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Co-integration and Causality Analysis on Developed Asian Markets For Risk Management & Portfolio Selection

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Abstract

Both practitioners and academicians demand a linkage model across financial markets, particularly among regional capital markets, for both risk management and portfolio selection purposes. Researchers frequently use co-integration and causality analysis in investigating the dependence or co-movement of three or more stock markets in different countries. However, they conducted the causality in mean tests but not the causality in variance tests.

This study assesses the co-integration and causal relations among seven developed Asian markets, i.e Tokyo, Hongkong, Korea, Taiwan, Shanghai, Singapore, and Kuala Lumpur stock exchanges, using more frequent time series data. It employs the recently developed techniques for investigating unit roots, co-integration, time-varying volatility, and causality in variance. For estimating portfolio market risk, this study employs Value-at-Risk with delta-normal approach. The results show whether fund managers would be able to diversify their portfolio in these developed stock markets either in long run or short run.

Keywords: Risk Management, Causality, Co-integration, Asian Stock Markets

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1 Introduction

In borderless investment activities, investors, portfolio managers, and policy makers seek for a model that can disclose linkage and causality across financial markets, especially markets in a neighboring area. The model will provide them better view of the markets' movement and, therefore, enable them to appropriately price underlying assets and their derivatives, as well as to hedge the associated portfolio risks. Cointegration analysis has been the most popular approach employed by academicians and stock market researchers in developing such a linkage and causality model.

Cointegration analysis was initially introduced through influential contributions by Granger (1981), Engle & Granger (1987), and Granger & Hallman (1991). Such an analysis can reveal regular stochastic tendencies in financial time series data and be useful for long-term investment analysis. The analysis considers the I (1) − I (0) type of cointegration in which linear permutations of two or more I (1) variables are I (0) (Christensen & Nielsen, 2003). In the bivariate case, if y_t and x_t are I (1) and hence in particular nonstationary (unit root) processes, but there exists a process e_t which is I (0) and a fixed β such that : $y_t = \beta' x_t + e_t$, then x_t and y_t are defined as cointegrated. Thus, the nonstationary series shift together in the sense that a linear permutation of them is stationary and therefore a regular stochastic trend is shared.

Granger & Hallman (1991) proves that investment decisions merely-based on short-term asset returns are inadequate, as the long-term relationship of asset prices is not considered. They also shows that hedging strategies developed based on correlation require frequent rebalancing of portfolios, whereas those developed strictly based on cointegration do not require rebalancing. Lucas (1997) and Alexander (1999), using applications of cointegration analysis to portfolio asset allocation and trading strategies, have proven that Index tracking and portfolio optimization based on cointegration rather than correlation alone may result in higher asset returns. Meanwhile, Duan and Pliska (1998), by developing a theory of option valuation with cointegrated asset prices, reveal that cointegration method can have a considerable impact on spread option price volatilities. Furthermore, economic policy makers must have comprehensive knowledge on transmission of price movements in regional equity markets, especially during periods of high volatility. Appropriate policy may be designed to lessen the degree of financial crises. Therefore, a research on cointegration and causality among regional equity markets is essential. Cointegration approach complements correlation analysis, as correlation analysis is appropriate for short-term investment decisions, while cointegration based strategies are necessary for long-term investment.

2 Objectives and Structure of the Study

This paper is aimed at identifying the long-run equilibrium relationship among seven developed Asian markets, i.e Tokyo, Hongkong, Korea, Taiwan, Shanghai, Singapore, and Kuala Lumpur stock exchanges, using more frequent time series data. The paper also aims at explaining risk performance of the observed markets.

Earlier part (section 3) of this paper focuses on one or more of the observed markets and the associated linkage among the markets, through sample data and key descriptive statistics. It is then followed by a brief description of VEC Model of Price Indices and Returns (section 4). The procedure employed in this paper was the one originally proposed by Hall and Milne (1994) and applied by Liu and Romilly (1997), Chandana and Paratab (2002), Liu, Burridge, and Sinclair (2002) who realized a causality analysis for integrated series of order one , I(1), with cointegration by generating a VEC. This mechanism enables us to study the relationships in multivariate causality framework in section 5. Finally, the results are concluded in Section 6.

