Journal of
Economics, Banking and Finance

Volume 2, Issue 1, 2008

An Analysis of Long Memory in the SSE's Component Index[1]

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Abstract

Stock returns can reflect the behavior of investors in the securities and financial markets. We test for the presence of long memory in the Shenzhen Stock Exchange (SSE) using the R/s and KPSS tests. In addition, the parameter of long memory is estimated by the LP regression method. This analysis provides significant evidence to show that returns recorded by the SSE's Component Index exhibit long memory processes. This evidence suggests that the SSE stock market is not efficient, contradicting the martingale model.

Keywords: Long memory Log-periodogram (LP) regression R/s and KPSS tests

1. Introduction

An efficient financial market is defined as a financial market in which current prices and returns fully reflect all available relevant information (Fama, 1970). As a result, security prices and returns are assumed to fluctuate randomly in the martingale model. However, there is a paradox: the hypothesis that stock markets are efficient will be true only if a large number of investors disbelieve in this efficiency. Does market efficiency always hold? For example, Alexander (1961) and Fama and Blume (1966) indicated that stock returns do not conform to a random walk model. Also, the stock market crash of October 19, 1987 leads us to question the efficiency of financial markets.

Many investors prefer a go-for-growth strategy for investment because they believe that countries with expected rapid growth are the best places to invest. Over the last decade, China's average annual GDP growth was 9.2%. However, China's stock markets, as the emerging markets, appear to dish up the worst combination: macroeconomic booms and high volatility of the stock markets. Is it confirmed the validity of the go-for-growth investment strategy? Does market efficiency hold in China's stock markets?

It has been suggested that the series realizations of financial asset returns from the remote past

[1] This work was presented in part at the 9th International Conference of International Business Information Management Association, Marrakech, Morocco, January 4-6, 2008.

can help predict future returns, a process called stochastic long memory. Mandelbrot (1971) found that if asset returns display long memory, the arrival of new market information cannot be fully arbitraged away, and that asset returns exhibit autocorrelations between observations separated in time. This leads to the possibility of consistent speculative profits.

Following Mandelbrot (1971), Jacobsen (1996) and Hiemstra and Jones (1997) applied the standard ARCH and Stochastic volatility models, but did not find any evidence for long-memory dependencies at the level of returns. Tim and Wright (2000) pointed out that these traditional models could not capture the long memory process because of the fact that shocks to the second moments of the returns died out at a fast exponential rate of decay. While other studies, for example, Granger and Ding (1994) and Lobato and Savin (1998), suggested that the long-run dependencies in the autocorrelation functions for return volatility were characterized by a slowly mean-reverting hyperbolic rate of decay, it appeared that the fractionally integrated ARMA model or ARFIMA could be used to describe and predict the returns and prices of financial assets.

It is difficult to estimate parameters of long memory in the ARFIMA model. Semiparametric log-periodogram regression (LP regression) is a well-known method for analyzing long memory processes (Geweke and Porter-Hudake, 1983; Robinson, 1995). It has been shown that LP regression is a better approach to long memory processes, as this method can obtain consistent estimations by a simple calculation. The original statistical measurement of long memory was the R/s statistic (rescaled range statistic) developed by Hurst (1951), and applied by Mandelbrot (1972). Statistical supplements of LP regression include Lo's (1991) modified rescaled range statistic (Lo R/s) and the KPSS test (Kwiatkowski, Phillips, Schmidt and Shin, 1992).

There are two stock exchanges in China. We select the Shenzhen Stock Exchange (SSE), as a typical representative one, to analyze the market efficiency in China's stock markets. The Shenzhen Stock Exchange (SSE) is a mutual and national stock exchange that provides a venue for securities trading, under the China Securities Regulatory Commission (CSRC). The SSE had about 600 listed companies and 800 listed securities at the end of 2006. Since its beginning in 1990, the SSE has blossomed into a major competitive market in China, with a market capitalization of around RMB 1 trillion (US$ 122 billion). On a daily basis, around 600,000 deals, valued at US$ 807 million, are made through the SSE[2].

