ARE THE MAIN AND SECOND BOARD ON THE KLSE INTEGRATED? SOME EMPIRICAL EVIDENCE

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ABSTRACT

Numerous studies have shown that in a fully integrated market, a large market has greater influence on a relatively smaller market. These findings suggest that prices in a larger market can be used to predict prices in the smaller market and subsequently, investors who use this information as a trading rule will reap abnormal rate of returns. The objective of the present paper is to determine the degree of market integration between the stock indices of the Main Board and Second Board of the Kuala Lumpur Stock Exchange. In this paper we employed a recently developed econometric technique on the cointegration of time series to examine the issue of market integration. Using monthly and weekly frequency data, our results suggest that the Main Board and Second Board of the Kuala Lumpur Stock Exchange are not cointegrated. This indicates that there is no long run relationship between the two stock indices. Since prices determined in jointly efficient markets cannot be cointegrated, the result is consistent with the efficient market hypothesis.

INTRODUCTION

Numerous studies on capital markets have sought to determine the linkages among national financial markets. In a segmented market, different markets are treated as independent of each other. It would be difficult to earn consistently abnormal profits by investing in a particular market based on the observed developments in other markets. If this being the case, it is then consistent with the notion of an informationally efficient stock market, that is, the growth of one market cannot be used (as a trading rule) to predict another market.

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Dwyer and Hafer (1988) pointed out that with the relaxation of exchange controls and rapid development in computer and communication technology, the cost of information and cross-border financial transactions have been greatly lowered. Subsequently, the result is a high degree of economic and financial integration among the international stock markets. Recently, a number of authors have addressed this key issue and through a variety of procedures found that international stock markets are fully integrated. The financial centers are closely linked, so a disturbance in one market may be fully transmitted to other markets around the world almost instantaneously.

Mathur and Subrahmanyam (1990) investigated the market efficiency of the Nordic stock markets using the vector autoregressive (VAR) model. They found that the stock markets of Norway, Denmark, Finland and Sweden are fully integrated. The evidence suggests that information on the growth of one market may be used to predict the growth of other markets. Among the Nordic markets, the Swedish market has greater influence on both the Norwegian and the Finnish markets. In another study, Eun and Shim (1989), using the same approach showed that nine stock markets, namely, Australia, Canada, France, Germany, Hong Kong, Switzerland, United Kingdom and United States are interdependent. They also showed that all the markets respond completely to external shocks (innovations) within two days. Earlier studies by Schollhammer and Sand (1987) and Khoury et al. (1987), all using Box and Jenkins (1970) ARIMA time series approach also arrived at the same conclusion.

An important conclusion that emerged from all these studies is that the United States market can be used to predict stock prices of other national markets. Taylor and Tonks (1989) and Shafie (1993), using the cointegration approach, as suggested by Granger (1986) and Engle and Granger (1987) found that international stock markets are cointegrated. In other words, their findings support the hypothesis that international equity/financial markets are fully integrated. Fisher and Palasvirta (1990), using cross-spectral analysis on annual data showed that there was increasing interdependence of major markets from 1986 to 1988.

Interestingly, some of these earlier studies showed that larger markets (in terms of number of traders and choice of traded stocks) can influence the performance of other relatively smaller markets. For instance, the empirical evidence provided by Eun and Shim (1989),

Taylor and Tonks (1989), Khoury et al. (1987) and Schollhammer and Sand (1987), all show that the United States market has strong influence on the other smaller markets like Denmark, France, Germany, Japan, United Kingdom, Australia, Canada, Hong Kong and Switzerland. Jennergen and Korsvold (1974) argued that the relatively smaller and less developed markets are usually constrained by accessibility to information and very often the conditions for market efficiency are rarely satisfied. These arguments are supported by Hong (1978), who shows that stock prices in the smaller stock exchange markets (e.g., Singapore, Hong Kong and Australia) are predictable, suggesting that larger stock markets (e.g., Japan) are more efficient. Cheung and Mark (1992) examine the causal relationships between the Asian and the developed markets. They conclude that the United States market is a global (leading) factor in the international equity markets. In a related work, Chang and Pinegar (1989) noted the following in their footnote:

'Stock prices may be less efficient for small than for large firms if small firms are ignored by institutional investors or if they are followed by relatively few analysts for whom the small firms' stocks are a low priority. This explanation is consistent with the infrequent trading and the relative scarcity of information observed among the small firms' stocks.'

