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The Weak-form Efficiency of Chinese Stock Markets: Thin Trading, Nonlinearity and Episodic Serial Dependencies

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Motivated by the shortcomings of earlier Chinese efficiency studies, the present paper re-examines the weak-form efficiency of Shanghai and Shenzhen Stock Exchanges. Specifically, our adopted methodologies mitigate the confounding effect of thin trading on return autocorrelation, detect both linear and nonlinear serial dependencies in the adjusted returns series, and capture the persistence of dependency structures over time. The result shows that the adjusted returns series from both markets follow a random walk for long periods of time, only to be interspersed with brief periods of strong linear and/or nonlinear dependency structures. This suggests that there are certain time periods when new information is not fully reflected into stock prices. Another interesting finding is that the existence of serial dependencies in both the Shanghai and Shenzhen Stock Exchanges follows one another closely after October 1997. It indicates that both markets respond in a similar way to influences from political, economic, social and institutional changes.

JEL Classifications: G14; G15; C49

Keywords: Nonlinearity; thin trading; market efficiency; China; stock market

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1. Introduction

In recent years, China has been in the limelight following her spectacular economic growth since the adoption of market-oriented reforms in 1978, with real GDP growth averaging 9.5 per cent per annum for the period 1979–2003. With her admission into the World Trade Organization (WTO) in December 2001, the development of the two stock markets located in Shanghai and Shenzhen will be watched even more closely by academics, investors and policy makers. Though both the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) are relatively young, with their respective inauguration in December 1990 and July 1991, China is the world's leading emerging stock market in terms of market capitalisation and Asia's second largest after Japan. By the end of September 2004, the number of listed companies on both exchanges stood at 1378, with a combined market capitalisation of 4.093 trillion Renminbi (approximately US\$495 billion), more than 70 million stock traders, and a trading volume that hit 62.65 billion shares in the month of September 2004.¹

The Chinese markets exhibit some unique 'Chinese characteristics' not found in other stock markets. This has prompted researchers to investigate various aspects of the stock markets since no generalisation can be made and to some extent no reference point exists. First, the ownership structure of a listed company can be classified into as many as five different classes: state-owned shares, legal-person shares, employee shares, tradable A-shares and shares only available to foreign investors. The distinguishing characteristic is that over 60 per cent of the total equities of listed companies are non-negotiable shares (state-owned shares, legal-person shares and employee shares) that cannot be traded on the exchanges (Qi et al. 2000, Wei and Varela 2003). Second, the tradable A- and B-shares markets are characterised by the dominance of individual investors with Chinese institutional investors such as the pension funds, insurance companies and securities companies accounting for less than 10 per cent of the total market capitalisation.²

¹ Data source: China Securities Regulatory Commission (CSRC), at <http://www.csrc.gov.cn/n575458/n4001948/index.html>. At the end of September 2004, the exchange rate was 8.27 Renminbi per U.S. dollar.

² In 2003, the Shanghai Stock Exchange had a total of 36,436,000 investor accounts, of which 35,266,000 were A-shares accounts, 980,600 were B-shares accounts and 189,400 institutional investors (Shanghai Stock Exchange Fact Book 2003, downloaded from http://www.sse.com.cn/sseportal/en_us/cs/about/factbook/factbook_us2003.pdf). For Shenzhen Stock Exchange, total individual investors in 2003 were 33,632,231, of which 33,040,600 were in A-shares market with

It is widely acknowledged that these individual investors trade like noise traders, subject to herd behaviour, and treat the market like a casino without considering the information or fundamentals related to firms (Ma 1996, Nam et al. 1999, Kang et al. 2002, Girardin and Liu 2003).³ Third, though both the A- and B-shares have identical ownership rights and dividends within the same company, the latter are traded at substantial discounts relative to the former, suggesting that Chinese investors pay higher prices for identical shares than their foreign counterparts (Bailey 1994, Ma 1996, Sun and Tong 2000, Gordon and Li 2003). This is indeed a big puzzle as shares traded on other Asian and European stock markets are sold at considerable premiums to foreigners (for specific examples, refer to Bailey et al. 1999). Fourth, the volatility of domestic A-shares is much higher than those of foreign B-shares, despite both are seemingly similar assets (Su and Fleisher 1999b, He et al. 2003). Fifth, though the phenomenon of initial public offering (IPO) underpricing is documented in other stock markets (for specific examples, see Mok and Hui 1998: 454), the degree of IPO underpricing in Chinese A-shares market is extremely large (Mok and Hui 1998; Su and Fleisher 1999a, Chen et al. 2004).

In addition to the aforementioned aspects, the efficiency of the Chinese stock markets is not exempted from the strict scrutiny of researchers in view of its profound significance to market regulators and investors. In general, the focus of extant literature is on the weak-form version of the efficient markets hypothesis (EMH), which asserts that stock prices fully reflect all information contained in the past price history of the market. The empirical investigations revolved around examining whether stock prices follow a random walk process (Laurence et al. 1997, Liu et al. 1997, Long et al. 1999, Mookerjee and Yu, 1999, Darrat and Zhong 2000, Lee et al. 2001, Groenewold et al. 2003 and 2004, Lima and Tabak 2004, Ma 2004, Seddighi and Nian 2004). Taken as a whole, no consensus could be reached on the weak-form efficiency of these Chinese stock markets. On one hand, Liu et al. (1997), Laurence et al. (1997), Long et al. (1999) and Lima and Tabak (2004) concluded that the Chinese markets are efficient as their respective stock returns do not exhibit

the remaining 591,631 in B-shares market. Institutional investors, on the other hand, accounted for only 0.5 per cent, with a mere figure of 182,523 (Shenzhen Stock Exchange Fact Book 2003, downloaded from <http://www.szse.cn/main/en/MarketStatistics/FactBook/>). For reasons behind the dominance of individual investors, refer to Kang et al. (2002: Footnote 7).

³ Nam et al. (1999: 79) provided some explanations for the speculative behaviour of these individual investors.

predictable patterns. On the other end of the spectrum, Mookerjee and Yu (1999) and Ma (2004) proclaim the markets as inefficient given that the random walk hypothesis is rejected by their efficiency tests.

However, the above-cited Chinese efficiency studies assumed deviation from a random walk is in the form of linear serial correlations, and market efficiency is a static characteristic that remains unchanged over the entire estimation period. Their shortcomings are further discussed in Section 2. Section 3 then outlines our proposed research framework to address the problem of thin trading, the possibility of non-linearity in the data generating process, and the persistency of serial dependencies over time. Following that, descriptions of the data and methodologies are provided. Section 5 presents the empirical results and provides plausible explanations for the contradicting empirical evidence in earlier Chinese efficiency studies. The final section then concludes the article.

2. The Weak-form Efficiency of Chinese Stock Markets: Literature Review

The present section contains a review of previous studies that addressed the weak-form efficiency of Chinese stock markets. Our discussions highlight their major shortcomings, in particular the robustness of results and methodologies employed.

Firstly, the efficiency findings reported by various authors (Liu et al. 1997 for both SHSE and SZSE, Laurence et al. 1997 and Lima and Tabak 2004 for A-shares markets in both SHSE and SZSE, and Long et al. 1999 for A- and B-shares markets in SHSE) are quite surprising given the widely shared perception that these Chinese stock markets are highly speculative, driven mainly by market rumours and individual investor sentiment. On the one hand, the trading of noise traders would lead to serially correlated stock returns. For instance, the theoretical model of De Long et al. (1990) shows that when noise traders follow a positive feedback trading strategy, the price pressure induces positive return autocorrelations at short horizons. On the other hand, their evidence is inconsistent with studies that examined the profitability of past-return based investment strategies in the Chinese markets. For instance, Kang et al. (2002) report statistically significant abnormal profits for some short-horizon contrarian and intermediate-horizon momentum strategies in the A-shares market. Based on 412 technical trading rules, Tian et al. (2002) find that these rules are quite successful in predicting

the stock price movements in both Chinese stock exchanges, allowing traders to make possible excess profits during the 1990s.

Secondly, though all the aforementioned Chinese studies employ the conventional and popular efficiency tests, they are not without defect. Laurence et al. (1997) and Mookerjee and Yu (1999) draw their conclusions based solely on the results of serial correlation and runs tests. Liu et al. (1997) only employ unit root tests to examine the random walk hypothesis, while the analyses in Groenewold et al. (2003, 2004) and Seddighi and Nian (2004) are conducted using autocorrelation and unit root tests. However, the Monte Carlo experiments performed by Lo and Mackinlay (1989) demonstrate that the above statistical tests are less powerful relative to the variance ratio tests in detecting serial correlations of stock returns. Moreover, Campbell et al. (1997) argue that the detection of a unit root cannot be used as a basis to support the random walk hypothesis, hence the efficiency of the underlying stock market since unit root tests are not designed to test for predictability of stock prices.⁴ As a result, many researchers either complement or rely on variance ratio tests in their empirical testing of the random walk hypothesis (Long et al. 1999, Darrat and Zhong 2000, Lee et al. 2001, Lima and Tabak 2004, Ma 2004). Unfortunately, emerging stock markets like China are typically characterised by thin trading and this institutional feature would induce spurious positive serial correlations in the market index returns (see, for example, Lo and MacKinlay, 1988, 1990; Miller et al. 1994). Our survey shows that none of the aforementioned Chinese efficiency studies adopt any adjustment procedures to purge the effect of thin trading on return autocorrelations, though some of them do acknowledge that thin trading could be the main source of their detected predictability (see Laurence et al., 1997; Groenewold et al. 2003, 2004).

