

Are Chinese Stock Markets Weak-form Efficient?

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Abstract

This paper evaluates whether or not Chinese stock markets are weak-form efficient, based on analysis of daily data of the Shanghai “A”, Shanghai “B”, Shenzhen “A”, Shenzhen “B”, Hang Seng, and Dow Jones Industrial Average indices from 2002 to 2005. Tests of the random walk hypothesis reveal return predictabilities for the Chinese share indices together with some evidence of increased predictability in the most recent period. The results of this study support the assertion that despite continual financial liberalisation and unparalleled growth, China’s stock markets are still not weak-form efficient.

I. Introduction

In recent years, studies have focused on the efficiency of stock markets in developing countries. Much of this research suggests that development of stock markets in countries which are at an appropriate stage of economic growth offers tremendous financial benefits to participants (Singh, 1999). China established its national stock exchanges in the early 1990s. Over the subsequent years, there has been a gradual liberation of regulations governing the financial system and stock markets in particular. The question is whether the continual financial liberalisation and growth of Chinese stock markets has made them more weak-form efficient.

While the Chinese stock markets have been widely praised for their contributions to the economy, they have also been criticised on fundamental issues such as market segmentation, market illiquidity, thin trading, government intervention, and lack of market transparency (Groenewold, Wu, Tang and Fan, 2004). These operational and allocational inefficiencies have inevitably constrained the flow of information, restricted market growth, but have also led to the emergence of predictable elements in Chinese stock market returns (Ma, 2004).

Laurence et al. (1997) study the daily indices data of the Chinese Shanghai (A and B index) and Shenzhen (A and B index), Hang Seng, and the Dow Jones Industrial Average (DJIA) from 1993 to 1996. They test weak-form efficiency in the Chinese markets and explore the statistical relationships and Granger (1969) causality among the Chinese stock markets with each other, and with the Hong Kong and U.S. stock markets. They find the existence of (i) weak-form efficiency in the market for A-shares but not B-shares, (ii) statistically weak linkages between the Chinese stock markets, (iii) a weak causal effect from the Hong Kong to the four Chinese stock markets, and (iv) a strong causal effect from the U.S. stock market to all four Chinese stock markets and the Hong Kong stock market.

Ma and Barnes (2001) examine weak-form efficiency by testing daily, weekly, and monthly indices returns of both the Shanghai (A and B) and Shenzhen (A and B) stock markets from 1990 to 1998. They use serial correlation coefficient tests, runs tests, and the

variance ratio test of Lo and MacKinlay (1988). The results suggest that all of the Chinese stock market indices exhibit correlated return patterns, with B-shares being more predictable than A-shares. They argue that (i) the correlated return patterns in indices can be employed in prediction of stock price changes, (ii) the correlated return pattern of individual B-shares means that future prices are predictable, (iii) Fama's (1965) benchmark for relative efficiency (36.36%) should be lowered because of the rapid communication of information in the modern market, and (iv) information in the Chinese stock markets is spurious and not transparent. Ma and Barnes (2001) conclude that China's stock markets are not weak-form efficient.

Chakravarty, Sarkar, and Wu (1998) and Chui and Kwok (1998) conducted analysis of the relationships between individual shares traded on the Shanghai and Shenzhen Markets, with outcomes that are generally complementary to the studies cited above of the relationships between the indices.

This paper examines the existence or otherwise of weak-form efficiency in Chinese stock markets. The paper employs various statistical techniques, such as random walk hypothesis (RWH), cointegration, and Granger (1969) causality tests to explore the above issues. Analysis of the integration between international and Chinese markets is reported in a separate paper by the authors (Niblock and Sloan, 2007) also presented at this conference.

The paper is organised as follows: Section II outlines the data required to implement the analysis and highlights the methodologies employed to examine weak-form efficiency. Empirical results and discussion are presented in Section III. Section IV is a summary and conclusion.

II. Data and Methodology

1. Data

The data used in this study consists of 955 daily closing price observations (adjusted for dividends and stock splits) for the Shanghai "A" (SHA), Shanghai "B" (SHB), Shenzhen "A"

(SZA), Shenzhen “B” (SZB), Hang Seng (HS), and DJIA indices. The chosen sample period is from 4 March 2002 through 28 October 2005. Furthermore, to identify possible time structural changes in the behaviour of the data, the sample is divided into two sub-samples covering the periods March 4 2002 to 31 December 2003, and 1 January 2004 to 28 October 2005. The stock indices data utilised in this study are obtained from Yahoo Finance’s historical price database. The econometrics software used to carry out the analysis in this study is GRET (Cottrell, 2006), and SPSS Version 13.0. The daily stock indices returns are calculated using the continuously compounded formula (Laurence et al., 1997):

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \quad (1)$$

where P_t is the index at time t , \ln is the natural logarithm, and R_t represents the log return series. Note that $R_t = \ln(P_t) - \ln(P_{t-1}) = \Delta \ln P_t$.

This study utilises Serial Correlation Coefficient Tests, Runs Tests and Variance Ratio tests to examine the validity of the Random Walk Hypothesis for Chinese stock markets. Subsequently the existence of relationships between the market indices is explored through tests for cointegration and Granger Causality.

2. *RWH - Serial Correlation Coefficient Tests*

The model for the serial correlation coefficient is:

$$\rho(k) = \frac{\text{Cov}[R_t, R_{t-k}]}{\sqrt{\text{Var}[R_t]}\sqrt{\text{Var}[R_{t-k}]}} = \frac{\text{Cov}[R_t, R_{t-k}]}{\text{Var}[R_t]}, \quad (2)$$

where $\rho(k)$ is the serial correlation coefficient of the time series R_t ; here R_t is the log return of the stock index at time t , and k is the lag of the period (Ma, 2004).