In this paper, we apply long memory models to examine the SSE's market efficiency. Three contributions will be considered in this paper. First, we review the traditional unit-root test and make a survey of the long memory models. Second, the long memory models could apply to testing the stock market efficiency and we find that the SSE's stock market is not efficient. Third, we give some explanations for China's casino-like stock markets.

[2] Retrieved on August 10, 2007, from http://www.sse.org.cn/.

The paper is organized as follows. In the next section we introduce the theory of long memory, discuss statistical tests (R/s, Lo R/s and KPSS), and review LP regression. Section 3 gives a statistical description of the SSE's Component Index return rates, tests the long memory of the stock return rates, and estimates the parameter of long memory by LP regression. Section 4 offers some conclusions.

2. Long Memory Process

For time series, the autocorrelations of a stationary process decay at an exponential rate. But in some settings, the autocorrelations remain persistently extremely high at long lags. Although it is clear that nonlinear models might be considered as a good method to examine the persistence at long lags, a typical nonlinear method would be hard to justify with any theory. To explain the persistence of the effects of shocks, models of long memory could show a very useful approach of the concept of nonstationarity.

Given a time series process y_t with autocorrelation function ρ_j at lag *j*, the process possesses long memory if the quantity $\lim_{n\to\infty}\sum_{j=-n}^{n}|\rho_j|$ is nonfinite (Mcleod and Hipel, 1978). In other words, the spectral density $f(\omega)$ is unbounded at low frequencies (Baillie, 1996). Long-memory models were first applied to econometrics by Granger and Joyeux (1980) and Hosking (1981). Robinson (1994) and Baillie (1996) have provided comprehensive reviews of this topic.

The ARFIMA model is the leading parametric long-memory time series model. y_t is defined as an ARFIMA (*p, d, q*) time series if

$$\phi(L)(1-L)^d(y_t-\mu)=\theta(L)\varepsilon_t \qquad (1)$$

where ε_t is a stationary and ergodic process with a bounded and positively valued spectrum at all frequencies, *L* is the lag operator, the polynomials $\phi(L)$ and $\theta(L)$ (of orders *p* and *q*, respectively) are assumed to have all of their roots outside the unit circle, and $d\in$(-0.5, 0.5) is the parameter that governs the memory of the series. This is the interval of values of d for which the process is stationary and invertible. For $0<d<0.5$, the series exhibits long memory or long-range dependence, its autocorrelations are all positive and the series decays at a hyperbolic rate. The range $-0.5<d<0$ is interpreted as showing anti-persistence or negative long memory.

Hassler, Marmol and Velasco (2006) showed that if $0.5 \le d < 1$ the process is mean-reverting with transitory memory, i.e. any random shock has only a temporary influence on the series. This is in contrast to the case when $d \ge 1$, where the process is both non-stationary and not mean-reverting with permanent memory, i.e. any random shock now has a permanent effect on the future path of the series.

2.1. Testing

2.1.1. The rescaled range statistic

The rescaled range statistic R_T/s_T (Hurst, 1951; Mandelbrot, 1972) is defined as

$$R_T = \max_{0 \le j \le T} \left\{ \sum_{j=1}^{T} (y_j - j\bar{y}) \right\} - \min_{0 \le j \le T} \left\{ \sum_{j=1}^{T} (y_j - j\bar{y}) \right\} \qquad (2)$$

$$s_T = \left\{ (1/T) \sum (y_t - \bar{y})^2 \right\}^{1/2} \qquad (3)$$

where

R_T is the range, s_T is the sample standard deviation, and $\bar{y}$ is the sample mean.

Taqqu (1975) and Lo (1991) showed that

$$p\lim_{T \to \infty} \left\{ T^{-H} (R_T / s_T) \right\} = c \qquad (4)$$

where c is constant.

