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Cross-correlations between Chinese A-share and B-share markets

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ABSTRACT

In this paper, we investigate the cross-correlations between Chinese A-share and B-share markets. Qualitatively, we find that the return series of Chinese A-share and B-share markets were overall significantly cross-correlated based on the analysis of a statistic. Quantitatively, employing the detrended cross-correlation analysis, we find that the cross-correlations were strongly multifractal in the short-term and weakly multifractal in the long-term. Moreover, the cross-correlations of small fluctuations were persistent and those of large fluctuations were anti-persistent in the short-term while cross-correlations of all kinds of fluctuations were persistent in the long-term. Using the method of rolling windows, we find that the cross-correlations were weaker and weaker over time, especially after the price-limited reform. We attribute the fact to the improvement of market efficiency. On the volatility series, our results show that the cross-correlations were much stronger than those between return series. Results from rolling windows show that the short-term cross-correlations between volatility series are still high now. We also provide some relevant discussions later.

1. Introduction

The pioneer, Peters [1,2] using Rescaled Range analysis (R/S) found the evidence of long-range auto-correlations in several financial markets implying the fact of inefficiency. Using R/S method, Cajueiro and Tabak [3] studied the long-range auto-correlations in merging markets and found that the markets became more and more efficient over time. This method was also used to detect the long-range auto-correlations in crude oil markets [4] and volatility series in stock markets [5]. However, Lo [6] found that R/S method which was sensitive to short-term auto-correlations could lead to a bias estimation of the long-range auto-correlations. To overcome this drawback, Peng et al. [7] proposed detrended fluctuation analysis (DFA) when they studied the auto-correlations of molecular chains in deoxyribonucleic acid (DNA). This method can avoid the spurious detection of apparent long-range auto-correlations that are an artifact of patchiness. Together with its multifractal generalization [8], DFA has been widely used to detect the long-range auto-correlations in financial markets. Alvarez-Ramirez et al. [9] using DFA investigated the auto-correlations in US stock markets and found that the breakthrough of the long-term trend of the scaling behavior occurred in 1972, at the end of the Bretton Woods system. Alvarez-Ramirez et al. [10] analyzed the auto-correlations of WTI crude oil markets and found that the market exhibited a time-varying short-term inefficient behavior that became efficient over time. Norouzzadeh and Rahmani [11] using MF-DFA described the multifractality of Iranian rial–US dollar exchange rate series and found that the main cause of that was long-range auto-correlations. In our previous works [12,13], DFA is also used to investigate the long-range auto-correlations in Chinese stock markets. We found that the markets were more and more efficient over time and the main breakthrough of the long-term trend of long-range auto-correlations was caused by the price-limited reform.

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Recently, Podobnik and Stanley [14] extended the DFA to investigate the long-range cross-correlations between two time series which have been widely tested in previous works [15–22], named detrended cross-correlation analysis (DCCA). DCCA method and its multifractal extension [23] have been used to detect the cross-correlations between two financial series in some papers [24,25].

In this paper, we analyze the cross-correlations between A-share and B-share markets in China. Our contribution is three-fold. First, we not only *qualitatively* analyze the cross-correlations between the return series of A-share and B-share markets employing the statistics recently proposed by Podobnik et al. [26], but also *quantitatively* study the cross-correlations using the detrended cross-correlation analysis [14,23]. Second, using the method of rolling windows, we investigate the evolution of cross-correlations. Third, besides the return series, we also investigate the cross-correlations between the volatility series of A-share and B-share markets. Some implications for modeling and the predictability are also discussed at last.

This paper is organized as follows: we provide the methodology in the next section. We show data description and empirical results in Sections 3 and 4, respectively. Section 5 provides some relevant discussions. Then, we conclude at the last section.