The standard deviation of $\rho(k)$ can be estimated as:

$$\sigma(\hat{\rho}(k)) = \sqrt{\frac{1}{n-k}}, \quad (3)$$

where n is the number of observations (Ma, 2004). Fuller (1976) demonstrates that the sample correlation coefficients $\hat{\rho}(k)$ are asymptotically independent and normally distributed with zero mean and standard deviation of $\sqrt{1/(n-k)}$. Therefore, when k is relatively small compared to the sample size n , the standard normal statistic x can be noted as:

$$x = \frac{n}{\sqrt{n-k}} \hat{\rho}(k) \stackrel{a}{\sim} N(0,1), \quad (4)$$

A simple test statistic for serial correlation is the LB-statistic due to Ljung and Box (1978). To test the joint hypothesis that all the serial correlation coefficients, $\rho(k)$ are simultaneously equal to zero, the LB statistic is applied:

$$LB = n(n+2) \sum_{k=1}^m \frac{\rho^2(k)}{n-k}, \quad (5)$$

where n is the number of observations and m is the maximum lag length (Ma, 2004). By summing the squared serial correlations, the LB-statistic is designed to detect departures from zero serial correlations in either direction and at any leads or lags (Ma, 2004).

3. *RWH - Runs Tests*

The following formulas inferred by Wallis and Roberts (1956) show the expected number of runs (M), and the standard error of runs (S_M) of the runs test:

$$M = \left[\frac{n(n-1) - \sum_{i=1}^3 \eta_i^2}{n} \right], \text{ and} \quad (6)$$

$$S_M = \left\{ \frac{\left[\sum_{i=1}^3 \eta_i^2 \left\langle \sum_{i=1}^3 \eta_i^2 + n(n+1) \right\rangle - 2n \sum_{i=1}^3 \eta_i^3 - n^3 \right]}{n^2(n-1)} \right\} \frac{1}{2}, \quad (7)$$

where n denotes the number of observations; $i = 1, 2,$ and 3 indicates the signs of plus, minus, and no change; and η_i symbolises the total numbers of changes of each type of signs.

However, for the purpose of this runs test, only positive and negative returns changes, not unchanged returns, are considered (Mood, 1940; Geary, 1970).

The standard normal statistic in the runs test of the actual number of runs (A_c) being equal to the expected number of runs (M) is:

$$K = \frac{A_c - M \pm (\frac{1}{2})}{S_M} \stackrel{a}{\sim} N(0,1), \quad (8)$$

where $\frac{1}{2}$ is the correction factor for continuity adjustment (Wallis and Roberts, 1956), in which the sign of the continuity adjustment is positive if $A_c \leq M$, and negative if $A_c \geq M$.

4. *RWH - Variance Ratio Tests*

The premise of the test is that variance estimated from the q -period returns should be q times as large as the variance estimated from one-period returns. Following Ma (2004) and with some manipulation, the Variance Ratio can be expressed as:

$$VR(q) \equiv \frac{Var(R_t^q)}{q \cdot Var(R_t)} = 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right) \rho(k) \quad (9)$$

Equation (9) shows that when the returns of the indices are uncorrelated, the serial correlation coefficients in lags one to q should be simultaneously near zero and the $VR(q)$ should be one (Ma, 2004). The standard normal test-statistics for the variance ratio test under the assumptions of homoskedasticity $Z(q)$ and heteroskedasticity $Z'(q)$ are those created by Lo and MacKinlay (1988):

$$Z(q) = \frac{VR(q) - 1}{\Phi(q)^{\frac{1}{2}}} \stackrel{a}{\sim} N(0, 1), \text{ and} \quad (10)$$

$$Z'(q) = \frac{VR(q) - 1}{\Phi'(q)^{\frac{1}{2}}} \stackrel{a}{\sim} N(0, 1), \quad (11)$$

where $\Phi(q)$ is the asymptotic variance of the variance ratio under the assumption of homoskedasticity, and $\Phi'(q)$ is the asymptotic variance of the variance ratio under the assumption of heteroskedasticity.

The asymptotic variance of the variance ratio under both homoskedasticity and heteroskedasticity are illustrated below:

$$\Phi(q) = \frac{2(2q-1)(q-1)}{3q(nq)}, \quad (12)$$

$$\Phi'(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right]^2 \cdot \hat{\delta}(j), \text{ where} \quad (13)$$

$$\hat{\delta}(j) = \frac{\sum_{t=j+1}^{nq} (p_t - p_{t-1} - \hat{\mu})^2 (p_{t-j} - p_{t-j-1} - \hat{\mu})^2}{\left[\sum_{t=1}^{nq} (p_t - p_{t-1} - \hat{\mu})^2 \right]^2}, \quad (14)$$

here nq states the number of observations, $\hat{\delta}(j)$ is the heteroskedasticity consistent estimator, in which p_t is the price of the index at time t , and $\hat{\mu}$ is the average return (Ma, 2004).

5. Cointegration

Essentially, if the two time series X_t and Y_t are both $I(1)$, then it is necessary that there exists a β such that the sequence:

$$z_t = y_t - \alpha - \beta x_t, \quad (15)$$

is $I(0)$ for X_t and Y_t to be cointegrated (Engle and Granger, 1987). The regression in Equation (15) is known as the cointegrating regression and measures the extent to which the system $X_t Y_t$ is out of equilibrium, where z_t is the equilibrium error and β is the cointegrating parameter. The simplest cointegration tests are based on the residuals of the OLS cointegrating regression (Engle and Granger, 1987). This involves regression of one variable on another and testing for the presence of a unit root.