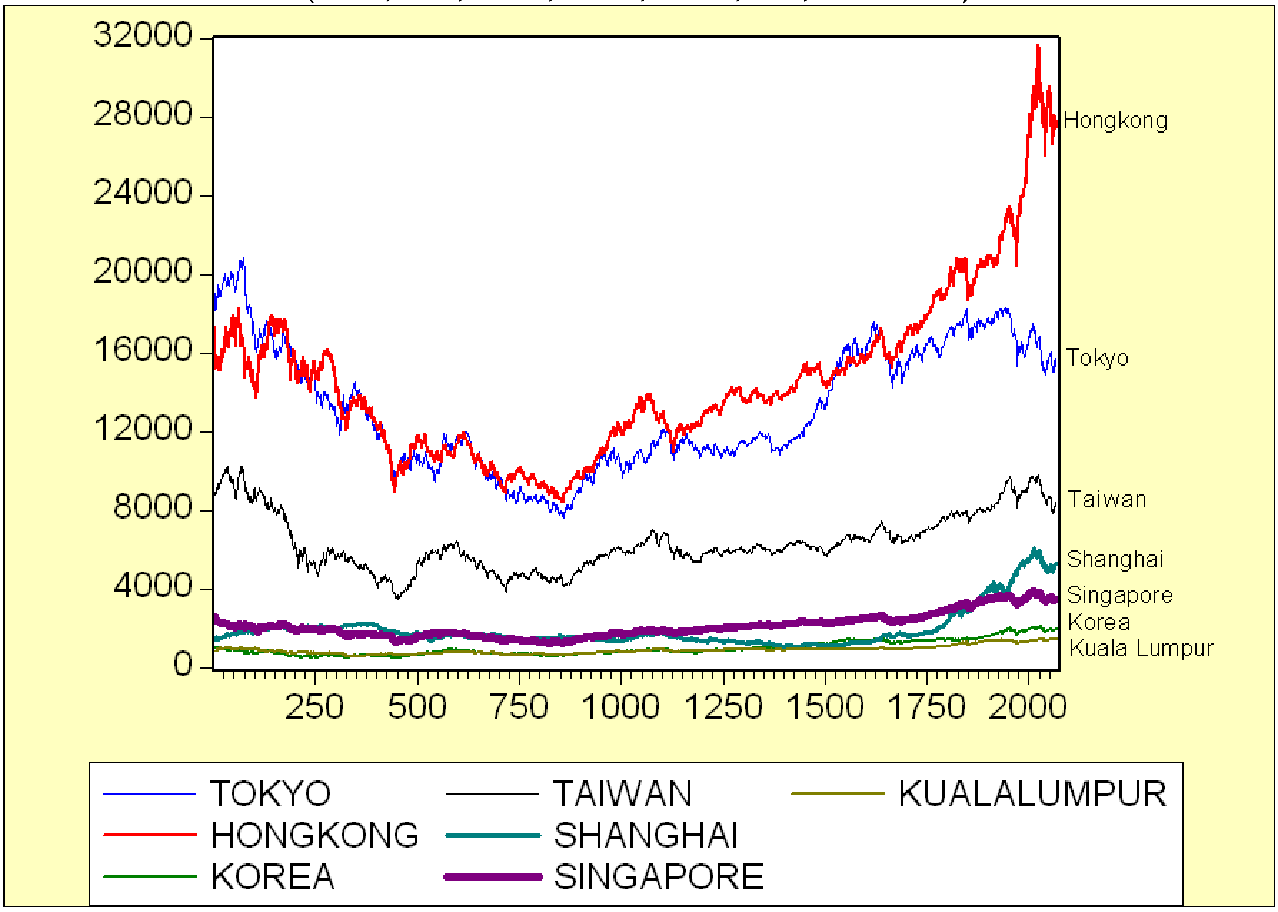
3 Sample Data and Descriptive Statistics

Sample data used in this study is taken from seven indices of prominent Asian economies, i.e Japan, China (Hongkong and Shanghai), Korea, Taiwan, Singapore, dan Malaysia. The observations are done in three periods, i.e. longer period (1/3/2000 – 12/31/2007), 1st shorter period (1/3/2000 – 12/31/2003), and 2nd shorter period (1/2/2004 – 12/31/2007). This division of observation periods is aimed at revealing the impact of particular economic condition on the indices, as well as assessing the cointegration in different durations.

All the indices have been adjusted to stock-splits, mergers and acquisition. We avoid transforming the three indices into a common currency. Instead, we use the nominal indices in domestic currency to evade problems associated with transformation due to fluctuations in cross-country exchange rates and also to avoid the restrictive assumption the relative purchasing power parity holds. In addition, we also implicitly assume that dividends are not vital to our analysis, as in general, dividends do not reveal the level of volatility that would be necessary to influence the null hypothesis of 'no cointegration', among a set of stock price indices (see Dwayer and Wallace 1992).

As can be seen from Figure 1, Hongkong and Tokyo indices record market capitalizations that are much higher than those of the other observed indices. At the end of 2007, Tokyo and Taiwan indices show negative growth, i.e. -19% and -3%, respectively, while the other indices record large positive growth. The indices of Shanghai, Korea, Kuala Lumpur, Hongkong, and Singapore log increases by 274%, 79%, 73%, 60%, and 35%, consecutively.

Figure 1
Movements of Major Asian Indices in the Observed Period
(N225, HSI, KS11, TWII, SSEC, STI, and KLSE)



Source: www.finance.yahoo.com

Table 1 shows that the return mean values in the longer period vary in negative-positive magnitudes. Tokyo and Taiwan indices show negative return means, i.e. -0.01% and -0.0024%, respectively. The rest observed indices record positive returns, and Shanghai shows the highest return (0.07%) during the observation period of 2000.1-2007.12. Meanwhile, in the same observation period, Korean index exhibits the highest risk level (the largest return standard deviation), i.e. 1.78%, and Kuala Lumpur index shows the lowest one, i.e. less than 1%. Table 1 also shows that the indices' skewness values are negative, except for that of Shanghai index, and that all indices have Kurtosis values larger than 3, which indicate fat-tails. Therefore, the Jarque-Bera (JB) values of the indices imply that none of the indices is normally distributed. The test statistic is computed as:

$$\frac{n}{6}\left[S^2+\frac{(K-3)}{4}^{2}\right] \quad (1)$$

Where S is skewness, and K is Kurtosis.

Table 1
The Indices' Return in Natural Logs
(Longer-Period)

	DLOG TOKYO	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG KUALALUMPUR
Mean	-0.0001	0.0002	0.0003	-2.38E-05	0.0007	0.0001	0.0003
Median	0.0000	0.0000	0.0006	0.0000	0.0000	5.26E-05	7.25E-05
Maximum	0.0722	0.0576	0.0770	0.0706	0.0940	0.0594	0.045027
Minimum	-0.0723	-0.0929	-0.1280	-0.1196	-0.0926	-0.0910	-0.0634
Std. Dev.	0.0135	0.0133	0.0178	0.0160	0.0145	0.0114	0.0091
Skewness	-0.1617	-0.3646	-0.5159	-0.3733	0.0488	-0.5122	-0.5999
Kurtosis	4.9539	6.8343	7.4122	7.1138	8.3333	7.9201	9.3807
Jarque-Bera	336.9933	1308.837	1764.046	1501.900	2444.669	2169.992	3621.604
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-0.2144	0.4443	0.5551	-0.0491	1.3294	0.2819	0.5351
Sum Sq. Dev.	0.3736	0.3620	0.6558	0.5256	0.4305	0.2672	0.1687
Observations	2062	2062	2062	2062	2062	2062	2062

Source: processed data

In the 1st shorter period 2000.1 – 2003.12, Shanghai index exhibits the only positive average return, i.e. 0.01%, as can be seen on Table 2. Tokyo index presents the lowest average return, i.e. -0.06%. In this period, the highest and the lowest risk levels, indicated by the standard deviation values, are shown by Korea and Kuala Lumpur indices, respectively. All indices show Kurtosis values that are larger than 3, indicating the fat-tails and leading to non-normal distribution.