2. Methodology

Conventionally, cross-correlation function functions were widely used to analyze the dynamics of natural systems. However, these techniques can only suit to situations for the stationary series. As an important fact, many kinds of time series are long-range correlated and nonstationary, and have the strong trends. We need to remove the trend which widely existed in the time series. The detrended cross-correlation analysis (DCCA) can well solve these problems and is a robust method of detecting the cross-correlations in nonstationary financial markets. DCCA method can be described as follows [14,23]:

Step 1. Consider two time series, $\{x_t, t = 1, \dots, N\}$ and $\{y_t, t = 1, \dots, N\}$, where N is the equal length of these two series. Then, we describe the "profile" of each series and get two new series, $xx_k = \sum_{t=1}^{k}(x_t - \bar{x})$ and $yy_k = \sum_{t=1}^{k}(y_t - \bar{y})$, $k = 1, \dots, N$.

Step 2. Divide the both profiles $\{xx_k\}$ and $\{yy_k\}$ into $N_s = int(N/s)$ nonoverlapping segments of equal length s. Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of each profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end of each profile. Thereby, $2N_s$ segments are obtained together. We set $10 < s < N/5$.

Step 3. We calculate the local trends $\widetilde{xx}_{(\lambda-1)s+j}$ and $\widetilde{yy}_{(\lambda-1)s+j}$ for each of the $2N_s$ segments by a least-square fit of each series. Then determine the co-moved variance

$$F^2(s,\lambda) \equiv \frac{1}{s}\sum_{j=1}^{s}\left[xx_{(\lambda-1)s+j} - \widetilde{xx}_{(\lambda-1)s+j}\right]\left[yy_{(\lambda-1)s+j} - \widetilde{yy}_{(\lambda-1)s+j}\right] \tag{1}$$

for $\lambda = 1, 2, \dots, N_s$ and

$$F^2(s,\lambda) \equiv \frac{1}{s}\sum_{j=1}^{s}\left[xx_{N-(\lambda-N_s)s+j} - \widetilde{xx}_{N-(\lambda-N_s)s+j}\right]\left[yy_{N-(\lambda-N_s)s+j} - \widetilde{yy}_{N-(\lambda-N_s)s+j}\right] \tag{2}$$

for $\lambda = N_s + 1, N_s + 2, \dots, 2N_s$. The trends $\widetilde{xx}_{(\lambda-1)s+j}$ and $\widetilde{yy}_{(\lambda-1)s+j}$ can be computed from linear, quadratic or high order polynomial fit of each profile for segment λ.

Step 4. Average over all segments to get the fluctuation function

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{\lambda=1}^{2N_s}\left[F^2(s,\lambda)\right]^{q/2}\right\}^{1/q} \tag{3}$$

for any real value $q \neq 0$ and

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{\lambda=1}^{2N_s}\ln\left[F^2(s,\lambda)\right]\right\}. \tag{4}$$

Step 5. Analyze the scale behavior of the fluctuation function through observe the log–log plots of $F_q(s)$ versus s. If two series are long-range cross-correlated, as a power-law

$$F_q(s) \sim s^{\alpha(q)}. \tag{5}$$

Here, the scaling exponent $\alpha(q)$ can be obtained by observing the slope of log–log plot of $F_q(s)$ versus s through the method of ordinary least squares (OLS). If scaling exponent $\alpha(q) > 0.5$, the cross-correlations between the kinds of fluctuations related to q of two series are persistent (positive). An increase of one price is likely to be followed by an increase of the other price. If scaling exponent $\alpha(q) < 0.5$, the cross-correlations between the kinds of fluctuations related to q of two series are anti-persistent (negative). An increase of one price is likely to be followed by a decrease of the other price. If $\alpha(q) = 0.5$, one series is not cross-correlated with the other, and the change of one price cannot affect the behavior the other price.