The testing procedure follows a two-stage estimation. Firstly, in order to test whether the series are cointegrated, it is important to check that each series is $I(1)$. Testing for the unit root (or non-stationarity) is conducted by utilising the Dickey-Fuller (DF) (Dickey and Fuller, 1979) and augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) regressions, which are defined respectively:

$$\Delta y_t = \alpha + \theta y_{t-1} + \varepsilon_t \quad (16)$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + \varepsilon_t \quad (17)$$

To allow for series with time trends, the basic DF and ADF equations are changed to:

$$\Delta y_t = \alpha + \delta_t + \theta y_{t-1} + \varepsilon_t \quad (18)$$

$$\Delta y_t = \alpha + \delta_t + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + \varepsilon_t \quad (19)$$

Once it is found that each series contains a single unit root, that is I(1), the second stage involves testing whether the series ‘X’ and ‘Y’ are cointegrated. Constructing test statistics from the residuals of the cointegrating regression tests presents a formal cointegration procedure:

$$Y_t = a + bX_t + z_t \quad (20)$$

If the series are not cointegrated, then a unit root exists in the residuals, and is therefore the null hypothesis when testing for cointegration between series. For the two series to be cointegrated, the time series of z_t must be I(0), that is, stationary.

The ADF test is then performed on the estimated residuals, z_t , from Equation (20):

$$\Delta z_t = (\rho - 1)z_{t-1} + \sum_{j=1}^q \phi_j \Delta z_{t-j} + \mu \quad (21)$$

If the series share a long-run relationship, then the series are cointegrated (Engle and Granger, 1987). Once it is established that the series are cointegrated, their dynamics can be utilised for the investigation of Granger (1969) causality. The methodology used in this study for testing cointegration between the level series of Chinese stock indices (LSHA_t, LSHB_t, LSZA_t and LSZB_t), consists of the Engle and Granger (1987) residual-based approach to cointegration. Engle-Granger cointegration is tested by constructing test statistics from the residuals of the equation that is based on Equation (20):

$$Y_t = \alpha_0 + \beta_1 X_t + z_t \quad (22)$$

The reverse cointegrating regression of Wahab and Lashgari (1993) is also considered:

$$X_t = \alpha'_0 + \beta_2 Y_t + z'_t \quad (23)$$

In terms of Equations (22) and (23), α_0 and α'_0 are intercepts, β_1 and β_2 are cointegrating parameters, and z_t and z'_t are the residuals. Also, the long-run equilibrium relationship between Equations (22) and (23) are linear. Ultimately, the linear equilibrium relationship between the two equations examines whether the cointegration test results are sensitive to the choice of the dependent variable.

The residuals of Equations (22) and (23) are then estimated using Ordinary Least Squares (OLS) regression, and can be shown as:

$$\hat{z}_t = Y_t - [\alpha_0 + \beta_1 X_t] \quad (24)$$

$$\hat{z}'_t = X_t - [\alpha'_0 + \beta_2 Y_t] \quad (25)$$

Following the estimation of the residuals, \hat{z}_t and \hat{z}'_t , the residual-based augmented Dickey-Fuller test (as in Equation (21)) is performed on the estimated residuals of the combined stock indices series:

$$\Delta z_t = (\rho - 1)z_{t-1} + \sum_{j=1}^q \phi_j \Delta z_{t-j} + \mu_t \quad (26)$$

6. *Granger Causality*

When one variable is identified as the “dependent” variable ‘Y’ and the other as the “explanatory” variable ‘X’, an implicit assumption that changes in the explanatory variable cause changes in the dependent variable is made. This is the notion of causality in which information about ‘X’ is expected to affect the conditional distribution of the future values of ‘Y’ (Ramanathan, 2002). If ‘X’ causes ‘Y’ and ‘Y’ causes ‘X’, then the two variables are jointly determined, that is, a feedback relationship exists. In many instances the apparent direction of causality is not clear; therefore it is appropriate to test for causal directions between the two variables. Granger (1969) causality tests are designed to examine whether two time series move in a lead-lag relationship, that is, one after the other, or

contemporaneously. When ‘X’ and ‘Y’ move contemporaneously, one provides no information for characterising the other (Ramanathan, 2002).

Granger (1969) suggests that returns in market ‘X’ Granger-cause returns in market ‘Y’ only if it can be shown that the past values of ‘X’ combined with past values of ‘Y’ provide statistically significant information on future values of ‘Y’. This *does not* necessarily mean that a change of ‘X’ will cause a subsequent change in ‘Y’. Moreover, the assumption that a change of ‘X’ will cause a subsequent change in ‘Y’ may be considered a spurious regression problem, whereby regression analysis indicates a relationship between two unrelated time series processes simply because each has a trend, is an integrated time series (such as a random walk), or both (Wooldridge, 2006).

Furthermore, it should be noted that causality is defined in terms of an ideal randomised controlled experiment in which different values of ‘X’ are applied experimentally and the subsequent effects on ‘Y’ are observed. In contrast, Granger causality implies that if market ‘X’ Granger-causes market ‘Y’, then market ‘X’ is a useful predictor of market ‘Y’, given the other variables in the regression (Ramanathan, 2002). Specifically, what this *does* mean is that the past values of ‘X’ appear to contain information that is useful for forecasting changes in ‘Y’, beyond that contained in the past values of ‘Y’. While “Granger predictability” is a more accurate term than “Granger causality”, the latter has become part of the jargon of econometrics (Stock and Watson, 2003).

