<u>Full Title:</u>	**THE WEAK-FORM EFFICIENCY OF CHINESE STOCK MARKETS: THIN TRADING, NONLINEARITY AND EPISODIC SERIAL DEPENDENCIES**

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<u>Abstract:</u>　　　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 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 responded in a similar way to influences from political, economic, social and institutional changes.

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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 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, they are the world's leading emerging stock market in terms of market capitalization, 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 capitalization 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 generalization 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% 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 characterized by

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

the dominance of individual investors with Chinese institutional investors such as the pension funds, insurance companies and securities companies accounting for less than 10% of the total market capitalization.[2] 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 views of its profound significance to market regulators and investors. In general, the focus of extant literature is on the weak-form

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[2] In 2003, the Shanghai Stock Exchange has a total of 36,436,000 investor accounts, of which 35,266,000 are A-shares accounts, 980,600 are B-shares accounts and 189,400 institutional investors (Shanghai Stock Exchange Fact Book 2003, downloaded from http://www.sse.com.cn/sseportal/en_us/ps/about/fact.shtml). For Shenzhen Stock Exchange, total individual investors in 2003 are 33,632,231, of which 33,040,600 are in A-shares market with the remaining 591,631 in B-shares market. Institutional investors, on the other hand, account for only 0.5%, 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.

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, 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 predictable patterns. On the other end of the spectrum, Mookerjee and Yu (1999) and Ma (2004) proclaimed the markets as inefficient given that the random walk hypothesis is rejected by their efficiency tests. In between are those studies that found evidence of returns predictability, yet avoided making inference on market inefficiency as these authors were mindful that the detected predictability could be spurious autocorrelation induced by thin trading.

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 nonlinearity 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 paper.

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 particularly 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; 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 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) showed that when noise traders follow a positive feedback trading strategy, the price pressure induces positive return autocorrelation 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) reported 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) found 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 employed the conventional and popular efficiency tests, they are not without defect. Laurence *et al.* (1997) and Mookerjee and Yu (1999) drew their conclusions based solely on the results of serial correlation and runs tests. Liu *et al.* (1997) only employed unit root tests to examine the random walk

hypothesis, while the analyses in Groenewold *et al*. (2003, 2004) and Seddighi and Nian (2004) were conducted using autocorrelation and unit root tests. However, the Monte Carlo experiments performed by Lo and Mackinlay (1989) demonstrated 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) argued 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 complemented or relied 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, as noted by Antoniou *et al*. (1997a, b), emerging stock markets like China are typically characterized by thin trading and this would introduce bias into the above autocorrelation-based tests of market efficiency. Specifically, it is well established in the literature that this institutional feature would induce spurious autocorrelation in stock returns that is not genuine predictability, but rather a statistical illusion (see, for example, Lo and MacKinlay, 1988, 1990; Miller *et al*., 1994). Surprisingly, no attempt has been made by these earlier studies to remove the impact of thin trading, though some of them did acknowledge that thin trading could be the culprit for the detected predictability in their studies (Laurence *et al*., 1997; Groenewold *et al*., 2003, 2004).

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[4] Darrat and Zhong (2000) and Li (2003b) also questioned 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, b) and Rahman and Saadi (2007, 2008).

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 was 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 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) acknowledged 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) argued 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) demonstrated 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) found 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 documented 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

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[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).

correlations does not necessarily imply efficiency as returns series can be linearly uncorrelated and at the same time nonlinearly dependent. This piece of advice has been given to researchers almost three decades ago by Granger and Andersen (1978), and then follow-up by Granger (1983) in his appropriately titled 'Forecasting white noise'. Specifically, the latter demonstrated that one can never be sure time series with zero autocorrelation is not forecastable. In fact, it is well-known now time series generated by bilinear and nonlinear moving average 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 proceeded 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 focused 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) wrote: "*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) argued that it is not sensible to address the issue of market efficiency/inefficiency for stock markets in Central and Eastern European transition economies that have just emerged out of the former communist bloc such as Bulgaria and Hungary. The main reason is that when a market first opens, it is hardly credible for the market to be efficient since it takes time for the price discovery process to become known. However, as markets operate and market microstructures develop, within a finite amount of time, they are likely to become more efficient. Hence, the more relevant research question is whether and how these infant markets are becoming more efficient, and this certainly cannot be answered by classical steady-variable approaches that assume a fixed level of market efficiency throughout the entire estimation period. On a theoretical ground, the adaptive markets hypothesis (AMH) of Lo (2004, 2005) hypothesized 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.