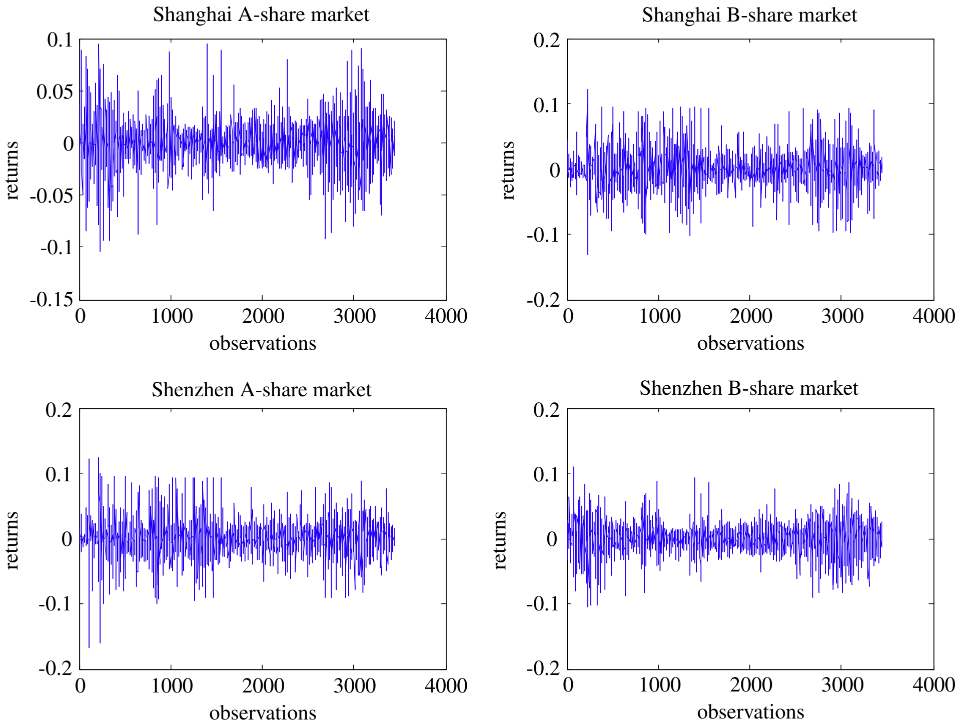

Fig. 1. Returns of Chinese A-share and B-share markets.

3. Data

A-shares are also common shares labeled as RMB which are issued by domestic companies and are bought and sold by domestic citizen. B-shares are RMB special shares which are issued by domestic companies which registered domestically, but the investors of B-shares are strained in the area of foreign citizens. The nominal values of B-shares are labeled as RMB but they are traded using US dollars (in Shanghai) and Hong Kong dollars (in Shenzhen). The total amount of the capital in B-share market is strictly restricted by Chinese government. Chinese government set up Shanghai A-share and B-share index on February 21st, 1992 and Shenzhen A-share and B-share index on December 19th, 1995.

We choose daily closing data of prices of Shanghai A-share market, Shanghai B-share market, Shenzhen A-share market and Shenzhen B-share market from January 2nd, 1996 to April 1st, 2010. Let P_t denote the price of crude oil on day t. The daily price return, r_t, is calculated as its logarithmic difference, $r_t = \log(P_t) - \log(P_{t-1})$. The graphical representation of returns of these four markets is illustrated in Fig. 1.

4. Empirical results

4.1. Preliminary analysis

Podobnik et al. [26] introduced a cross-correlation statistic in analogy to the Ljung-Box (LJB) test [27]. For two time series, $\{x_t, t = 1, \ldots, N\}$ and $\{y_t, t = 1, \ldots, N\}$, the test statistic

$$Q_{cc}(m) = N^2 \sum_{i=1}^{m} \frac{X_i^2}{N - i}. \tag{6}$$

Here, the cross-correlation function

$$X_i = \frac{\sum_{k=i+1}^{N} x_k y_{k-i}}{\sqrt{\sum_{k=1}^{N} x_k^2 \sum_{k=1}^{N} y_k^2}}. \tag{7}$$

The cross-correlation statistic $Q_{cc}(m)$ is approximately $\chi^2(m)$ distributed with m degrees of freedom. The statistic can be used to test the null hypothesis that none of the first m cross-correlation coefficient is different from zero.