The purpose of this study is to examine the degree of market integration between the Main and Second Board stock indices in the Kuala Lumpur Stock Exchange (KLSE). In particular, the objective is to test for the long run relationship between the two stock indices. The empirical results will enable us to know how stock prices are priced nationally. The Second Board was launched in November 1988 with the primary purpose to allow small and medium sized companies with good growth prospects to raise funds from the capital market. It is relatively small compared to the Main Board. As at December 1992, there were 52 companies listed on the Second Board with a total market capitalisation of RM2.9 billion. The total number of companies listed constituted about 14 percent of the total number of listed companies, and contributed only about one percent of the total market capitalisation in the KLSE. In this paper we hypothesised that due to the high degree of sophistication in the KLSE, the two stock indices are integrated.

costate that the residual, v_1 is white noise. The choice of the optimum has length L is determined by using Schwert's (1989) entered which is given by the following two

EMPIRICAL METHODOLOGY

The Test for the Order of Integration

Test for cointegration consists of two steps. The first step is to determine the order of integration of the individual series. The test will determine the dynamic property of a time series which may be described in terms of number of times to be differenced to achieve stationarity. A time series Y_t that requires no such differencing to obtain stationarity is denoted as $Y_t \sim I(0)$. While a series that is not initially stationary and requires first-order differencing to achieve stationarity is said to be I(1). An integrated series such as $Y_t \sim I(2)$ is said to grow at an increasing rate, $Y_t \sim I(1)$ series to appear to grow at a constant rate while $Y_t \sim I(0)$ series to appear to be trendless. Thus, if two time series Y_t and X_t are integrated of different order, say $Y_t \sim I(2)$ and $X_t \sim I(1)$ respectively, then they will drift apart over time with no tendency of returning to some equilibrium path. In other words, they cannot be cointegrated. Regressing of Y_t on X_t will result in a spurious regression problem, as the residuals will violate the underlying assumptions of ordinary least squares (OLS).

If on the other hand, the two series Y_t and X_t are both I(1), then it is generally true that the linear combination of these series will also be I(1) so that a regression of Y_t on X_t will also produce spurious results. This is because the residual is also I(1), and it violates the assumptions of OLS. However, in a special case where a linear combination of two I(1) variables results in a variable (residual) of order I(0), then the two series are said to be cointegrated. This regression is permissible since the residual is I(0) or stationary, as it satisfies the Gauss-Markov assumption.

We employed Augmented Dickey and Fuller (1981) unit root test to determine the order of integration of the individual series. The test is the t-statistic on parameter α from the following equation

$$\Delta X_t = \delta_0 + \alpha X_{t-1} + \sum_{i=1}^L \delta_i \Delta X_{t-i} + \nu_t \tag{1}$$

where Δ is the first-difference operator and v_t is the disturbance term. The role of the lagged dependent variables in the Augmented Dickey-Fuller (ADF) regression Equation (1) is to ensure that the residual, v_t is white noise. The choice of the optimum lag length L is determined by using Schwert's (1989) criteria which is given by the following two

formulations: $L_4=int[4(T/100)^{1/4}]$ and $L_{12}=int[12(T/100)^{1/4}]$, where T is the total number of sample observations.

The null hypothesis, H_0 : X_t is I(1), is rejected (in favour of I(0)) if α is found to be negative and statistically significantly different from zero. The computed t-statistic on parameter α , is compared with the critical value tabulated in MacKinnon (1991). If a time trend t is included in Equation (1), we have the following Equation (2) which is used to determine whether the series is trend-stationary (TS),

$$\Delta X_t = \delta_0 + \theta t + \beta X_{t-1} + \sum_{i=1}^{L} \delta_i \Delta X_{t-i} + \tau_t$$
 (2)

Here, if parameter β is negative and significantly different from zero then X_t is said to be trend-stationary. The difference between a difference-stationary process (DSP) and a trend-stationary process (TSP) is that, the former requires differencing to achieve stationarity (Dickey and Fuller, 1979). However, for TSP, stationarity is achieved by inclusion of a time trend variable. It is important to check for the correct form of non-stationary behaviour of the time because a difference-stationary process which is stochastic cannot be cointegrated with a trend-stationary process which, on the other hand, is deterministic. Nelson and Plosser (1982), however, have demonstrated that most economic time series can be described as a difference-stationary process.

A formal test to check whether X_t has a stochastic trend rather than a deterministic trend is to use the standard likelihood ratio test, Φ_3 (see Dickey-Fuller, 1981). The estimated value of Φ_3 is then compared with the critical value of Φ_3 tabulated in Dickey and Fuller (1981). If the calculated Φ_3 is less than the critical value of F_3 , we cannot reject the null hypothesis that, H_0 : $\beta=0$ and $\theta=0$. On the other hand, to test that X_t has a stochastic trend, no deterministic trend and no drift is to test the null hypothesis that, H_0 : $\beta=0$, $\theta=0$ and $\delta=0$, and calculate Φ_2 . If the estimated value of Φ_2 is less than the critical value of Φ_2 in Dickey and Fuller (1981), we may conclude that X_t is a random walk with no drift.

