888	-15.18577*	-15.40158*
2	1395.597	43.32569*	1.92E-12*	-15.62755*	-14.97395	-15.36241
3	1405.856	18.98604	2.05E-12	-15.56156	-14.61748	-15.17859
4	1415.572	17.53261	2.21E-12	-15.48933	-14.25476	-14.98851
5	1429.877	25.15684	2.26E-12	-15.46985	-13.94478	-14.85119
6	1440.960	18.98206	2.40E-12	-15.41333	-13.59778	-14.67684
7	1452.707	19.57880	2.53E-12	-15.36445	-13.25841	-14.51011
8	1459.133	10.41378	2.84E-12	-15.25440	-12.85788	-14.28222

Table 2 Panel D: VAR Lag Order Selection Criteria for Group Three

Lag	LogL	LR	FPE	AIC	SC	HQ
0	403.6150	NA	1.19E-07	-4.593275	-4.520653	-4.563815
1	1358.792	1855.459	2.44E-12	-15.38841	-15.02530*	-15.24111*
2	1375.785	32.22838*	2.41E-12*	-15.39983*	-14.74623	-15.13469
3	1381.705	10.95570	2.71E-12	-15.28397	-14.33988	-14.90099
4	1389.379	13.84800	2.99E-12	-15.18826	-13.95369	-14.68744
5	1399.109	17.11179	3.22E-12	-15.11620	-13.59114	-14.49754
6	1407.756	14.80926	3.51E-12	-15.03168	-13.21613	-14.29518
7	1421.605	23.08088	3.62E-12	-15.00695	-12.90091	-14.15261
8	1429.987	13.58458	3.97E-12	-14.91939	-12.52286	-13.94721

Table 2 Panel E: VAR Lag Order Selection Criteria for Five Variables in First Difference

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1693.362	NA	1.83E-15	-19.74693	-19.65507*	-19.70965*
1	1733.736	77.91486*	1.53E-15*	-19.92674*	-19.37557	-19.70310
2	1747.367	25.50714	1.74E-15	-19.79376	-18.78329	-19.38375
3	1763.448	29.15353	1.94E-15	-19.68945	-18.21967	-19.09308
4	1780.612	30.11177	2.13E-15	-19.59780	-17.66871	-18.81506
5	1793.961	22.63889	2.46E-15	-19.46153	-17.07313	-18.49242
6	1808.757	24.22741	2.79E-15	-19.34219	-16.49448	-18.18671
7	1828.216	30.72540	3.02E-15	-19.27739	-15.97037	-17.93554
8	1846.896	28.40164	3.30E-15	-19.20346	-15.43714	-17.67525

* indicates lag order selected by the criterion
Maximum lag length: 8
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 3 Panel A: Cointegration Test Results for All Five Markets

Variables: LUS LJA LHK LTW LSK

Number of Lags in the VECM: 1

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical Value
None	0.128113	59.106	68.52	76.07
At most 1	0.08917	33.4706	47.21	54.46
At most 2	0.050907	16.0061	29.68	35.65
At most 3	0.030998	6.2363	15.41	20.04
At most 4	0.001861	0.3483	3.76	6.65

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	1% Critical Value
None	0.128113	26.32235	33.46	38.77
At most 1	0.08917	17.93255	27.07	32.24
At most 2	0.050907	10.03167	20.97	25.52
At most 3	0.030998	6.045743	14.07	18.63
At most 4	0.001861	0.357722	3.76	6.65

*(**) denotes rejection of the hypothesis at the 1%(5%) level

Observations: 192

Trace Statistic is adjusted by being multiplied by (T-N*P)/T=0.9739

Table 3 Panel B: Cointegration Test Results for Group One

Variables: LHK LTW LSK

Number of Lags in the VECM: 1

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical Value
None	0.099135	30.5837**	29.68	35.65
At most 1	0.04973	10.8536	15.41	20.04
At most 2	0.006401	1.2135	3.76	6.65