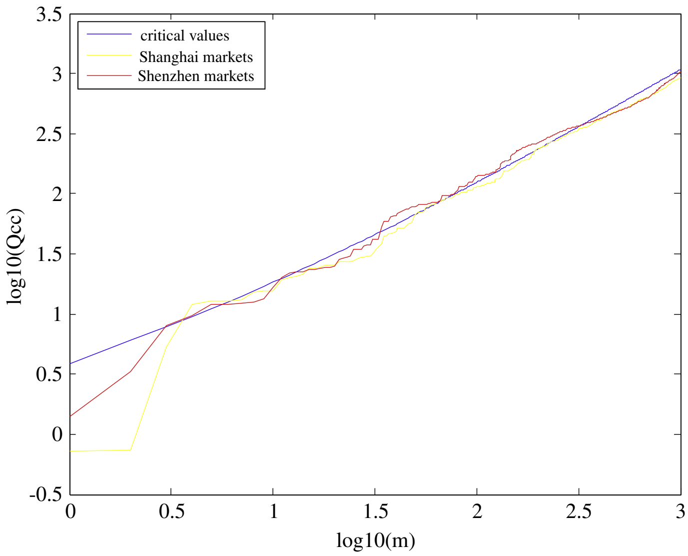

Fig. 2. The cross-correlation statistics.

Fig. 2 shows the cross-correlation statistics for two pairs of return series in Shanghai and Shenzhen markets. The degrees of freedom vary from 10^0 to 10^3. As a comparison, we also show the critical values for the $\chi^2(m)$ distribution at the 5% level of significance in Fig. 2.

In Fig. 2, we can find that the cross-correlation statistics $Q_{cc}(m)$ for two pair of return series are always larger than the critical values for the $\chi^2(m)$ distribution at the 5% level of significance. It seems that for $m > 2.5$, $Q_{cc}(m)$ are all smaller than critical values. However, the statistics $Q_{cc}(m)$ have the trend of being close to the critical values with m increasing and are nearly equal to the critical values at $m = 10^3$. Thus, we can overall reject the null hypothesis of no cross-correlations. In other words, the long-range cross-correlations existed between Shanghai A-share and B-share markets, also between Shenzhen A-share and B-share markets.

4.2. Detrended cross-correlation analysis

As suggested in Podobnik et al. [26], the cross-correlation test based on the statistics in Eq. (6) can *only* be used to test the presence of cross-correlations only *qualitatively*. In order to test the presence of cross-correlations *quantitatively*, we need the DCCA method which can estimate the cross-correlation exponent. We show the log–log plots of fluctuation function $F_q(s)$ versus time scale s A-share and B-share markets in Shanghai in Fig. 3 and for two stock markets in Shenzhen in Fig. 4, respectively.

In Figs. 3 and 4, we can find that only one line cannot fit the log–log plots of $F_q(s)$ versus time scale s well. We define the "crossover", s^*, as the turning point when the linear trend of the curves underwent a fundamental change. The short-term behavior of financial market is easily influenced by the market external factors such as the major events while the long-term behavior is determined by the internal factors. With the time evolving, the short-term shocks gradually decay for the effects of long-term supply and demand mechanism in the markets [9]. The scaling exponents for $s < s^*$ can reflect the short-range correlations which also imply the correlated behaviors in the short-term. Then, the scaling exponents for $s > s^*$ imply the correlated behaviors in the long-term. Thus, we can say that the "crossover" can reflect the lasting period of the effects of the factors which determine the market short-term behavior. We can find the "crossover" at about $\log 10(s^*) = 2.25$ (178 days, about 8.5 months). We provide the slopes of each line, just the scaling exponents for $s < s^*$ and $s > s^*$ in Table 1.

