

# Long-term correlations and multifractal analysis of trading volumes for Chinese stocks

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## Abstract

We investigate the temporal correlations and multifractal nature of trading volume of 22 liquid stocks traded on the Shenzhen Stock Exchange in 2003. We find that the trading volume exhibits size-dependent non-universal long memory and multifractal nature. No crossover in the power-law dependence of the detrended fluctuation functions is observed. Our results show that the intraday pattern in the trading volume has negligible impact on the long memory and multifractality.

*Key words:* Econophysics; Trading volume; Intraday pattern; Correlation; Multifractality  
*PACS:* 89.65.Gh, 02.50.-r, 89.90.+n

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## 1 Introduction

As implied by a well-known adage in the Wall Street that it takes volume to move stock prices, trading volume contains much information about the dynamics of price formation. For instance, the investigation of price-volume relationship has a long history in finance [1], attracting more and more interest of physicists, and recently has been studied at the transaction level [2, 3, 4, 5, 6]. In addition, the distributions of trading volumes at different time scales have been found to have power-law right tails for different stock markets [7, 8, 9, 10, 11], which can account at least partly the power-law tails of returns [6, 12, 13, 14]. The distributions of trading volumes for Chinese stocks have also been reported to have power-law tails [6, 15, 16].

Another important feature of trading volumes is its long-range temporal correlation. Lobato and Velasco used a two-step semiparametric estimator in the frequency domain for the long-memory parameter  $d$  of daily trading volume for 30 stocks composing DJIA from 1962 to 1994 and find that  $d = 0.30 \pm 0.08$  [17], which amount to the Hurst index  $H = d + 0.5 = 0.80 \pm 0.08$ . Gopikrishnan et al performed detrended fluctuation analyses of trading volume for 1000 largest US stocks over the two-year period 1994-1995 [7]. They found that, the trading volumes at different time scales (from 15 min to 390 min) show stronger correlations with  $H = 0.83 \pm 0.02$ . Bertram used the autocorrelation and variance plots to investigate the memory effect of high-frequency trading volumes for 200 most actively traded stocks on the Australian Stock Exchange spanning the period January 1993 - July 2002, and found that the average Hurst index is  $H = 0.79 \pm 0.03$  [18]. Qiu et al conducted similar analysis on 18 liquid Chinese stocks from 2004 to 2006 and reported that  $H = 0.83$ , which does not depend on the intraday pattern [16].

By investigating the TAQ data sets of 2674 stocks in the period 2000-2002, Eisler and Kertész found that the strength of correlations depends on the liquidity of stocks so that the Hurst index increases logarithmically with the average trading volume or the company size [8, 9, 19, 20, 21]. There is also evidence showing that trading volumes possess multifractal nature in different markets, such as the high-frequency trading volumes of 30 DJIA constituent stocks [22], of New York Stock Exchange stocks [23] and of the Korean stock index KOSPI [24]. These properties have not been studied for the Chinese market, which will be investigated in this work.

The paper is organized as follows. We give a brief description of the data in Section 2. The intraday pattern, temporal correlations and multifractal nature of trading volume are studied in Section 3, where we will show that the intraday pattern has negligible impact on the temporal correlations and multifractal nature. Section 4 concludes.

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## 2 Data sets

We analyze an ultra-high-frequency database containing 22 Chinese stocks traded on the Shenzhen Stock Exchange in 2003. It records the sizes of all individual transactions. The 22 stocks investigated in this work cover a variety of industry sectors such as financials, real estate, conglomerates, metals & nonmetals, electronics, utilities, IT, transportation, petrochemicals, paper & printing and manufacturing. Our sample stocks were part of the 40 constituent stocks included in the Shenzhen Stock Exchange Component Index in 2003 [6, 15, 25]. The market started with an opening call auction period from 9:15 A.M. to 9:25 A.M. followed by a 5-min cooling period, and then the market entered the double continuous auction period [6, 15, 25]. We focus on the trades occurred in the double continuous auction period.