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	1% Critical Value
None	0.099135	20.04487	20.97	25.52
At most 1	0.04973	9.793815	14.07	18.63
At most 2	0.006401	1.232925	3.76	6.65

*(**) denotes rejection of the hypothesis at the 1%(5%) level

Observations: 192

Trace Statistic is adjusted by being multiplied by (T-N*P)/T=0.9843

Table 3 Panel C: Cointegration Test Results for Group Two

Variables: LUS LHK LTW LSK

Number of Lags in the VECM: 1

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical Value
None	0.122405	48.9518**	47.21	54.46
At most 1	0.079853	24.4062	29.68	35.65
At most 2	0.042786	8.7616	15.41	20.04
At most 3	0.002875	0.5413	3.76	6.65

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	1% Critical Value
None	0.122405	25.0695	27.07	32.24
At most 1	0.079853	15.97852	20.97	25.52
At most 2	0.042786	8.395793	14.07	18.63
At most 3	0.002875	0.552869	3.76	6.65

*(**) denotes rejection of the hypothesis at the 1%(5%) level

Observations: 192

Trace Statistic is adjusted by being multiplied by (T-N*P)/T=0.9791

Table 3 Panel D: Cointegration Test Results for Group Three

Variables: LJA LHK LTW LSK

Number of Lags in the VECM: 1

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical Value
None	0.107282	40.7702	47.21	54.46
At most 1	0.054529	19.4366	29.68	35.65
At most 2	0.043887	8.8958	15.41	20.04
At most 3	0.002439	0.4591	3.76	6.65

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5% Critical Value	1% Critical Value
None	0.107282	21.789	27.07	32.24
At most 1	0.054529	10.76578	20.97	25.52
At most 2	0.043887	8.616833	14.07	18.63
At most 3	0.002439	0.468917	3.76	6.65

*(**) denotes rejection of the hypothesis at the 1%(5%) level

Observations: 192

Trace Statistic is adjusted by being multiplied by (T-N*P)/T=0.9791

Table 4 Panel A: Estimates of Cointegrating Vector and Adjustment Coefficients for Group One

	LHK	LTW	LSK	CONSTANT
Cointegrating Vector Normalized on LHK	1.000000	-1.191904 (0.26698) [-4.46439]	1.783357 (0.35273) [5.05589]	-10.75680
Adjustment Coefficients	-0.002997 (0.01244) [-0.24098]	0.020678 (0.01456) [1.42027]	-0.043496 (0.01623) [-2.67939]	

Standard Error in ( ) & t-Statistics in [ ]

Table 4 Panel B: Estimates of Cointegrating Vector and Adjustment Coefficients for Group Two

	LUS	LHK	LTW	LSK	CONSTANT
Cointegrating Vector Normalized on LUS	1	-3.021013 (0.87896) [-3.43704]	2.672413 (0.94821) [2.81838]	-3.712245 (0.80828) [-4.59275]	22.52427
Adjustment Coefficients	0.00842 (0.00483) [1.74386]	0.001447 (0.00600) [0.24102]	-0.012506 (0.00701) [-1.78283]	0.021445 (0.00790) [2.71611]	

Standard Error in ( ) & t-Statistics in [ ]

Table 5 Panel A:

Testing Whether Stock Markets Enter The Relevant Cointegrating Vector and Whether Stock Markets Adjust to The Relevant Cointegrating Vector for Group One

Zero Restriction	β_{HK}	β_{TW}	β_{SK}
Chi-Square	2.534858	2.573017	7.968861*

Zero Restriction	α_{HK}	α_{TW}	α_{SK}
Chi-Square	0.046982	1.543369	6.260442**

*(**)*** denotes rejection of the hypothesis at the 1%(5%)10% level

Table 5 Panel B:

Testing Whether Stock Markets Enter The Relevant Cointegrating Vector and Whether Stock Markets Adjust To The Relevant Cointegrating Vector for Group Two

Zero Restriction	β_{US}	β_{HK}	β_{TW}	β_{SK}
Chi-Square	0.195243	2.187955	3.895794**	8.117088*