For $q = 2$, the scaling exponent is just similar to the Hurst exponent calculated from the method of DFA. When $q = 2$, the scaling exponent for two Shanghai stock markets is 0.5357 for $s < s^*$ indicating that Shanghai A-share market and B-share market are weakly cross-correlated in the short-term. The scaling exponent for two Shenzhen stock markets is 0.5541 for $s < s^*$ implying the similar cross-correlated behavior to those between two Shanghai markets. For $s > s^*$, the scaling exponent for two Shanghai markets is 0.6610, larger than that for $s < s^*$ indicating that they are moderately cross-correlated in the long-term. The cross-correlations between two Shenzhen markets are also similar to those between two Shanghai markets in the long-term.

For other values of q, the scaling exponents indicate the cross-correlated behaviors between the kinds of fluctuations related to q. We provide the scaling exponents with q varying from -10 to 10 for two Shanghai markets in Fig. 5 and for two Shenzhen markets in Fig. 6, respectively.

From Figs. 5 and 6, for $s < s^*$, we can find that for Shanghai A-share market and B-share market, the scaling exponents decrease from larger than 0.7 to smaller than 0.3 indicating that the cross-correlated behaviors are multifractal in the short-term. Moreover, the scaling exponents for $q < 0$ are larger than 0.5 indicating the cross-correlated behaviors of small

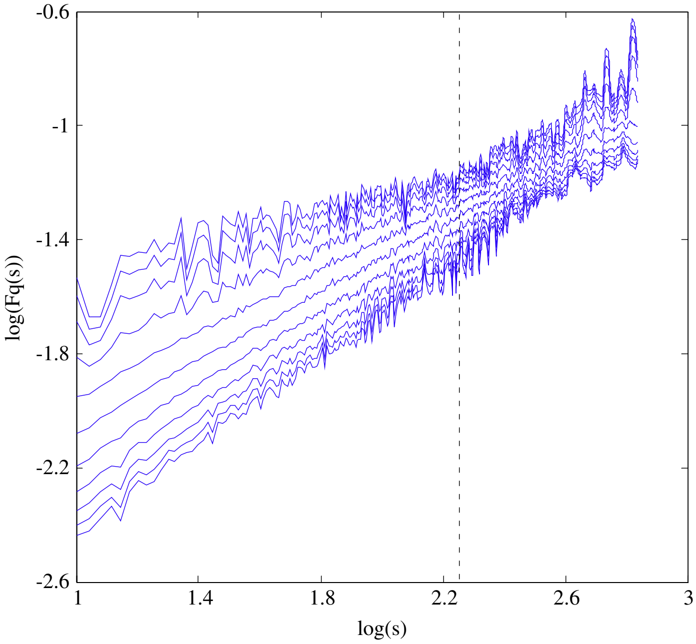

Fig. 3. Log–log plots of $F_q(s)$ versus s for returns of Shanghai A-share and B-share markets.

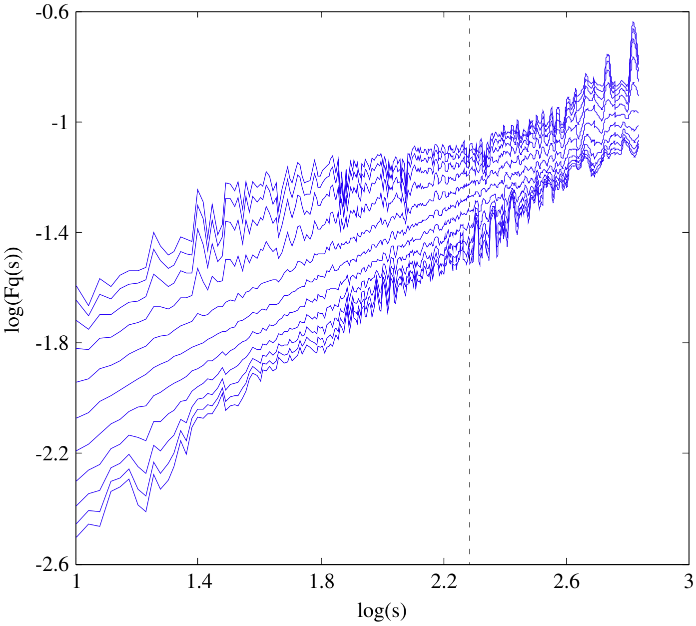

Fig. 4. Log-log plots of $F_q(s)$ versus s for returns of Shenzhen A-share and B-share markets.