In extant literature, Emerson *et al.* (1997) proposed a time-varying parameter model to capture the changing degree of market efficiency over time. 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, formalized by Zalewska-Mitura and Hall (1999) as "Test for Evolving Efficiency", was 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, b), 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, b) 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 autocorrelation induced by thin trading and led to incorrect verdict on market inefficiency, since no adjustment procedure was adopted by the author to purge the thin trading effect. For instance, Li (2003a) attributed 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 stock market, the research framework adopted should: (1) mitigate the confounding effect of thin trading on 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 autocorrelation due to thin trading are available in existing literature, they were only adopted by a handful of efficiency studies (Antoniou *et al*., 1997a, b; 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 paper to deal with the problem of thin trading was proposed by Miller *et al*. (1994). Briefly, the analysis in Miller *et al*. (1994) demonstrated that the observed price changes can be adjusted by (1- φ) 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: 507-510). 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- φ) 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 small 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.

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[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 are 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 have A-shares counterparts listed on the Chinese domestic stock exchanges.

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 28 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 1378 listed companies on both stock exchanges as at September 2004, only 1238 listed companies offer A-shares, while 24 firms issue B-shares only. There are 86 firms that issue both A- and B-shares to domestic and foreign investors respectively. In terms of market capitalization 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- January 2, 1991; and Shenzhen- April 3, 1991) to 12/31/2003. 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 analyses, the index data are transformed into a series of continuously compounded percentage returns, $R_t = 100 * \ln(p_t / p_{t-1})$, 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 another, indicating that the Shanghai SE Composite Price Index moved hand-in-hand with its Shenzhen counterpart. Even more striking is that the peaks and troughs in both indices occurred around the same time. It could be that their movements were 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. The government took strict measures to punish the offenders as well as to ease 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 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 was proposed by Miller *et al*. (1994) and followed by Antoniou *et al*. (1997a, b), 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:

$$R_t = \alpha_0 + \varphi\, R_{t-1} + e_t \tag{1}$$

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:

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

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, b) argued 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 was 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 $\{y(t_k), y(t_k+1),..., y(t_k+n-1)\}$. The next non-overlapped window is $\{y(t_{k+1}), y(t_{k+1}+1),..., y(t_{k+1}+n-1)\}$, where $t_{k+1} = t_k + n$.

The data in each time window is standardized 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 standardized observations that can be written as:

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

for each $t = 1, 2, ...n$ 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 realizations 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 bicorrelation 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 bicorrelations 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

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[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) faulted Jenkins and Watts (1968) and Box and Jenkins (1970) for blurring the definitions of whiteness and independence. In particular, 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 bicorrelations. This concern is well directed given that the assumption of Gaussianity is rather restrictive for financial time series, and the bicorrelations are in general not zero for a non-Gaussian white noise series (see Hinich and Patterson, 1985 for a specific example).

generating process, then $C_{ZZ}(r) \neq 0$ or $C_{ZZZ}(r,s) \neq 0$ for at least one r value or one pair of r and s values respectively.

The r sample correlation coefficient is:

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

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:

$$C = \sum_{r=1}^{L} \left[C_{ZZ}(r) \right]^2 \sim \chi_L^2 \tag{5}$$

The (r,s) sample bicorrelation coefficient is:

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

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

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

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

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 and bicorrelations 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 bicorrelations 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 were split into a set of equal-length non-overlapped moving time windows of 31 observations, so as to minimize 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 1/8/1991 and ends on 2/19/1991, second window runs 2/20/1991-4/3/1991, third window is 4/4/1991-5/16/1991, and so on. For Shenzhen, the period 4/9/1991-5/21/1991 falls in the first window, second window covers 5/22/1991-7/3/1991, 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 bicorrelations or nonlinear dependence in that particular window. 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% 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% (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*

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

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% and -0.02% 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.

<<Insert Table 1 about here>>

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, 4 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 summarized 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 7 windows, which is equivalent to 6.42% 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 8 windows (7.34%). In the case Shenzhen, the total numbers of significant *C* and *H* windows are 3 (2.80%) and 7 (6.54%) 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.