Zero Restriction	α_{US}	α_{HK}	α_{TW}	α_{SK}
Chi-Square	2.70644***	0.040359	1.683327	3.11883***

*(**)*** denotes rejection of the hypothesis at the 1%(5%)10% level

Table 6: Results of VAR Pairwise Granger Causality/MWALD Test

Dependent variable	LUS	LJA	LHK	LTW	LSK
∑LUS	182.56275*	27.572265*	15.946351*	23.853439*	24.193492*
∑LJA	1.721714	221.52495*	6.5135091**	0.14630917	0.29708779
∑LHK	6.45E-02	1.5032968	128.06176*	1.6055855	2.8147652
∑LTW	1.4366848	0.22927797	1.1297749	209.2613*	0.53891129
∑LSK	2.710639	4.8022674***	1.1297749	0.23746271	93.931369*

*(**)*** denotes rejection of the null hypothesis at 1% (5%)10% level

Dependent variables are in the first row

Numbers in the table are Chi-Square Statistics with df 2

"∑X"denotes the null hypothesis that the coeffients of the lagged value of "X" are jointly zero.

Table 7: Generalized Impulse Response

Response of DUS:

Period	DUS	DJA	DHK	DTW	DSK
1	0.02997	0.007144	0.016245	0.007355	0.011838
2	-0.002709	-3.23E-05	-0.003064	-0.00417	-0.005134
3	-0.00085	-0.000382	-0.000242	0.00036	0.000415
4	0.000237	6.03E-05	0.000184	0.000118	0.000141
5	2.65E-06	1.19E-05	-2.34E-05	-3.25E-05	-3.69E-05
6	-1.02E-05	-6.53E-06	-2.02E-06	-1.21E-08	-9.57E-07
7	9.45E-07	1.24E-06	3.35E-07	1.13E-06	1.76E-06
8	4.98E-07	-1.82E-07	4.09E-07	-2.26E-08	-2.06E-07
9	-1.84E-07	7.56E-08	-2.09E-07	-1.04E-07	-5.16E-08
10	2.89E-08	-4.07E-08	6.11E-08	3.72E-08	1.73E-08

Response of DJA:

Period	DUS	DJA	DHK	DTW	DSK
1	0.006852	0.028741	0.008748	0.007164	0.00851
2	0.009357	-0.002011	0.00367	0.001128	-0.001342
3	-0.00298	0.000286	-0.002235	-0.001757	-0.001026
4	0.000308	-0.00028	0.000542	0.000518	0.000293
5	1.58E-05	0.000131	-1.07E-04	-7.46E-05	4.42E-06
6	6.39E-06	-4.27E-05	3.76E-05	9.64E-06	-1.72E-05
7	-9.74E-06	1.37E-05	-1.80E-05	-5.32E-06	3.41E-06
8	4.18E-06	-5.05E-06	7.37E-06	2.97E-06	2.27E-08
9	-1.31E-06	1.96E-06	-2.64E-06	-1.17E-06	-1.04E-07
10	4.21E-07	-7.36E-07	9.27E-07	3.97E-07	1.53E-09

Response of DHK:

Period	DUS	DTW	DSK	DJA	DSK
1	0.019757	0.011095	0.036449	0.013402	0.020922
2	0.006113	0.004949	-0.004058	-0.002205	-0.004037
3	-0.001814	-0.00198	0.000199	-0.000679	-0.000757
4	-0.000183	0.000447	-0.000347	0.000129	0.000278
5	0.000196	-1.20E-04	0.000224	7.32E-05	9.83E-06
6	-5.39E-05	4.88E-05	-8.22E-05	-4.36E-05	-1.85E-05
7	1.08E-05	-1.99E-05	2.51E-05	1.32E-05	3.06E-06
8	-3.29E-06	7.26E-06	-8.32E-06	-3.59E-06	3.29E-07
9	1.47E-06	-2.54E-06	3.12E-06	1.22E-06	-2.11E-07
10	-6.05E-07	9.07E-07	-1.19E-06	-4.84E-07	3.05E-08