fluctuations are persistent (positive) in the short-term. The scaling exponents for $q > 3$ are smaller than 0.5 indicating the cross-correlated behaviors of large fluctuations are anti-persistent (negative) in the short-term. However, for $s > s^*$, the values of $\alpha(q)$ weakly depend on the values of q indicating that the long-term cross-correlated behavior is weakly multifractal. Moreover, all of the values of $\alpha(q)$ are larger than 0.5 indicating that the long-term cross-correlated behaviors are persistent. The long-term behaviors of the stock markets are all determined by the fundamentals of Chinese economy. The long-term situations of economic fundamentals could make the same effects on all of the stock markets. Thus, the cross-correlations of all of the large and small fluctuations between A-share and B-share markets were persistent. The cross-correlated situations between two Shenzhen stock markets are similar to those between two Shanghai markets.

The overall analysis cannot well capture the dynamics of cross-correlations over time. Similar to the works in Refs. [3–5,9,10], we use the method of rolling windows to investigate the evolution of short-term cross-correlations over

Table 1
Scaling exponents for return series with q varying from −10 to 10.

q	Shanghai A-share and B-share markets		Shenzhen A-share and B-share markets	
	$S < S^*$	$S > S^*$	$S < S^*$	$S > S^*$
−10	0.7401	0.6090	0.7561	0.6918
−8	0.7258	0.5950	0.7426	0.6674
−6	0.7069	0.5795	0.7237	0.6394
−4	0.6811	0.5668	0.6964	0.6140
−2	0.6457	0.5672	0.6585	0.6047
0	0.5982	0.5967	0.6103	0.6187
2	0.5357	0.6610	0.5541	0.6455
4	0.4548	0.7184	0.4853	0.6648
6	0.3753	0.7454	0.4188	0.6714
8	0.3181	0.7544	0.3721	0.672
10	0.2803	0.7558	0.3411	0.6715

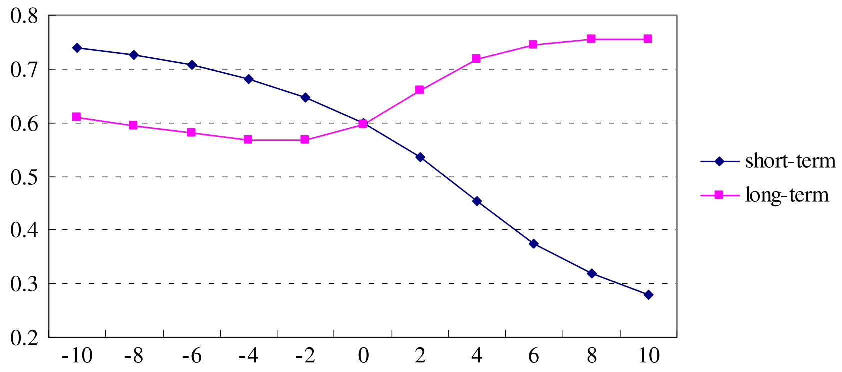

Fig. 5. Scaling exponents for Shanghai A-share and B-share markets with q varying from −10 to 10.

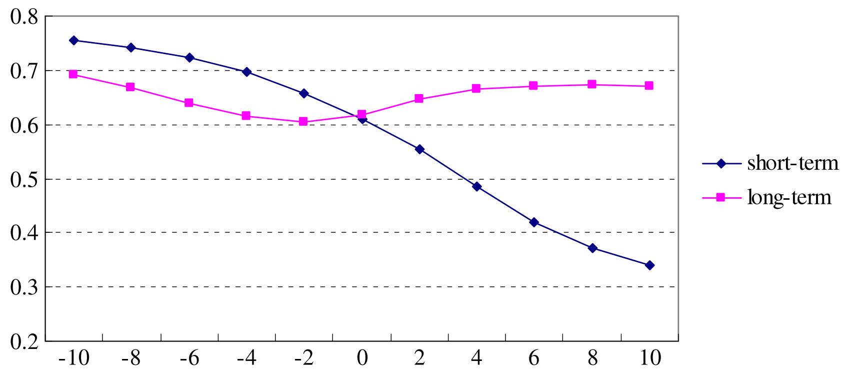

Fig. 6. Scaling exponents for Shenzhen A-share and B-share markets with q varying from −10 to 10.