Thirdly, another common institutional feature that these Chinese efficiency studies have neglected is the possible existence of nonlinear serial dependence in stock returns series (Antoniou et al. 1997a, Appiah-Kusi and Menyah 2003).⁵ Empirically, after it is first reported by Hinich and Patterson (1985), more and more evidence has emerged to suggest nonlinear dependence in stock returns is a universal phenomenon (see references cited

⁴ Darrat and Zhong (2000) and Li (2003b) also question the use of unit root tests by earlier studies to examine the efficiency of Chinese stock markets. For recent critiques on the application of unit root tests, see Saadi et al. (2006a, 2006b) and Rahman and Saadi (2007, 2008).

⁵ For factors that might induce nonlinear dependence in stock returns series, interested readers can consult Antoniou et al. (1997a), Sarantis (2001) and Lim et al. (2006).

in Lim et al. 2006). In fact, based on the success of the artificial neural network model in forecasting Chinese stock prices, Darrat and Zhong (2000) acknowledge that prices may be better captured by nonlinear processes. The possible existence of nonlinear dependence in stock returns has important implication on the validity of weak-form EMH as it suggests the potential of returns predictability. Brooks and Hinich (1999) argue that if nonlinearity is present in the conditional first moment, it may be possible to devise a trading strategy based on nonlinear model which is able to yield higher returns than a buy-and-hold rule. Neftci (1991) demonstrates that in order for technical trading rules to be successful, some form of nonlinearity in stock prices is necessary. In testing the primary hypothesis that graphical technical analysis methods may be equivalent to nonlinear forecasting methods, Clyde and Osler (1997) find that technical analysis works better on nonlinear data than on random data and the use of technical analysis can generate higher profits than a random trading strategy if the data generating process is nonlinear. Indeed, there are a number of studies that document the profitability of nonlinear trading rules (see, for example, Gençay 1998; Fernández-Rodríguez et al. 2000; Andrada-Félix et al. 2003).

It is worth highlighting that the statistical tests adopted in earlier Chinese efficiency studies are not capable of detecting nonlinearity since they are all designed to uncover linear relationships between the returns and their past values. However, the lack of linear correlations does not necessarily imply efficiency as returns series can be linearly uncorrelated and at the same time nonlinearly dependent. In fact, it has been highlighted three decades ago by Granger and Andersen (1978) that one can never be sure time series with zero autocorrelation is not forecastable. For instance, it is well-known that time series generated by bilinear autoregressive, nonlinear moving average and threshold autoregressive processes exhibit zero autocorrelation yet possess predictable nonlinearities in mean. Hence, even if the returns series appear 'random' to autocorrelation-based tests, it still leaves wide open the question of whether higher-order temporal correlations exist. Until and unless this has been diagnosed, no convincing conclusion for independence of price changes can be offered. Motivated by the above concern, a number of studies have questioned the validity of inferences on market efficiency drawn from autocorrelation-based tests, and proceed to conduct a re-examination using statistical tools that are designed to account for nonlinear dependence (see, for example, Al-Loughani and Chappell 1997; Antoniou et al. 1997a; Blasco et al. 1997; Freund et al. 1997; Kohers et al. 1997; Chappel et al. 1998;

Opong et al. 1999; Freund and Pagano 2000; Hamill et al. 2000; Poshakwale 2002; Appiah-Kusi and Menyah 2003; Hassan et al. 2003; Narayan 2005; Panagiotidis 2005).

Finally, all these Chinese studies focus on the all-or-nothing notion of absolute market efficiency, handing down the verdict of whether a market is or is not weak-form efficient for the whole sample period under study. However, it is unreasonable to expect the market to be efficient all the time. Self and Mathur (2006: 3154) write:

The true underlying market structure of asset prices is still unknown. However, we do know that, for a period of time, it behaves according to the classical definition of an efficient market; then, for a period, it behaves in such a way that researchers are able to systematically find anomalies to the behavior expected of an efficient market.

On the other hand, Emerson et al. (1997) argue that it is not sensible to test market efficiency in its absolute sense for stock markets in Central and Eastern European transition economies that have just emerged out of the former communist bloc. This is because it takes time for the price discovery process to become known, the market microstructures to develop, and market participants to become more experienced. Hence, the more relevant research question is whether and how these infant markets are becoming more efficient. Unfortunately, this cannot be answered by classical steady-variable approaches that assume a fixed level of market efficiency throughout the estimation period. On a theoretical ground, the adaptive markets hypothesis (AMH) of Lo (2004, 2005) hypothesises that market efficiency is not an all-or-none condition but is a characteristic that varies continuously over time and across markets, which is likely the result of institutional changes in the stock markets as well as the entry and exit of various market participants.

Motivated by the above concern, Emerson et al. (1997) track the changing degree of market efficiency over time by using a state space model. In their proposed framework, the time-varying autoregressive coefficients are used to gauge the changing degree of predictability, and hence evolving weak-form market efficiency. If the market under study becomes more efficient over time, the smoothed time-varying estimates of the autocorrelation coefficient would gradually converge towards zero and become insignificant. The framework, formalised by Zalewska-Mitura and Hall (1999) as a 'Test for Evolving Efficiency', is subsequently adopted to assess the evolution of

efficiency for stock markets in Central and Eastern European transition economies (Zalewska-Mitura and Hall 2000; Rockinger and Urga 2000, 2001), China (Li, 2003a, 2003b), Africa (Jefferis and Smith 2004, 2005), and Jordan (Maghyereh 2005). Though the time-varying framework proposed by Emerson et al. (1997) has relaxed the assumption of static equilibrium, the focus is still limited to linear correlations. In this regard, the statistical inferences drawn from Li (2003a, 2003b) for the Chinese stock markets should be met with scepticism. On one hand, the evidence of significant autocorrelation coefficients during certain time periods could be spurious return autocorrelation induced by thin trading and leads to incorrect verdict on market inefficiency, since no adjustment procedure is adopted by the author to purge the thin trading effect. For instance, Li (2003a) attributes the high predictability reported for both Shanghai and Shenzhen stock returns during the earlier stages of development to market inefficiency as well as market illiquidity. On the other hand, for those periods with no evidence of linear predictability, the possibility that the underlying returns series are nonlinearly dependent could not be ruled out.

3. An Overview of the Research Framework

It is clear then from our literature review that predictability is assumed by earlier Chinese efficiency studies to take the form of linear correlations, and market efficiency is a static characteristic that remains unchanged over the entire estimation period. However, with the availability of advanced statistical tests, these two assumptions have been found to be inappropriate. Methodologically, in examining the efficiency of a stock market, the research framework adopted should: (1) mitigate the confounding effect of thin trading on return autocorrelation; (2) detect both linear and nonlinear serial dependencies; (3) capture the persistence of deviation from a random walk over time.

While adjustment procedures to correct for spurious return autocorrelation due to thin trading are available in existing literature, they are only by a handful of efficiency studies (Antoniou et al. 1997a, 1997b; Abraham et al. 2002; Appiah-Kusi and Menyah 2003; Hassan et al. 2003; Al-Khazali et al. 2007; Rayhorn et al. 2007). The methodology adopted in this article to deal with the problem of thin trading is proposed by Miller et al. (1994). Briefly, the analysis in Miller et al. (1994) demonstrates utilised that the observed price changes can be adjusted by $(1 - \phi)$ to remove the impact of thin trading in the calculation of returns, where the parameter ϕ measures

the degree of trading infrequency. In applying their model to index returns, a moving average (MA) model where the number of moving average components is equal to the number of non-trading days should be estimated (Miller et al. 1994: 507–10). However, given the difficulties in identifying the non-trading days, the authors showed that it is equivalent to estimating an autoregressive (AR) model of order one, and the residuals from such a model are scaled up by $(1 - \phi)$ to remove the impact of thin trading in the returns calculation.

To detect both linear and nonlinear serial dependencies in the returns series, we employ two test statistics proposed by Hinich and Patterson (1995, 2005). The first one is a portmanteau correlation test statistic, denoted as the *C* statistic, which is a modified version of the Box-Pierce *Q*-statistic. Unlike the *Q*-statistic that is usually applied to the residuals of a fitted autoregressive moving average (ARMA) model, the *C* statistic is a function of the standardized observations and the number of lags used depends on the sample size. Despite these differences, both the *Q* and *C* statistics perform the same function, that is, to detect the presence of linear dependence in the form of significant autocorrelations or known as second-order correlations. The second test statistic is the portmanteau bicorrelation test statistic denoted as the *H* statistic, which is a third-order extension of the standard correlation test for white noise. The orientation for this test is based on the premise that the bicorrelations should all be equal to zero if a time series is generated by a linear Gaussian process. Conversely, if a process generating a time series has non-zero bicorrelations, then the process is nonlinear. Hence, the portmanteau bicorrelation test relies on the zero bicorrelation property of linear process to test for the presence of nonlinear serial dependence, and the *H* statistic is able to pick up many types of nonlinearity in the conditional mean that generate third-order nonlinear dependence. On the other hand, this nonlinearity test is the preferred choice for two reasons. First, it has good small-sample properties (Hinich and Patterson 1995, 2005; Hinich 1996). Second, the test suggests an appropriate functional form for a nonlinear forecasting equation. In particular, Brooks and Hinich (2001) demonstrated via their proposed univariate bicorrelation forecasting model that the bicorrelations can be used to forecast the future values of the series under consideration. Given the possibility that serial dependencies, linear and nonlinear, detected in the full sample could actually be triggered by those strong significant results in a few sub-periods, both the *C* and *H* statistics are computed in non-overlapped moving sub-samples or known as time windows.