Hurst (1951) informally writes the above as $\log[E(R_T / s_T)] \approx c + H[\log(T)]$, and the Hurst coefficient is estimated by taking the slope coefficient of a regression of $\log[E(R_T / s_T)]$ on $[\log(T)]$ for different values of t. An estimated value of H exceeding 0.5 shows long memory.

2.1.2. Lo R/s

Anis and Lloyd (1976) demonstrated the small sample bias of the R/s statistic, while Lo (1991) showed that the classical R/s test is excessively sensitive to “short-range dependence” (e. g. ARMA components) and heteroskedasticity. Lo’s modified version of the statistic takes into account this short-range dependence by performing a Newey-West correction (using a Bartlett window) to derive a consistent estimate of the long-range variance of the time series.

Lo R/s statistic is

$$Q_T = R_T / \sigma_T(q) \qquad (5)$$

$$\sigma_T^2(q) = c_0 + 2\sum_{j=1}^{q} w_j(q)c_j \qquad (6)$$

where

c_j is the *j*th-order sample autocovariance of y_t;

$w_j(q)$ is the Bartlett window weight of $w_j(q) = 1 - [j/(q+1)]$, for q<T.

Lo (1991) showed that in the presence of long memory $T^{-1/2}Q_t$ weakly converges to the range of a Brownian Bridge. The distribution function of the range, *F (x)*, given by Kennedy (1976) and Siddiqui (1976), is $F(x) = \sum_{j=\infty}^{\infty}(1-4x^2j^2)\exp(-2x^2j^2)$. Lo (1991) gives the critical values for the test.

2.1.3. The KPSS test

The KPSS test (Kwiatkowski et al., 1992) differs from common unit root tests (such as the Dickey-Fuller test and Augmented Dickey-Fuller test) by being designed to test an I (0) null hypothesis versus an I (1) alternative. This test may be conducted under the null hypothesis of either trend stationarity or level stationarity. The trend stationarity test takes the residuals e_t from a regression of y_t on an intercept and time trend and calculates

$$\eta_\tau = T^{-2}\sum S_t^2 / \sigma_T^2(q) \qquad (7)$$

where

$$S_t = \sum_{j=1}^{t} y_j \qquad (8)$$

The level stationarity test η_μ is also based on (7) except that the residuals are derived from a regression on the intercept only. According to Lee and Schmidt (1996), the two KPSS tests are consistent against an I (d) alternative, and can be used in conjunction with those tests to investigate the possibility that a series is fractionally integrated (that is, neither I (1) nor I (0)). Baillie (1996) shows that the Dickey-Fuller test performs relatively poorly in distinguishing between the I (1) null hypothesis and the I (d)[3] alternative. Inferences from the KPSS test are

[3] The y_t process defined by Eq. (1) and for d≠0 is said to be I (d).

complementary to those based on the Dickey-Fuller distribution.

2.2. Estimation

The most widespread estimation method of the memory parameter d with observed series is the log-periodogram estimator (Geweke and Porter-Hudak, 1983) (GPH). The GPH method takes advantage of semi-parametric methods — a spectral regression estimator based on a regression of the ordinates of the log spectral density on the trigonometric function — to evaluate d without explicit specification of the “short memory” (ARMA) parameters of the series. Baillie (1996) suggests that the estimator exploits the theory of linear filters to describe the process $(1-L)^d y_t = u_t$, where $u_t \sim$ I (0), as

$$f(\omega)_y = \left|1-e^{-i\omega}\right|^{-2d} f(\omega)_u \tag{9}$$

where

$f(\omega)_y$ and $f(\omega)_u$ are the spectral densities of y_t and u_t respectively.

Equation (8) can be written as

$$\log\left\{f_y(\omega_j)\right\} = \log\{f_u(0)\} - d\log\left\{4\sin^2(\omega_j/2)\right\} + \log\left\{f_u(\omega_j)/f_u(0)\right\} \tag{10}$$

d is estimated from a regression based on (9) using spectral ordinates $\omega_1, \omega_2, \ldots\omega_m$, from the periodogram of y_t. Robinson (1992, 1995) considers various frequency domain approaches when estimating the long-range dependency parameter. One of the innovations of Robinson’s estimator is that it is not restricted to using a small fraction of the ordinates of the empirical periodogram of the series. The estimator also allows for the removal of one or more initial ordinates and for the averaging of the periodogram over adjacent frequencies.

