Universidad de Navarra

Facultad de Ciencias Económicas y Empresariales

Working Paper nº 12/11

Stock market prices in China. Efficiency, mean reversion, long memory volatility and other implicit dynamics

Luis A. Gil-Alana
University of Navarra
Pamplona, Spain

Yun Cao
CEMFI
Madrid, Spain

Stock market prices in China. Efficiency, mean reversion, long memory volatility and other implicit dynamics
Luis A. Gil-Alana and Yun Cao
Working Paper No.12/11
November 2011

ABSTRACT

This paper analyzes the long-term dynamics of Chinese stock market prices, using the data series of daily closing spot price indices from Shanghai and Shenzhen stock markets, two major stock exchange markets in China. Both autoregressive and fractional models have been employed: in the former case, we implement standard unit root tests to determine the nonstationarity; while for the fractional I(d) models, we use a parametric testing procedure developed by Robinson (1994) and a semiparametric estimation method based on a "local" Whittle estimate of d (Robinson, 1995). The results show strong evidence in favour of unit roots and thus lack of mean reverting behaviour for the log-prices series, when using both the classical methods based on integer degrees of differentiation but also when applying fractionally integrated techniques. On the other hand, when examining the volatility processes by means of studying the absolute and the squared returns series, the results strongly support the view of fractional integration in all cases, with the orders of integration fluctuating in the range (0, 0.5). This implies stationary long memory in volatility.

Luis A. Gil-Alana
University of Navarra
Faculty of Economics
Edificio Biblioteca, E. Este
E-31080 Pamplona, Spain
alana@unav.es

Yun Cao
Centro de Estudios Monetarios y Financieros
CEMFI
Madrid, Spain
yc.cecy@gmail.com

1. Introduction

The statistical modelling of financial time series data such as asset prices plays an important role in portfolio management. Despite the extensive theoretical and empirical literature of the last thirty years, there is still no consensus on what might be the most adequate model specification for many financial series. Thus, for example, whether asset returns of asset prices are predictable or not is still controversial. While the efficiency market hypothesis suggests that they should follow an I(1) random walk (see Fama, 1970; Summers, 1986), other authors have found evidence of mean reversion in their behaviour (see, e.g., Poterba and Summers, 1988 and Fama and French, 1988). The standard econometric approach to settle this issue empirically relies on establishing the (integer) order of integration of the series by carrying out nonstationary unit root tests. However most of the methods employed in this context have extremely low power if the true data generating process is integrated of a fractional order. Therefore, the possibility of fractional orders of integration with a slow rate of decay has also been taken into account. Time series exhibiting long memory or fractional integration are characterized by a strong dependence between distant observations in time, which implies that their autocorrelation functions decay hyperbolically contrary to the faster exponential decay which characterizes traditional autoregressive moving average models. Moreover, these models (based on a non-integer degree of differentiation) imply the existence of a degree of predictability in the time series behavior, rejecting thus the hypothesis of efficiency in the stock markets.

Long memory specifications have been used for financial data: Crato (1994), Cheung and Lai (1995), Barkoulas and Baum (1996), Barkoulas, Baum, and Travlos (2000), Sadique and Silvapulle (2001), Henry (2002), Tolvi (2003) and Gil-Alana (2006) among others. For developed markets, Crato (1994) studied the stock index of the G-7 using a fractionally integrated autoregressive moving average (ARFIMA) model, which allows the integration order to take non-integer value between 0 and 1; Mills (1993) applied a similar model to UK stock series; Barkoulas and Baum (1996) and Hiemstra and Jones (1997), not only focused on the stock indices, but also examined individual U.S. stocks. Both of these find evidence of statistically significant long memory for some stocks; Lillo and Farmer (2004) studied the long memory properties for the signs of order in London Stock Exchange using the Hurst exponent. Using also a fractional model, Caporale and Gil-Alana (2002) found that there is no permanent component in US stock market returns, since the series examined is close to being I(0). Caporale and Gil-Alana (2007) decomposed the stochastic process followed by US stock prices into a long-run component described by the fractional differencing parameter (d) and a short-run (ARMA) structure. Empirical support for non-linear asset pricing models (such as the one by Dittmar, 2002) has also been found (see, inter alia, Hossein and Sonnie, 2008).

On the other hand, several studies have reported favorable evidence of long memory dynamics for emerging and developing markets: Madhusoodanan (1998), provides evidence of long memory on the individual stocks in the Indian Stock Exchange, and Golaka (2002) also gives significant indication of long memory for all time lags in India; Similar evidence on the Greek financial market is given by Barkoulas, Baum and Travlos (2000); the stock market in Finland is analyzed by Tolvi (2003); In addition, Costa and Vasconcelos (2003) investigated the Ibovespa index of the São Paulo Stock Exchange and appeared to have detected the existence of long memory; Matos et al. (2004) found similar evidence by analyzing the time series structure of the Portuguese stock market index from 1993 to 2001, and Disario et al. (2007) for the daily returns of the Istanbul Stock Exchange National 100 Index.

Since developing markets do not always seem to behave as expected, and more precisely, the efficient market hypothesis may not necessarily hold for returns of stocks in emerging markets, it is more likely that long memory will be detected in them. In this paper, we look at the data for the case of China. Since Chinese stock market is one of the largest emerging financial markets, we expect to find the existence of long memory in the results of our analysis.

The case of stock market in China has been investigated in some recent papers. Thus, for example, Qian et al. (2008) performed threshold unit root tests developed by Caner and Hansen (2001) and applied them to the Shanghai Stock Exchange Composite (SSEC) index for the time period 1990m12 – 2007m6. They obtained evidence of non-linear behaviour with two regimes and unit roots in the two regimes. In another recent paper, Gu and Zhou (2009) provide evidence of long memory in the volatility of Chinese stock returns. Similar evidence is also found in Ren and Zhou (2008), Ren, Gu and Zhou (2009) and Ren, Guo and Zhou (2009). Our results support the view that the Chinese stock market is inefficient, with the volatility process presenting also a degree of predictability in its behaviour.

This paper innovates with respect to the above literature in the use of I(d) techniques in both the returns and the volatility in the Chinese stock market. Moreover, we use a methodology that is supposed to be the most efficient one in the context of fractional integration.

The structure of the paper is as follows. Section 2 briefly describes the main features of the Chinese stock market, focussing on the Shanghai and Shenzhen indices.

Section 3 deals with the methodology used in the paper based on unit roots and fractional integration. Section 4 describes the empirical results, while Section 5 contains some concluding comments.

2. The stock market in China

Many investors 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 one of the emerging markets, with high degree of governmental and public interventions, appear to dish up the worst combination: macroeconomic booms and high volatility of the stock markets. Does market efficiency hold in China's stock markets?

Various methodologies have been used to test the efficient market hypothesis for Chinese stock markets: Charles and Darne (2009) analyze the efficiency of the Chinese stock markets using variance ratio tests and conclude that RMB (Chinese currency) denominated shares (A-shares) appear to follow a random-walk. They explained that liquidity; market capitalization and information asymmetry can play a role in explaining the weak form efficiency. Beltratti et al. (2009) analyze the stock price effects of the changes in ownership structure derived of the conversion of non-tradable shares into tradable ones in 2005-2006, and find that the price of stocks are characterized by lower liquidity; inactive investors and less transparency before the reform tend to benefit most from it. Thus, they conclude that the recent financial reforms significantly improved Chinese stock market fundamentals.