The tickers of the 22 stocks investigated are the following: 000001 (Shenzhen Development Bank Co. Ltd), 000002 (China Vanke Co. Ltd), 000009 (China Baoan Group Co. Ltd), 000012 (CSG holding Co. Ltd), 000016 (Konka Group Co. Ltd), 000021 (Shenzhen Kaifa Technology Co. Ltd), 000024 (China Merchants Property Development Co. Ltd), 000027 (Shenzhen Energy Investment Co. Ltd), 000063 (ZTE Corporation), 000066 (Great Wall Technology Co. Ltd), 000088 (Shenzhen Yan Tian Port Holdings Co. Ltd), 000089 (Shenzhen Airport Co. Ltd), 000429 (Jiangxi Ganyue Expressway Co. Ltd), 000488 (Shandong Chenming Paper Group Co. Ltd), 000539 (Guangdong Electric Power Development Co. Ltd), 000541 (Foshan Electrical and Lighting Co. Ltd), 000550 (Jiangling Motors Co. Ltd), 000581 (Weifu High-Technology Co. Ltd), 000625 (Chongqing Changan Automobile Co. Ltd), 000709 (Tangshan Iron and Steel Co. Ltd), 000720 (Shandong Luneng Taishan Cable Co. Ltd), and 000778 (Xinxing Ductile Iron Pipes Co. Ltd).

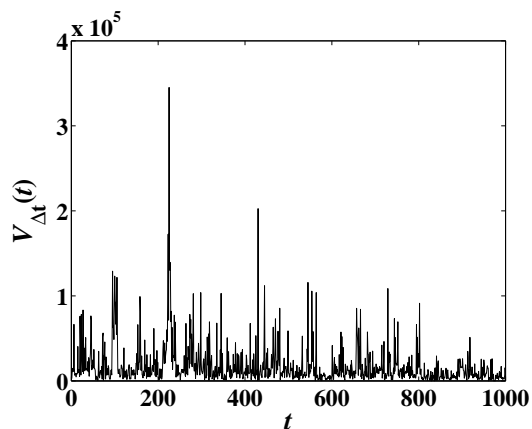


Fig. 1. A segment of the time series of 1-min trading volume  $V_{\Delta t}$  for stock 000001.

Let  $v_i$  be the size of the  $i$ -th trade for a given stock and  $N \equiv N_{\Delta t}$  the number of

trades in a fixed time interval  $\Delta t$ . Then the trading volume at time scale  $\Delta t$  is

$$V_{\Delta t} = \sum_{i=1}^N v_i. \quad (1)$$

A segment of the time series of 1-min trading volume  $V_{\Delta t}$  for stock 000001 is illustrated in Fig. 1.

### 3 Results

#### 3.1 Intraday pattern

Many researches report that there exist intraday patterns in the trading volume but with different shapes [7, 16, 26, 27, 28, 29]. Figure 2 gives the intraday pattern of trading volume for stock 000002 and the average for all 22 stocks. The average trading volume increases and then decreases in the morning, with two mild peaks at about 10:00 and 11:00. At the first minute in the afternoon, there is a significant jump, which is simply due to the fact that orders submitted in the noon closing period (11 : 30 – 13 : 00) are executed at 13:00. Afterwards, we see a monotonic increase in the average trading volume. Our result is quite similar to that in Refs. [16, 29], and the intraday pattern does not has a U-shape.

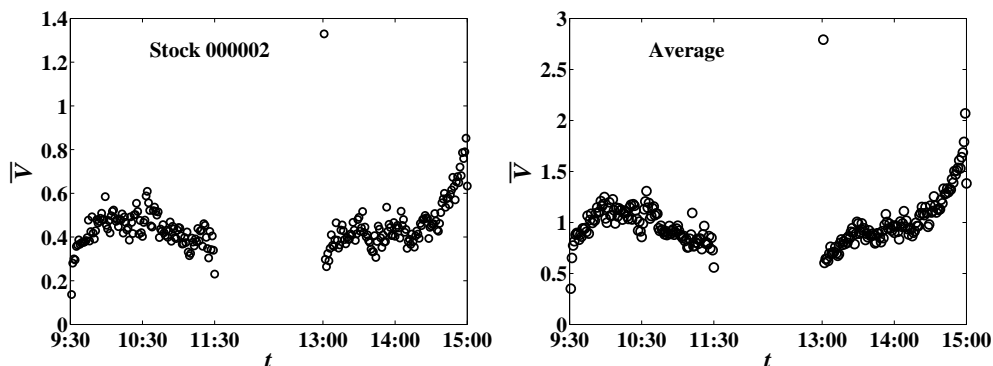


Fig. 2. Intraday pattern of trading volumes is given. Stock 000002 (code number) is shown as an example of individual stock in the left plot, while average result of 22 stocks is listed in the right.