3. Empirical Tests and Estimations of Data

3.1. Defining the rates of returns

The returns can be described by two measurements. For the observed sequence $P1_t$ and $P2_t$ of the SSE’s Component Index[4], $t=1, 2, \ldots, n$, we define $P1_t$ as the last index and $P2_t$ as the average index, which is equal to (the high index + the low index) /2. Hence, the last rates of

[4] Retrieved on August 15, 2007, from http://cn.finance.yahoo.com.

returns $R1_t$ and the average rates of returns $R2_t$ are $R1_t = (P1_t - P1_{(t-1)}) / P1_{(t-1)}$ and $R2_t = (P2_t - P2_{(t-1)}) / P2_{(t-1)}$. The full sample is shown in Figure 1 and 2, spanning the period from November 3, 2003 through January 31, 2007, with a total of 756 observations of rates of returns per day.

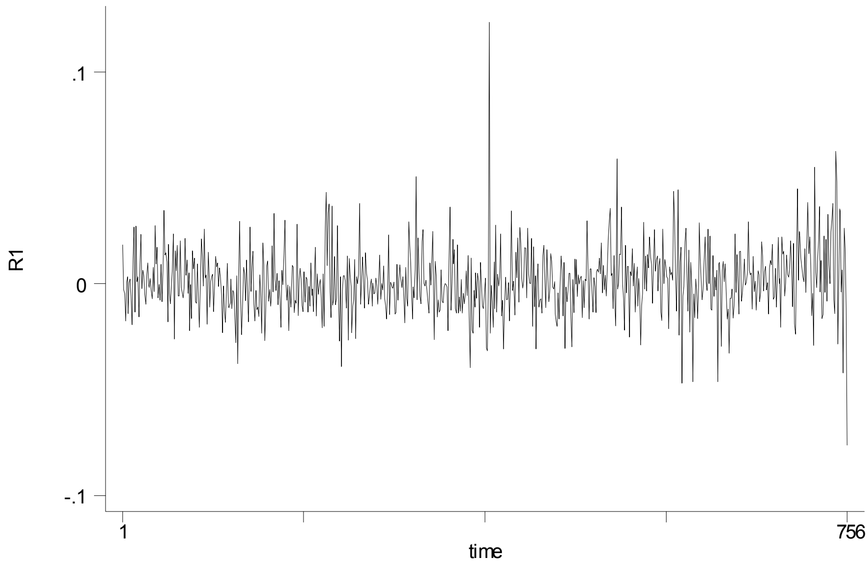

Figure 1 R1 rates of return from November 3, 2003 through January 31, 2007

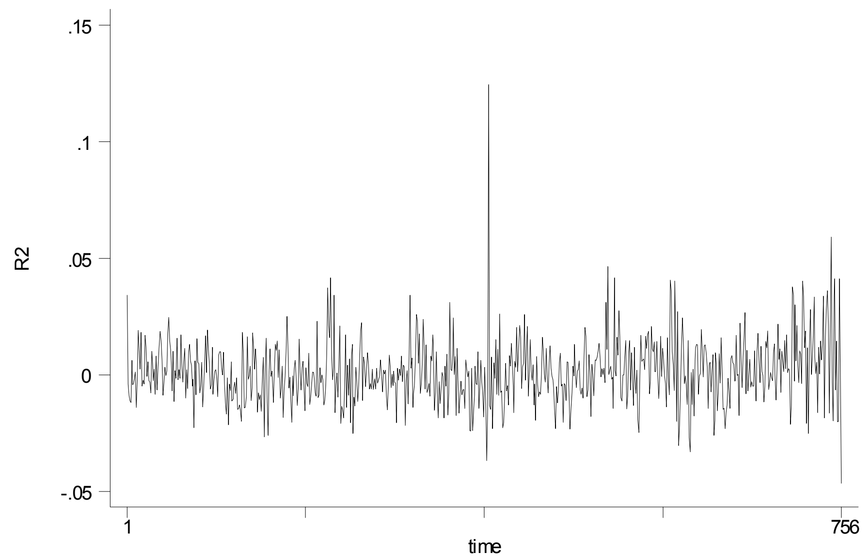

Figure 2 R2 rates of return from November 3, 2003 through January 31, 2007

Table 1 shows summary statistics. R1 had an observed mean of 0.00126 (standard deviation 0.016) with a maximum of 0.123 and a minimum of -0.076, and R2 had an observed mean of

0.00129 (standard deviation 0.014) with a maximum of 0.124 and a minimum of -0.047.

Table 1 Summary statistics of $R1_t$ and $R2_t$

	Observations mean	Standard deviation	minimum	maximum
R1	0.00126	0.016	-0.076	0.123
R2	0.00129	0.014	-0.047	0.124

3.2. Testing

3.2.1. The Lo R/s test

The null hypothesis of the Lo R/s test is that the series is not a long-memory time series. Table 2 shows that the critical values are: 90% - 0.86, 1.75; 95% - 0.81, 1.86; and 99% - 0.72, 2.10.

Table 2 Critical values for the null hypothesis of the Lo R/s test

90%	95%	99%