Other researchers have reported that China's stock market has unique attributes that challenge traditional asset pricing models and the theory of rationality. For instance, Lee et al. (2001) examined time-series features of stock returns and volatility in China's stock exchanges. They provided strong evidence of time-varying volatility and indicated that volatility is highly-persistent and predictable. Moreover, evidence in support of a fat-tailed conditional distribution of returns was found. Kang et al. (2002) suggest that the lack of rigorous stock analysis and research may have led to the perception that prices are driven by sentiment as much as by other factors. Drew et al. (2003) suggest that the Chinese market is difficult to comprehend using conventional analysis. The authors document in their result that book-to-market equity generates on average a negative monthly return that may come from investors' misvaluation. Burdekin and Redferin (2009) present evidence that individuals react to the real return on deposits (the risk-free asset) and equity markets relative performance and risk perception. Finally, Eun and Huang (2007) find that while the market risk (beta) is not priced, there is a significantly negative relationship between firm-specific risk and expected returns in China.

According to historical data, there are two main boom and two bust periods in China's stock market since April 1999: The first pronounced boom started in the autumn of 2006 and ended early 2008, while a shorter stock market boom occurred around mid-2009. The first identified bust in China's stock market was between end-1999 and early 2000, the second between mid-2004 and mid-2005. In fact, during last decade, the Chinese financial system has been subjected to substantial reforms with far reaching consequences. These reforms process has helped in dramatic improvement in transparency level in financial markets including stock market. There have been significant changes in the regulations for smooth and efficient functioning of capital market in the country. The country has also experienced the mild contagion effect of financial crisis in international markets and successfully sailed through the period of

Asian crisis not significantly jeopardizing the interest of the domestic economy. The market has undergone substantial changes due to the introduction of hedging products like futures and options. Risk management system has been changing in keeping pace with change in the scenario. The international investors' access to the domestic market has also helped in increasing liquidity. All these helped in better dissemination of information and hence possibly increased the level of efficiency in asset prices.

On the background of this, it has become important to test the existence of long memory in the Chinese market taking the stock market data during the time when substantial regulatory changes have taken place and the market practices have changed dramatically and various hedge products have been introduced to improve the risk management.

3. Methodology

To determine the degree of nonstationarity in economic and financial time series data, unit root testing procedures have been widely employed. Among them, the Augmented Dickey-Fuller (ADF, Dickey and Fuller, 1979) test has been the most widely used. In its simplest version, this procedure uses the model,

$$(1 - \alpha L)\, y_t \; = \; u_t, \qquad (1)$$

where u_t is a white noise process, and where the unit root corresponds to the null:

$$H_o: \quad \alpha \; = \; 1. \qquad (2)$$

In this context, the process is stationary as long as $|\alpha| < 1$. It contains a unit root if $\alpha = 1$, and the process is explosive in case of $|\alpha| > 1$. Thus, we observe an abrupt change in the limit behavior around the unit root case. On the other hand, we can consider fractional alternatives of form:

$$(1-L)^d y_t \; = \; u_t, \qquad (3)$$

where the unit root corresponds now to the null,

$$H_o: \quad d \; = \; 1. \qquad (4)$$

In this case, y_t is covariance stationary as long as d is smaller than 0.5, and then, as d increases above 0.5 throughout 1, the process is becoming "*more nonstationary*" in the sense for example that the partial sums increase in magnitude with d. Nevertheless, we do not observe an abrupt change around the case of a unit root as in the autoregressive models. The models in (1) and (3) can be extended to the case of weak autocorrelation (e.g., ARMA) for the I(0) error term u_t. Thus, for example, if u_t is ARMA(p, q) in (3), y_t is said to be a fractional ARIMA (ARFIMA(p, d, q)) process and displays long memory as long as d is positive.

In this paper we will employ procedures based on the two types of alternatives just presented, that is, autoregressive and fractional models of form as in (1) and (3). In the former case, we will implement ADF tests along with other standard unit root methods like the tests of Phillips and Perron (PP, 1988) and Kwiatkowski et al. (KPSS, 1992). Using the fractional specification, we will make use of a parametric testing procedure developed by Robinson (1994) and a semiparametric estimation method based on a "local" Whittle estimate of d (Robinson, 1995). We briefly present the two fractional methods.[1]

Robinson's (1994) method is a testing procedure based on the Lagrange Multiplier (LM) principle that uses the Whittle function in the frequency domain. It tests the null hypothesis:

[1] We do not describe the unit root methods since they have been widely employed in economics during the last twenty years.

$$H_o : d = d_o , \qquad (5)$$

for any real value d_o, in a model given by equation (3), where x_t can be the errors in a regression model of form:

$$y_t = \beta' z_t + x_t \qquad t = 1, 2, ... \qquad (6)$$

where y_t is the time series we observe; z_t is a (kx1) vector of exogenous variables; β is a (kx1) vector of unknown parameter and x_t is given by (3). Based on H_o (5), Robinson (1994) showed that, under certain very mild regularity conditions, the LM-based statistic $(\hat{r})$ satisfies:

$$\hat{r} \rightarrow_{dtb} N(0, 1) \qquad as \ T \rightarrow \infty,$$

where " $\rightarrow_{dtb}$ " stands for convergence in distribution, and this limit behaviour holds independently of the regressors used in (6) and the specific model for the I(0) disturbances u_t in (3). Moreover, Gaussianity is not a requirement, a moment condition of only 2 being necessary, and this method is the most efficient one in the Pitman sense against local departures from the null. [2]

As in other standard large-sample testing situations, Wald and LR test statistics against fractional alternatives will have the same null and limit theory as the LM test of Robinson (1994). In fact, Lobato and Velasco (2007) essentially employed such a Wald testing procedure, and though this and other recent methods such as the one developed by Demetrescu et al (2008) have been shown to be robust with respect to even unconditional heteroscedasticity (Kew and Harris 2009) they require an efficient estimate of d, and therefore the LM test of Robinson (1994) seems computationally more attractive.

[2] The functional form of this procedure can be found in any of the numerous empirical applications based on his tests (e.g. Gil-Alana and Robinson 1997; Gil-Alana 2000; Gil-Alana and Henry 2003; etc.).

Additionally we employ a semiparametric method (Robinson 1995) which is essentially a local 'Whittle estimator' in the frequency domain, using a band of frequencies that degenerates to zero. The estimator is implicitly defined by:

$$\hat{d} = \arg\min_{d} \left(\log \overline{C(d)} - 2\, d\, \frac{1}{m}\sum_{s=1}^{m} \log \lambda_s \right), \qquad (7)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^{m} I(\lambda_s)\, \lambda_s^{2d}, \qquad \lambda_s = \frac{2\pi s}{T}, \qquad \frac{1}{m} + \frac{m}{T} \rightarrow 0,$$

where $I(\lambda_s)$ is the periodogram of the raw time series, x_t, given by:

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t\, e^{i \lambda_s t} \right|^2,$$

and d $\in$ (-0.5, 0.5). Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\,(\hat{d} - d^{*}) \rightarrow_{dtb} N(0, 1/4) \quad as\ T \rightarrow \infty,$$

where d^* is the true value of d. This estimator is robust to a certain degree of conditional heteroskedasticity (Robinson and Henry 1999) and is more efficient than other semi-parametric competitors.