<<Insert Table 2 about here>>

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) hypothesized that economic events are important in generating temporal dependence in the stock market.[9] While his empirical investigation focused 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 hypothesized to be a source of temporal dependence, Table 2 provides the time periods during which these linear and nonlinear dependencies occurred so that future study could identify the major events that contributed 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, Figure 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 (i.e. one

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[9] The sources of index return autocorrelation are still very much been 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.

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. Figure 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 pattern in only 12 out of a total 109 time windows, which is equivalent to 11.01%. Similarly, serial dependencies are detected in only 9.34% 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.

<<Insert Figure 2 about here>>

<<Insert Figure 3 about here>>

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 found a higher degree of predictability at the early stage of market development up to early 1993. The latter attributed such predictability partly to market illiquidity. This apparent contradiction is not surprising as our analysis utilizes returns series that have corrected for the effects of thin trading. Specifically, spurious autocorrelation brought about by thin trading documented in Li (2003a) has been removed through the adjustment procedure, and hence the magnitude of serial correlations presence in the adjusted returns series is substantially reduced. The Shanghai stock market enjoyed 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 was 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 characterized 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 enjoyed 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 attained 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. (1999) found that both markets are efficient for the period of 5/21/1992-12/18/1995. However, a closer inspection of Figure 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) found 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 autocorrelation could be the result of thin trading that characterized 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 re-examines 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 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 summarized 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 responded 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.

Acknowledgements

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Table 1: Descriptive Statistics

| | SHSE | | SZSE | |
	Returns	Adjusted Returns	Returns	Adjusted Returns
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 statistic	2937535	2184064	43787.23	44293.99
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 2: Correlation and Bicorrelation Tests in Moving Time Windows

	SHSE_ADR	SZSE_ADR
Total number of windows	109	107
Total number of significant *C* windows	7	3
Dates of significant *C* 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 *H* windows	8	7
Dates of significant *H* 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 *C* and *H* windows	12	10
Dates of significant *C* and *H* 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