Table 2
The Indices' Return in Natural Logs
(Shorter-Period 1)

	DLOG TOKYO	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG KUALALUMPUR
Mean	-0.0006	-0.0003	-0.0002	-0.0004	0.0001	-0.0003	-4.91E-05
Median	0.0000	0.0000	0.0000	-0.0002	0.0000	-0.0002	0.0000
Maximum	0.0722	0.0543	0.0768	0.07060	0.094008	0.0491	0.0450
Minimum	-0.0723	-0.0929	-0.1281	-0.1196	-0.065430	-0.0910	-0.0634
Std. Dev.	0.0156	0.0151	0.0218	0.0192	0.013171	0.0132	0.0106
Skewness	-0.0410	-0.3822	-0.4081	-0.2475	0.780999	-0.4803	-0.5290
Kurtosis	4.3829	6.2792	5.9726	5.7660	11.3595	7.0961	8.1070
Jarque-Bera	82.525	487.5159	408.6000	339.5060	3109.800	761.1274	1169.614
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	-0.5627	-0.2894	-0.2508	-0.3574	0.1090	-0.3454	-0.0507
Sum Sq. Dev.	0.2518	0.2360	0.4896	0.378400	0.1788	0.1790	0.1160
Observations	1032	1032	1032	1032	1032	1032	1032

Source: processed data

In the 2nd shorter period, 2004.1 - 2007.12, Shanghai index shows the highest return average, i.e. 0.12%, while both Tokyo and Taiwan indices show the lowest return average, i.e. 0.03%. Table 3 reveals that combination of the respective Skewness and Kurtosis values leads to non-normal distribution, as none of the Skewness is zero and none of the Kurtosis is 3.

Overall, Shanghai index consistently shows positive and the highest returns, while Tokyo index always exhibits the lowest returns in all observed periods. In the risk side, Kuala Lumpur index consistently shows the most stable price movements in all periods. The risks of Korean index are the highest in the longer period and in the 1st shorter period. In the 2nd shorter period, Shanghai index record the highest risk level, which confirms the assumption of "high-risk for high-return".

Table 3
The Indices' Return in Natural Logs
(Shorter-Period 2)

	DLOG TOKYO	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG KUALALUMPUR
Mean	0.0003	0.0007	0.0008	0.0003	0.0012	0.0006	0.0006
Median	0.0000	0.0005	0.0011	0.0002	0.0003	0.0008	0.0005
Maximum	0.0360	0.0576	0.0553	0.0542	0.0789	0.0594	0.0426
Minimum	-0.0557	-0.0514	-0.0718	-0.0691	-0.0926	-0.0404	-0.0475
Std. Dev.	0.0109	0.0111	0.0127	0.0120	0.0156	0.0092	0.0071
Skewness	-0.3642	-0.1590	-0.5640	-0.6347	-0.4209	-0.3671	-0.5521
Kurtosis	4.6220	6.0532	5.6688	7.2350	6.5910	6.9585	8.6336
Jarque-Bera	135.5358	404.0112	359.9088	838.0596	583.2805	694.9572	1412.996
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	0.3494	0.7312	0.8067	0.3053	1.2164	0.6272	0.5926
Sum Sq. Dev.	0.1214	0.1255	0.1657	0.1470	0.2511	0.0878	0.0524
Observations	1029	1029	1029	1029	1029	1029	1029

Source: processed data

Table 4 reveals the correlation between two observed indices. Correlation between Singapore and Hongkong indices is the highest, while that between Tokyo and Shnghai indices is the lowest. All indices connected with Shanghai index show very low correlation coefficients, which imply that an investor would achieve the expected diversification if she/he involves Shanghai index in her/his indices portfolio.

Table 4
Correlation Matrix of Indices' Return in Log
(Longer-Period)

	DLOG JAPAN	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG MALAYSIA
DLOG JAPAN	1.000	0.515	0.517	0.342	0.080	0.491	0.277
DLOG HONGKONG	0.515	1.000	0.558	0.368	0.167	0.625	0.372
DLOG KOREA	0.517	0.558	1.000	0.449	0.046	0.518	0.322
DLOG TAIWAN	0.342	0.368	0.449	1.000	0.052	0.377	0.235
DLOG SHANGHAI	0.080	0.167	0.046	0.052	1.000	0.102	0.098
DLOG SINGAPORE	0.491	0.625	0.518	0.377	0.102	1.000	0.416
DLOG MALAYSIA	0.277	0.372	0.322	0.235	0.098	0.416	1.000

Source: Processed Data

On Table 5, we can see that, again, Singapore-Hongkong index-pair demonstrates the highest correlation coefficient (0.59). Meanwhile, indices of Shanghai, Taiwan, and Kuala Lumpur show weak correlation with other indices in the region.