The unit root test on the first-difference of the variables may be carried out by using the following regression

$$\Delta^2 X_t = \delta_0 + \alpha \Delta X_{t-1} + \sum_{t=1}^L \delta_t \Delta^2 X_{t-t} + \omega_t$$
 (3)

Here the null hypothesis, H_0 : X_t is I(2), is rejected (in favor of I(1)) if α is found to be negative and statistically significantly different from zero.

The Cointegration Test

The second step in the cointegration analysis is to test whether the linear combination of the series that are non-stationary in levels are cointegrated. To conduct the test, we follow Engle and Granger (1987) two-step procedure for testing the null hypothesis of no cointegration. First, we run the following cointegrating regression

$$X_t = \gamma_0 + \gamma_1 Y_t + \eta_t \tag{4}$$

and then the unit root test is conducted on the residual η_t as follows

$$\Delta \eta_t = \varphi \eta_{t-1} + \varepsilon_t$$
 and we have a super region and a super region (5)

The null hypothesis H_O : $\varphi=0$, that is, X_t and Y_t are not cointegrated is tested by means of t-statistic on parameter φ . The critical value is tabulated in MacKinnon (1991). If t_{φ} is smaller than the tabulated critical value, then X_t and Y_t are said to be cointegrated. For quick and approximate result, Engle and Granger (1987) recommended the cointegrating regression Durbin-Watson (CRDW) statistic. The statistic is widely used and is computed as follows

$$CRDW = [\sum_{t=2}^{T} (\eta_t \cdot \eta_{t-1})^2] / [\sum_{t=1}^{T} \eta_t^2]$$
 (6)

The null hypothesis of no cointegration is rejected in favor of cointegration for values of *CRDW* which are significantly different from zero. The critical values for *CRDW* are given in Engle and Yoo (1987).

The Granger Causality Approach

Traditionally, the efficiency market hypothesis is usually examined using Granger's (1969) causality test. Granger's definition of causality is based on the predictability of a time series. Formally, the proposition can be stated as follows: if $\sigma^2(x/x,y) < \sigma^2(x/x)$, then y is said to cause x. The term $\sigma^2(x/x,y)$ is the prediction error variance of x derived from the information set that includes past values of x and y. The term $\sigma^2(x/x)$ is the variance of the prediction error of x based on information contained only in the past values of x. If, however, $\sigma^2(y/y,x) < \sigma^2(y/y,x) < \sigma^2(y/y,$

(y/y) then x is said to cause y. Bi-directional causality is said to occur when the above occur simultaneously. Finally, if $\sigma^2(x/x) < \sigma^2(x/x,y)$ and $\sigma^2(y/y) < \sigma^2(y/y,x)$, then the two series are temporally unrelated and therefore independent of each other.

A direct test of Granger causality between X_t and Y_t can be determined using the following equations

$$\Delta X_{t} = \alpha_{0} + \sum_{i=1}^{N} \alpha_{i} \Delta X_{t-i} + \sum_{j=1}^{N} \beta_{j} \Delta Y_{t-j} + \mu_{It}$$
(7)

$$\Delta Y_{t} = \gamma_{0} + \sum_{i=1}^{N} \gamma_{i} \Delta X_{t-i} + \sum_{j=1}^{N} \delta_{j} \Delta Y_{t-j} + \mu_{2t}$$
(8)

where μ_{It} and μ_{2t} are independent, and $E[\mu_{Ib}\mu_{Is}]=0$, $E[\mu_{2b}\mu_{2s}]=0$, and $E[\mu_{Ib}\mu_{2s}]=0$, for all $t\neq s$.

From Equations (7) and (8), unidirectional causality from X to Y can be established if the estimated coefficients on the lagged variable X are significantly different from zero in Equation (8), and the estimated coefficients on the lagged variable Y as a group are not significantly different from zero in Equation (7). This finding would imply Y is predictable using innovation in X.

Causality from Y to X would be implied if the estimated coefficients on the lagged variable Y as a group are significantly different from zero in Equation (7), and the coefficients of the lagged variable X as a group in Equation (8) are not significantly different from zero. This finding would suggest that Y is a useful predictor for X.

If, however, the estimated coefficients of the lagged variables of both X and Y as a group in Equations (7) and (8) are significantly different from zero, then bi-directional causality is implied between X and Y. This finding would imply that one variable can be used to predict the other and *vice versa*.

Finally, if the estimated coefficients on the lagged variables of both X and Y as a group in Equations (7) and (8) are not significantly different from zero, then no causality is implied between X and Y and the two series are unrelated to (or independent of) each other.