Although there exists further refinements of this procedure, (Velasco 1999; Phillips and Shimotsu 2004; Abadir et al 2007; etc.), these methods require additional user-chosen parameters, and the estimates of d may be very sensitive to the choice of these parameters. In this respect, the method of Robinson (1995) seems computationally simpler.

4. Data and empirical results

The series examined in this work are the closing spot price indices, at a daily frequency, from Shanghai and Shenzhen stock markets, two of the stock exchange markets in China. The two indices are the Shanghai Composite Index, which is an index of all stocks (A-shares and B-shares) that are traded at the Shanghai Stock Exchange (SSE), and the Shenzhen Component Index, which is an index of 40 selected stocks that are traded at the Shenzhen Stock Exchange (SZSE). We choose these two indices since they are the two most typical references of indicating Chinese stock market situations. The time range of both these two indices is January 04, 1999 to July 09, 2010: a total of 2,779 observations individually, obtained from the Bloomberg database. We do not start the sample earlier because, before 1999, trading was not very active and information disclosure requirements were rather poor. The returns are computed as logarithmic differences of the original index series.

[Insert Figure 1 about here]

Figure 1 displays the time series plots of the original indices, their logged values and the returns, computed as the first differences of the logged indices. The values are very similar for the two series and also between the original and the log-transformed data. The returns series may display a degree of conditional heteroskedasticity though this is irrelevant for our purpose of detecting long memory and the order of integration of the series since the methods employed in the paper are robust against heteroskedastic errors.

As mentioned above, before analyzing the long memory in returns, first, we test whether the log-transformed indices and/or the returns are stationary/nonstationary, using ADF, PP and KPSS unit root tests. These tests differ in the null hypothesis. The null hypothesis of the ADF and PP tests is that the series has a unit root; while that of KPSS test is that the series is stationary I(0).

[Insert Table 1 about here]

Table 1 reports the results based on the three unit root tests, using both the log-transformed series and their first differences (the returns), for the two indices. As we can see, the three procedures give similar results: for the log-transformed series, both the ADF and the PP tests indicate that we cannot reject their null hypotheses, which indicates that the series are nonstationary I(1); while the KPSS test results support the rejection of its null hypothesis, which also means that the series are nonstationary; on the other hand, for the returns, the ADF and the PP tests show evidence of stationary I(0) returns; while the KPSS test statistics also indicate evidence of stationarity.

As a conclusion, the results reported so far and based on integer degrees of differentiation using AR alternatives clearly indicate that the log-prices series are nonstationary I(1) and consequently that the returns are I(0). However, as earlier mentioned the results displayed above may be biased due to the low power of these tests in the context of fractional alternatives.[3] Thus, in what follows we consider fractional models.

[3] The low power of standard unit root tests in the context of fractional integration has been studied among others by Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

First, we employ Robinson's (1994) parametric approach, and the results in terms of the estimated values of d are reported in Table 2. We report the estimated values of d in a model given by

$$y_t = \alpha + \beta t + x_t; \quad (1 - L)^d x_t = u_t, \qquad (5)$$

where y_t is the observed time series; α and β are the coefficients corresponding respectively to the intercept and a linear trend, and x_t is supposed to be an I(d) process. Thus, u_t is I(0) and given the parametric nature of this method we must specify its functional form. We will first assume that u_t is white noise. Then we will consider the case of autocorrelated errors, supposing that u_t is an AR(1) model, and finally we will impose the exponential spectral model of Bloomfield (1973). This is a non-parametric approach for modeling u_t that produces autocorrelations decaying exponentially as in the AR(MA) case. The main advantage of the Bloomfield approach is that it mimics the behavior of ARMA structures with a small number of parameters. Moreover, it is stationary independently of the values of its coefficients unlike what happens in the AR case.[4]

[Insert Table 2 about here]

Table 2 displays the estimates of d (along with the 95% confidence bands corresponding to the non-rejection values of d using Robinson's (1994) tests) for the three types of disturbances (white noise, AR and Bloomfield) for the three standard cases

[4] See Gil-Alana (2004) for the advantages of the model of Bloomfield (1973) in the context of Robinson's (1994) tests.

of: i) no regressors (i.e., $\alpha = \beta = 0$ a priori in (5)), an intercept (α unknown and $\beta = 0$ a priori), and an intercept with a linear time trend (i.e., α and β unknown).

The upper part of the table refers to the Shanghai Composite Index. We observe here that if u_t is white noise the estimated value of is very close to 1 and the unit root null cannot be rejected. Therefore, according to this simple specification, this stock market may be efficient. However, allowing for autocorrelated errors, the estimated values of d are slightly above 1 (around 1.04) and the unit root null is now rejected at conventional statistical levels.

The results for the Shenzhen Component Index are displayed in the lower part of the table. In general, the values are slightly higher than in the other series. If we do not include deterministic terms the I(1) null cannot be rejected, however, this hypothesis is decisively rejected in favor of d > 1 with an intercept and/or a linear trend.[5]

[Insert Figure 2 about here]

Figure 2 refers to the semiparametric method of Robinson (1995). We display the estimates of d along with the 95% confidence interval corresponding to the I(1) case. The horizontal axis refers to the bandwidth number while the vertical one represents the estimates of d. We observe that if the bandwidth number is low, the estimates are above the I(1) interval in the two series. In case of large bandwidth numbers, the estimates of the Shanghai index are within the unit root case, while those of the Shenzhen are still

[5] Though not reported the time trend coefficients were found to be statistically insignificant in all cases while the intercepts were found significantly different from zero. According to this specification, d is found to be slightly above 1 in the two series.

above 1.[6] This is consistent with the results reported for the parametric case where a slightly higher degree of integration is observed in the Shenzhen index over the Shanghai Composite Index. Nevertheless, these results strongly reject the hypothesis of mean reversion in the two Chinese stock markets.

Next we focus on the volatility processes and use two measures as proxies for the volatility: the squared and the absolute returns. These two measures have been widely employed in the financial literature to measure volatility. Thus, for example, absolute returns were employed among others by Ding et al. (1993), Granger and Ding (1996), Bollerslev and Wright (2000), Gil-Alana (2005), Cavalcante and Assaf (2004), Sibbertsen (2004) and Cotter (2005), whereas squared returns were used in Lobato and Savin (1998), Gil-Alana (2003), Cavalcante and Assaf (2004) and Cotter (2005).

[Insert Tables 3 and 4 about here]

Tables 3 and 4 report the unit root tests results for the absolute and the squared returns in the two markets, respectively. As we can see, the three unit root tests give contradictory results: with the ADF and the PP tests, we reject the null hypothesis of nonstationarity I(1) in both absolute and squared returns; while using the KPSS tests, we reject the null hypothesis, indicating that absolute and squared returns series are I(1). As argued before, these inconsistent results might come from the too restrictive assumptions imposed by the standard unit root tests and that only consider integer degrees of differentiation. So, next we consider the possibility of fractional orders of integration, allowing for a slow rate of decay in the autocorrelations.