Response of DTW:

Period	DUS	DJA	DHK	DTW	DSK
1	0.010914	0.010882	0.016053	0.043659	0.020701
2	0.011927	0.001765	0.003912	-0.001122	0.003196
3	-0.002598	-0.000518	-0.001377	-0.001697	-0.002537
4	-8.84E-05	2.33E-05	-7.12E-05	0.000336	0.000467
5	0.000137	-1.85E-05	0.000136	2.66E-05	8.10E-06
6	-2.58E-05	2.13E-05	-4.45E-05	-2.49E-05	-1.82E-05
7	2.22E-06	-1.03E-05	1.10E-05	5.97E-06	2.15E-06
8	-9.86E-07	3.56E-06	-3.47E-06	-1.26E-06	4.58E-07
9	7.26E-07	-1.16E-06	1.42E-06	4.94E-07	-1.54E-07
10	-3.12E-07	4.08E-07	-5.63E-07	-2.30E-07	2.65E-09

Response of DSK:

Period	DUS	DJA	DHK	DTW	DSK
1	0.019613	0.014701	0.028502	0.023544	0.049654
2	0.011166	0.002026	0.004095	-0.00104	-0.006281
3	-0.003265	-1.33E-04	-0.002928	-0.001882	-0.001029
4	1.70E-04	-0.000369	0.000657	0.000541	0.000325
5	5.49E-05	0.00018	-1.25E-04	-5.92E-05	2.47E-05
6	1.09E-05	-5.65E-05	5.01E-05	7.56E-06	-2.36E-05
7	-1.46E-05	1.79E-05	-2.47E-05	-7.36E-06	3.30E-06
8	5.70E-06	-6.66E-06	9.86E-06	4.16E-06	4.22E-07
9	-1.68E-06	2.59E-06	-3.45E-06	-1.56E-06	-1.80E-07
10	5.40E-07	-9.65E-07	1.20E-06	5.16E-07	-2.99E-09

Table 8: Variance Decomposition

DUS

Period	DUS	DTW	DSK	DJA	DHK
1	100	0	0	0	0
2	97.10476	1.401644	1.09328	0.396589	0.003728
3	97.01086	1.436006	1.133561	0.414284	0.005286
4	97.01033	1.436325	1.133572	0.414276	0.005498
5	97.01004	1.436446	1.133662	0.414336	0.005515

DTW

Period	DUS	DTW	DSK	DJA	DHK
1	6.022214	93.97779	0	0	0
2	12.41467	87.36241	0.000847	0.004175	0.217898
3	12.67473	86.96773	0.082659	0.018519	0.256358
4	12.67238	86.95556	0.09156	0.018987	0.261516
5	12.67306	86.95403	0.091688	0.019083	0.262139

DSK

Period	DUS	DTW	DSK	DJA	DHK
1	15.60283	15.14161	69.25557	0	0
2	18.58456	14.17563	66.73448	0.132903	0.372423
3	18.8634	14.13848	66.37271	0.154588	0.470824
4	18.85755	14.14291	66.3486	0.165699	0.485244
5	18.857	14.14263	66.34635	0.166958	0.487065

DJA

Period	DUS	DTW	DSK	DJA	DHK
1	5.682941	3.871829	2.268639	88.17659	0
2	14.03646	3.489303	5.100944	77.20597	0.167318
3	14.76778	3.55906	5.08146	76.33856	0.253142
4	14.76689	3.577925	5.077803	76.3064	0.27099
5	14.76606	3.578393	5.07764	76.3042	0.273703

DHK

Period	DUS	DTW	DSK	DJA	DHK
1	29.38189	5.859845	10.19348	0.715856	53.84893
2	28.65567	6.194189	11.45736	2.645983	51.04679
3	28.69631	6.159507	11.38633	2.801561	50.9563
4	28.68484	6.158709	11.38844	2.812595	50.95542
5	28.68509	6.158256	11.3881	2.814256	50.9543

Cholesky Ordering: DUS DTW DSK DJA DHK

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