The Error Correction Model Approach

To estimate Equations (7) and (8), the series are required to be stationary in their level form. Conventionally, the variables are transformed in their first-difference form or using some filter rule as suggested by Box and Jenkins (1970) to induce stationarity. However, Granger and Newbold (1977) pointed out that the danger in differencing is that potential valuable long-run information contained in the variable expressed in levels are lost. More recently, Engle and Granger (1987) have demonstrated that if two non-stationary variables are cointegrated, a vector autoregression in the first-difference is misspecified. It was shown in Granger (1988) that, if X_b and Y_t are both I(1), but are cointegrated then they will be generated by an Error Correction model of the following form,

$$\Delta X_t = -\theta_l z_{l:t-l} + lagged[\Delta X_b \Delta Y_t] + \varepsilon_{lt}$$
(9)

$$\Delta Y_t = -\theta_2 z_{2,t-1} + lagged[\Delta X_b \Delta Y_t] + \varepsilon_{2t}$$
(10)

where one of the $\theta s \neq 0$, z_1 and z_2 are the error correction terms, and εs are finite-order moving averages. According to Equation (9) there are two possible sources of causation of X_t by Y_{t-1} either through the z_{t-1} term, if $\theta_1 \neq 0$, and through ΔY_t term if they are present in the equation. Without z_{t-1} being explicitly used, the model will be misspecified and the possible value of lagged Y_t in forecasting X_t will be missed.

Rewriting Equations (7) and (8) in order to take into account the error correction term, we have the following Error Correction model suggested by Granger (1988),

$$\Delta X_{t} = \alpha_{0} + \sum_{i=1}^{K} \alpha_{i} \Delta X_{t-i} + \sum_{j=1}^{N} \beta_{j} \Delta Y_{t-j} - \theta_{1} z_{1,t-1} + \mu_{1t}$$
(11)

$$\Delta Y_{t} = \gamma_{0} + \sum_{i=1}^{K} \gamma_{i} \Delta X_{t-i} + \sum_{j=1}^{N} \delta_{j} \Delta Y_{t-j} - \theta_{2} z_{2,t-1} + \mu_{2t}$$
(12)

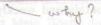
where z_{t-I} is the lagged residual from estimating the regression between X and Y in levels. Granger (1988) pointed out that, based on Equation (11), the null hypothesis that Y does not *Granger cause* X is rejected not only if the coefficients on the lagged variable Y are jointly significantly different from zero, but also if the coefficient on z_{t-I} is significant. The Error Correction model also provides for the finding that Y *Granger cause* X, if z_{t-I} is significant even though the coefficients on lagged variable Y are not jointly significantly different from

zero. Furthermore, the importance of αs and βs represent the short-run causal impact, while θ gives the long-run impact. In determining whether X Granger cause Y, the same principle applies with respect to Equation (12).

Before we can estimate Equations (7) and (8), we have to determine whether the z_{t-1} terms in Equations (11) and (12) are valid or not. To ascertain the validity of the z_{t-1} term, we estimate the cointegrating regressions comprising the two variables, that is, X_t and Y_t . If the residual z_t of the linear combination of X_t and Y_t is I(0), then z_{t-1} should be included in Equations (7) and (8) and therefore Equations (11) and (12) are appropriate for the Granger causality testing. If on the other hand, z_t is not I(0), then Equations (7) and (8) are the appropriate causality testing.

Data Used in the Study

In this study we used both monthly and weekly time series data for the Main Board and Second Board stock price indices at Kuala Lumpur Stock Exchange (KLSE). The stock indices were collected from various issues of the Investors Digest published monthly by KLSE. We used the Emas and Composite stock indices to represent the Main Board in KLSE. The data used in the analysis covers February 1991 to May 1995 for monthly data, giving us a total number of 52 observations. The weekly data covers the second week of February 1991 to the fourth week of May 1995. The total number of observations for the weekly frequency is 230. The span of the data is sufficient to absorb both foreign and domestic shocks. The investigation by Cha and Cheung (1993) showed that disturbances in financial markets in Asia are fully absorbed within three weeks. All data used in the analysis are transformed into natural logs before estimation.