Table 5
Correlation Matrix of Indices' Return in Log
(Shorter-Period 1)

	DLOG TOKYO	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG KUALALUMPUR
DLOG TOKYO	1.000	0.498	0.481	0.276	0.035	0.457	0.200
DLOG HONGKONG	0.498	1.000	0.547	0.290	0.103	0.594	0.301
DLOG KOREA	0.481	0.547	1.000	0.386	-0.031	0.501	0.271
DLOG TAIWAN	0.276	0.290	0.386	1.000	-0.005	0.315	0.148
DLOG SHANGHAI	0.035	0.103	-0.031	-0.005	1.000	0.026	0.029
DLOG SINGAPORE	0.457	0.594	0.501	0.315	0.026	1.000	0.341
DLOG KUALALUMPUR	0.200	0.301	0.271	0.148	0.029	0.341	1.000

Source: Processed Data

Correlation coefficients in the 2nd shorter period are consistent with those in the 1st shorter period. Singapore-Hongkong index-pair again exhibits the highest correlation coefficient (0.684), while Shanghai is constantly weakly correlated with other observed indices.

Table 6
Correlation Matrix of Indices' Return in Log
(Short-Period 2)

	DLOG TOKYO	DLOG HONGKONG	DLOG KOREA	DLOG TAIWAN	DLOG SHANGHAI	DLOG SINGAPORE	DLOG KUALALUMPUR
DLOGTOKYO	1.000	0.548	0.610	0.496	0.138	0.559	0.439
DLOGHONGKONG	0.548	1.000	0.595	0.544	0.251	0.684	0.517
DLOGKOREA	0.610	0.595	1.000	0.621	0.163	0.564	0.454
DLOGTAIWAN	0.496	0.544	0.621	1.000	0.133	0.520	0.441
DLOGSHANGHAI	0.138	0.251	0.163	0.133	1.000	0.198	0.191
DLOGSINGAPORE	0.559	0.684	0.564	0.520	0.198	1.000	0.572
DLOGKUALALUMPUR	0.439	0.517	0.454	0.441	0.191	0.572	1.000

Source: Processed Data

In general, if an investor is to develop a portfolio of Asian indices, Shanghai index can be the first choice, as it consistently proves ineffectual correlation with other observed Asian indices. Contrarily, Hongkong index may increase the risk of such an Asian-indices portfolio as it consistently shows high correlation with other indices.

4 VEC Model of Price Indices and Returns

This study assesses the long-term equilibrium relationship as well as the short-term dynamics among the seven equity markets using the Johansen and Juselius (1990) model. If the indices share a common stochastic trend, then they are considered cointegrated (Christensen & Nielsen, 2003). The presence of cointegration relation forms the basis of the Vector Error Correction (VEC) specification. Below is vector auto-regressive (VAR) model of order *p:*

$$X_t = \mu \sum_{i=1}^{p} A X_{t-1} + \varepsilon_t \qquad (2)$$

where, X_t is a column vector of variables, here, the log price indices, μ, is a vector of constants, and ε_t is a vector of innovations, random errors usually assumed to be contemporaneously correlated but not autocorrelated, and p is the number of lags of variables in the system.

If the variables in the vector X, are integrated of order, say one, 1(1), and are also cointegrated, that cointegration restriction has to be included in the VAR in equation (2). The Granger Representation Theorem (Engle and Granger, 1987) states that variables, individually determined by permanent shocks, are cointegrated, if and only if there is a vector error correction representation of the time series data. With this restriction imposed, a VAR model is referred to as VEC. Variables in the model enter the equation in their first derivatives, and the error correction terms are added to the model. Consequently, the VEC has cointegration relations built into the specification so that it confines the long-term behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-term dynamics. Biases from long-term equilibrium are corrected through a series of partial short-term adjustments.

The VEC representation of equation (3), following Johansen and Juselius (JJ) is:

$$\Delta X_t = \mu + \sum_{i=1}^{p} \Gamma \Delta X_{t-1} + \alpha\beta' X_{t-1} + \varepsilon_t \qquad (3)$$

where,

Γ are (m x m) coefficient matrices (i = 1,2, ..., k),
α, β are (m x r) matrices, so that $0 < r < m$,
where r is the number of linear combinations of the elements in X_t that are affected only by transitory shocks.

Matrix β is the cointegrating matrix of r cointegrating vectors, β_1 β_2,...., β_i. The β vectors represent estimates of the long-run cointegrating relationship between the variables in the system. The error correction terms, B' X_{t-1}, are the mean reverting weighted sums of cointegrating vectors. The matrix a is the matrix of error correction coefficients that measure the speed at which the variables adjust to their equilibrium values. It is obvious that the model in equation 3 is the standard VAR in the first differences of X_t, augmented by the error correction terms, *a* B' X_t. The JJ method provides maximum likelihood estimates of a and B'

5 Empirical Estimation and Results

The very early phase in the estimation process is deciding the order of integration of the individual price index series in natural log levels. The logs of the indices, denoted as *N225, HSI, KS11, TWII, SSEC, STI,* and *KLSE*, are tested for unit roots using the augmented Dickey-Fuller (ADF) (1979) test using the lag structure indicated by Schwarz Bayesian Information Criterion (SBIC). The p-values used for the tests are the MacKinnon (1996) one-sided *p*-values. The test results, as can be seen on Table 7, indicate that the null hypothesis, the price index in log levels contains a unit root, cannot be rejected for each of the seven price series. Then, unit root tests are performed on each of the price index series in log first differences. The null hypothesis of a unit root could be rejected for each of the time series. No further tests are performed, since each of the series is found to be stationary in log first differences. The finding that each price series is non-stationary implies that each of the observed markets is weakly efficient.