[6] The bandwidth determines the trade-off between the bias and the variance in the estimation of d.

First we look at the absolute returns using the parametric method of Robinson (1994). The results are displayed in Table 5. We see that in all cases and for the two series, the estimates are in the range (0, 0.5) implying long memory and stationary returns.[7] As before, the estimates of d are slightly higher for the Shenzhen than for the Shanghai series, and another feature observed in the two series is that the estimated values of d differ across the different types of disturbances. Thus, if u_t is white noise, the values are around 0.16 in the two series; using AR(1) disturbances they are around 0.23 for the Shanghai absolute returns and around 0.24 for the Shenzhen returns, and finally, using the model of Bloomfield (1973) the values are around 0.26 in the two cases. Because of this, we also implement a semiparametric approach that is robust to the type of I(0) disturbances.

[Insert Table 5 and Figure 3 about here]

Figure 3 displays the values for the absolute returns using the semiparametric "local" Whittle method of Robinson (1995). In this figure we also display the 95% confidence bands for the I(0) and the I(1) cases. We observe that, independently of the bandwidth number, the estimates are outside the two confidence bands, which is consistent with the previous results of fractional orders of integration.

[Insert Table 6 and Figure 4 about here]

[7] Remember that in the I(d) case, the process is stationary if $d < 0.5$. On the other hand, if $0.5 \leq d < 1$ the process is no longer covariance stationary though it is still mean reverting.

Table 6 and Figure 4 are similar to the above but referring now to the squared returns. As with the absolute values, the estimated values of d are in the range (0, 0.5) implying stationary long memory volatility. Here we observe much higher values for the Shenzhen squared returns compared with those of the Shanghai index, especially in the case of autocorrelated errors. The long memory property observed in the volatility process is consistent with the results obtained in other more developed markets, implying inefficiencies and predictability in the volatility processes. Other more elaborated models taking into account noise effects, such as the long memory stochastic volatility (LMSV) models or the fractionally integrated exponential generalized autoregressive conditional heteroskedasticity (FIEGARCH) models can also be implemented in these series to examine the long memory in the volatility.

5. Concluding comments

In this article we have examined the dynamics underlying the Chinese stock market indices. In particular we have focussed on two well-known indices, the Shanghai Composite Index and the Shenzhen Component Index, daily, for the time period January 04, 1999 – July 09, 2010. In both cases, the results are similar to those obtained in other stock markets. Thus, for the log-prices series we obtain strong evidence in favour of I(d) models with d equal to or higher than 1, and thus implying lack of mean reverting behaviour. This result is obtained when using both the classical methods based on integer degrees of differentiation but also when applying fractionally integrated techniques. Moreover, it is consistent with the results obtained in Qian et al. (2008) though these authors use a completely different methodology. The fact that the two series may present a degree of long memory after first differences indicates a degree of predictability in their behaviour and thus, lack of efficiency in the Chinese stock market.

On the other hand we have also examined the volatility processes by means of studying the absolute and the squared returns series. The results here strongly support the view of fractional integration in all cases, with the orders of integration fluctuating in the range (0, 0.5). This implies long memory in volatility: the series are still covariance stationary but the autocorrelations are positive and take longer to disappear than in the I(0) (short memory) case. Again this result is in line with that obtained by other authors when using other methodologies (Ren and Zhou, 2008; Gu and Zhou, 2009; etc.) and imply a degree of predictability in the volatility series.

The existence of long memory in Chinese stock market suggests that the future volatility depends on its past realizations and therefore, is predictable: that is, the market indices consist of the impact of news and shocks occurred in the recent (and no so-recent) past, showing that speculative earnings could be gained by predicting stock prices, which is inconsistent with the efficient market hypothesis. The next step in this context should be to correctly determine the most adequate specification for these two series, which is crucial for financial analysts in order to forecast the short (and long) run evolution of the prices. In line with this, multivariate methods still in the context of fractional integration may be conducted in these two series, and based on the fact that the two individual series may display the same degree of integration, the possibility of fractional cointegration is a future avenue that will be investigated in future papers.

References

Abadir, K.M., W. Distaso and L. Giraitis. 2007. Nonstationarity-extended local Whittle estimation. *Journal of Econometrics* 141: 1353-84.

Barkoulas, J.T. and C.F. Baum, 1996, Long term dependence in stock returns. Economics Letters 53, 253-259.

Barkoulas, J.T., C.F. Baum and N. Travlos, 2000, Long memory in the Greek stock market. Applied Financial Economics 10, 177-184.

Beltratti, A., Bortolotti, B., and Caccavaio, M., 2009, Who gains from financial reforms? Evidence from the Chinese Stock Market, working paper, Bocconi University, FEEM and Torino University.

Bloomfield, P., 1973, An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Bollerslev, T., Wright, J.H., 2000, High frecuency data, frequecy domain inference and volatility forecasting, Review of Economics and Statistics 83, 596-602.

Burdekin, R.C.K. and Redferin, L., 2009, Sentiment effects on Chinese share prices and savings deposits: The post-2003 experience, China Economic Review 20, 246-261.

Caner, M. and B. Hansen, 2001, Threshold autoregression with a unit root, Econometrica 69, 1555-1596.

Cavalcante, J., Assaf, A., 2004, Long range dependence in the returns and volatility of the Brazilian stock market, European Review of Economics and Finance 3, 5-22.

Caporale, G.M. and L.A. Gil-Alana, 2002, Fractional integration and mean reversion in stock prices, Quarterly Review of Economics and Finance 42, 599-609.

Caporale, G.M. and L.A. Gil-Alana, 2007, Long run and cyclical dynamics in the US stock market, CESifo Working Paper no. 2046.

Charles, A. and Darne, O., 2009, The random walk hypothesis for Chinese stock markets: Evidence from variance ratio tests, Economic Systems 33, 117-126.

Cheung, Y.- W. and K.S. Lai, 1995, A search for long memory in international stock market returns. Journal of International Money and Finance 14, 597-615.

Costa, R.L. and Vasconcelos, G.L, 2003, Long-range correlations and nonstationarity in the Brazilian stock market, Physica A. 329, 231-248.

Cotter, J., 2005, Uncovering long memory in high frequency UK futures, European Journal of Finance 11, 325-337.

Crato, N., 1994, Some international evidence regarding the stochastic behaviour of stock returns. Applied Financial Economics 4, 33-39.

Demetrescu, M., V. Kuzin and U. Hassler. 2008. Long memory testing in the time domain. *Econometric Theory* 24: 176-215.

Dickey, D. and W.A. Fuller (1979) Distributions of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427-431.

Diebold, F.X., and G.D. Rudebusch (1991). "On the power of Dickey-Fuller test against fractional alternatives". *Economics Letters,* 35: 155-160.

Ding, Z., Granger, C.W.J., Engle, R.F., 1993, A long memory property of stock markets returns and a new model, Journal of Empirical Finance 1, 83-106.