THE EMPIRICAL RESULTS

The Integration Test Results

Tables 1 and 2 report the results of the integration tests on the levels of stock price indices for the monthly and weekly data respectively. Throughout the analysis, apart from the augmented Dickey-Fuller (ADF) test, we also report the test results based on the Phillips-Perron (PP) non-parametric approach for integration and cointegration tests. Further, the choice of lag truncation parameter is also based on the autocorrelation function (ACP) as suggested by Campbell and Perron (1991). For the monthly data, results based on Equation

(2) suggest that the hypothesis that the series are trend-stationary in levels can be rejected. In all cases, the results based on both ADF and PP tests, and with three variants of truncation lag parameters, indicate that the calculated test statistics, t_{β} and $Z(t_{\beta})$ are consistently not significant at the five percent level. On the other hand, results based on Equation (1) show that, in all cases, the hypothesis that the series are $I(\theta)$ can be rejected at the five percent level of significance. Similar conclusions are also derived for the stock prices using weekly data. In all cases, either based on Equation (2) or (1), the ADF and PP tests suggest that the hypothesis that the three stock price series are $I(\theta)$ can be rejected at the five percent level. Therefore, we conclude that the stock price indexes, either using monthly or weekly data, are nonstationary in levels.

Results of first-differencing the stock series for both monthly and weekly data are presented in Table 3. We can clearly see that, both ADF and PP test results suggest that the hypothesis that the series are I(2) can be rejected. In all cases (except for ADF, L_{12} =10 or 14), results in Table 3 indicate that the test statistics t_{α} and $Z(t_{\alpha})$ are significant at the five percent level. Therefore, we conclude that the three stock price indices are integrated series, that is, I(1). Furthermore, the significance of $Z(\Phi_{I})$ suggest the presence of drift term in Equation (1).

The Cointegration Test Results

Since all the stock series are of the same order of integration, that is, I(1), we can then determine whether their linear combination will result in an I(1) residual. The results of the cointegration tests are presented in Table 4. For CRDW, the results indicate that the null hypothesis of no cointegration cannot be rejected at the five percent level. In all cases, the calculated CRDW statistics for both monthly and weekly data are smaller than the critical value tabulated in Engle and Yoo (1987).

The relevant test statistics for the Phillips-Perron tests are $Z(\iota_{\beta})$, $Z(\Phi_3)$ and $Z(\Phi_2)$ for Equation (2), and $Z(\iota_{\alpha})$ and $Z(\Phi_1)$ for Equation (1). These adjusted test statistics are transformations of the regression t-statistic so that they allow for the effects of serially correlated and heterogenously distributed innovations. See Phillips and Perron (1988) for the details on the estimation procedure and the distribution of the test statistics.

²The determination of the lag length, L, follows the procedure recommended in Campbell and Perron (1991); starting at some maximum value of L^* , the lag length is selected as the largest L for which the t-statistic on the last included lag is significant at the 10 percent significant level. A lag length of L=0 is selected if none is significant.

Turning to the test statistics t_{φ} of the ADF and $Z(t_{\varphi})$ of PP tests, in all cases, the calculated t_{φ} and $Z(t_{\varphi})$ are larger than the critical values tabulated in MacKinnon (1991). These results suggest that the relationships between the stock series, that is, between Main and Second Board are not cointegrated. This implies that there is no long run relationship between Emas and Second Board, and between Composite and Second Board indices.

The Causality Test Results

The cointegration results given above imply that the traditional Granger causality test using Equations (7) and (8) are in order. The results of the Granger causality analysis using N equals 3 and 10 for monthly data, and setting N equals 4 and 14 for weekly data, are presented in Table 5. The F-statistics are calculated as follows

$$F^*_{(N, T-K-N-1)} = [(SEE_1 - SEE_2)/N] / [SEE_2/(T-2N-1)]$$
(13)

where SEE_I is the sum of squared errors from the restricted Equation (1) with the restriction that all βs equal zero. SEE_2 is the sum of squared errors of the unrestricted Equation (7). T is the number of observations and N is the truncation lag length chosen. Under the null hypothesis, the calculated F^* is distributed as F with (N, T-2N-1) degrees of freedom. For a suitably large F^* , we can reject the null hypothesis that Y does not $Granger\ cause\ X$. Similarly, the F-statistic is computed based on Equation (8) to test the null hypothesis X does not $Granger\ cause\ Y$. For the monthly data, the results show that the hypothesis that the Second Board does not $Granger\ cause\ Main\ Board\ and\ vice\ versa\ cannot\ be\ rejected\ at$ the five percent level of significance. However, results using weekly data suggest that the null hypothesis that Second Board does not $Granger\ cause\ Main\ Board\ cannot\ be\ rejected\ at$ the null hypothesis that Main Board does not $Granger\ cause\ Second\ Board\ can be\ rejected\ at\ the five\ percent\ level\ of\ significance\ This\ implies\ that\ there\ is\ unidirectional\ causality\ running\ from\ Main\ Board\ to\ the\ Second\ Board\ stock\ price\ indices\ Thus, in\ the\ short\ run,\ using\ weekly\ data,\ market\ participants\ can\ use\ either\ the\ Emas\ index\ or\ Composite\ index\ to\ predict\ the\ Second\ Board\ stock\ index.$

CONCLUSION

Numerous studies have provided evidence to support the hypothesis that the equity markets are fully integrated and that larger markets have greater influence on relatively smaller markets. This implies that prices in a larger market can be used to predict prices in a

smaller market and subsequently, market participants who use this information as their trading rule will reap abnormal rate of returns.