Table 7
Augmented Dickey Fuller (ADF) Unit Root Test of Indices

Daily Closing Price Indices	Period	Lag	Test Statistic	SIC Values
N255	**Long**	**1**	-45.546	-5.772
HSI	**Long**	**1**	-25.744	-5.821
KS11	**Long**	**1**	-45.161	-5.208
TWII	**Long**	**1**	-23.727	-5.433
SSEC	**Long**	**1**	-44.851	-5.625
STI	**Long**	**1**	-44.654	-6.107
KLSE	**Long**	**1**	-38.782	-6.590
N255	**Short 1**	**1**	-32.237	-5.466
HSI	**Short 1**	**1**	-30.836	-5.534
KS11	**Short 1**	**1**	-32.086	-4.801
TWII	**Short 1**	**1**	-16.924	-5.057
SSEC	**Short 1**	**1**	-30.942	-5.809
STI	**Short 1**	**1**	-30.659	-5.812
KLSE	**Short 1**	**1**	-27.364	-6.266
N255	**Short 2**	**1**	-32.120	-6.195
HSI	**Short 2**	**1**	-17.270	-6.160
KS11	**Short 2**	**1**	-31.461	-5.881
TWII	**Short 2**	**1**	-31.414	-6.005
SSEC	**Short 2**	**1**	-32.240	-5.461
STI	**Short 2**	**1**	-33.491	-6.516
KLSE	**Short 2**	**1**	-15.997	-7.070

Source: Processed Data

*** at 1% level of Significance
** at 5% level of Significance
* at 5% level of Significance

The second phase involves an assessment on the seven market series for cointegration. The cointegration test is to determine whether or not the seven non-stationary price indices share a common stochastic trend. The estimated cointegrating equation is as follows:

$$lN255_t = \alpha_0 + \alpha_1 lHSI_t + \alpha_2 lKS11_t + lTWII + lSSEC + lSTI + LKLSE + \varepsilon_t \quad (4)$$

All the indices are found cointegrated in the three different observation periods, at the significance level of 5%. This indicates that an investor may not form an efficient portfolio if he/she includes the observed indices in his/her portfolio, as the intended diversification may not be achieved.

JJ estimation procedure that uses the maximum likelihood method is then employed. The cointegration tests assume no deterministic trends in the series and use lag intervals 1 to 1 as suggested by the SBIC for appropriate lag lengths. However, it would not have made any difference even if we have chosen AIC (Akaike Information Criterion) because both the AIC and SBIC suggested the same lag length as well as the assumptions for the test. The assumptions of the test are that the indices in log levels have no deterministic trends and the cointegrating equation has an intercept but no intercept in the VAR.

The trace test, which tests the null hypothesis of *r* cointegrating relations against *k* cointegrating relations, where *k* is the number of endogenous variables, for *r* = 0,1, ……*k.* If there are *k* cointegrating relations, it implies that there is no cointegration between each pair of the seven series. The maximum eigen value test which tests the null of *r* cointegrating relations against the alternative of *r* + 1 cointegrating relations, results indicated one cointegrating equation at the 5% percent level of significance. The critical values used from Osterwald-lenum (1992) are slightly different from those reported in JJ (1990). The cointegrating relationship is normalized on *N255.* The cointegrating vector of the seven daily price indices, normalized on *lN255* is: [1 3.1 -0.4 -3.23 -0.33 -5.27 5.09]. The cointegrating equation indicates that *N255* and *HSI* indices adjust one-to-one in the long-run, and results in a value greater than 1 for the rest indices, except for *KS11.*

We test for market indices cointegration between the pairs, and find that all the pairs are cointegrated. The test results are not presented, as our focus is the relationship among the seven markets. The finding that the market indices are cointegrated means that there is one linear combination of the seven price series that forces these indices to have a long-term equilibrium relationship even though the indices may wander away from each other in the short-run. It also implies that the returns on the indices are correlated in the long-term. The message for long-term international investors is that it does not matter, in terms of portfolio returns, whether investors in the observed Asian countries hold a fully diversified portfolio of stocks contained in all of the seven indices or hold portfolios consisting of all stocks of only one index.

Cointegration between the portfolio and the index is assured when there is at least one portfolio of stocks that has stationary tracking error, that is, the difference between the portfolio of stocks and the stock index is stationary, or to put it differently, the price spread between the two is mean-reverting. However, in the short-run, the two may deviate from each other with the potential for higher returns on the portfolio relative to the index. So, investors may still be able to earn excess returns in the short-run by holding a portfolio of stocks from the seven markets.

The final phase is the estimation of the three variable VEC model. In terms of this study analysis, the estimated vector error-correction model of price indices has the following form:

$$\Delta lN255_t = \alpha_0 + \sum \beta_{1i} \Delta lHSI_t + \sum \beta_{2i} \Delta lKS11_t + \sum \beta_{3i} \Delta lTWII + \sum \beta_{4i} \Delta lSSEC + \sum \beta_{5i} \Delta lSTI + \sum \beta_{6i} \Delta lKLSE + \lambda_1 Z_{t-1} + \varepsilon_t \tag{4}$$

where Δl are the first log differences of the seven market indices lagged p periods, Z_{t-1} are the equilibrium errors or the residuals of the cointegrating equations, lagged one period, and λ_i are the coefficients of the error-correction term. The lag lengths for the series in the system are determined according to the SIC. The suggested lag lengths are one to one. No restrictions are imposed in identifying the cointegrating vectors. The coefficients of the error correction terms are denoted by λ.

The estimated results can be seen on Table 8, 9, and 10. The estimated coefficient values of the lagged variables along with the t-statistics are presented without the asymptotic standard errors corrected for degrees of freedom for want of space, and will be available from the authors. On the bottom of the tables, the log likelihood values, the AIC and SBIC are reported.

Three types of inference, concerning the dynamics of the seven markets, can be drawn from the reported results of the VEC model in Table 8, 9, and 10. The first one concerns whether the left hand side variable in each equation in the system is endogenous or weakly exogenous. The second type of inference is about the speed, degree, and direction of adjustment of the variables in the system to restore equilibrium following a shock to the system. The third type of inference is associated with the direction of short-run causal linkages between the seven markets.