The empirical procedure for testing Granger (1969) causality from market ‘X’ to market ‘Y’ and market ‘Y’ to market ‘X’ involves estimating the following autoregressive (AR) models of order p and q :

$$Y_t = \sum_{i=1}^p \alpha_i Y_{t-i} + \sum_{j=1}^q \beta_j X_{t-j} + \mu_t \quad (27)$$

$$X_t = \sum_{i=1}^p \alpha_i X_{t-i} + \sum_{j=1}^q \beta_j Y_{t-j} + \nu_t, \quad (28)$$

where μ_t and v_t are white noise, p is the order of the lag Y , and q is the order of the lag for X (Stock and Watson, 2003). Essentially, the orders of the lags p and q are arbitrary and are usually chosen to be large. Alternatively, tests can be carried out for different values of the lags to ensure that conclusions are robust and not model-dependent (Ramanathan, 2002).

The restricted models are therefore:

$$Y_t = \sum_{i=1}^p \alpha_i Y_{t-i} + v_t \quad (29)$$

$$X_t = \sum_{i=1}^p \alpha_i X_{t-i} + v_t \quad (30)$$

The standard Wald F -statistic provides a formal test for Granger causality:

$$F = \frac{(SSR_1 - SSR_2) / q}{SSR_2 / (n - p - q)}, \quad (31)$$

where n is the number of observations used in the unrestricted models of Equations (27) and (28), SSR_1 is the sum of squared residuals for Equations (27) and (28), respectively, SSR_2 is the sum of squared residuals for Equations (29) and (30), respectively, and p and q are as defined previously (Stock and Watson, 2003). Specifically, a statistically significant F -statistic indicates unidirectional Granger causality from market 'X' to market 'Y', or unidirectional Granger causality from the interchanged market 'Y' to market 'X'. If both sets of 'X' and 'Y' F -statistics are statistically significant, then a feedback or bidirectional Granger causal relationship exists. Moreover, if the F -statistics are statistically insignificant in both regressions than Granger causal independence is evident (Stock and Watson, 2003).

III. Results and Discussion

1. Summary Statistics Results

The results of the summary statistics are illustrated in Table 1. For the Shanghai and Shenzhen markets the annualised daily log returns are all negative, except for SHA Period 1 and SZB Period 1. The large negative returns, particularly in Period 2, suggest poor index

performances across all four markets. However, the standard deviations are also large, indicating that the Chinese stock indices displayed volatile behaviour over all periods. The measures of central tendency and dispersion indicate that the Chinese stock markets underperformed in all periods and were riskier than the established markets of Hong Kong and the U.S. Moreover, strong economic growth is normally linked to positive stock market performance (Wooldridge, 2006). Considering the explosive growth of the Chinese economy in recent times, the poor performance of Chinese stock markets is uncharacteristic.

2. *Results for RWH - Serial Correlation Coefficient Tests*

The results for the daily serial correlation tests are illustrated in Table 2¹. The correlated return patterns in the A-share indices differ from the B-share indices. The findings suggest that the Shenzhen markets display more evidence of return predictability than the Shanghai markets, and that B-share markets are more predictable than A-share markets. Furthermore, the B-share markets of both Shanghai and Shenzhen have significant first order serial correlation coefficients in Period 2 and the combined periods. This is considerable as it shows that the previous day's returns in B-share markets can help predict current day returns. This, along with the other statistically significant findings is evidence of a direct violation of weak-form efficiency.

To investigate whether all the daily serial correlations between the returns from lags of one to twenty-four are simultaneously equal to zero, Ljung-Box statistics are further examined. Notably, the LB-statistic (42.65) of the combined periods of SZA rejected the null hypothesis at the 5% significance level. The exception of SZA (combined periods) indicates that returns may be correlated.

An anomaly was discovered whereby the magnitude of the LB-statistics and serial correlation coefficients across all four indices increases from Period 1 to Period 2. One interpretation of this result is that the Chinese stock markets are becoming less efficient. The

¹ Analogous analysis was also performed on weekly data, with the results showing little evidence of serial correlation. Full test results are available from the authors.

increasing Ljung-Box statistic from Period 1 to Period 2 shows that all the serial correlation coefficients are becoming simultaneously different from zero which indicates both return predictability and weak-form inefficiency. This is an important finding as the Efficient Market Hypothesis (EMH) suggests that as a stock market becomes more established and mature over time, so does its level of efficiency (Fama, 1970). Therefore, it is questionable whether the reform and financial liberalisation of Chinese stock markets are actually improving market efficiency.

3. Results for RWH - Runs Tests

The results for the empirical runs tests are highlighted in Table 3. It is apparent that “B” stock indices over the one- and two-day returns show more evidence of a departure from randomness than “A” stock indices. The departure from randomness for the one-day returns of SZB combined periods and two-day returns of SHB, SZA, and SZB combined periods suggests an element of short-term return predictability. The runs test results indicate that return predictability is apparent in one- and two-day returns of the Chinese stock indices, particularly the B-share markets of Period 2 and the combined periods. The robust statistical findings of the B-share markets, like the daily serial correlation coefficient tests, show that these markets may not be weak-form efficient.

Moreover, like the daily serial correlation coefficient test, the increase of the runs test statistics from Period 1 to Period 2 may indicate a decline in Chinese stock market efficiency. Period 1 displays no statistical significance in the runs tests, while for Period 2 findings are statistically significant. These findings are in stark contrast to the expectation that stock markets should become more efficient over time (Fama, 1970). They also refute the EMH, indicating elements of weak-form inefficiency in Chinese stock markets.