time. The length of each window is fixed to be 250 business days (about a year). The step is 1 day. We calculate out the scaling exponent for two pairs of series in each window for $q = 2$. The graphical representations are shown in Figs. 7 and 8. The time in x-axis is the date of the last day in each window.

In Fig. 7, we can find that the scaling exponent was gradually close to 0.5 with window moving indicating that the cross-correlations between Shanghai A-share and B-share markets were weaker and weaker over time. The main reason is that Chinese stock market gradually became more and more efficient. That is also to say, the predictability of Chinese stock markets based on the history of themselves and the other markets was lower and lower. Moreover, at the end of 1997, the scaling exponents dropped abruptly from larger than 0.7 to close to 0.5. We attribute this decrease of the degree of cross-correlations to the price-limited reform implemented by the government which greatly improved the efficiency of Chinese stock markets [12,13]. However, we also should notice that, the scaling exponents are still larger than 0.5 indicating that two Shanghai stock markets were weakly positively cross-correlated now. Analogous results can be obtained from the situations for two Shenzhen stock markets from Fig. 8.

For robustness, we adjust the length of each window to be 175 business days and show the graphical representations in Figs. 9 and 10. We can also get the similar results to those from Figs. 5 and 6.

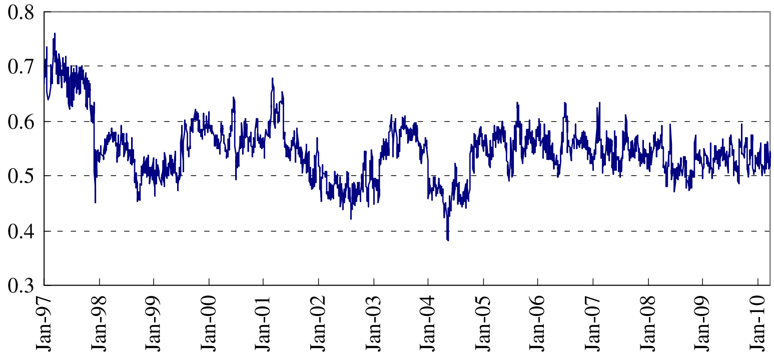

Fig. 7. Scaling exponents for $q = 2$ for two Shanghai markets with window moving. The length of each window is fixed to be 250 days.

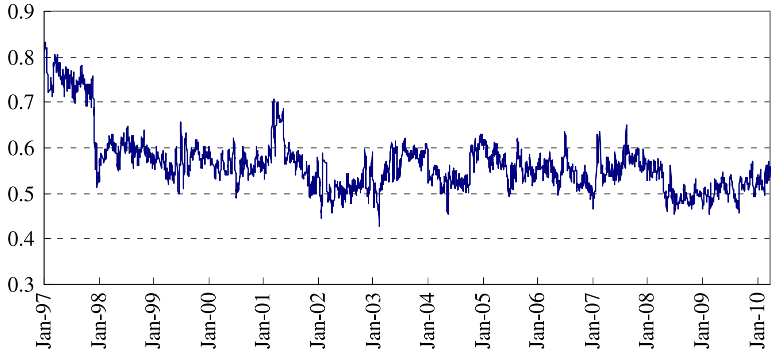

Fig. 8. Scaling exponents for $q = 2$ for two Shenzhen markets with window moving. The length of each window is fixed to be 250 days.