4. The Stock Market Data and Methodologies

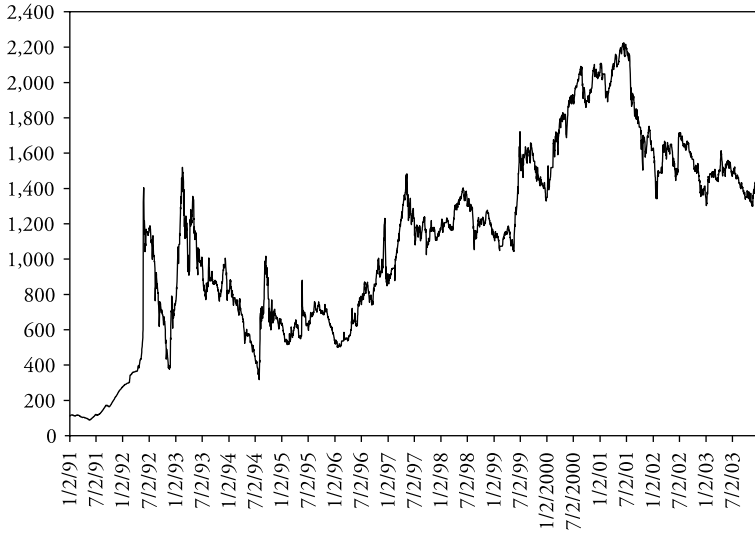
4.1 Data description

In China, a local firm can issue two different classes of shares to be traded on SHSE or SZSE, but cross-listing of shares at the two official exchanges is not permitted.⁶ The A-shares, denominated and traded in Chinese currency, are restricted to domestic investors. On the other hand, the B-shares, also denominated in Renminbi, are traded in foreign currency (U.S. dollars in Shanghai and Hong Kong dollars in Shenzhen) and restricted to foreign investors. However, the Chinese government has gradually relaxed the share tradability restriction. Since 19 February 2001, local investors with foreign currency accounts are allowed to trade the B-shares, while trading of A-shares is opened to international institutional investors in December 2002 under the Qualified Foreign Institutional Investor (QFII) scheme. According to China Securities Regulatory Commission (CSRC), of the 1,378 listed companies on both stock exchanges as at September 2004, 1,238 listed companies offered only A-shares, while 24 firms issued B-shares only. There were 86 firms that issued both A- and B-shares to domestic and foreign investors respectively. In terms of market capitalisation and the level of activity, A-shares dominated the Chinese stock markets, and B-shares have been illiquid and less active since inception.

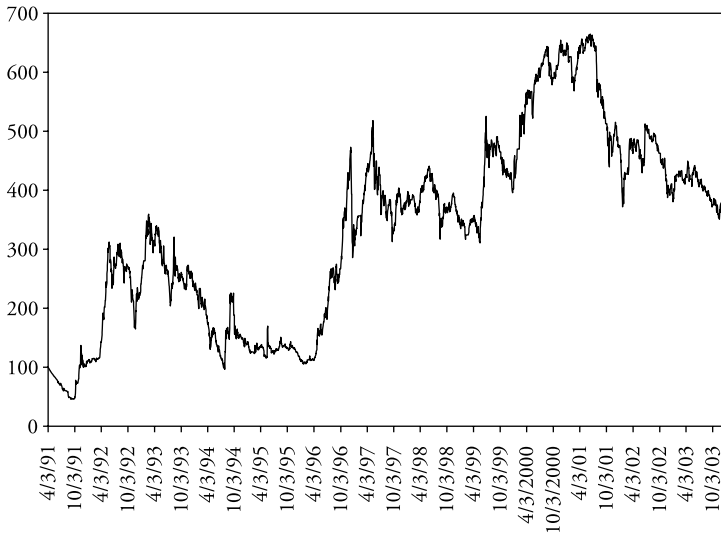
The data in this study consist of daily closing prices for Shanghai SE Composite Price Index and Shenzhen SE Composite Price Index, covering the sample period from the earliest available date in *Datastream* database (Shanghai—2 January 1991; and Shenzhen—3 April 1991) to 31 December 2003. These indices are price-weighted series of all listed stocks on the two exchanges, excluding dividends. The base value of the Shanghai SE Composite Price Index is 100 points in December 1990 while the base date for Shenzhen SE Composite Price Index is April 1991. The time series plots in Figure 1 illustrate the evolution of these two Chinese stock market indices over the selected sample period. In our empirical analysis, the index data are transformed into a series of continuously compounded percentage returns,

⁶ Chinese firms with approval from the government may list their shares on foreign stock exchanges as H-shares. At the end of September 2004, there were 104 H-shares traded in the U.S., U.K., Singapore and Hong Kong, with Hong Kong Stock Exchange the preferred venue. Of these, 29 firms had A-shares counterparts listed on the Chinese domestic stock exchanges.

Figure 1
Time Series Plots for Chinese Stock Market Indices
Shanghai SE Composite Price Index



Shenzhen SE Composite Price Index



$R_t = 100 * \ln(p_t/p_{t-1})$ where p_t is the closing price of the index on day t , and p_{t-1} the price on the previous trading day.

A close inspection of Figure 1 reveals that the two time series plots are mirror reflection of each other, indicating that the Shanghai SE Composite Price Index moves hand-in-hand with its Shenzhen counterpart. Even more striking is that the peaks and troughs in both indices occur around the same time. It could be that their movements are driven by the same underlying factors, as discussed in great detail by Groenewold et al. (2004: 9–25). Several notable accounts are quoted and presented here: (1) The double-digits economic growth and high inflation rate in year 1992 have boosted trading in the two Chinese stock exchanges. The Shanghai SE Composite Price Index peaked at 1536.82 on 15 February 1993, while the Shenzhen SE Composite Price Index reached its peak of 359.44 on 22 February 1993, as compared to their base values of 100 in December 1990 and April 1991 respectively; (2) Prior to 1994, the state banks were dominant in share trading. However, banks were required to quit their direct involvement in the stock markets in 1994. Consequently, bank stock-broking departments and subsidiaries became independent broker houses. The withdrawal of large sums of funds by the state banks from both stock exchanges and the government's anti-inflation measures led directly to the share market stagnation between early 1994 to April 1996. During this period, the composite indices in both exchanges reached their respective troughs on 29 July 1994, with Shanghai SE Composite Price Index bottomed at 333.92 and Shenzhen SE Composite Price Index fell to 96.56; (3) From April 1996, the two Chinese stock exchanges enjoyed a strong rally, only to be halted by the 'Black Monday' on 16 December 1996 due to the disclosure of illicit speculation by the Shenzhen Development Bank. Apart from punishing the offenders, the government also took several measures to reduce the overheating of the markets. As a result, both the Shanghai and Shenzhen composite stock indices fell dramatically; (4) Chinese stock markets experienced booming period from year 2000 onwards until mid of 2001 due to investor confidence in the Chinese economy. China's admission into the World Trade Organization, the establishment of a venture capital market in both stock exchanges, the entry of pension funds into the stock market, and the lifting of share tradability restriction that allows local investors to trade the B-shares, are

among those factors identified to be responsible for the bullish trading during this period. The strong investor sentiment has pushed the two composite stock indices upward to reach the highest point in their history on 13 June 2001, with 2242.42 points for Shanghai SE Composite Price Index, and 664.85 points recorded for Shenzhen SE Composite Price Index; (5) The strong rally in both exchanges was reversed when the government implemented the state share reduction in July 2001 to solve the non-tradable share problem. Since then, both the Shanghai and Shenzhen stock markets never recovered to their previous peaks but experienced great fluctuations due to the uncertainty surrounding the state share reduction scheme.

4.2 Adjustment procedure for thin trading

The methodology adopted here to deal with the problem of thin trading is proposed by Miller et al. (1994) and followed by Antoniou et al. (1997a, 1997b), Appiah-Kusi and Menyah (2003), Hassan et al. (2003), Al-Khazali et al. (2007) and Rayhorn et al. (2007). Specifically, this model involves estimating the following equation:

$$R_t = \alpha_0 + \varphi R_{t-1} + e_t \quad (1)$$

where R_t is the returns on day t , R_{t-1} the returns on the previous trading day, α_0 and φ are parameters to be estimated, and e_t are the residuals.

The residuals e_t and parameter φ from Equation (1) are then used to estimate the adjusted returns as follows:

$$R_t^{adj} = \frac{e_t}{(1 - \varphi)} \quad (2)$$

where R_t^{adj} is the return at time t , adjusted for thin trading.