Table 8
VEC Estimated Results
Longer Period

Variables $\Delta lN255$ $\Delta lHSI$ $\Delta lKS11$ $\Delta lTWII$ $\Delta lSSEC$ $\Delta lSTI$ $\Delta lKLSE$

	$\Delta lN255$	$\Delta lHSI$	$\Delta lKS11$	$\Delta lTWII$	$\Delta lSSEC$	$\Delta lSTI$	$\Delta lKLSE$
Error Correction term (λ_i)	-0.0070**	-0.0074	-0.0050	-0.0114***	0.0003	-0.1376**	-0.0166***
$\Delta lN255$ **(-1)**	-0.0728***	-0.7423*	0.0020	0.0068	0.0167	-0.0376	0.0097
$\Delta lHSI$ **(-1)**	0.0699**	0.0087	0.0211	0.0413	0.0437	0.0038	-0.0245
$\Delta lKS11$ **(-1)**	0.0292	0.0319	-0.0192	0.0290	-0.0041	0.0063	-0.0226
$\Delta lTWII$ **(-1)**	-0.0110	-0.0249	-0.0208	-0.0562**	0.0148	-0.0267	0.0147
$\Delta lSSEC$ **(-1)**	-0.0289	-0.0389*	-0.0223	-0.0093	0.0016	0.0052	-0.0088
$\Delta lSTI$ **(-1)**	0.0881**	0.1496***	0.1283***	0.1152***	-0.0001	0.0672**	0.0594**
$\Delta lKLSE$ **(-1)**	-0.0773**	-0.0903**	-0.1000**	0.0575	-0.0044	-0.0601*	0.1441***
R-Squared	0.0124	0.0135	0.0035	0.0181	-0.0009	0.0039	0.0349
F-Statictic	4.2365	4.5286	1.9126*	5.7346***	0.7573	2.0086**	10.2980***

Log likelihood : 43.840,78
SIC : -42,37702

Source: Processed Data
*** at 1% level of Significance
** at 5% level of Significance
* at 10% level of Significance

The error correction parameter, estimated for the error correction term, is sometimes called the speed of adjustment and it indicates how quickly the economy moves back to the long run equilibrium after a shock. On Table 8, we can see that error correction term coefficients that are not significant belong to *HIS, KS11,* and *SSEC*. This means that these indices are weakly exogenous to the system. The weak exogeniety of the indices further implies that the markets are the initial receptor of external shocks, and it in turn, will transmit the shocks to the other markets in the observed region. As a result, the equilibrium relationship of the seven markets is disturbed. The adjustment back to equilibrium can be inferred from the signs and magnitude of the coefficients, λ_1, *($\Delta lHSI$ equation)*, λ_2 *($\Delta lKS11$equation)*, and λ_3, *($\Delta lSSEC$ equation)*. The negative sign means that the respective index will pose shock to the other indices in the observed region. In this sense, *STI* will give the largest negative impact on the other observed Asian markets, since it has the greatest error term coefficient. *N225, TWII, STI,* and *KLSE* show error term coefficients that are even significant at significance level of 1%.

On Table 9, we can see that, using daily price index during 2000-2003, *HIS*'s error correction term is -0.129 but not significant, while the rest indices show significant error correction term coefficients. Compared to figures on Table 8, number of insignificant coefficients (at significance level of 5%) on Table 9 is less. In this period, *STI* is still the most significant shock-creator among the regional indices, recording coefficient of -0.033.

Table 9
VEC Estimated Results
Short-Period 1

Variables $\Delta lN255$ $\Delta lHSI$ $\Delta lKS11$ $\Delta lTWII$ $\Delta lSSEC$ $\Delta lSTI$ $\Delta lKLSE$

	$\Delta lN255$	$\Delta lHSI$	$\Delta lKS11$	$\Delta lTWII$	$\Delta lSSEC$	$\Delta lSTI$	$\Delta lKLSE$
Error Correction term (λ_i)	-0.0149**	-0.1290	-0.0226***	-0.0275***	-0.0205***	-0.0335***	-0.0289***
$\Delta lN255$ **(-1)**	-0.0626	-0.0736**	0.0313	0.0231	0.0126	-0.0283	0.0283
$\Delta lHSI$ **(-1)**	0.0515	0.0366	0.0157	0.0268	0.0138	-0.0042	-0.0487*
$\Delta lKS11$ **(-1)**	0.0504*	0.0247	-0.0214	0.0176	0.0141	-0.0003	-0.0279
$\Delta lTWII$ **(-1)**	-0.0028	-0.0072	-0.0133	-0.0421	0.0123	-0.0139	0.0238
$\Delta lSSEC$ **(-1)**	-0.0368	-0.0823**	-0.0267	-0.0048	0.0409	-0.0055	-0.0100
$\Delta lSTI$ **(-1)**	0.0498	0.1278***	0.1195*	0.1142*	-0.0125	0.0986**	0.0479
$\Delta lKLSE$ **(-1)**	-0.1054**	-0.1351***	-0.1259*	0.0454	-0.0050	-0.0998**	0.1610***
R-Squared	0.0107	0.0167	0.0073	0.0195	0.0068	0.0138	0.0477
F-Statictic	2.3896**	3.1842***	1.9491**	3.5545***	1.8809*	2.7998***	7.4507***

Log likelihood : 19.692,57
SIC : -37,76653

Source: Processed Data
*** at 1% level of Significance
** at 5% level of Significance
* at 10% level of Significance

More drastic change can be seen on the results of the third test, presented on Table 10. In this period, *N255, KS11, TWII,* and *STI* show insignificant error correction term coefficients. *KS11* records a decrease in the coefficient by 0.0027, which means the index lowers its pressure to the system in the future. The error correction term coefficients of *TWII, KS11,* and *STI* show insignificant potential impacts on the regional market equilibrium. In this period, KLSE becomes the largest shock-creator in the observed region..