Disario, R., Saraoglu, H., McCarthy, J. and Li, H., 2008, Long memory in the volatility of an emerging equity market: the case of Turkey, Journal of International Financial Markets, Institutions &. Money 18, 4, 305-312.

Dittmar, R.F., 2002, Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross Section of Equity Returns, Journal of Finance, American Finance Association, vol. 57(1), 369-403.

Drew, M. E., Naughton, T. and Veeraraghavan, M., 2003. Firm size, book-to-market equity and security returns: Evidence from the Shanghai Stock Exchange, Australian Journal of Management 28, 119-139.

Eun, C.S. and Huang, W., 2007, Asset pricing in China's domestic stock markets: Is there a logic?, Pacific-Basin Finance Journal 15, 452-80.

Fama, E.F., 1970, Efficient capital markets: a review of theory and empirical work, Journal of Finance 25, 383-417.

Fama, E.F. and K.R. French, 1988, Permanent and transitory components of stock prices, Journal of Political Economy 96, 246-273.

Gil-Alana, 2000, Mean reversion in real exchange rates, Economics Letters, 69,3, 285-288.

Gil-Alana, L.A., 2003, Fractional integration in the volatility of asset returns, European Review of Economics and Finance 2, 41-52.

Gil-Alana, L.A, 2004, The use of the model of Bloomfield as an approximation to ARMA processes in the context of fractional integration, Mathematical and Computer Modelling 39, 429-436.

Gil-Alana, L.A., 2005, Long memory in daily absolute and squared returns in the Spanish stock market, Advances in Investment Analysis and Portfolio Management 1, 198-217.

Gil-Alana, L.A., 2006, Fractional integration in daily stock market returns. Review of Financial Economics 15, 28-48.

Gil-Alana, L.A. and B .Henry (2003) Fractional integration and the dynamics of UK unemployment, Oxford Bulletin of Economics and Statistics 65, 221-240.

Gil-Alana, L.A. & Robinson, P.M. (1997). Testing of unit roots and other nonstationary hypotheses in macroeconomic time series. Journal of Econometrics, 80, 24

Golaka, C. N., 2002, Long memory and Indian stock market- an empirical evidence manuscript, WDM Department, Mumbai.

Granger, C.W.J., Ding, Z., 1996, Varieties of long memory models, Journal of Econometrics 73, 61-78.

Gu, G.-F. and W.-X. Zhou, 2009, Emergence of long memory in stock volatility from a modified Mike-Farmer model, EPL Europhysics Letters 86, 48002.

Hasslers, U., and J. Wolters (1994). "On the power of unit root tests against fractional alternatives". *Economics Letters*, 45: 1-5.

Henry, O.T., 2002, Long memory in stock returns. Some international evidence. Applied Financial Economics 12, 725-729.

Hiemstra, C. and J.D. Jones, 1997, Another look at long memory in common stock returns, Journal of Empirical Finance 4, 373-401.

Hossein, A. and K. Sonnie, 2008, Evaluating a nonlinear asset pricing model on international data, International Review of Financial Analysis 17, 604-621.

Kang, J., Liu, M.-H. and Ni, S.X., 2002, Contrarian and momentum strategies in the China stock market: 1993-2000, Pacific Basin Finance Journal 10, 243-265.

Kew, H. and D. Harris. 2009. Heteroskedasticity robust testing for a fractional unit root. *Econometric Theory* 25: 1734-53.

Kwiatkowski, D., P. C. B. Phillips, P. Schmidt, and Y. Shin, 1992, Testing the null hypothesis of stationarity against the alternative of a unit root, Journal of Econometrics 54, 159-178.

Lee, C.F., G.M. Chen and O.M. Rui, 2001, Stock returns and volatility on China stock markets, Journal of Financial Research 24, 523-543.

Lee, D., and Schmidt, P (1996). "On the power of the KPSS test of stationarity against fractionally integrated alternatives". *Journal of Econometrics*, 73: 285-302.

Lillo, L. and J.D. Farmer, 2004, The long memory of the efficient market, Studies in Nonlinear Dynamics &. Econometrics 8(3).

Lobato, I.N., Savin, N.E., 1998, Real and spurious long memory properties of stock market data, Journal of Business and Economic Statistics 16, 261-268.

Lobato, I. and C. Velasco. 2007. Efficient Wald tests for fractional unit roots. *Econometrica* 75: 575-89.

Madhusoodanan, T. P., 1998, Persistence in the Indian stock market returns: An application of variance ratio test, Vikalpa 23(4), 61-73.

Matos, J.A.O., S.M.A. Gama, H.J. Rusking and J.A.M.S. Duarte, 2004, An econophysics approach to the Portuguese stock index-PSI-20, Physica A.: Statistical Mechanics and its Applications 342, 665-676.

Mills, T. C., 1993, Is there long memory in UK stock returns?, Applied Financial Economics 3, 303-306.

Phillips, P.C.B. and P. Perron, 1988, Testing for a unit root in time series regression, Biometrika 75, 335-346.

Phillips, P.C.B. and K. Shimotsu. 2004. Local Whittle estimation in nonstationary and unit root cases. Annals of Statistics 32, 656-92.

Poterba, J.M. and L.H. Summers, 1988, Mean reversion in stock prices: evidence and implications, Journal of Financial Economics 22, 27-59.

Qian, X.-Y., F.-T. Song and W.-X. Zhou, 2008, Nonlinear behavior of the Chinese SSEC index with a unit root: Evidence from threshold unit root tests, Physica A 387, 503-510.

Ren, F., G.-F. Gu and W.-X. Zhou, 2009, Scaling and memory in the return intervals of realized volatility, Physica A 388, 22, 4787-4796.

Ren, F., L. Guo and W.-X. Zhou, 2009, Statistical properties of volatility return intervals of Chinese stocks, Physica A 388, 6, 88-890.

Ren, F. and W.-X., 2008, Multiscaling behavior in the volatility return intervals of Chinese indices, EPL Europhysics Letters 84, 68001.

Robinson, P.M., 1994, Efficient tests of nonstationary hypotheses. Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M., 1995. Gaussian semiparametric estimation of long range dependence. *Annals of Statistics* 23, 1630-1661.

Robinson, P.M. and M. Henry. 1999. Long and short memory conditional heteroskedasticity in estimating the memory in levels. *Econometric Theory* 15: 299-336.

Sadique, S. and P. Silvapulle, 2001, Long-term memory in stock market returns. International evidence. International Journal of Finance and Economics 6, 59-67.

Sibbertsen, P., 2004, Long memory in volatilities of German stock returns, Empirical Economics 29, 477-488.

Summers, L.H., 1986, Does the stock market rationally reflect fundamental values?, Journal of Finance 41, 591-601.

Tolvi, J., 2003, Long memory and outliers in stock market returns. Applied Financial Economics 13, 495-502.

Velasco, C. 1999. Gaussian semiparametric estimation of nonstationary time series. *Journal of Time Series Analysis 20*: 87-127.