The objective of our paper is to determine the degree of market integration in the KLSE market between the Main Board and Second Board stock indices. In this study we employed a recently developed econometric technique on the cointegration of time series to examine the issue of market integration. The empirical evidence we obtained using both monthly and weekly data suggest that the Emas and Composite indices and the Second Board index are not cointegrated. This implies that there is no long run relationship between Main and Second Board stock indices. In other words, the Main and Second Board stock price indices are not integrated. Since prices determined in jointly efficient markets cannot be cointegrated, this is consistent with the efficient market hypothesis.

Nevertheless, in the short run, our weekly data suggest that there is unidirectional causality running from Main to the Second Board stock price indices. This will imply that, in the short run, market participants can use the Emas and/or Composite stock price indices to predict the movement of the Second Board index. In terms of benefit to investors, our results suggest that it pays for investors to diversify into Second Board counters, since the two sectors of the market are less than fully integrated in the long run.

Table 1: Results of Integration Tests for Series in Levels for Monthly Data

Stock Series		Result	s base	a on Equation Φ_2	lation (.	Φ_3	Results	t_{α}	Φ_I
		$\frac{t_{\beta}}{Z(t_{\beta})}$		$Z(\Phi_2)$	$Z(\Phi_i)$	$Z(\Phi_3)$	(4))2		$Z(\Phi_l)$
. Augmented I	Dickey	-Fuller (A	DF) T	est Resu	ilts				
Augmented I A. Lag based or	Auto	correlation	ı funct	ion (ACI	F)				
Emas		-2.47(2)		2.33		3.08		-0.89(2)	0.78
Composite				2.39		2.91		0.55(5)	0.77
SecondB		-1.96(3)		1.51		1.94		-0.80(3)	0.63
B. Lag based or	ı Schu	vert's, $L_4 =$	3						
Emas		-2.30		2.16		2.71		-0.65	0.70
Composite		-2.37		2.39		2.91		0.00	0.77
SecondB		-1.96				1.94		-0.80	0.63
C. Lag based of	Cala	want'n T	- 10						
C. Lag basea of	n Schv	veris, L ₁₂	-10						
Emas		-2.51		2.67		3.62			1.66
Composite				2.65		3.47			1.53
SecondB				3.20		4.56		-1.29	1.04
II. Phillips-Per	ron (I	PP) Test R	esults						
II. Phillips-Per A. Lag based o	n Aut	ocorrelatio	n func	tion (AC	CF)				
Emas		-1.82(1)		1.66		1.66		-0.67(1)	1.08
Composite				1.92		1.98			1.21
SecondB		-1.58(1)		1.34		1.36		-1.22(1)	8bnox 1.41
B. Lag based o	n Sch	wert's, L ₄ :	= 3						
Ol Essa		-1.99		1.78		2.01		-0.75	1.00
Emas Composite		-2.15							disogmo 1.15
SecondB								-1.29	1.38
C. Lag based of	on Sch	wert's, L ₁₂	= 10						
Emas						2.11			0.99
Composite						2.28			aliaoquio 1.19
SecondB						1.64		-1.27	1.3

Notes: For Equation (2): Critical values for $t\beta$ and $Z(t\beta)$ at five percent level is -3.49 (MacKinnon, 1991). Critical values for Φ_3 , $Z(\Phi_3)$ and Φ_2 and $Z(\Phi_2)$ at five percent level are 6.73 and 5.13 respectively (Dickey and Fuller, 1981).

For Equation (1): Critical values for t_{α} and $Z(t_{\alpha})$ at five percent level is -2.91 (MacKinnon, 1991). Critical values for Φ_1 and $Z(\Phi_1)$ at five percent level is 4.86 (Dickey and Fuller, 1981).

Figures in the parentheses are the selected lag length.