The above model assumes that the non-trading adjustment is constant throughout the estimation period. However, Antoniou et al. (1997a, 1997b) argue that this assumption is realistic only for highly liquid developed markets. In the context of emerging stock markets that went through structural changes, it is more likely that the required adjustment will vary through time. To account for this possibility, Equation (1) is estimated recursively to obtain residuals used to calculate the adjusted returns in Equation (2).

4.3 The portmanteau C and H statistics in non-overlapped moving time windows

The research framework adopted in this study is first proposed by Hinich and Patterson (1995), later published as Hinich and Patterson (2005), to detect epochs of transient dependence in a discrete-time pure white noise process. In the literature, this approach has been widely applied on financial time series data (see references cited in Lim et al. 2006). Let the sequence $\{y(t)\}$ denote the observed sampled data process, where the time unit t is an integer. The test procedure employs equal-length non-overlapped time windows, thus if n is the window length, then the k -th window is $\{y(t_k), y(t_k + 1), \dots, y(t_k + n - 1)\}$. The next non-overlapped window is $\{y(t_{k+1}), y(t_{k+1} + 1), \dots, y(t_{k+1} + n - 1)\}$ where $t_{k+1} = t_k + n$.

The data in each time window is standardised to have a sample mean of zero and a sample variance of one by subtracting the sample mean of the window and dividing by its standard deviation in each case. Define $Z(t)$ as the standardised observations that can be written as:

$$Z(t) = \frac{y(t) - m_y}{s_y} \quad (3)$$

for each $t = 1, 2, \dots, n$ where m_y and s_y are the sample mean and sample standard deviation of the window.

The null hypothesis for each time window is that the transformed data $\{Z(t)\}$ are realisations of a stationary pure white noise process. Thus, under the null hypothesis, the correlation coefficients $C_{ZZ}(r) = E[Z(t)Z(t+r)] = 0$ for all $r \neq 0$, and the biconrelation coefficients $C_{ZZZ}(r,s) = E[Z(t)Z(t+r)Z(t+s)] = 0$ for all r, s except when $r = s = 0$.⁷ The alternative hypothesis is that the process in the window has some non-zero correlations or biconrelations in the set $0 < r < s < L$, where L is the number of lags that define the window. In other words, if there exists second-order linear or third-order nonlinear dependence in the data generating process, then $C_{ZZ}(r) \neq 0$ or $C_{ZZZ}(r,s) \neq 0$ or for at least one r value or one pair of r and s values respectively.

⁷ Briefly, if the correlation is equal to zero for all $r \neq 0$, then the series is white noise. It is important to note that all pure white noise series is white, but the converse is not true unless the series is Gaussian. Hinich and Patterson (1985: 70) blame Jenkins and Watts (1968) and Box and Jenkins (1970) for blurring the definitions of whiteness and independence. In particular,

The r sample correlation coefficient is:

$$C_{ZZ}(r) = (n-r)^{-\frac{1}{2}} \sum_{t=1}^{n-r} Z(t)Z(t+r) \quad (4)$$

The C statistic, which is developed to test for the existence of non-zero correlations (i.e. linear dependence) within a window, and its corresponding distribution are:

$$C = \sum_{r=1}^L [C_{ZZ}(r)]^2 \sim \chi^2_L \quad (5)$$

The (r, s) sample bicornelation coefficient is:

$$C_{ZZZ}(r, s) = (n-s)^{-1} \sum_{t=1}^{n-s} Z(t)Z(t+r)Z(t+s) \quad \text{for } 0 \leq r \leq s \quad (6)$$

The H statistic, which is developed to test for the existence of non-zero bicornelations (that is, nonlinear dependence) within a window, and its corresponding distribution are:

$$H = \sum_{s=2}^L \sum_{r=1}^{s-1} G^2(r, s) \sim \chi^2_{L(L-1)/2} \quad (7)$$

where $G(r, s) = \frac{1}{(n-s)^2} C_{ZZZ}(r, s)$

For both the C and H statistics, the number of lags L is specified as $L = n^b$ with $0 < b < 0.5$ where b is a parameter under the choice of the user. All lags up to and including L are used to compute the correlations

many early investigators implicitly assumed that observed time series is Gaussian and test for white noise using the correlation structure, hence ignoring the information regarding possible nonlinear relationships that are found in the bicornelations. This concern is well directed given that the assumption of Gaussianity is rather restrictive for financial time series, and the bicornelations are in general not zero for a non-Gaussian white noise series (see Hinich and Patterson 1985, for a specific example).

and b correlations in each window. Based on the results of Monte Carlo simulations, Hinich and Patterson (1995, 2005) recommended the use of $b = 0.4$ which is a good compromise between (1) using the asymptotic result as a valid approximation for the sampling properties of H statistic for moderate sample sizes, and (2) having enough sample b correlations in the statistic to have reasonable power against non-independent variates.

Another element that must be decided upon is the choice of the window length. In fact, there is no unique value for the window length. The larger the window length, the larger the number of lags and hence the greater the power of the test, but it increases the uncertainty on the event time when the serial dependence occurs. As noted by Brooks and Hinich (1998), the window length should be sufficiently long to provide adequate statistical power and yet short enough for the test to be able to pinpoint the arrival and disappearance of those transient dependencies. In this study, the data are split into a set of equal-length non-overlapped moving time windows of 31 observations, so as to minimise the loss of observations at the end of the sample. This gives a total of 109 windows for the adjusted returns series of Shanghai SE Composite Price Index and 107 windows for the Shenzhen data. In the case of Shanghai, the first window starts from 8 January 1991 and ends on 19 February 1991, second window runs from 20 February 1991 to 3 April 1991, third window is 4 April 1991 to 16 May 1991, and so on. For Shenzhen, the period 9 April 1991 to 21 May 1991 falls in the first window, second window covers 22 May 1991 to 3 July 1991, and the remaining windows move in a similar manner until the end of the sample.

Both the C and H statistics for each window in this study are computed using the T23 program.⁸ Instead of reporting the test statistics as chi-square variates, the program transforms the computed statistics to p -values based on the appropriate chi square cumulative distribution value, which indicates the lowest significance level at which the null hypothesis can be rejected. If the p -value for the C statistic in a particular window is sufficiently low, then one can reject the null hypothesis of pure white noise that has zero correlation, indicating the presence of linear dependence in that window. In a similar vein, a rejection of the null hypothesis by the H statistic suggests the presence of non-zero b correlations or nonlinear dependence in that particular window.

⁸The T23 program written by Melvin J. Hinich can be downloaded from his webpage at <http://web.austin.utexas.edu/hinich/>.

In the present study, a window is defined as significant if either the C or H statistic rejects the null hypothesis of pure white noise at the specified threshold level (cut-off point) for the p -value, which is set at 1 per cent in our empirical analysis. In other words, the null hypothesis is rejected when the p -value of the test statistic is less than or equal to the threshold level of 0.01. We use a strict threshold so that only the most extreme deviations from this null hypothesis are flagged. Hence, if the serial dependencies are present in the data but are not particularly strong, it may not be possible for them to generate a large test statistic to cross this threshold, in which case they will remain undetected.

Given that the distributions for both the C and H statistics hold asymptotically, resampling with replacement that satisfies the null hypothesis of pure white noise is used to determine a threshold level for the p -value that has a test size of 1 per cent (for descriptions of the resampling method, see Hinich and Serletis 2007). For the Shanghai data, the bootstrapped threshold levels for the p -values of the C and H statistics are 0.0321 and 0.00948 respectively. In the case of Shenzhen, the bootstrapped thresholds are 0.0305 (C statistic) and 0.0144 (H statistic). Hence, the null hypothesis in each window is rejected when the p -value of the C or H statistic is less than or equal to the above bootstrapped threshold that corresponds to our earlier specified nominal level of 0.01.

5. Empirical Results

5.1 Descriptive statistics

Table 1 provides the descriptive statistics for both the returns and adjusted returns series after correcting for thin trading. Looking at the mean values, the thin trading adjustment has resulted in negative average daily returns of -0.10 per cent and -0.02 per cent for both the SHSE and SZSE, respectively, though the magnitudes are not large. In general, the adjustment procedure does not alter the distribution of both the returns and adjusted returns series. For instance, all series, both before and after adjustment, exhibit some degree of right-skewness, and are highly leptokurtic in which the tails of their respective distributions taper down to zero more gradually than do the tails of a normal distribution. Given the non-zero skewness levels and excess kurtosis, the Jarque-Bera (JB) test statistic strongly rejects the null of normality for all series. It is worth highlighting that the analysis in subsequent section is performed only on the adjusted returns series.