#### 3.2 Size-dependent correlation in trading volume

We investigate the temporal correlations of trading volumes based on the detrended fluctuation analysis (DFA) [30, 31] which is a special case of the multifractal DFA

method [32]. If the time series are long-range power-law correlated, the detrended fluctuation function  $F_q(s)$  versus  $s$  could be describe as follow,

$$F_q(s) = \langle [F^2(s)]^{q/2} \rangle^{1/q} \sim s^{h(q)}, \quad (2)$$

where  $s$  is the length of each segments (time window size) and  $F^2(s)$  is the variance of the detrended time series in a given segment after removing a linear trend, while  $h(q)$  is the generalized Hurst exponent. When  $q = 2$ , we have

$$F_2(s) \sim s^H, \quad (3)$$

which gives the well-known Hurst exponent  $H$ .

We perform DFA on the 1-min original trading volume data and the deseasonalized (or adjusted) data after removing the intraday pattern for each stock. Fig. 3(a) illustrates the power-law dependence of  $F_2(s)$  on  $s$  for stock 000002. In addition, the two curves are almost parallel, indicating that the intraday pattern has negligible impact on the memory effect of trading volume. The results are similar for other stocks. The slopes of the best fitted linear lines in Fig. 3(a) give the estimates of the Hurst indexes for the original data ( $H_1$ ) and the adjusted data ( $H_2$ ), which are presented in Table 1. The average Hurst indexes are  $\bar{H}_1 = 0.88 \pm 0.05$  and  $\bar{H}_2 = 0.89 \pm 0.04$ . We also plot  $H_2$  against  $H_1$  in Fig. 3(b) to show that  $H_2 \approx H_1$ . A careful scrutiny shows that  $H_2$  is slightly greater than or equal to  $H_1$ . We note that there is no crossover in the DFA plot of trading volume for Chinese stocks, which should be compared to the fact that there is no consensus for the presence of crossover [7, 9].

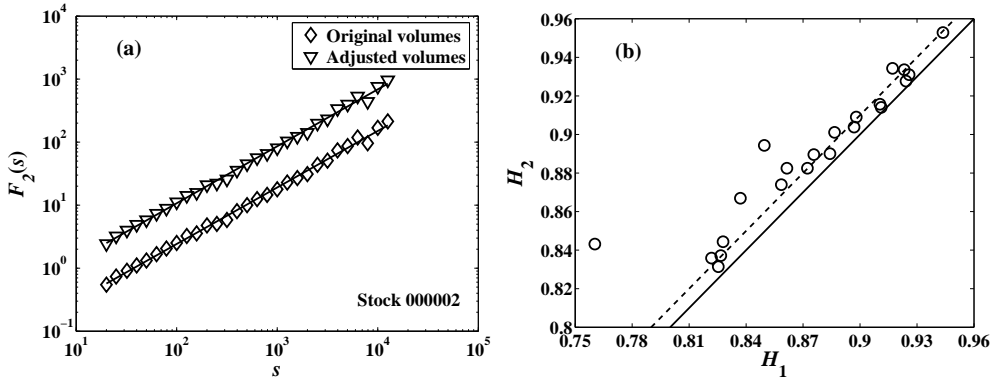


Fig. 3. Detrended fluctuation analysis of 1-min trading volume. (a) Dependence of  $F_2(s)$  on  $s$  for original and deseasonalized trading volumes for stock 000002. (b) Relationship between the Hurst indexes  $H_1$  and  $H_2$  of original and deseasonalized trading volumes. The solid line is  $H_2 = H_1$  and the dashed line is  $H_2 = H_1 + 0.01$ .

It is important to stress that the Hurst index varies from one stock to another, which depends on the company size or average trading volume of a stock. In Fig. 4, we present the dependence of the Hurst indexes of trading volumes on different logarithmic values of  $\langle V \rangle$ , the sample average of  $V_{\Delta t}$  for individual stocks. We find that

there is a linear relationship for both original and deseasonalized data:

$$H_i = H_i^* + \gamma_{H_i} \log \langle V \rangle, \quad i = 1, 2 \quad (4)$$

where the base of log is 10,  $\gamma_{H_1} = 0.06 \pm 0.03$  for the original data, and  $\gamma_{H_2} = 0.05 \pm 0.03$  for the adjusted data. The relation (4) was first observed by Eisler and Kertész for the traded value (also called dollar volume or capital flow, defined by the trading volume times stock price), and they found that  $\gamma_H = 0.06 \pm 0.01$  for NYSE stocks and  $\gamma_H = 0.05 \pm 0.01$  for NASDAQ stocks [8, 9, 19]. Jiang et al verified the relationship for the traded values of about 1500 Chinese stocks and obtained that  $\gamma_H = 0.013 \pm 0.001$  [33]. Since large average trading volume corresponds roughly to large company size (or capitalization), our results show that larger company has stronger correlation in the trading volume. We note that the relation (4) is observed for the first time for trading volume in this work.

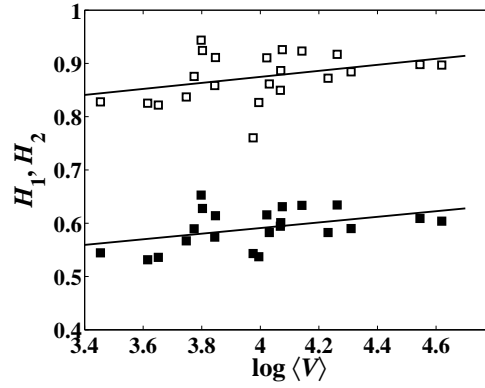


Fig. 4. Logarithmic dependence of Hurst index on average trading volume for the original data ( $\square$ ) and adjusted data ( $\blacksquare$ ). The data points for the adjusted trading values have been shifted vertically downwards for better visibility.

### 3.3 Mean-variance analysis

We now conduct the mean-variance analysis on the time series of trading volume. For each stock, the mean  $\langle V_{\Delta t} \rangle$  and the variance  $\sigma_{\Delta t}^2$  are calculated for different time scales  $\Delta t$ . Since  $V_{\Delta t}$  is additive, the mean-variance analysis gives [34]

$$\sigma_{\Delta t} \sim \langle V_{\Delta t} \rangle^\beta, \quad (5)$$

where  $\langle \cdot \rangle$  denotes time averaging. Fig. 5(a) illustrates the power-law dependence of  $\sigma_{\Delta t}$  with respect to  $\langle V_{\Delta t} \rangle$  in double logarithmic coordinates for three time windows  $\Delta t = 1$  min, 0.5 trading day (120 min) and 20 trading days and for the original data. For the deseasonalized data,  $\langle V \rangle \equiv 1$  so that the mean-variance does not apply. The slopes of the best linear fits give the estimates of  $\beta$  at different time scales  $\Delta t$ . Fig. 5(b) plots  $\beta$  as a function of  $\Delta t$  for the original trading volume data,

which has a logarithmic trend,

$$\beta = \beta^* + \gamma_\beta \log \Delta t, \quad (6)$$

where  $\gamma_\beta = 0.059 \pm 0.001$ . We find that the following relation holds

$$\gamma_\beta \approx \gamma_{H_i}, \quad i = 1, 2, \quad (7)$$

which has been well verified for the traded values for different stock markets including developed [8, 19] and emerging stock markets [33].

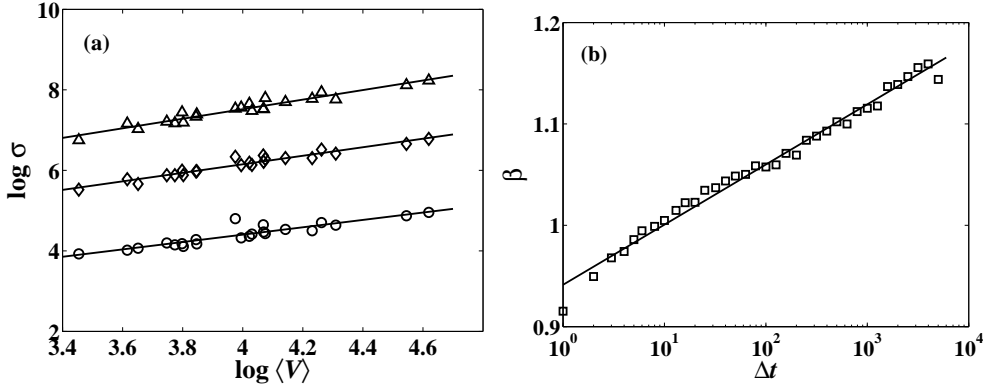


Fig. 5. Mean-variance analysis of trading volume. (a) Power-law dependence of  $\sigma_{\Delta t}$  on  $\langle V_{\Delta t} \rangle$  for  $\Delta t = 1$  min ( $\circ$ ), 120 min ( $\diamond$ ) and 20 days ( $\triangle$ ) for the original data. (b) Logarithmic dependence of the scaling exponent  $\beta$  on the time scale  $\Delta t$  for the original data.