Table 10
VEC Estimated Results
Short Period 2

Variables $\Delta lN255$ $\Delta lHSI$ $\Delta lKS11$ $\Delta lTWII$ $\Delta lSSEC$ $\Delta lSTI$ $\Delta lKLSE$

	$\Delta lN255$	$\Delta lHSI$	$\Delta lKS11$	$\Delta lTWII$	$\Delta lSSEC$	$\Delta lSTI$	$\Delta lKLSE$
Error Correction term (λ_i)	-0.0051	-0.0256***	-0.0023	-0.0334	-0.0085**	0.0105	-0.0289***
$\Delta lN255$ **(-1)**	-0.0841**	-0.0822	-0.0873	-0.0301	0.0001	-0.0502	-0.0406
$\Delta lHSI$ **(-1)**	0.0996**	-0.0424	0.0429	0.0595	0.1105	0.0011	0.0249
$\Delta lKS11$ **(-1)**	-0.0269	0.0529	0.0363	0.0627	-0.0308	0.0247	0.0192
$\Delta lTWII$ **(-1)**	-0.0437	-0.0987	-0.0857*	-0.0836**	-0.0074	-0.0785**	-0.0379
$\Delta lSSEC$ **(-1)**	-0.0355	-0.0150	-0.0287	-0.0088	-0.0244	0.0078	-0.0096
$\Delta lSTI$ **(-1)**	0.1636***	0.1802***	0.1365**	0.1152*	0.0498	-0.0345	0.0959***
$\Delta lKLSE$ **(-1)**	0.0045	0.0729	0.0155	0.0667	-0.0530	0.1123**	0.1070***
R-Squared	0.0186	0.0228	0.0045	0.0276	0.0019	0.0074	0.0448
F-Statictic	3.4342***	3.9997***	1.5780	4.6382***	1.2417	1.9503**	7.0111***

Log likelihood : 22.465,29
SIC : -43,44618

Source: Processed Data
*** at 1% level of Significance
** at 5% level of Significance
* at 10% level of Significance

From the above vector error correction tests, we can see that the decline in log likelihood values is consistent with the decrease of observation period. Meanwhile, the length of observation period does not affect the SIC value, which represents the suitability and fitness of a model. The SIC value resulting from the 2nd Shorter period test is larger than that from the longer period test. Overall, *STI* and *KLSE* prove to be consistently significant index, as it produces significant coefficients all assessment periods. Thus, these indices are proven cointegrated with other observed indices, and inclusion of the indices in a portfolio may prevent an investor from forming an optimum portfolio.

Table 11
VEC Granger Causality

Dependant Variable	$\Delta lN255$	$\Delta lHSI$	$\Delta lKS11$	$\Delta lTWI$	$\Delta lSSEC$	$\Delta lSTI$	$\Delta lKLSE$	**Causality**
Full-Period								
$\Delta lN255$	-	0.007	0.992	0.801	0.552	0.119	0.670	HSI->N255
$\Delta lHSI$	0.025	-	0.676	0.281	0.153	0.763	0.245	N255->HSI
$\Delta lKS11$	0.188	0.139	-	0.245	0.882	0.757	0.164	-
$\Delta lTWII$	0.695	0.243	0.502	-	0.710	0.156	0.281	-
$\Delta lSSEC$	0.154	0.072	0.495	0.755	-	0.614	0.405	HSI->SSEC
$\Delta lSTI$	0.012	0.000	0.006	0.007	0.887	-	0.010	N255->STI HSI->STI KS11->STI TWII->STI KLSE->STI
$\Delta lKLSE$	0.033	0.011	0.037	0.175	0.958	0.050	-	N255->KLSE HSI->KLSE KS11->KLSE STI->KLSE
Short Period 1								
$\Delta lN255$	-	0.057	0.523	0.725	0.647	0.378	0.322	HSI->N255
$\Delta lHSI$	0.233	-	0.938	0.489	0.637	0.711	0.070	KLSE->HSI
$\Delta lKS11$	0.088	0.377	-	0.574	0.711	0.996	0.167	N255->KS11
$\Delta lTWII$	0.996	0.812	0.837	-	0.541	0.518	0.141	-
$\Delta lSSEC$	0.346	0.022	0.552	0.929	-	0.869	0.849	HSI->SSEC
$\Delta lSTI$	0.249	0.007	0.070	0.064	0.718	-	0.117	HSI->STI KS11->STI TWII->STI
$\Delta lKLSE$	0.033	0.005	0.056	0.420	0.873	0.014	-	N255->KLSE HSI->KLSE KS11->KLSE STI->KLSE
Short Period 2								
$\Delta lN255$	-	0.164	0.120	0.748	0.986	0.201	0.125	-
$\Delta lHSI$	0.025	-	0.496	0.334	0.102	0.984	0.339	N255->HSI
$\Delta lKS11$	0.546	0.141	-	0.110	0.599	0.490	0.596	-
$\Delta lTWII$	0.245	0.030	0.071	-	0.986	0.022	0.196	HSI->TWII KS11->TWII STI->TWII
$\Delta lSSEC$	0.121	0.636	0.323	0.582	-	0.582	0.566	-
$\Delta lSTI$	0.003	0.004	0.051	0.076	0.559	-	0.006	N255->STI HSI->STI KS11->STI TWII->STI KLSE->STI
$\Delta lKLSE$	0.948	0.183	0.736	0.257	0.601	0.029	-	STI->KLSE

Source: Processed Data
*** at 1% level of Significance
** at 5% level of Significance
* at 10% level of Significance

On Table 11, we can see that causal relationships exist among the observed markets. In the longer period data assessment, we may notice that *HIS* and *N225* show a two-way relationship. Such a relationship also applies to the pair of *KLSE* and *STI.* Similarly, a change in *HSI* affects the other observed indices, such as *SSEC, STI,* and *KLSE.* Therefore, we can infer that there are some stocks listed simultaneously in more than one market, and that the macroeconomic variables between two economies in the observed region are strongly correlated.