Table 1
Descriptive Statistics

	<i>SHSE</i>		<i>SZSE</i>	
	<i>Returns</i>	<i>Adjusted Returns</i>	<i>Returns</i>	<i>Adjusted Returns</i>
Mean	0.0724	-0.0982	0.0400	-0.0206
Median	0.0000	-0.0871	0.0000	-0.0558
Maximum	71.9152	72.2043	27.2152	28.1306
Minimum	-17.9051	-21.9904	-23.3607	-23.1099
Std deviation	2.7816	2.9214	2.4895	2.5737
Skewness	6.1133	5.3515	0.9104	0.7973
Kurtosis	146.6914	126.9417	20.6845	20.8175
JB normality test	2937535	2184064	43787.23	44293.99
statistic(<i>p</i> -value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

5.2 Detecting epochs of linear and nonlinear serial dependencies

This section proceeds to detect brief periods of deviation from a random walk for both stock exchanges. With a window length of 31 observations, four lags are used to compute the correlations and bicorrelations in each window. As elaborated in earlier section, the research framework looks for those windows in which the time series exhibit behaviour that departs significantly from the null hypothesis of pure white noise in terms of linear serial dependence (significant correlations detected by the *C* statistic) or nonlinear serial dependence (significant bicorrelations detected by the *H* statistic). The results are summarised in Table 2, highlighting those windows where non-zero correlations or bicorrelations are detected by the portmanteau test statistics. For the Shanghai data, the null hypothesis is rejected by the *C* statistic in seven windows, which is equivalent to 6.42 per cent of the total windows in our sample. On the other hand, the presence of strong non-zero bicorrelations has triggered the rejection of the null hypothesis by the *H* statistic in eight windows (7.34 per cent). In the case of Shenzhen, the total numbers of significant *C* and *H* windows are three (2.80 per cent) and seven (6.54 per cent), respectively. As a whole, these findings reveal that the adjusted returns series for both indices follow a random walk for long periods of time, only to be interspersed with brief periods of strong linear and/or nonlinear dependency structures. It is worth noting that in all cases, nonlinear dependence in the adjusted returns series occurs more frequently than the linear correlations, and hence should not be discarded when examining the weak-form efficiency of a stock market.

Table 2
Correlation and Bicorrelation Tests in Moving Time Windows

	<i>SHSE_ADR</i>	<i>SZSE_ADR</i>
Total number of windows	109	107
Total number of significant <i>C</i> windows	7	3
Dates of significant <i>C</i> windows	4/4/91–5/16/91 (0.0086) 2/3/92–3/16/92 (0.0197) 10/10/95–11/21/95 (0.0241) 12/17/96–1/28/97 (0.0075) 1/29/97–3/12/97 (0.0075) 9/10/99–10/22/99 (0.0175) 10/5/00–11/16/00 (0.0202)	3/3/93–4/14/93 (0.0191) 9/25/96–11/6/96 (0.0227) 10/10/00–11/21/00 (0.0167)
Total number of significant <i>H</i> windows	8	7
Dates of significant <i>H</i> windows	4/4/91–5/16/91 (0.0000) 9/7/92–10/19/92 (0.0002) 10/27/94–12/8/94 (0.0022) 4/1/96–5/13/96 (0.0025) 1/29/97–3/12/97 (0.0077) 9/3/97–10/15/97 (0.0064) 9/10/99–10/22/99 (0.0000) 12/7/99–1/18/00 (0.0005)	9/30/91–11/11/91 (0.0109) 12/31/93–2/11/94 (0.0007) 2/21/96–4/3/96 (0.0010) 4/4/96–5/16/96 (0.0000) 9/8/97–10/20/97 (0.0102) 9/15/99–10/27/99 (0.0006) 12/10/99–1/21/00 (0.0021)
Total number of significant <i>C</i> and <i>H</i> windows	12	10
Dates of significant <i>C</i> and <i>H</i> windows	4/4/91–5/16/91 2/3/92–3/16/92 9/7/92–10/19/92 10/27/94–12/8/94 10/10/95–11/21/95 4/1/96–5/13/96 12/17/96–1/28/97 1/29/97–3/12/97 9/3/97–10/15/97 9/10/99–10/22/99 12/7/99–1/18/00 10/5/00–11/16/00	9/30/91–11/11/91 3/3/93–4/14/93 12/31/93–2/11/94 2/21/96–4/3/96 4/4/96–5/16/96 9/25/96–11/6/96 9/8/97–10/20/97 9/15/99–10/27/99 12/10/99–1/21/00 10/10/00–11/21/00

Notes: *SHSE_ADR*—Adjusted returns series for Shanghai SE Composite Price Index.
SZSE_ADR—Adjusted returns series for Shenzhen SE Composite Price Index.
 Values in parentheses indicate the *p*-values of the test statistics.

Another important implication is that statistical tests employed should be capable of uncovering epochs of transient temporal dependence. This would facilitate researchers to identify those events in which their impacts

are only grasped over a period of time by investors, instead of instantaneous responses advocated by the classical EMH (see Brooks et al. 2000; Rockinger and Urga 2000; Ammermann and Patterson 2003; Li 2003a; Lim et al. 2006). Nawrocki (1996) hypothesises that economic events are important in generating temporal dependence in the stock market.⁹ While his empirical investigation focuses on autocorrelation coefficient, the conjecture applies equally to the formation of nonlinear dependence. For instance, Hinich and Serletis (2007) postulated that when surprises hit the market, the adjustment process generally generates a pattern of nonlinear price movements relative to previous movements, because the traders are unsure of how to react and hence they respond slowly. Given that informational events are hypothesised to be a source of temporal dependence, Table 2 provides the time periods during which these linear and nonlinear dependencies occur so that future study could identify the major events that contribute to these gradual market reactions.

Unlike the focus of most conventional efficiency studies, returns predictability in the present framework accommodates both linear and nonlinear dependencies detected via the C and H statistics respectively. Hence, plotting both test statistics in a single graph would provide a better view of the occurrence of serial dependencies over time. For clarity, Figures 2 and 3 plot only those significant C and H windows, while insignificant windows are omitted. The horizontal axis shows the time window, while the vertical axis is the percentile (that is, one minus the p -value) for the portmanteau test statistics. Thus, a very significant window is plotted as a value near 1.0. The dates these series depart from pure white noise either due to significant C or H statistics or both are provided in the final panel of Table 2. Figures 2 and 3 clearly demonstrate that the adjusted returns for both series follow a pure white noise process for long periods of time, only to be interspersed with brief periods of strong linear and/or nonlinear dependency structures. In the case of Shanghai, the series move in a significantly non-random and dependent

⁹The sources of index return autocorrelations are still very much debated in existing literature (see Ahn et al. 2002). One of the explanations given is it reflects delayed price adjustment to the arrival of new information. In fact, several papers have developed formal speed of adjustment estimators to gauge the speed with which new information is reflected in stock prices (see, for example, Amihud and Mendelson 1989; Damodaran 1993; Theobald and Yallup 1998, 2004). These estimators are functions of autocorrelations since both price under- and over-reactions would induce particular autocorrelation patterns into the return series.

Figure 2
 Significant *C* and *H* Windows for Adjusted Returns Series of SHSE

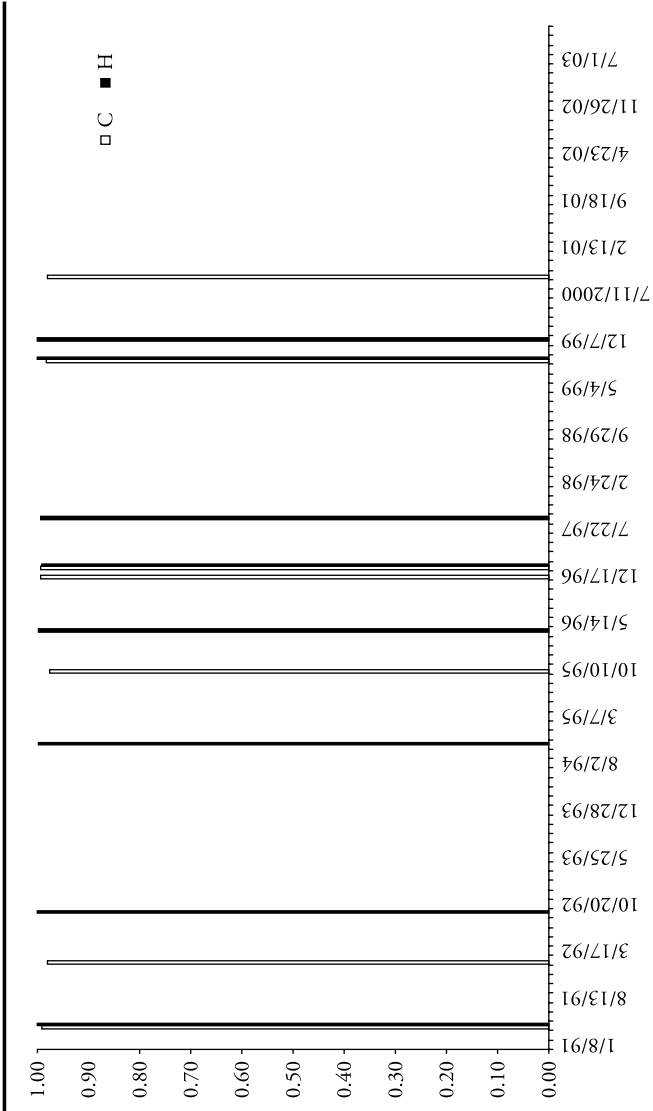
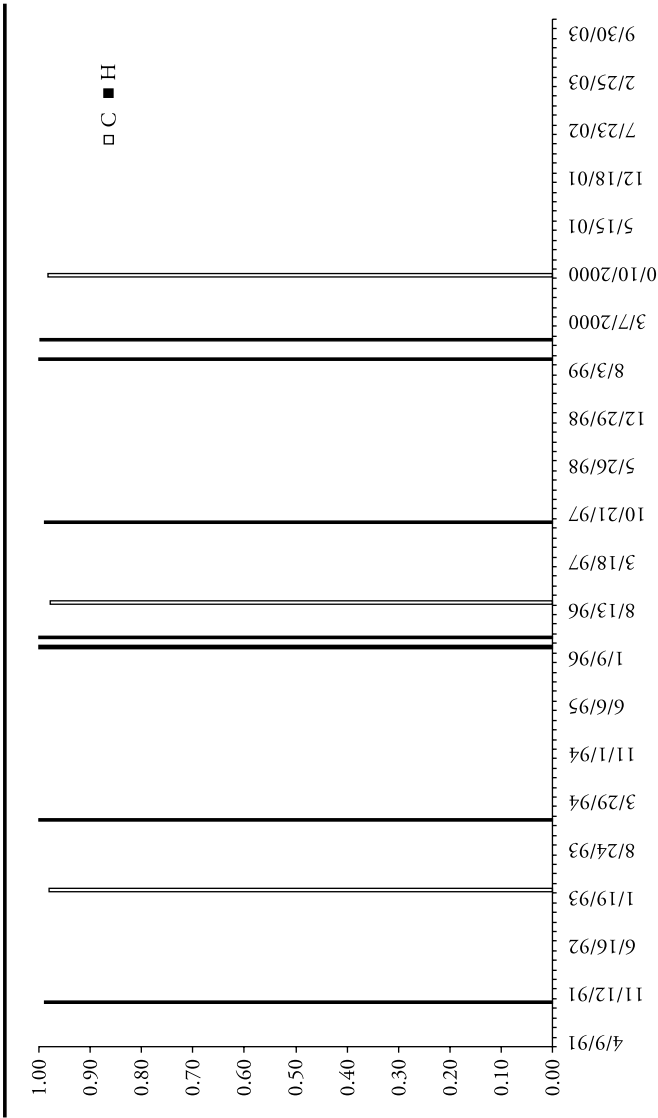