4. Results for RWH - Variance Ratio Tests

The daily variance ratio test results are presented in Table 4. In these tests, the results under the assumption of homoskedasticity show that the daily behaviour of the “A” and “B”

indices of both the Shanghai and Shenzhen markets only departs from randomness in some cases. The results under the assumption of heteroskedasticity are also presented in Table 4. Overall, it can be concluded that the daily A-share indices returns of both Shanghai and Shenzhen are random, thus implying weak-form efficiency. With no significant findings for A-share indices returns across all periods and intervals, it is clear that the variance ratio test supports the proposition of random price changes in these markets.

However, the daily variance ratio test results clearly illustrate the possibility of return predictability for the B-share markets. Significant findings for B-share indices for intervals two and four in both Period 2 and the combined periods suggest elements of return predictability and weak-form inefficiency.

Analogous testing of weekly data gave rise to no significant results findings² and supports the hypothesis that weekly returns in Chinese stock markets are random, and therefore substantiates the proposition of weak-form efficiency like the other weekly tests of the RWH. These results uphold the notion that stock markets can factor and absorb information more effectively over longer periods of time (Fama, 1970). Thus, over longer time periods stock markets may become more informationally efficient and less predictable.

5. *Results for Unit Root Tests*

Table 5 reports the most significant results of the standard DF and ADF tests for the level series $LSHA_t$, $LSHB_t$, $LSZA_t$, and $LSZB_t$. With only a few exceptions, the results suggest non-stationarity of the indices across all periods. Overall, the evidence fails to lead to the rejection of the null of a unit root in the level series at the 5% or 1% significance level, indicating that $LSHA_t$, $LSHB_t$, $LSZA_t$, and $LSZB_t$, are non-stationary.

The differenced series, ΔSHA_t , ΔSHB_t , ΔSZA_t , and ΔSZB_t , are then checked for the presence of a unit root. The most significant results for the DF and ADF unit root tests on the differenced series are presented in Table 6. The results clearly show that the first differences series are stationary for all periods, at all lag lengths, whether a trend is included in the DF

² Full test results are available from the authors.

and ADF equation or not. Ultimately, the DF and ADF tests comprehensively reject the null hypothesis of a unit root at the 5% or 1% significance level for the first differenced series. This implies that the differenced series, ΔSHA_t , ΔSHB_t , ΔSZA_t , and ΔSZB_t , are stationary and thus $I(0)$. Therefore, the original level series, LSHA_t , LSHB_t , LSZA_t , and LSZB_t , are $I(1)$, that is, contain a single unit root.

6. *Results for Engle-Granger Cointegration Tests*

Significant results are illustrated in Table 7. The results indicate that cointegrating relationships exist between some Chinese stock indices over different time periods and lag lengths³. In particular, the domestic SHA market is cointegrated with the domestic SZA market and the international SHB market. Furthermore, the international SHB market is cointegrated with the domestic SZA market at high order lag lengths.

However, after reversing the cointegration equation (Equation (22) in Section II) it is apparent that the amount of stock indices combinations that accept the null hypothesis diminishes. This implies that the selection of the dependent variable is sensitive in the cointegration equation (see Equation's (22) and (23) in Section II) and thus supports the use of this technique (Wahab and Lashgari, 1993).

The reversal of the cointegration equation reveals similar significant results to specification one, whereby $\text{SHB} - \text{SHA}$, $\text{SZA} - \text{SHA}$, and $\text{SZA} - \text{SHB}$ are all cointegrated over different time periods and lag lengths. This implies that the bivariate stock indices combinations have interchangeable cointegrating relationships between each other (Wahab and Lashgari, 1993). Once again, this supports the use of the reverse cointegration equation. Notably, the majority of the significant results of the Engle-Granger tests are discovered in Period 2 which again supports the findings of the RWH tests mentioned previously.

³ Two cointegrating equations are tested and involve the forward and reverse cointegrating equations, that is Equation's (22) and (23) (in Section II), and are labelled as specifications one and two, respectively (Wahab and Lashgari, 1993).

7. *Results for Granger Causality Tests*

Considering the outcomes of the Engle-Granger cointegration tests, it is appropriate to conduct Granger causality tests in an attempt to understand whether the lead-lag relationships of Chinese stock indices returns “Granger-cause” each other amongst themselves in a unidirectional or bidirectional causal sense.

A summary of the most significant test results is shown in Table 8. The results on balance reject the null hypothesis of non-Granger causality. Moreover, this confirms the proposition that the Chinese stock indices combinations mentioned are representative of causal relationships in the Granger sense. Overall, the results suggest that the Chinese A-share market returns Granger-cause B-share market returns. This shows that the domestic Chinese A-share markets have a significant influence on the international B-share markets of both Shanghai and Shenzhen. Additionally, the international B-share markets have had an influence on each other in recent times. There is also evidence of bidirectional Granger causality between the domestic Shanghai A-share market and the international Shenzhen B-share market between Shenzhen A and B markets. This result implies that unrelated stock markets, both in a geographical and operational sense, can have a significant influence on one market “Granger-causing” returns in the other. Also, the discovery of an eight day lag pattern between most statistically significant combinations of the Chinese stock indices returns indirectly suggests an element of market inefficiency implying that information generated in Chinese markets is taking approximately eight days to be interpreted and absorbed by both the domestic and international markets. As stock markets should incorporate “all information” immediately, these results challenge weak-form efficiency in Chinese stock markets.