[0.86， 1.75]	[0.81， 1.86]	[0.72， 2.10]

According to equation (5), the Lo R/s of $R1_t$ and $R2_t$ can be calculated and are shown in Table 3. This shows that the null hypothesis can be rejected at the 95% confidence level. Hence, $R1_t$ and $R2_t$ are long-range dependent.

Table 3 The Lo R/s of $R1_t$ and $R2_t$

	test statistic	lags[5]	numbers
$R1_t$	2.06	0	755
$R2_t$	2.17	4	752

3.2.2. The DFGLS and KPSS test

First, we perform the modified Dickey-Fuller t test (DFGLS) with a null hypothesis of I (1). This test differs from the common augmented Dickey-Fuller test because the time series is transformed via a Generalized Least Squares regression prior to performing the test. Elliot, Rothenberg and Stock (1996) and Stock and Watson (2003) showed that this test has significantly higher power than the common augmented Dickey-Fuller test.

In table 4 the absolute value of the DFGLS tau test statistic for $R1_t$ and $R2_t$ both exceed the absolute 5% critical value. Hence, the time series of $R1_t$ and $R2_t$ are not I (1).

[5] The maximum lag order for the test is calculated from the sample size and the first-order autocorrelation coefficient of variable using the data-dependent rule of Andrews (1991), assuming that the dgp (data generation process) is AR (1).

Table 4 DFGLS for $R1_t$ and $R2_t$

lags	DFGLS tau test statistic		5%critical value
	$R1_t$	$R2_t$	
6	-4.143	-3.093	-2.854
5	-4.868	-3.568	-2.856
4	-5.337	-4.035	-2.858
3	-6.455	-4.681	-2.860
2	-8.344	-5.672	-2.861
1	-11.907	-8.483	-2.863

Second, we perform the KPSS tests for $R1_t$ and $R2_t$. Tables 5 and 6 show that the KPSS test statistic for $R1_t$ and $R2_t$ both exceed the critical value of 5%. We conclude that the time series of $R1_t$ and $R2_t$ are not I (0).