Figure 1: Time Series Plots for Chinese Stock Market Indices

Shanghai SE Composite Price Index
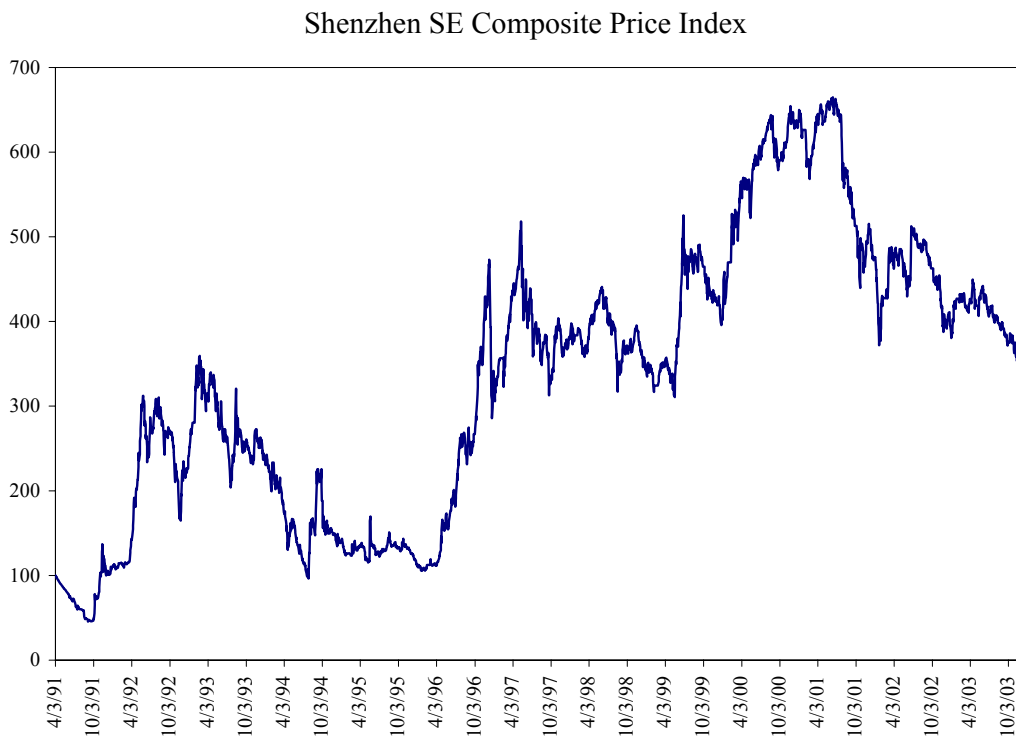

Shenzhen SE Composite Price Index

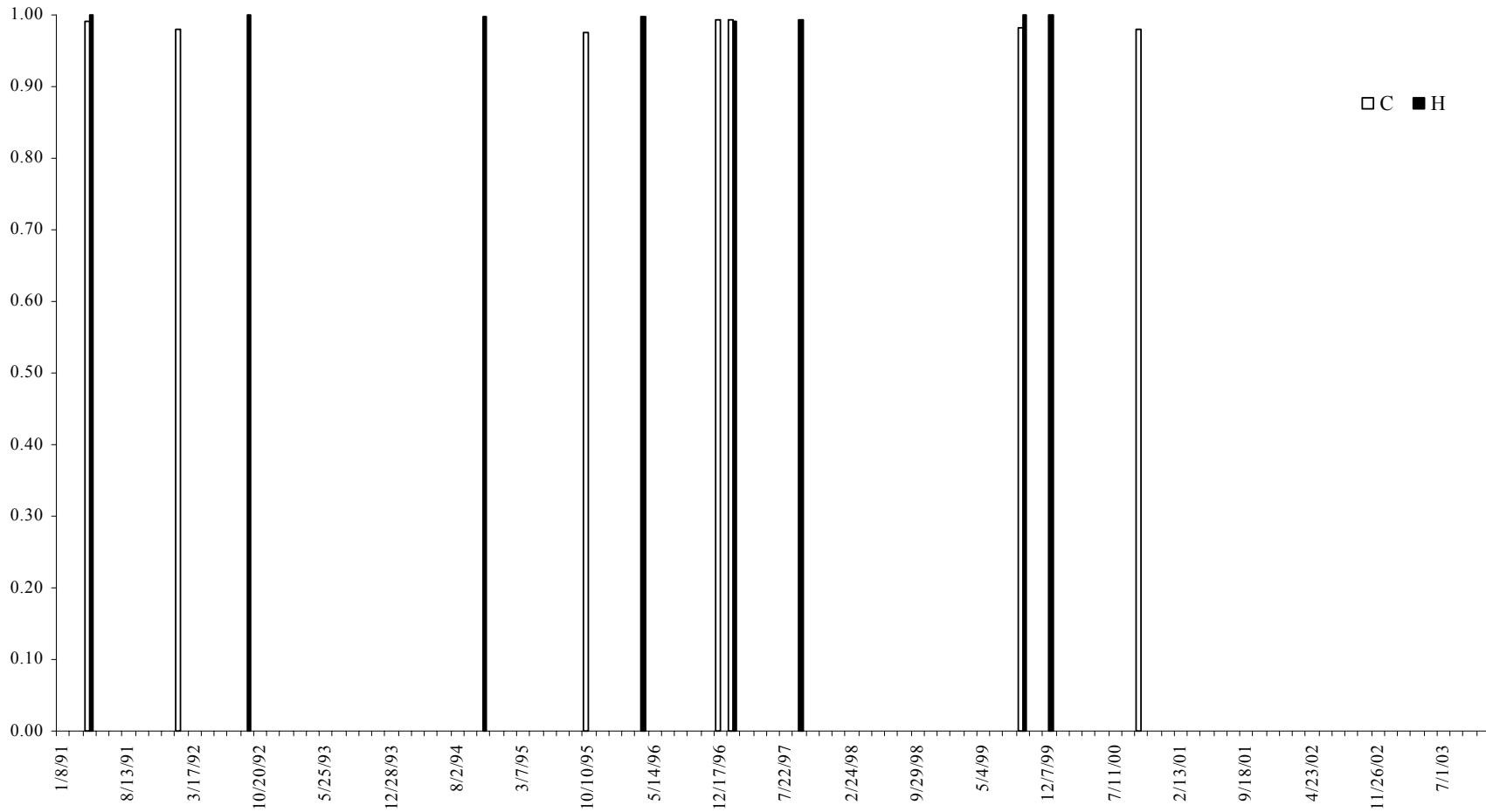Figure 2: Significant *C* and *H* Windows for Adjusted Returns Series of SHSE

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