In the 1st shorter period, only the pair of HIS-KLSE shows two-way causal relationship. Meanwhile, *HSI* change leads to change in *N225, SSEC, STI,* and *KSLE.* A change in *KLSE* may result from changes in *N225, KS11,* and *STI.* In the 2nd shorter period, causal relationships exist in the pairs of *STI-TWII* and *STI-KLSE.* N225 causes a change in HSI, while a change in TWII may result from changes in HSI, KS11, and STI.

It is worth noting that HSI consistently shows one-way causal relationship with STI in the three observation periods. The pair of STI-KLSE shows consistent causal relationship in all observation periods. This pair even exhibits two-way causal relationship in the 2nd shorter period. We may conclude that these three indices have proven to have strong causal relationships that are beneficial for a portfolio diversification.

Table 12
Return and
Value at Risk (VaR)

PERIOD	Parameter	TOKYO	HONGKONG	KOREA	TAIWAN	SHANGHAI	SINGAPORE	KUALA LUMPUR
Full-Period	Mean	-0.0001	0.0002	0.0003	-2.38E-05	0.0007	0.0001	0.0003
	VAR	0.022	0.022	0.029	0.026	0.024	0.019	0.015
Short-Period 1	Mean	-0.0006	-0.0003	-0.0002	-0.0004	0.0001	-0.0003	-4.91E-05
	VAR	0.026	0.025	0.036	0.032	0.022	0.022	0.017
Short-Period 2	Mean	0.0003	0.0007	0.0008	0.0003	0.0012	0.0006	0.0006
	VAR	0.018	0.018	0.021	0.020	0.026	0.015	0.012

PERIOD	HIGHEST RETURN	LOWEST RETURN	RETURN DOMINANCE
Full-Period	consistent	not consistent	positive and negative
Short-Period 1	not consistent	consistent	negative return dominance
Short-Period 2	consistent	not consistent	positive return dominance

Source: Processed Data

Meanwhile, the risk performance of each of the observed markets is assessed using delta normal based Value at Risk. Using variance of each market displayed on Table 12, number of observations that vary across the observed markets, and significance level of 95%, our calculation ends up with the delta-normal-based-Value at Risk as shown on Table 12. On the table, we can see that the highest risk or the greatest VaR belongs to *KS11* (in longer and 1st shorter period), and to *SSEC* (in 2nd shorter period). The results in longer observation period and 1st shorter period demonstrate violation to the longtime acceptable convention in Finance, "High Return for High Risk", as *SSEC* exhibits the highest returns, while *KS11* bears the highest risks in these periods. The convention, however, is proven in the 2nd shorter period.

Portfolio Strategy

In an optimum portfolio formation process, there are many approaches that can be used, such as beta-based mean-variace analysis, B/M value analysis, P/E ratio analysis, portfolio diversification, etc. Findings of this study recommend several points for portfolio development, i.e.:

Correlation coefficient approach. This approach may provide positive outputs if the formation process employs returns with the lowest correlation coefficients between stocks or indices. In this study, *SSEC* has the lowest correlation coefficients in all observation periods. Moreover, in the shorter periods, almost all indices show increasing correlation coefficient. Therefore, this study recommends the use of longer period of observation for the portfolio selection process. It is woth noting that the correlation is related to return, not the price or the index, as it focuses more on the stationary process.

Cointegration approach. This approach focuses more on the potential new equilibrium resulting from long run relationship magnitude. This study reveals that *STI* and *KLSE* are significantly cointegrated to other indices in the observed region.

VEC model approach. This method stresses on the calculation of coefficient error term, which reflects potential future shock resulting from an index or stock. This study empirically proves that *HSI, KS11,* and *SSEC* are shock-creator indices in the future equilibrium. This implies that one can build an optimum index portfolio by including only one of the three into a basket of the other four indices. The three indices cannot be put in one portfolio as they tend to move in the same direction. However, the relationships among the indices can be determined through the associated VEC value. HIS, TWII, STI, and KLSE have VEC values that are greater than 1. KS11's VEC is less than 1, while N225's VEC equal to 1. This evidence implies that KS11 moves faster than the rest observed indices.

Causality relationship approach. This method assess the one-way and two-way causal relationship between markets or assets. This study shows that STI may experience the most changes resulting from changes in N255, HSI, KS11, TWII, and KLSE. In developing a portfolio, we may discard STI as it also proves strong correlation with other indices. The two-way causal relationships between STI and TWII, as well as between STI and KLSE indicate that the inclusion of the three indices will not provide an optimum portfolio. The granger-causality model is very helpful when one is to assess short-term portfolio.

Risk volatility approach. This method focuses on assessment on return volatility of an index or asset. This study reveals that there is no consistent, linear relationship between risk and return. In the three observation periods, the high-return indices are not necessarily high-risk indices, and vice versa. Therefore, this study does not recommend the risk-return based portfolio selection.

6 Summary and Conclusions

This paper attempts to assess relationships among the neighboring Asian indices by employing Econometric models. The results may show the best solution for one who is interested in forming a portfolio by including Asian indices in the investment basket. This study reveals that approaches in forming a portfolio will be much related to the selected assessment models. Mean-variance assessement model, for instance, is in fact very much related to the associated cointegration and ECM tests. Different portfolio selection approach will give different portfolio outputs. Different assessment's length of observation period also will result in different outputs, as the duration may affect the correlation coefficient as well as the volatility.

The formation of new equilibrium between markets can also be of great consideration when one is to develop a portfolio. This is so, since causal relationship between markets may affect the expected diversification in a portfolio. Strong causal relationship, regardless the direction, will accelerate formation of a new equilibrium between markets. Therefore, investor needs to carefully examine the magnitude of inter-market relationships. The existence of a linear combination of the seven indices that forces these indices to have a long-term equilibrium relationship implies that the indices are perfectly correlated in the long run and diversification among these seven equity markets can not benefit international portfolio investors. However, there can be excess returns in the short run. None of the aforementioned approaches provides similar recommendations. Thus, the portfolio selection will rely much on the investor's preference in chosing the associated assessment components.

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