### 3.4 Multifractal analysis

In this section, we employ the MF-DFA method [32] to investigate the multifractal nature of trading volumes. In this procedure, the  $q$ -th order fluctuation function  $F_q(s)$  versus  $s$  is analyzed for different  $q$ . We vary the value of  $s$  in the range from  $s_{\min} = 20$  to  $s_{\max} = M/4$  ( $M$  is the length of a series), since  $F_q$  becomes statistically unreliable for very large scales  $s$ , and systematic deviations will be involved for very small scales  $s$ . The relationship between  $h(q)$  and the mass scaling exponents  $\tau(q)$  in the conventional multifractal formalism based on the partition functions [32, 35] is formalized as follows,

$$\tau(q) = qh(q) - D_f, \quad (8)$$

where  $D_f$  is the fractal dimension of the geometric support of the multifractal measure (in our case  $D_f = 1$ ). According to the Legendre transform [35], we have

$$\alpha = h(q) + qh'(q) \quad \text{and} \quad f(\alpha) = q(\alpha - h(q)) + 1, \quad (9)$$

providing the estimation of strength of singularity  $\alpha$  and its spectrum  $f(\alpha)$ .

Fig. 6 illustrates an example the multifractal analysis for stock 000002. It is evidence from Fig. 6(a) that  $\tau(q)$  is a non-linear function of  $q$ , which is a hallmark for the presence of multifractality. There is no remarked discrepancy observed between the original and adjusted data of trading volumes. To further clarify the negligible influence of the intraday pattern on the multifractal nature of trading volumes, we calculate two characteristic values  $\Delta h = h_{\max} - h_{\min}$  and  $\Delta\alpha = \alpha_{\max} - \alpha_{\min}$  respectively for each time series. The results of  $\Delta h$  and  $\Delta\alpha$  are listed in Table 1. The results are presented in Fig. 6(b). We see that  $\Delta h_1 \approx \Delta h_2$  and  $\Delta\alpha_1 \approx \Delta\alpha_2$ , indicating that the intraday pattern in the trading volume has negligible impact on the multifractal nature.

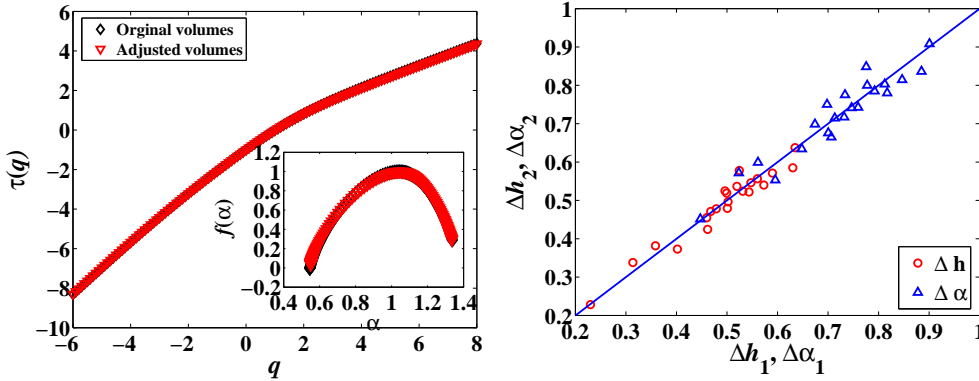


Fig. 6. Multifractal detrended fluctuation analysis of trading volumes for stock 000002. (a) Non-linear dependence of  $\tau(q)$  with respect to  $q$  and the multifractal spectrum  $f(\alpha)$  in the inset. (b) Negligible impact of intraday pattern on the multifractal nature of trading volumes.