Figure 3
 Significant *C* and *H* Windows for Adjusted Returns Series of SZSE



pattern in only 12 out of a total 109 time windows, which is equivalent to 11.01 per cent. Similarly, serial dependencies are detected in only 9.34 per cent of the total windows for Shenzhen data. This suggests that both stock exchanges in China are efficient most but not all the time, as strong evidence of episodic serial dependencies indicates delayed price adjustment to the arrival of new information during those identified sub-periods.

A careful examination of Figure 2 reveals that serial dependence is detected as early as the first sub-period of 4/4/1991–5/16/1991 for the adjusted returns series of Shanghai SE Composite Price Index. However, these dependency structures disappear in subsequent time windows, only to re-emerge in 1992 (2/3/92–3/16/92 and 9/7/92–10/19/92). This finding is in contrast to those conducted by Li (2003a) who finds a higher degree of predictability at the early stage of market development up to early 1993. The latter attributes such predictability partly to market illiquidity. This apparent contradiction is not surprising as our analysis utilizes returns series that have been corrected for the effects of thin trading. Specifically, spurious return autocorrelation brought about by thin trading documented in Li (2003a) have been removed through the adjustment procedure and hence the magnitude of serial correlations in the adjusted returns series is substantially reduced. The Shanghai stock market enjoys two years of quiescent period following that, with no significant serial dependence been detected from 10/20/1992–10/26/1994. This relatively long period of market efficiency is again attained during 10/16/1997–9/9/1999 and 11/17/2000–12/31/2003. Between those years, the dependency structures appear sporadically with their behaviour being characterised as episodic.

Figure 3 reveals that serial dependencies in the Shenzhen data exhibit similar episodic behaviour over the whole sample period. The Shenzhen Stock Exchange also enjoys three long periods of market efficiency with each covering more than two years during 2/12/1994–2/20/1996, 10/21/1997–9/14/1999 and 11/22/2000–12/31/2003. It is worth highlighting that SHSE also attains efficiency during the last two sub-periods. In fact, after October 1997, Shenzhen Stock Exchange seems to move hand-in-hand with its Shanghai counterpart. Even the existence of serial dependencies occurs around the same time period (SHSE: 9/10/1999–10/22/1999, 12/7/1999–1/18/2000, 10/5/2000–11/16/2000; SZSE: 9/15/1999–10/27/1999, 12/10/1999–1/21/2000, 10/10/2000–11/21/2000). This is not surprising given our earlier observation in Figure 1 that the movements in both indices follow one another closely, mainly due to the fact that they are driven by the

same underlying factors. This is consistent with the argument of Li (2003a: 356) that the two markets are after all in the same country and subjected to the influence of the same political, economic, social and institutional changes. Another interesting observation is that after October 1997, the significant dependency structures in both markets appear less frequent. This improved market efficiency can be attributed to a series of regulations and laws promulgated and enforced by the Chinese authorities during the third development stage (Li 2003a: 355).

The present findings provide some plausible explanations to the contradicting evidence documented in earlier studies for both stock exchanges using similar aggregate price indices. For instance, the unit root test results of Liu et al. (1997) find that both markets are efficient for the period of 5/21/1992–12/18/1995. However, a closer inspection of Figures 2 and 3 reveals that predictable patterns do exist during this sample period. The failure of the unit root test is due to two reasons: firstly, the test is not capable of detecting nonlinearity in the underlying series; secondly, the short burst of linear serial correlations is not strong enough to cause a rejection in the null hypothesis of the ADF unit root test. Moreover, the unit root test is not designed to detect predictability (Campbell et al. 1997). In contrast, Mookerjee and Yu (1999) find that both the SHSE and SZSE are inefficient for the sample period 12/19/1990–12/17/1993 and 4/3/1991–12/17/1993, respectively. Their inefficiency finding is not surprising as Table 2 shows that the *C* statistic detects significant linear dependence during the above sub-periods. With regard to the conflicting evidence documented in the literature, some authors (Groenewold et al. 2003, Ma 2004) argued that examining efficiency over the largest possible sample sizes might be able to clarify some of the ambiguity. However, this will not be the best solution given the episodic occurrence of serial dependencies, which would go undetected in full sample analysis.

6. Conclusion

Earlier Chinese efficiency studies assumed that deviation from a random walk is in the form of linear serial correlations, and market efficiency is a static characteristic that remains unchanged over the entire estimation period. The inference drawn from autocorrelation-based tests is on shaky ground due to two major criticisms: (1) evidence of significant return autocorrelation could be the result of thin trading that characterises most emerging stock markets;

(2) the lack of linear correlations does not necessarily imply efficiency as returns series can be linearly uncorrelated and at the same time nonlinearly dependent. On the other hand, it is unreasonable to expect the stock market to be efficient all the time. Given the shortcomings of prior studies, the present paper reexamines the weak-form efficiency of two Chinese stock markets located in Shanghai and Shenzhen. The methodology proposed by Miller et al. (1994) is adopted to address the issue of spurious return autocorrelation induced by thin trading, while the test statistics proposed by Hinich and Patterson (1995, 2005) are computed in non-overlapped moving sub-samples to detect the persistence of linear and nonlinear serial dependencies over time.

Our main findings can be summarised as follows. Firstly, after correcting for thin trading, there is still evidence of serial correlations in the adjusted returns series for both markets. Secondly, nonlinear dependence occurs more frequently than the linear correlations, justifying the need to test for nonlinearity when examining the weak-form efficiency of a stock market. Thirdly, the two Chinese markets are found to be efficient most but not all the time. Specifically, their adjusted returns series follow a random walk for long periods of time, only to be interspersed with brief periods of strong linear and/or nonlinear dependency structures. This suggests that there are certain time periods when new information is not fully reflected into stock prices. Though this piece of evidence taken as a whole does not represent an outright rejection of the weak-form EMH, to view market efficiency as a continuous variable consistent with the reported empirical results, the adaptive markets hypothesis is a better framework.

Another interesting finding is that the existence of serial dependencies in both the Shanghai and Shenzhen Stock Exchanges follows one another closely after October 1997. It suggests that both markets respond in a similar way to influences from political, economic, social and institutional changes. In line with our *a priori* expectation, we do find frequent short bursts of significant serial dependencies in the earlier stages of market development, but they appear less frequent when the market matures over time. This can be attributed to a series of regulations and laws promulgated and enforced by the market regulators during the third development stage (Li 2003a: 355). However, the issue of whether the legal environment of a country matters for stock market efficiency requires further empirical investigations, which is made possible with data provided by the law and finance literature (see La Porta et al. 1998). Specifically, this would require extending the present

framework to a broad cross-section of countries and then explore the determinants for these cross-country differences in the total number of windows with significant serial dependencies. Besides market regulations, other potential determinants with accessible country-level data are the degree of stock market development, market liquidity, returns volatility and the extent of stock market openness.