Table 2: Results of Integration Tests for Series in Levels for Weekly Data

Stock Series Results based on Equation (2)					2)	Results based on Equation (1)		
	t_{β}		Φ_2		Φ_3		t_{α}	Φ_1
	$Z(t_{\beta})$		$Z(\Phi_2)$		$Z(\Phi_3)$		$Z(t_{\alpha})$	$Z(\Phi_l)$
. Augmented Dickey	-Fuller (A	DF) To	est Result	s	F (ed2	Piller (ad Direct	esocie wa L'Adgosa
A. Lag based on Auto	correlation	i functi	ion (ACF)				
Emas	-2.49(8)		2.40		3.17		0.75(8)	0.70
Composite	-1.65(0)		1.92		1.37		0.85(0)	1.87
	2.28(11)		1.90		2.61	1	.11(11)	0.86
B. Lag based on Schw	vert's, $L_4 =$	4						
Emas	-1.82		1.75		1.73		-0.46	0.99
Composite	-1.91		1.94		1.92		-0.47	1.09
SecondB	-1.69		1.32		1.45		-1.06	1.09
C. Lag based on Schv	vert's, L ₁₂ =	= 14						
Emas	-1.86		1.76		1.74		-0.63	1.08
Composite	-2.06		2.06		2.14		-0.66	1.15
SecondB	-1.88		1.48		1.78		-1.00	0.94
II. Phillips-Perron (F	P) Test R	esults	Into Sec	and De				
A. Lag based on Auto	ocorrelatio	n func	tion (ACI	(+)				
Emas	-1.52(1)		1.64		1.16		-0.76(1)	1.59
Composite	-1.76(1)		1.93		1.57		-0.90(1)	1.73
SecondB	-1.47(1)		1.43		1.26		-1.28(1)	1.71
B. Lag based on Sch	wert's, L ₄ =	= 4						
Emas	-1.62		1.65		1.32		-0.80	1.49
Composite	-1.80		1.94		1.64		-0.90	1.72
SecondB	-1.58		1.47		1.41		-1.30	1.60
C. Lag based on Schwert's, $L_{12} = 14$								
Emas	-1.80		1.71		1.62		-0.87	1.30
Composite	-2.01		2.04		2.03		-0.96	1.5
SecondB	-1.86		1.64		1.86		-1.38	1.5

Notes: For Equation (2): Critical values for t_{β} and $Z(t_{\beta})$ at five percent level is -3.43 (MacKinnon, 1991). Critical values for Φ_3 , $Z(\Phi_3)$ and Φ_2 and $Z(\Phi_2)$ at five percent level are 6.34 and 4.75 respectively (Dickey and Fuller, 1981).

For Equation (1): Critical values for t_{α} and $Z(t_{\alpha})$ at five percent level is -2.87 (MacKinnon, 1991). Critical values for Φ_1 and $Z(\Phi_1)$ at five percent level is 4.63 (Dickey and Fuller, 1981).

Figures in the parentheses are the selected lag length.

Table 3: Results of Integration Tests for Series in First-Differenced for Monthly and Weekly Data

Stock Series	1.002	Mor	nthly	Weekly		
Stock Series		t_{α}	Φ_I	t_{α}	Φ_1	
		$Z(t_{\alpha})$	$Z(\Phi_1)$	$Z(t_{\alpha})$	$Z(\Phi_l)$	
		DE Tot Doculto		Using Monthly D		
I. Augmented Dic A. Lag based on A	key-Fuller (A) Autocorrelation	Function (ACF)				
Line			TADES FIRERE	2.62(1.4)	656	
Emas		-3.77(2)	7.12	-3.62(14)	6.56	
Composite		-3.62(3)	6.56	-3.84(14)	7.40	
SecondB		-3.71(3)	6.92	-3.83(10)	7.37	
B. Lag based on S	chwert's, $L_4 =$	$3 (or L_4 = 4)$				
1.53		(0)	VEO (B	-6.45	20.84	
Emas		-3.63	6.62	-6.54	21.41	
Composite		-3.62	6.56		17.59	
SecondB		-3.71	6.92	-5.93	17.39	
100x-	3.12	- 3.03(1)=-				
C. Lag based on S	Schwert's, L_{12} =	$= 10 \ (or \ L_{12} = 14)$				
Emas		-1.44	1.04	-3.62	6.56	
Composite		-1.63	1.33	-3.84	7.40	
SecondB		-1.52	1.16	-4.14	8.59	
II. Phillips-Perro	n (PP) Test Re	esults				
A. Lag based on	Autocorrelatio	n Function (ACF)	and a second second			
Emas		-8.36(1)	34.99	-11.79(1)	69.50	
Composite		-8.15(1)	33.27	-12.99(1)	84.46	
SecondB		-6.45(1)	20.85	-12.51(1)	78.34	
B. Lag based on	Schwert's L. =	$3 (or I_A = 4)$				
D. Lug Duseu on	<i>3011110113</i> , 24	(0) =4				
Emas		-8.28	34.50	-11.72	68.69	
Composite		-8.11	32.99	-12.93	83.62	
SecondB		-6.49	21.12	-12.47	77.80	
Seconds		/C1:181 E -	0.15			
C. Lag based on	Schwert's, L ₁₂	$= 10 (or L_{12} = 14)$				
Emas		-8.29	34.51	-11.85	70.2	
Composite		-8.16	33.32	-13.02	84.7	
SecondB		-6.45	20.77	-12.70	80.8	

Note: For monthly data: Critical values for t_{α} and $Z(t_{\omega})$ at five percent level is -2.91 (MacKinnon, 1991). Critical values for Φ_1 and $Z(\Phi_1)$ at five percent level is 4.86 (Dickey and Fuller, 1981). For weekly data: Critical values for t_{α} and $Z(t_{\alpha})$ at five percent level is -2.87 (MacKinnon, 1991). Critical values for Φ_1 and $Z(\Phi_1)$ at five percent level is 4.63 (Dickey and Fuller, 1981). Figures in the parentheses are the selected lag length.