Figure 1: Original time series, log-transformation and their corresponding returns

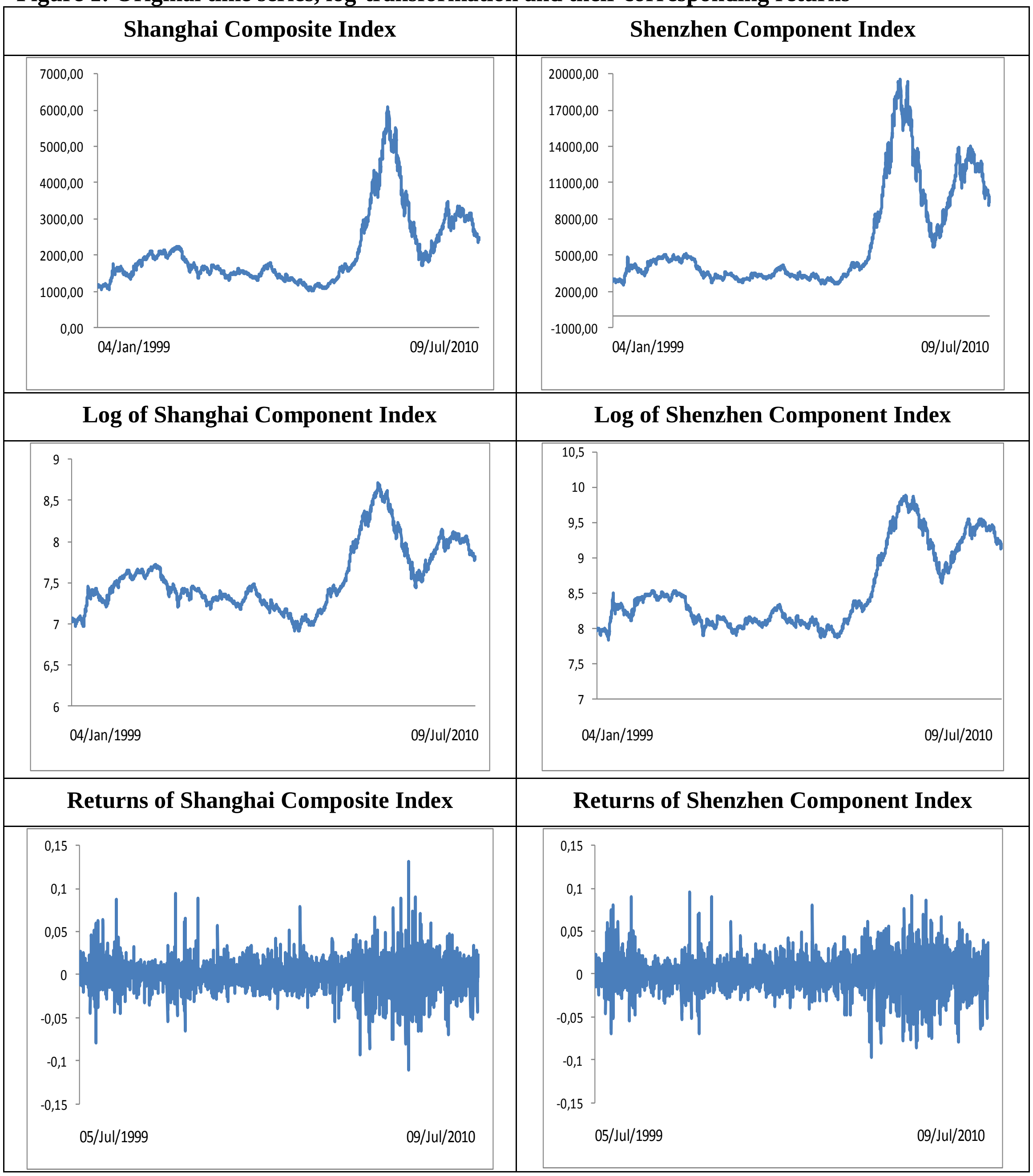


Table 1: Unit Root Tests in the log prices indices and the returns

	Shanghai Composite Index		Shenzhen Component Index	
	Level	**Difference**	**Level**	**Difference**
ADF	-1.448 (-3.433)	-53.495 (-3.433)	-0.786 (-3.433)	-28.670 (-3.433)
PP	-1.466 (-3.433)	-53.489 (-3.433)	-0.861 (-3.433)	-50.625 (-3.433)
KPSS	2.490 (0.739)	0.130 (0.739)	3.728 (0.739)	0.120 (0.739)

The significance level is 1%.

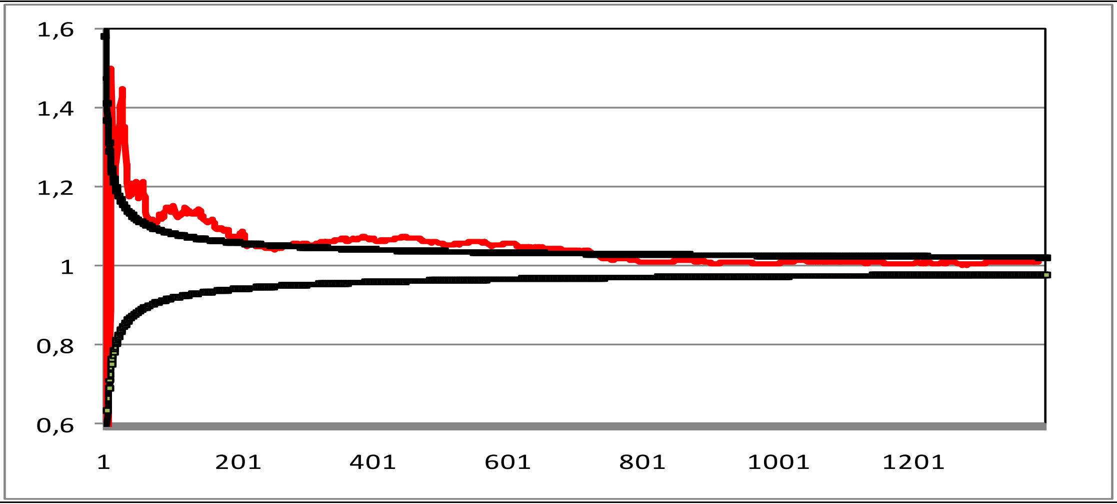
Table 2: Estimates of d in the (log-) stock market indices

i) Shanghai Composite Index			
	No regressors	With an intercept	With a linear trend
White noise	1.000 (0.977, 1.026)	1.009 (0.990, 1.031)	1.009 (0.990, 1.031)
AR (1)	-----	1.038 (1.009, 1.070)	1.038 (1.009, 1.070)
Bloomfield (1)	1.000 (0.962, 1.041)	1.043 (1.013, 1.081)	1.043 (1.013, 1.080)
i) Shenzhen Component Index			
	No regressors	With an intercept	With a linear trend
White noise	1.001 (0.978, 1.027)	1.042 (1.021, 1.065)	1.042 (1.021, 1.065)
AR (1)	-----	1.040 (1.011, 1.073)	1.041 (1.011, 1.073)
Bloomfield (1)	1.001 (0.963, 1.042)	1.042 (1.012, 1.073)	1.042 (1.012, 1.073)