Like the Engle-Granger cointegration test, the Granger causality test has established direct statistical associations between the stock indices. Although the Granger causality test results do not determine the presence or absence of weak-form efficiency per se, they support the findings of the RWH and cointegration tests.

IV. Summary and Conclusions

This paper reported tests for weak-form efficiency in the four Chinese stock markets of Shanghai “A”, Shanghai “B”, Shenzhen “A”, and Shenzhen “B” and explored the presence of cointegration and Granger causality (1969) relationships as an indication of the presence of inter-market influences over the period 2002 - 2005. The study did not seek to examine whether the return predictabilities could give rise to profitable trading strategies, once transaction costs and risk were taken into account. The findings reported in this paper are consistent with those of Laurence et al. (1997), relating to earlier periods.

Evidence of weak form inefficiency was found in the results of all tests administered when daily returns were considered. Moreover the test results seem to indicate a relative decline in efficiency (or more evidence of inefficiency in the latter period as compared to the first period). Weekly return data did not show evidence of weak form inefficiency, implying that information was absorbed into the markets over time periods longer than one or two days.

After establishing via Dickey-Fuller tests that the level series of stock indices contained a unit root, Engle-Granger cointegration tests were employed. The results provided statistical confirmation that some combinations of the stock indices were cointegrated. The Granger causality tests also indicated statistically significant relationships amongst Chinese stock indices returns.

In conclusion, this study indicates that weak-form inefficiencies are prevalent in Chinese stock markets despite efforts by the government in terms of financial reform and improved regulation. It is hoped that the ongoing removal of obstructive regulations and the development of more appropriate legislation by the Chinese authorities will ultimately create more optimal conditions for market efficiency, and will allow the financial markets to perform a stronger role in supporting ongoing economic development in China.

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Table 1. Descriptive Statistics for Shanghai, Shenzhen, Hong Kong, and U.S. Markets

Statistics	Period 1	Period 2	Combined Periods
SHA Market			
Annualised Daily Return	0.08%	-16.92%	-8.41%
Standard Deviation	1.17%	1.28%	1.23%
Skewness	1.423	0.633	0.966
Kurtosis	8.098	1.503	4.244
Min. Return	-3.16%	-3.96%	-3.96%
Max. Return	8.84%	5.64%	8.84%
Observations	478	477	955
SHB Market			
Annualised Daily Return	-15.82%	-29.86%	-22.84%
Standard Deviation	1.36%	1.59%	1.48%
Skewness	1.025	-0.119	0.318
Kurtosis	7.142	4.855	5.855
Min. Return	-4.57%	-8.78%	-8.78%
Max. Return	9.23%	6.90%	9.23%
Observations	478	477	955
SZA Market			
Annualised Daily Return	-6.95%	-19.03%	-12.99%
Standard Deviation	1.20%	1.38%	1.29%
Skewness	1.092	0.381	0.658
Kurtosis	6.51	1.124	3.188
Min. Return	-3.52%	-5.15%	-5.15%
Max. Return	8.65%	5.45%	8.65%
Observations	478	477	955
SZB Market			
Annualised Daily Return	11.91%	-19.78%	-3.92%
Standard Deviation	1.50%	1.55%	1.52%
Skewness	0.923	-0.050	0.403
Min. Return	-4.38%	-6.13%	-6.13%
Max. Return	9.29%	5.51%	9.29%
Observations	478	477	955
HS Market			
Annualised Daily Return	9.81%	6.43%	8.12%
Standard Deviation	1.09%	0.86%	0.98%
Skewness	0.093	-0.203	-0.002
Kurtosis	0.754	1.746	1.233
Min. Return	-4.18%	-3.64%	-4.18%
Max. Return	3.60%	3.52%	3.60%
Observations	478	477	955

Table 1. (Continued)

Statistics	Period 1	Period 2	Combined Periods
DJIA Market			
Annualised Daily Return	0.43%	-0.26%	0.09%
Standard Deviation	1.33%	0.66%	1.05%
Skewness	0.408	0.031	0.418
Kurtosis	1.987	0	3.606
Min. Return	-4.75%	-1.88%	-4.75%
Max. Return	6.16%	2.04%	6.16%
Observations	478	477	955

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, SZB is Shenzhen “B”, HS is Hang Seng, and DJIA is Dow Jones Industrial Average. Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Data are collected from Yahoo Finance. Annualised Daily Returns are calculated as: Arithmetic Mean x 250 (trading days).

Table 2. Serial Correlations and Ljung-Box Statistics of Daily Returns for the Shanghai and Shenzhen Markets

	Lags	Coefficient	L-B Stat
SHA			
Period 1	12	*0.1039	24.68
Period 2	19	*-0.1205	30.39
Combined Periods	5	*-0.0716	36.23
SHB			
Period 1	5	*-0.1082	14.02
Period 2	16	*-0.1112	30.44
Combined Periods	1	*0.0727	26.93
SZA			
Period 1	13	*-0.0966	24.37
Period 2	19	*-0.1137	35.39
Combined Periods	19	*-0.0734	*42.65
SZB			
Period 1	7	*0.1066	28.85
Period 2	1	*0.1109	31.54
Combined Periods	1	*0.0725	29.68

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, and SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Ljung-Box statistics are computed using 24 lags. Standard normal and *chi-square* critical values obtained from Cottrell (2006).

* Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Table 3. Runs Tests on Returns for Shanghai and Shenzhen Markets

Markets	Period 1			Period 2			Combined Periods		
	Act.	Exp.	K-stat.	Act.	Exp.	K-stat.	Act.	Exp.	K-stat.
<i>1-day</i>									
SHA	236	240	-0.366	218	239.5	* -1.971	454	478.5	-1.586
SHB	240	240	0.000	210	239.5	** -2.704	450	478.5	-1.845
SZA	228	240	-1.099	223	239.5	-1.513	451	478.5	-1.781
SZB	227	240	-1.191	212	239.5	* -2.521	438	478.5	** -2.623
<i>2-day</i>									
SHA	117	120.5	-0.454	115	120	-0.650	231	239.5	-0.779
SHB	106	120.5	-1.880	107	120	-1.689	213	239.5	* -2.429
SZA	108	120.5	-1.621	106	120	-1.819	214	239.5	* -2.338
SZB	106	120.5	-1.880	109	120	-1.429	214	239.5	* -2.338
<i>3-day</i>									
SHA	70	80.5	-1.671	80	80.5	-0.080	150	160	-1.123
SHB	76	80.5	-0.716	80	80.5	-0.080	156	160	-0.449
SZA	76	80.5	-0.716	83	80.5	-0.398	158	160	-0.225
SZB	82	80.5	0.239	77	80.5	-0.557	158	160	-0.225
<i>4-day</i>									
SHA	60	60.5	-0.092	66	60.5	1.013	126	120	0.780
SHB	61	60.5	0.092	61	60.5	0.092	121	120	0.130
SZA	58	60.5	-0.460	65	60.5	0.829	122	120	0.260
SZB	69	60.5	1.565	59	60.5	-0.276	128	120	1.039
<i>5-day</i>									
SHA	49	48.5	0.103	48	49	-0.205	96	96.5	-0.073
SHB	53	48.5	0.928	53	49	0.821	106	96.5	1.378
SZA	51	48.5	0.516	39	49	* -2.052	90	96.5	-0.943
SZB	49	48.5	0.103	47	49	-0.410	96	96.5	-0.073

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, and SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Act is Actual Runs, Exp is Expected Runs, and *K*-stat is (Actual Runs - Expected Runs)/Standard Error of Runs. Standard normal critical values obtained from Cottrell (2006). * Statistically significant at the 5% level. ** Statistically significant at the 1% level.

Table 4. Variance Ratio Tests for Intervals 2, 4, 8, and 16 on the Daily Returns of the Shanghai and Shenzhen Markets

	Q	VR(q)	Z(q)	Z'(q)
SHA				
Period 1	4	1.0851	0.9927	0.8201
Period 2	2	1.0507	1.1065	1.0272
Combined Periods	4	1.0867	1.4298	1.2410
SHB				
Period 1	4	1.0579	0.6757	0.5763
Period 2	4	1.2254	**2.6287	*1.9760
Combined Periods	4	1.1493	*2.4615	1.9049
SZA				
Period 1	4	1.0880	1.0257	0.7400
Period 2	4	1.1430	1.6675	1.5528
Combined Periods	4	1.1153	1.9013	1.5723
SZB				
Period 1	4	1.0787	0.9177	0.7102
Period 2	2	1.1148	*2.5041	*2.5117
Combined Periods	4	1.1406	*2.3190	*1.9771

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, and SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. q is the interval of observations; $VR(q)$ is the variance ratio. $Z(q)$ is distributed as a standard normal value under the assumption of homoskedasticity. $Z'(q)$ is distributed as a standard normal value under the assumption of heteroskedasticity. Standard normal critical values obtained from Cottrell (2006). * Statistically significant at the 5% level. ** Statistically significant at the level 1% level.

TABLE 5. DF and ADF Unit Root Tests for the Level Series of Stock Indices

	Lag Order	DF/ADF (No Trend)	Lag Order	DF/ADF (Trend)
SHA				
Period 1	12	-2.3856	4	-2.9802
Period 2	14	-1.1452	1	-2.9705
Combined Periods	14	-1.2962	3	-2.5103
SHB				
Period 1	19	-1.3810	1	-2.8240
Period 2	14	-1.1396	11	-2.9620
Combined Periods	12	-1.0343	12	-3.3704
SZA				
Period 1	4	-1.3413	1	*-3.6257
Period 2	14	-1.1013	14	-3.0947
Combined Periods	14	-1.0344	1	-3.2262
SZB				
Period 1	18	-1.221	7	-1.6374
Period 2	14	-1.7066	14	-2.8855
Combined Periods	14	-2.0547	14	-1.943

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Critical values -2.86 (5% level) and -3.43 (1% level) for No Trend, and critical values -3.41 (5% level) and -3.96 (1% level) for Trend obtained from MacKinnon (1996). * Statistically significant at the 5% level. ** Statistically significant at the level 1% level.

Table 6. DF and ADF Unit Root Tests for the First Differenced Series of Stock Indices

	Lag Order	DF (No Trend)	DF (Trend)	Lag Order	ADF (No Trend)	ADF (Trend)
SHA						
Period 1	0	** -21.049	** -21.027	1	** -14.783	** -14.767
Period 2	0	** -20.849	** -20.833	1	** -15.121	** -15.112
Combined Periods	0	** -29.688	** -29.688	1	** -21.167	** -21.171
SHB						
Period 1	0	** -21.522	** -21.499	1	** -15.244	** -15.225
Period 2	0	** -19.704	** -19.688	1	** -14.538	** -15.529
Combined Periods	0	** -29.587	** -29.571	1	** -21.237	** -21.225
SZA						
Period 1	0	** -20.924	** -20.917	1	** -14.672	** -14.670
Period 2	0	** -20.241	** -20.231	1	** -14.958	** -14.955
Combined Periods	0	** -29.240	** -29.237	1	** -20.970	** -20.971
SZB						
Period 1	0	** -21.682	** -21.716	1	** -15.016	** -15.057
Period 2	0	** -19.452	** -19.457	1	** -14.888	** -14.900
Combined Periods	0	** -28.923	** -28.931	1	** -21.097	** -21.110

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Critical values -2.86 (5% level) and -3.43 (1% level) for No Trend, and critical values -3.41 (5% level) and -3.96 (1% level) for Trend obtained from MacKinnon (1996). * Statistically significant at the 5% level. ** Statistically significant at the level 1% level.