Table 5 Critical value of the KPSS test for H_0

H_0	10%	5%	1%
Trend stationary	0.119	0.146	0.216
Level stationary	0.347	0.463	0.739

Table 6 The KPSS tests for $R1_t$ and $R2_t$ [6]

lag order	test statistic			
	trend stationarity		level stationarity	
	$R1_t$	$R2_t$	$R1_t$	$R2_t$
0	0.185	0.283	0.921	1.34
1	0.184	0.251	0.909	1.17
2	0.191	0.25	0.931	1.15
3	0.19	0.239	0.918	1.09
4	0.186	0.23	0.887	1.04
5	0.181	0.224	0.856	1
6	0.179	0.22	0.841	0.975

According to the DFGLS tests and KPSS tests for $R1_t$ and $R2_t$, we have shown that the time series of the rates of returns of the SSE's Component Index are fractionally integrated (that is, neither I (1) nor I (0)).

3.3. LP regression (spectral regression) — the GPH estimator

A major issue in the application of the GPH estimator is to determine the number of ordinates (m). Diebold and Rudebusch (1989) proposed that m might be equal to $T^{-1/2}$.

[6] Autocovariances weighted by Bartlett Kernel.

All LP regression estimates are almost equal, as 27≤m≤29 (see table 7). For a total of 756 observations, the GPH estimator can be set as m= $756^{1/2}$ =28.

Table 7 LP regression estimates (Est d) for various ordinates

Est d	m						
	27	28	29	30	31	32	33
$R1_t$	0.192	0.193	0.193	0.197	0.21	0.194	0.23
$R2_t$	0.233	0.233	0.231	0.239	0.255	0.239	0.278

Table 8 shows that the GPH estimates of $R1_t$ and $R2_t$ are both greater than 0 and less than 0.5.

Table 8 GPH estimates of fractional differencing parameter

	m	Est d	std. err	t (H_0: d=0)
$R1_t$	28	0.193	0.107	1.8
$R2_t$	28	0.233	0.119	1.97

3.4. Discussion

Although Chinese trading in goods and services is competitive market, Chinese capital markets have extensive controls. Interest rates are strictly regulated and Chinese citizens are barred from investing overseas so that they have to take their chances with poorly regulated domestic investment. What matter to investors is the dividend accruing to them? In China, the tiny dividend yields reflect the very low intrinsic value of stocks. The capital controls distort the truth of investment information and have serious effect on capital coordination. On the other hand, the tiny dividend could lead to speculation, which is similar to casino, instead of long-term strategy. The result will make the stock market non-efficiency. Our empirical tests and estimation showed the conclusion from the standpoint of the current pressing problems, China's long-standing repression of its capital markets and the low profit margins which are being squeezed for the list companies.

4. Conclusion

The martingale model states that future returns are unpredictable in the presence of random walk process and it shows that the market is efficient. There is a lot of literature showing that stock markets are not always efficient.

It is well known that the concept of stock market efficiency underlies a number of assumptions, for example, a lot of market participants, the very rapid release of information, the sufficient capital outflows, and the opening capital markets. On balance, the evidence indicates that market for common stocks listed on the New York Stock Exchange (NYSE) is reasonably efficient (Van Horne and Wachowicz Jr, 2001). However, no one claimed the theory is perfect. Such market imperfections as institutional restraints, many innocent investors, and the insider trading could have some adverse effects on the market efficiency. As the emerging markets, China's stock markets are preceding with caution followed many imperfections. Therefore, the crux of the matter is whether China's stock markets are efficient.

Unit root tests are often used to test the market efficiency. If the root differs from one in either direction, than an altogether different set of statistical tools is called for (Greene, 2002). Models of long memory could be considered as a very useful approach of the concept of nonstationarity.

In this paper, we adopted long memory models to examine the SSE's market efficiency in China. We have found significant evidence of long memory features in the returns series of the SSE's Component Index, using the R/s and KPSS tests and the LP regression method. This finding proved that stock return movements in the SSE are influenced by realizations from the remote past. This evidence suggests that the SSE stock market is not efficient, and it shows that statistical results also tally with the current actual situation of China's stock markets.

Acknowledgements

This research was partially supported by the Ministry of Education, Science, Sports and Culture, Granted-in-Aid for Exploratory Research, 19651071, 2007.
The authors would like to thank the anonymous reviewers for their valuable comments.

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