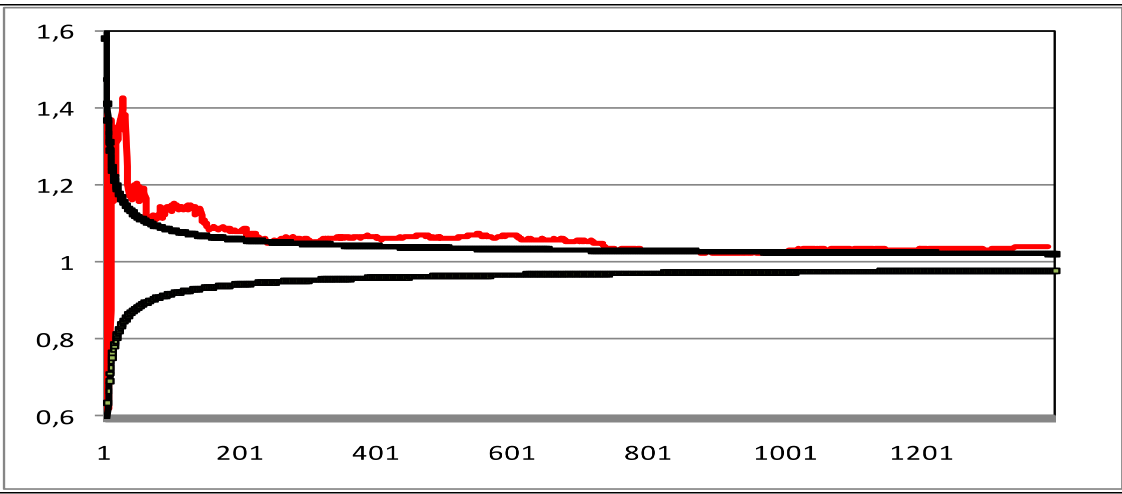
The estimates are the Whittle estimates in the frequency domain (Dahlhaus, 1989). The values in parenthesis are the 95% confidence intervals of the non-rejection values using Robinson's (1994) parametric tests.

Figure 2: Estimates of d based on the Whittle method of Robinson (1995)

Shanghai Composite Index



Shenzhen Component Index



The horizontal axe refers to the bandwidth number while the vertical one to the estimates of d. We also report the 95% confidence band for the I(1) case.

Table 3: Unit Root Tests in the absolute returns

	Shanghai Composite Returns		Shenzhen Component Returns	
	Level	**Difference**	**Level**	**Difference**
ADF	-9.646 (-3.433)	-23.414 (-3.433)	-7.591 (-3.433)	-26.186 (-3.433)
PP	-63.309 (-3.433)	-488.091 (-3.433)	-64.206 (-3.433)	-439.527 (-3.433)
KPSS	1.810 (0.739)	0.009 (0.739)	1.907 (0.739)	0.012 (0.739)

The significance level is 1%.

Table 4: Unit Root Tests in the squared returns

	Shanghai Composite Returns		Shenzhen Component Returns	
	Level	**Difference**	**Level**	**Difference**
ADF	-23.955 (-3.433)	-20.601 (-3.433)	-10.479 (-3.433)	-24.690 (-3.433)
PP	-51.531 (-3.433)	-545.769 (-3.433)	-60.593 (-3.433)	-424.039 (-3.433)
KPSS	1.652 (0.739)	0.0193 (0.739)	1.560 (0.739)	0.007 (0.739)

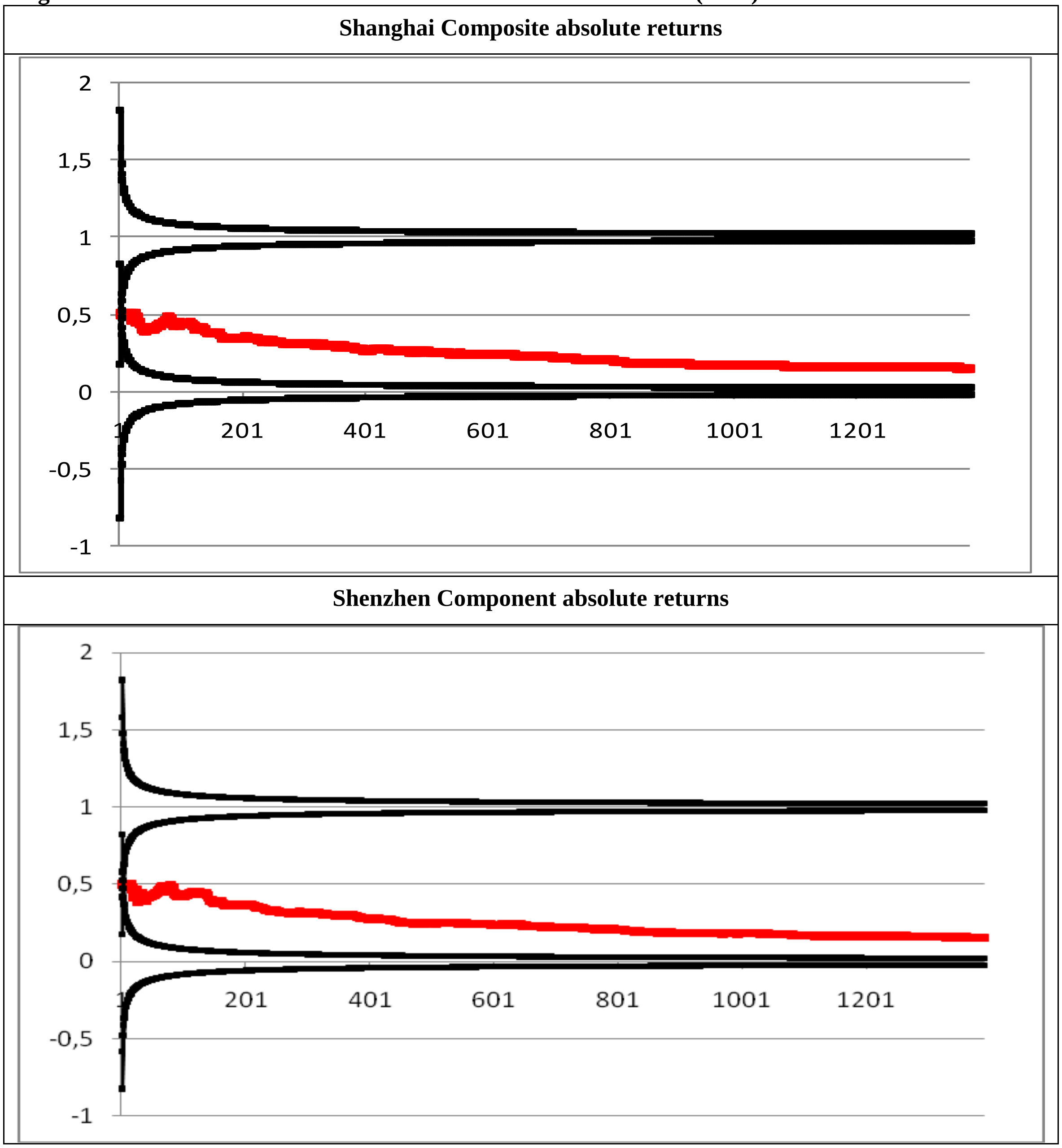
The significance level is 1%.