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REFERENCES

- Abraham, A., F.J. Seyyed and S.A. Alsakran** (2002), 'Testing the Random Walk Behavior and Efficiency of the Gulf Stock Markets', *Financial Review*, 37(3): 469–80.
- Ahn, D.H., J. Boudoukh, M. Richardson and R.F. Whitelaw** (2002), 'Partial Adjustment or Stale Prices: Implications from Stock Index and Futures Return Autocorrelations', *Review of Financial Studies*, 15(2): 655–89.
- Al-Khazali, O.M., D.K. Ding and C.S. Pyun** (2007), 'A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit', *Financial Review*, 42(2): 303–17.
- Al-Loughani, N. and D. Chappell** (1997), 'On the Validity of the Weak-form Efficient Markets Hypothesis Applied to the London Stock Exchange', *Applied Financial Economics*, 7(2): 173–76.
- Amihud, Y. and H. Mendelson** (1989), 'Index and Index-futures Returns', *Journal of Accounting, Auditing and Finance*, 4(4): 415–31.
- Ammermann, P.A. and D.M. Patterson** (2003), 'The Cross-sectional and Cross-temporal Universality of Nonlinear Serial Dependencies: Evidence from World Stock Indices and the Taiwan Stock Exchange', *Pacific-Basin Finance Journal*, 11(2): 175–95.
- Andrada-Félix, J., F. Fernandez-Rodríguez, M.D. Garcia-Artiles and S. Sosvilla-Rivero** (2003), 'An Empirical Evaluation of Non-linear Trading Rules', *Studies in Nonlinear Dynamics and Econometrics*, 7(3): Article 4.
- Antoniou, A., N. Ergul and P. Holmes** (1997a), 'Market Efficiency, Thin Trading and Non-linear Behaviour: Evidence from an Emerging Market', *European Financial Management*, 3(2): 175–90.
- Antoniou, A., N. Ergul, P. Holmes and R. Priestley** (1997b), 'Technical Analysis, Trading Volume and Market Efficiency: Evidence from an Emerging Market', *Applied Financial Economics*, 7(4): 361–65.
- Appiah-Kusi, J. and K. Menyah** (2003), 'Return Predictability in African Stock Markets', *Review of Financial Economics*, 12(3): 247–70.

- Bailey, W.** (1994), 'Risk and Return on China's New Stock Markets: Some Preliminary Evidence', *Pacific-Basin Finance Journal*, 2(2-3): 243-60.
- Bailey, W., P. Chung and J.K. Kang** (1999), 'Foreign Ownership Restrictions and Equity Price Premiums: What Drives the Demand for Cross-border Investments?', *Journal of Financial and Quantitative Analysis*, 34(4): 489-511.
- Blasco, N., C.D. Rio and R. Santamaría** (1997), 'The Random Walk Hypothesis in the Spanish Stock Market: 1980-1992', *Journal of Business Finance and Accounting*, 24(5): 667-83.
- Box, G.E.P. and G.M. Jenkins** (1970), *Times Series Analysis, Forecasting and Control*. San Francisco: Holden-Day.
- Brooks, C. and M.J. Hinich** (1998), 'Episodic Nonstationarity in Exchange Rates', *Applied Economics Letters*, 5(11): 719-22.
- (1999), 'Cross-correlations and Cross-bicorrelations in Sterling Exchange Rates', *Journal of Empirical Finance*, 6(4): 385-404.
- (2001), 'Bicorrelations and Cross-bicorrelations as Non-linearity Tests and Tools for Exchange Rate Forecasting', *Journal of Forecasting*, 20(3): 181-96.
- Brooks, C., M.J. Hinich and R. Molyneux** (2000), 'Episodic Nonlinear Event Detection: Political Epochs in Exchange Rates', in D. Richards (ed.), *Political Complexity: Political Epochs in Exchange Rates*, pp. 83-98. Michigan: Michigan University Press.
- Campbell, J.Y., A.W. Lo and A.C. MacKinlay** (1997), *The Econometrics of Financial Markets*. Princeton: Princeton University Press.
- Chappel, D., J. Padmore and J. Pidgeon** (1998), 'A Note on ERM Membership and the Efficiency of the London Stock Exchange', *Applied Economics Letters*, 5(1): 19-23.
- Chen, G., M. Firth and J.B. Kim** (2004), 'IPO Underpricing in China's New Stock Markets', *Journal of Multinational Financial Management*, 14(3): 283-302.
- China Securities Regulatory Commission**, <http://www.csrc.gov.cn/n575458/n4001948/index.html>, accessed 1 December 2006.
- Clyde, W.C. and C.L. Osler** (1997), 'Charting: Chaos Theory in Disguise?', *Journal of Futures Markets*, 17(5): 489-514.
- Damodaran, A.** (1993), 'A Simple Measure of Price Adjustment Coefficients', *Journal of Finance*, 48(1): 387-400.
- Darrat, A.F. and M. Zhong** (2000), 'On Testing the Random-walk Hypothesis: A Model Comparison Approach', *Financial Review*, 35(3): 105-24.
- De Long, J.B., A. Shleifer, L.H. Summers and R.J. Waldmann** (1990), 'Positive Feedback Investment Strategies and Destabilizing Rational Speculation', *Journal of Finance*, 45(2): 379-95.
- Emerson, R., S.G. Hall and A. Zalewska-Mitura** (1997), 'Evolving Market Efficiency with an Application to Some Bulgarian Shares', *Economics of Planning*, 30(2-3): 75-90.
- Fernández-Rodríguez, F., C. González-Martel and S. Sosvilla-Rivero** (2000), 'On the Profitability of Technical Trading Rules based on Artificial Neural Networks: Evidence from the Madrid Stock Market', *Economics Letters*, 69(1): 89-94.
- Freund, W.C., M. Larrain and M.S. Pagano** (1997), 'Market Efficiency before and after the Introduction of Electronic Trading at the Toronto Stock Exchange', *Review of Financial Economics*, 6(1): 29-56.
- Freund, W.C. and M.S. Pagano** (2000), 'Market Efficiency in Specialist Markets before and after Automation', *Financial Review*, 35(3): 79-104.

- Gençay, R.** (1998), 'The Predictability of Security Returns with Simple Technical Trading Rules', *Journal of Empirical Finance*, 5(4): 347–59.
- Girardin, E.** and **Z. Liu** (2003), 'The Chinese Stock Market: A Casino with "Buffer Zones"?', *Journal of Chinese Economic and Business Studies*, 1(1): 57–70.
- Gordon, R.H.** and **W. Li.** (2003), 'Government as a Discriminating Monopolist in the Financial Market: The Case of China', *Journal of Public Economics*, 87(2): 283–312.
- Granger, C.W.J.** and **A.P. Andersen** (1978), *An Introduction to Bilinear Time Series Models*. Göttingen: Vandenhoeck and Ruprecht.
- Groenewold, N., S.H.K. Tang** and **Y. Wu** (2003), 'The Efficiency of the Chinese Stock Market and the Role of the Banks', *Journal of Asian Economies*, 14(4): 593–609.
- Groenewold, N., Y. Wu, S.H.K. Tang** and **X.M. Fan** (2004), *The Chinese Stock Market: Efficiency, Predictability and Profitability*. Cheltenham: Edward Elgar.
- Hamill, P.A., K.K. Opong** and **D. Sprevak** (2000), 'The Behaviour of Irish ISEQ Index: Some New Empirical Tests', *Applied Financial Economics*, 10(6): 693–700.
- Hassan, K.M., W.S. Al-Sultan** and **J.A. Al-Saleem** (2003), 'Stock Market Efficiency in the Gulf Cooperation Council Countries (GCC): The Case of Kuwait Stock Exchange', *Scientific Journal of Administrative Development*, 1(1): 1–21.
- He, Y., C. Wu** and **Y.M. Chen** (2003), 'An Explanation of the Volatility Disparity between the Domestic and Foreign Shares in the Chinese Stock Markets', *International Review of Economics and Finance*, 12(2): 171–86.
- Hinich, M.J.** (1996), 'Testing for Dependence in the Input to a Linear Time Series Model', *Journal of Nonparametric Statistics*, 6(2–3): 205–21.
- Hinich, M.J.** and **A. Serletis** (2007), 'Episodic Nonlinear Event Detection in the Canadian Exchange Rate', *Journal of the American Statistical Association*, 102(477): 68–74.
- Hinich, M.J.** and **D.M. Patterson** (1985), 'Evidence of Nonlinearity in Daily Stock Returns', *Journal of Business and Economic Statistics*, 3(1): 69–77.
- (1995), 'Detecting Epochs of Transient Dependence in White Noise', Mimeo, University of Texas at Austin.
- (2005), 'Detecting Epochs of Transient Dependence in White Noise', in M.T. Belongia and J.M. Binner (eds.), *Money, Measurement and Computation*, pp. 61–75. London: Palgrave Macmillan.
- Jefferis, K.** and **G. Smith** (2004), 'Capitalisation and Weak-form Efficiency in the JSE Securities Exchange', *South African Journal of Economics*, 72(4): 684–707.
- (2005), 'The Changing Efficiency of African Stock Markets', *South African Journal of Economics*, 73(1): 54–67.
- Jenkins, G.M.** and **D. Watts** (1968), *Spectral Analysis and Its Applications*. San Francisco: Holden-Day.
- Kang, J., M.H. Liu** and **S.X. Ni** (2002), 'Contrarian and Momentum Strategies in the China Stock Market: 1993–2000', *Pacific-Basin Finance Journal*, 10(3): 243–65.
- Kohers, T., V. Pandey** and **G. Kohers** (1997), 'Using Nonlinear Dynamics to Test for Market Efficiency among the Major U.S. Stock Exchanges', *Quarterly Review of Economics and Finance*, 37(2): 523–45.
- La Porta, R., F. Lopez-de-Silanes, A. Shleifer** and **R. Vishny** (1998), 'Law and Finance', *Journal of Political Economy*, 106(6): 1113–55.