## 4 Conclusion

We have studied the temporal correlations and multifractal nature of trading volume for 22 most actively traded Chinese stocks on the Shenzhen Stock Exchange. Detrended fluctuation analysis shows that the trading volumes at different time scales possess non-universal long memory, whose Hurst index  $H$  depends logarithmically on the average trading volume as  $H = H^* + \gamma_H \log \langle V \rangle$ . The mean-variance unveils that the scaling exponent  $\beta$  depends logarithmically on the time scale as  $\beta = \beta^* + \gamma_\beta \log \Delta t$ . Empirical evidence shows that  $\gamma_H = \gamma_\beta$ , consistent with the theoretical derivation. The investigation of the size-dependent non-universal correlation in trading volume has not been conducted before. Multifractal detrended fluctuation analysis confirms that the trading volume exhibits multifractal nature. Comparing the results obtained from the original trading volume data and the adjusted data after removing the intraday pattern, we conclude that the intraday pattern has negligible impact on the temporal correlations and multifractal nature of trading volumes.



In general, the results obtained for the Shenzhen Stock Exchange in this paper are qualitatively the same as other emerging and developed markets. However, there are some differences. There are studies showing that there is a crossover phenomenon in the power-law relation between the detrended fluctuation function and the scale for some markets, which is not observed for the Shenzhen Stock Exchange. Also, the multifractal spectra differ from one market to another with different singularity width, which is usually determined by the distribution and the correlation structure of the time series showing the idiosyncrasy of different markets.

### **Acknowledgments:**

This work was partly supported by the National Natural Science Foundation of China (70501011 and 70502007), the Shanghai Educational Development Foundation (2008SG29), the China Scholarship Council (2008674017), and the Program for New Century Excellent Talents in University (NCET-07-0288).

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## 5 Appendix

Table 1

Appendix table. The subscript “1” means original data and the subscript “2” stands for adjusted data.

Stock code	$H_1$	$H_2$	$\Delta h_1$	$\Delta h_2$	$\Delta \alpha_1$	$\Delta \alpha_2$
000001	$0.90 \pm 0.015$	$0.91 \pm 0.014$	0.40	0.37	0.60	0.55
000002	$0.90 \pm 0.009$	$0.90 \pm 0.009$	0.55	0.55	0.79	0.78
000009	$0.88 \pm 0.009$	$0.89 \pm 0.008$	0.56	0.56	0.81	0.80
000012	$0.83 \pm 0.005$	$0.84 \pm 0.005$	0.46	0.45	0.65	0.63
000016	$0.92 \pm 0.006$	$0.93 \pm 0.006$	0.36	0.38	0.56	0.60
000021	$0.91 \pm 0.015$	$0.92 \pm 0.015$	0.52	0.58	0.78	0.85
000024	$0.88 \pm 0.005$	$0.89 \pm 0.005$	0.50	0.52	0.70	0.75
000027	$0.92 \pm 0.016$	$0.93 \pm 0.016$	0.46	0.42	0.71	0.67
000063	$0.89 \pm 0.007$	$0.90 \pm 0.007$	0.57	0.54	0.82	0.78
000066	$0.91 \pm 0.009$	$0.91 \pm 0.009$	0.50	0.50	0.73	0.72
000088	$0.82 \pm 0.007$	$0.84 \pm 0.007$	0.54	0.52	0.76	0.74
000089	$0.85 \pm 0.011$	$0.89 \pm 0.008$	0.63	0.64	0.90	0.91
000429	$0.94 \pm 0.014$	$0.95 \pm 0.014$	0.23	0.23	0.45	0.45
000488	$0.86 \pm 0.007$	$0.88 \pm 0.007$	0.47	0.47	0.67	0.70
000539	$0.76 \pm 0.007$	$0.84 \pm 0.008$	0.63	0.59	0.88	0.84
000541	$0.83 \pm 0.009$	$0.84 \pm 0.009$	0.48	0.48	0.71	0.71
000550	$0.93 \pm 0.017$	$0.93 \pm 0.017$	0.50	0.52	0.73	0.78
000581	$0.84 \pm 0.006$	$0.87 \pm 0.006$	0.52	0.54	0.78	0.80
000625	$0.87 \pm 0.012$	$0.88 \pm 0.011$	0.59	0.57	0.85	0.81
000709	$0.92 \pm 0.010$	$0.93 \pm 0.010$	0.31	0.34	0.52	0.57
000720	$0.83 \pm 0.007$	$0.83 \pm 0.007$	0.50	0.48	0.70	0.68
000778	$0.86 \pm 0.008$	$0.87 \pm 0.007$	0.53	0.52	0.75	0.74