Table 7. Engle-Granger Residual-based Bivariate Cointegration Tests of the Stock Indices

	Lag Order	Specification One	Lag Order	Specification Two
		<i>SHA - SHB</i>		<i>SHB - SHA</i>
Period 1	4	*-2.8810	20	-2.1870
Period 2	1	*-2.9438	1	*-2.8899
Combined Periods	3	-2.6051	3	-2.4592
		<i>SHA - SZA</i>		<i>SZA - SHA</i>
Period 1	4	-1.6798	23	-0.5673
Period 2	8	** -4.5099	8	** -4.4414
Combined Periods	15	-2.0766	15	-1.9113
		<i>SHA - SZB</i>		<i>SZB - SHA</i>
Period 1	12	-2.1135	18	-1.1334
Period 2	11	-1.6950	11	-2.1058
Combined Periods	14	-1.0559	11	-1.9754
		<i>SHB - SZA</i>		<i>SZA - SHB</i>
Period 1	20	*-3.1983	20	*-3.0181
Period 2	7	*-3.0518	7	*-2.9876
Combined Periods	3	** -3.5669	17	** -3.6928
		<i>SHB - SZB</i>		<i>SZB - SHB</i>
Period 1	19	-1.2447	18	-1.3152
Period 2	14	-2.3653	14	-2.7421
Combined Periods	12	-0.4889	14	-2.0218
		<i>SZA - SZB</i>		<i>SZB - SZA</i>
Period 1	12	-1.4923	7	-1.4413
Period 2	12	-1.5213	11	-1.9908
Combined Periods	14	-0.7917	14	-2.0087

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, and SZB is Shenzhen “B”.

Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. Critical values for the t-statistics [-2.76 (5% level) and -3.34 (1% level)] are obtained from MacKinnon (1996). * Statistically significant at the 5% level. ** Statistically significant at the level 1% level.

Table 8. Bivariate Granger Causality Tests

Causality Among the Chinese Markets

	SHA to SHB			Causal Flow	SHB to SHA		
	Lag Order (p)	Lag Order (q)	F-stat		Lag Order (p)	Lag Order (q)	F-stat
Period 1	5	5	2.8778		5	5	1.6451
Period 2	8	8	*3.7455	←	6	6	1.5993
Combined Periods	8	8	2.5554		6	6	2.7216

	SHA to SZA			Causal Flow	SZA to SHA		
	Lag Order (p)	Lag Order (q)	F-stat		Lag Order (p)	Lag Order (q)	F-stat
Period 1	5	5	2.0070		5	5	1.7906
Period 2	3	3	1.5748		6	6	1.4965
Combined Periods	5	5	1.8830		5	5	2.5400

	SHA to SZB			Causal Flow	SZB to SHA		
	Lag Order (p)	Lag Order (q)	F-stat		Lag Order (p)	Lag Order (q)	F-stat
Period 1	8	8	*3.2660	↔	8	8	*3.0664
Period 2	1	1	2.9515		8	8	1.7194
Combined Periods	8	8	*3.3438	↔	8	8	*3.2340

	SHB to SZA			Causal Flow	SZA to SHB		
	Lag Order (p)	Lag Order (q)	F-stat		Lag Order (p)	Lag Order (q)	F-stat
Period 1	5	5	2.2803		5	5	2.8997
Period 2	3	3	2.0151	→	8	8	*3.1736
Combined Periods	1	1	2.1326		8	8	2.6672

	SHB to SZB			Causal Flow	SZB to SHB		
	Lag Order (p)	Lag Order (q)	F-stat		Lag Order (p)	Lag Order (q)	F-stat
Period 1	5	5	**5.2056	←	5	5	2.9086
Period 2	1	1	*3.1200	↔	1	1	*3.0123
Combined Periods	7	7	*3.4758	←	1	1	2.8190

Table 8. (Continued)

	SZA to SZB			<i>Causal Flow</i>	SZB to SZA		
	Lag Order (<i>p</i>)	Lag Order (<i>q</i>)	<i>F</i> -stat		Lag Order (<i>p</i>)	Lag Order (<i>q</i>)	<i>F</i> -stat
Period 1	8	8	*4.0647	↔	8	8	*4.0867
Period 2	1	1	3.0020		3	3	1.7236
Combined Periods	8	8	*3.6772	↔	8	8	*3.6639

Note: SHA is Shanghai “A”, SHB is Shanghai “B”, SZA is Shenzhen “A”, and SZB is Shenzhen “B”. Period 1 is from 4/3/02 to 31/12/03 and Period 2 is from 1/1/04 to 28/10/05. “→” and “←” symbolises unidirectional causality, while “↔” symbolises bidirectional or feed back causality. Critical values for the *F*-statistics (3.01 (5% level) and 4.63 (1% level)) are obtained from Cottrell (2006). * Statistically significant at the 5% level. ** Statistically significant at the level 1% level.