Table 5: Estimates of d in the absolute stock market returns

ii) Shanghai Composite absolute returns			
	No regressors	With an intercept	With a linear trend
White noise	0.162 (0.147, 0.178)	0.165 (0.151, 0.181)	0.156 (0.141, 0.172)
AR (1)	0.235 (0.213, 0.260)	0.236 (0.215, 0.259)	0.228 (0.205, 0.252)
Bloomfield (1)	0.260 (0.231, 0.290)	0.259 (0.234, 0.283)	0.247 (0.222, 0.279)
ii) Shenzhen Component absolute returns			
	No regressors	With an intercept	With a linear trend
White noise	0.166 (0.152, 0.182)	0.168 (0.154, 0.183)	0.159 (0.144, 0.175)
AR (1)	0.247 (0.225, 0.272)	0.246 (0.225, 0.269)	0.238 (0.215, 0.263)
Bloomfield (1)	0.264 (0.242, 0.305)	0.262 (0.241, 0.293)	0.257 (0.232, 0.287)

The estimates are the Whittle estimates in the frequency domain (Dahlhaus, 1989). The values in parenthesis are the 95% confidence intervals of the non-rejection values using Robinson's (1994) parametric tests.

Figure 3: Estimates of d based on the Whittle method of Robinson (1995)



The horizontal axe refers to the bandwidth number while the vertical one to the estimates of d. We also report the 95% confidence band for the I(1) case.

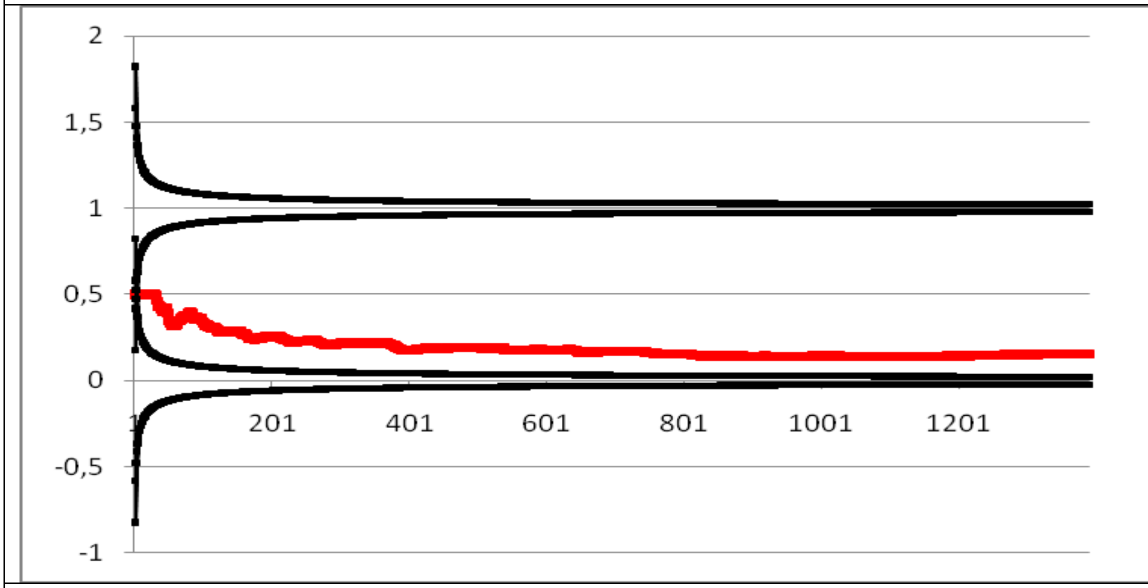
Table 6: Estimates of d in the squared stock market returns

iii) Shanghai Composite squared returns			
	No regressors	With an intercept	With a linear trend
White noise	0.161 (0.142, 0.182)	0.163 (0.145, 0.184)	0.156 (0.137, 0.178)
AR (1)	0.158 (0.136, 0.183)	0.162 (0.140, 0.187)	0.151 (0.127, 0.177)
Bloomfield (1)	0.161 (0.130, 0.183)	0.163 (0.134, 0.194)	0.152 (0.125, 0.181)
iii) Shenzhen Component squared returns			
	No regressors	With an intercept	With a linear trend
White noise	0.143 (0.128, 0.160)	0.145 (0.130, 0.162)	0.138 (0.122, 0.155)
AR (1)	0.208 (0.186, 0.234)	0.211 (0.189, 0.235)	0.203 (0.180, 0.225)
Bloomfield (1)	0.226 (0.197, 0.254)	0.227 (0.206, 0.257)	0.219 (0.194, 0.249)

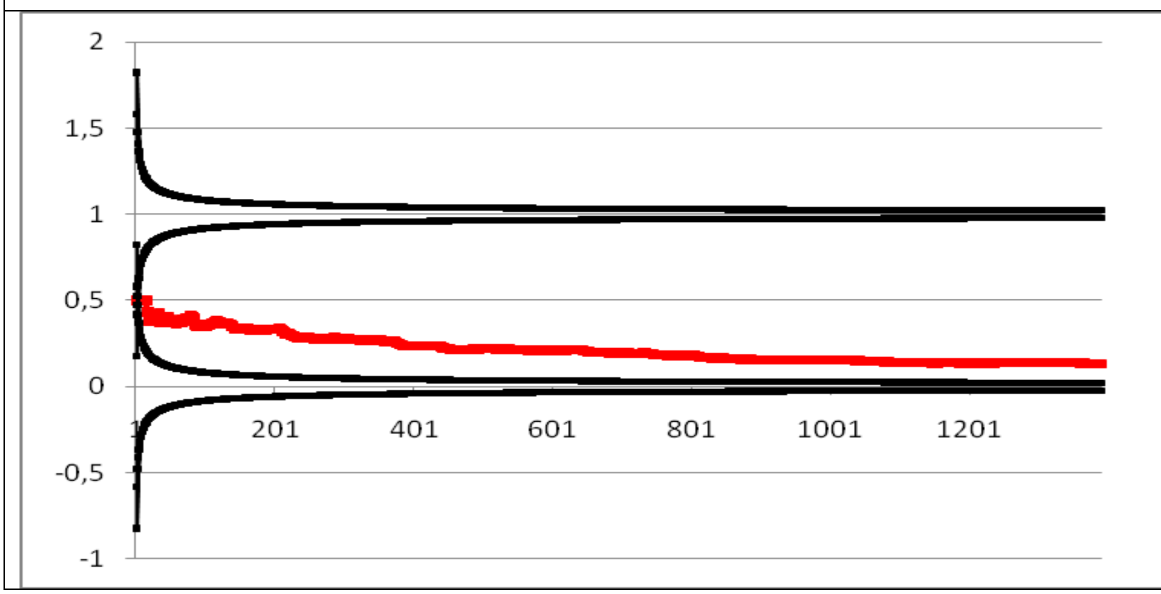
The estimates are the Whittle estimates in the frequency domain (Dahlhaus, 1989). The values in parenthesis are the 95% confidence intervals of the non-rejection values using Robinson's (1994) parametric tests.

Figure 4: Estimates of d based on the Whittle method of Robinson (1995)

Shanghai Composite squared returns



Shenzhen Component squared returns



The horizontal axe refers to the bandwidth number while the vertical one to the estimates of d. We also report the 95% confidence band for the I(1) case.