Table 4: Results of Cointegration Tests

Cointegrating Regressions	CRDW	$t_{\varphi}, Z(t_{\varphi})$	$t_{arphi_{i}}$ $Z(t_{arphi})$	<i>tφ</i> ,
(a)Z Z(a) Z(a)	(0 P) (0) S Z(0)	ACF	$L_{4}=3$ $L_{4}=4$	$Z(t_{\varphi})$ $L_{12}=10$ $L_{12}=14$
I. Results Using Monthly Data				Augmented I
A. Augmented Dickey-Fuller (A	DF) Test Resul	ts		
SecondB=f(Emas)	0.43	-2.81(0)	-2.97	-1.86
Emas=f(SecondB)	0.43	-2.63(0)	-2.73	-1.68
SecondB=f(Composite)	0.38	-2.29(0)	-2.72	-1.66
Composite=f(SecondB)	0.39	-2.14(0)	-2.47	-1.53
B. Phillips-Perron (PP) Test Res				
SecondB=f(Emas)	0.43	2.02(1)	2.10	Etimope 21
Emas=f(SecondB)	0.43	-3.03(1) -2.85(1)	-3.12 -2.95	-3.00 -2.87
SecondB=f(Composite)	0.38	-2.57(1)	-2.64	-2.41
Composite=f(SecondB)	0.39	-2.41(1)	-2.47	-2.25
II. Results Using Weekly Data				
A. Augmented Dickey-Fuller (A	DF) Test Result	S		
SecondB=f(Emas)	0.15	-2.75(12)	-2.85	2.00
Emas=f(SecondB)	0.15	-2.51(12)	-2.62	-2.80 -2.55
SecondB=f(Composite)	0.12	-2.56(12)	-2.42	-2.67
Composite=f(SecondB)	0.12	-2.34(12)	-2.17	-2.46
3. Phillips-Perron (PP) Test Res	ults			
Garage ID CVT	2112	PA.5. 1.41		
SecondB=f(Emas) Emas=f(SecondB)	0.15	-3.18(12) -3.00(12)	-2.93 -2.75	-3.21 -3.04
()		2.00(12)	-2.13	-3.04

Notes: For monthly data: Critical values for t_{φ} and $Z(t_{\varphi})$ at five percent level is -3.45 (MacKinnon, 1991). Critical value for CRDW at five percent level is 0.78 (Engle and Yoo, 1987). For weekly data: Critical values for t_{φ} and $Z(t_{\varphi})$ at five percent level is -3.36 (MacKinnon, 1991). Critical value for CRDW at five percent level is 0.20 (Engle and Yoo, 1987). Figures in the parentheses are the selected lag length.

-2.76(12)

-2.60(12)

-2.47

-2.31

-2.79

-2.63

0.12

SecondB=f(Composite)

Composite=f(SecondB)

Table 5: Results of Granger Causality Tests

Main Board Indices	SecondB does not Granger cause Main Board Indices	Main Board does not Granger cause Second	
Oxford-Bullett	n of Economics and Statistics		
A. Results Using Mo			
Emas	F1 = 1.82 F2 = 0.59	F1 = 0.41 $F2 = 0.45$	Independent Independent
Composite	F1 = 1.11 F2 = 0.75	FI = 0.52 F2 = 0.86	Independent Independent
B. Results Using We	eekly Data		
Emas	F1 = 0.86 F2 = 1.39	FI = 4.80 $F2 = 2.07$	Emas Granger cause SecondB
Composite	F1 = 0.51 F2 = 1.44	F1 = 4.33 $F2 = 2.06$	Composite Granger cause SecondB

Notes: For monthly data: F1 (or $F_{3,41}$) and F2 (or $F_{10,20}$) refer to three and ten lags respectively. Critical values for F1 and F2 at five percent level are 2.84 and 2.32 respectively. For weekly data: F1 (or $F_{4,211}$) and F2 (or $F_{14,181}$) refer to four and fourteen lags respectively. Critical values for F1 and F2 at five percent level are 2.37 and 1.67 respectively.

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Others?