- Laurence, M., F. Cai and S. Qian** (1997), 'Weak-form Efficiency and Causality Tests in Chinese Stock Markets', *Multinational Finance Journal*, 1(4): 291–307.
- Lee, C.F., G.M. Chen and O.M. Rui** (2001), 'Stock Returns and Volatility on China's Stock Markets', *Journal of Financial Research*, 24(4): 523–43.
- Li, X.M.** (2003a), 'China: Further Evidence on the Evolution of Stock Markets in Transition Economies', *Scottish Journal of Political Economy*, 50(3): 341–58.
- (2003b), 'Time-varying Informational Efficiency in China's A-share and B-share Markets', *Journal of Chinese Economic and Business Studies*, 1(1): 33–56.
- Lim, K.P., M.J. Hinich and R.D. Brooks** (2006), 'Events that Shook the Market: An Insight from Nonlinear Serial Dependencies in Intraday Returns', SSRN Working Paper, available at <http://ssrn.com/abstract=912603>, accessed on 1 December 2006.
- Lima, E.J.A. and B.M. Tabak** (2004), 'Tests of the Random Walk Hypothesis for Equity Markets: Evidence from China, Hong Kong and Singapore', *Applied Economics Letters*, 11(4): 255–58.
- Liu, X., H. Song and P. Romilly** (1997), 'Are Chinese Stock Markets Efficient? A Cointegration and Causality Analysis', *Applied Economics Letters*, 4(8): 511–15.
- Lo, A.W.** (2004), 'The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective', *Journal of Portfolio Management*, 30(5): 15–29.
- (2005), 'Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis', *Journal of Investment Consulting*, 7(2): 21–44.
- Lo, A.W. and A.C. MacKinlay** (1988), 'Stock Market Prices do not Follow Random Walk: Evidence from a Simple Specification Test', *Review of Financial Studies*, 1(1): 41–66.
- (1989), 'The Size and Power of the Variance Ratio in Finite Samples', *Journal of Econometrics*, 40(2): 203–38.
- (1990), 'An Econometric Analysis of Nonsynchronous Trading', *Journal of Econometrics*, 45(1–2): 181–212.
- Long, D.M., J.D. Payne and C. Feng** (1999), 'Information Transmission in the Shanghai Equity Market', *Journal of Financial Research*, 22(1): 29–45.
- Ma, S.** (2004), *The Efficiency of China's Stock Market*. Aldershot: Ashgate.
- Ma, X.** (1996), 'Capital Controls, Market Segmentation and Stock Prices: Evidence from the Chinese Stock Market', *Pacific-Basin Finance Journal*, 4(2–3): 219–39.
- Maghyereh, A.** (2005), 'Electronic Trading and Market Efficiency in an Emerging Market: The Case of the Jordanian Capital Market', *Emerging Markets Finance and Trade*, 41(4): 5–19.
- Miller, M.H., J. Muthuswamy and R.E. Whaley** (1994), 'Mean Reversion of Standard and Poor's 500 Index Basis Changes: Arbitrage-induced or Statistical Illusion?' *Journal of Finance*, 49(2): 479–513.
- Mok, H.M.K. and Y.V. Hui** (1998), 'Underpricing and Aftermarket Performance of IPOs in Shanghai, China', *Pacific-Basin Finance Journal*, 6(5): 453–74.
- Mookerjee, R. and Q. Yu** (1999), 'An Empirical Analysis of the Equity Markets in China', *Review of Financial Economics*, 8(1): 41–60.
- Nam, S.K., K.S. Park and Y.K. Kim** (1999), 'Agenda for Capital Market Reforms in the PRC', in ADB, *A Study of Financial Markets, Vol.4: People's Republic of China*, pp. 68–98. Manila: ADB.
- Narayan, P.K.** (2005), 'Are the Australian and New Zealand Stock Prices Nonlinear with a Unit Root?' *Applied Economics*, 37(18): 2161–66.

- Nawrocki, D.N.** (1996), 'Market Dependence and Economic Events', *Financial Review*, 31(2): 287–312.
- Neftci, S.N.** (1991), 'Naive Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of "Technical Analysis"', *Journal of Business*, 64(4): 549–71.
- Opong, K.K., G. Mulholland, A.F. Fox and K. Farahmand** (1999), 'The Behavior of Some UK Equity Indices: An Application of Hurst and BDS Tests', *Journal of Empirical Finance*, 6(3): 267–82.
- Panagiotidis, T.** (2005), 'Market Capitalization and Efficiency: Does it Matter? Evidence from the Athens Stock Exchange', *Applied Financial Economics*, 15(10): 707–13.
- Poshakwale, S.** (2002), 'The Random Walk Hypothesis in the Emerging Indian Stock Market', *Journal of Business Finance and Accounting*, 29(9–10): 1275–99.
- Qi, D., W. Wu and H. Zhang** (2000), 'Shareholding Structure and Corporate Performance of Partially Privatized Firms: Evidence from Listed Chinese Companies', *Pacific-Basin Finance Journal*, 8(5): 587–610.
- Rahman, A.H. and S. Saadi** (2007), 'Is South Korea's Stock Market Efficient? A Note', *Applied Economics Letters*, 14(1): 71–74.
- (2008), 'Random Walk and Breaking Trend in Financial Series: An Econometric Critique of Unit Root Tests', *Review of Financial Economics*, 17(3): 204–12.
- Rayhorn, C., M.K. Hassan, J.S. Yu and K.R. Janson** (2007), 'Emerging Market Efficiencies: New Zealand's Maturation Experience in the Presence of Non-linearity, Thin Trading and Asymmetric Information', *International Review of Finance*, 7(1–2): 21–34.
- Rockinger, M. and G. Urga** (2000), 'The Evolution of Stock Markets in Transition Economies', *Journal of Comparative Economics*, 28(3): 456–72.
- (2001), 'A Time Varying Parameter Model to Test for Predictability and Integration in Stock Markets of Transition Economies', *Journal of Business and Economic Statistics*, 19(1): 73–84.
- Saadi, S., D. Gandhi and S. Dutta** (2006a), 'Testing for Nonlinearity and Modeling Volatility in Emerging Capital Markets: The Case of Tunisia', *International Journal of Theoretical and Applied Finance*, 9(7): 1021–50.
- Saadi, S., D. Gandhi and K. Elmawazini** (2006b), 'On the Validity of Conventional Statistical Tests Given Evidence of Non-synchronous Trading and Non-linear Dynamics in Returns Generating Process', *Applied Economics Letters*, 13(5): 301–05.
- Sarantis, N.** (2001), 'Nonlinearities, Cyclical Behaviour and Predictability in Stock Markets: International Evidence', *International Journal of Forecasting*, 17(3): 459–82.
- Seddighi, H.R. and W. Nian** (2004), 'The Chinese Stock Exchange Market: Operations and Efficiency', *Applied Financial Economics*, 14(11): 785–97.
- Self, J.K. and I. Mathur** (2006), 'Asymmetric Stationarity in National Stock Market Indices: An MTAR Analysis', *Journal of Business*, 79(6): 3153–74.
- Shanghai Stock Exchange**, '2003 Fact Book', http://www.sse.com.cn/sseportal/en_us/cs/about/factbook/factbook_us2003.pdf, accessed 1 December 2006.
- Shenzhen Stock Exchange**, 'Fact Book 2003', <http://www.szse.cn/main/en/MarketStatistics/FactBook/>, accessed 1 December 2006.
- Su, D. and B.M. Fleisher** (1999a), 'An Empirical Investigation of Underpricing in Chinese IPOs', *Pacific-Basin Finance Journal*, 7(2): 173–202.

- Su, D.** and **B.M. Fleisher** (1999b), 'Why does Return Volatility Differ in Chinese Stock Markets?', *Pacific-Basin Finance Journal*, 7(5): 557–86.
- Sun, Q.** and **W.H.S. Tong** (2000), 'The Effect of Market Segmentation on Stock Prices: The China Syndrome', *Journal of Banking and Finance*, 24(2): 1875–02.
- Theobald, M.** and **P. Yallup** (1998), 'Measuring Cash-futures Temporal Effects in the UK Using Partial Adjustment Factors', *Journal of Banking and Finance*, 22(2): 221–43.
- (2004), 'Determining Security Speed of Adjustment Coefficients', *Journal of Financial Markets*, 7(1): 75–96.
- Tian, G.G., G.H. Wan** and **M. Guo** (2002), 'Market Efficiency and the Returns to Simple Technical Trading Rules: New Evidence from U.S. Equity Market and Chinese Equity Markets', *Asia-Pacific Financial Markets*, 9(3–4): 241–58.
- Wei, Z.** and **O. Varela** (2003), 'State Equity Ownership and Firm Market Performance: Evidence from China's Newly Privatized Firms', *Global Finance Journal*, 14(1): 65–82.
- Zalewska-Mitura, A.** and **S.G. Hall** (1999), 'Examining the First Stages of Market Performance: A Test for Evolving Market Efficiency', *Economics Letters*, 64(1): 1–12.
- (2000), 'Do Market Participants Learn? The Case of the Budapest Stock Exchange', *Economics of Planning*, 33(1–2): 3–18.