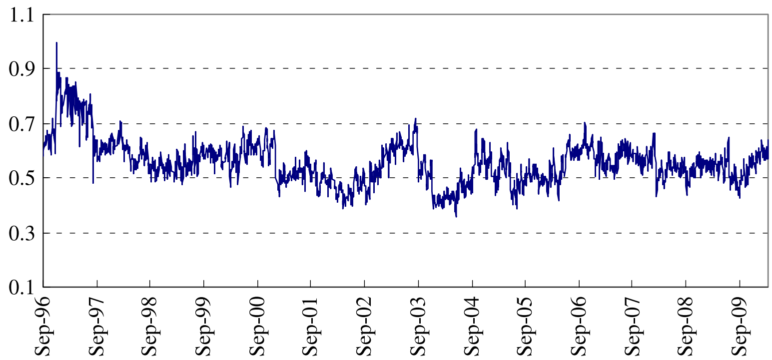

Fig. 9. Scaling exponents for $q = 2$ for two Shanghai markets with window moving. The length of each window is fixed to be 175 days.

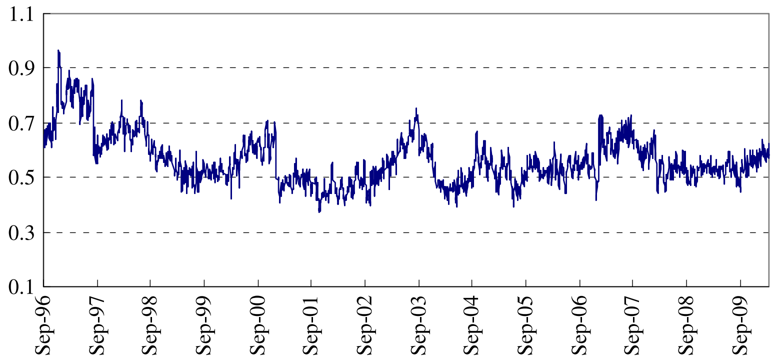

Fig. 10. Scaling exponents for $q = 2$ for two Shenzhen markets with window moving. The length of each window is fixed to be 175 days.

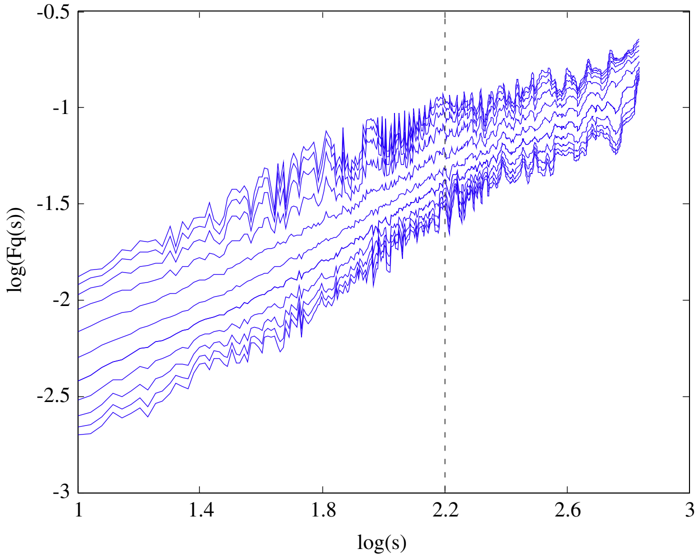

Fig. 11. Log-log plots of $F_q(s)$ versus s for volatilities of Shanghai A-share and B-share markets.

4.3. The cross-correlations between volatility series

The magnitude time series which can be taken as the proxy of volatility are always much more strongly auto-correlated than the return time series [4,5]. One may expect that magnitude cross-correlations are also much stronger than return cross-correlations. Podobnik et al. [31] studied long-range magnitude cross-correlations in collective modes of real-world data from finance, physiology, and genomics using time-lag random matrix theory. Their evidence supported the presence of strongly long-range cross-correlations. Thus, it is necessary to analyze the cross-correlations between the magnitude time series of stock markets.

The cross-correlation statistics $Q_{cc}(m)$ in Eq. (6) for the volatility series of two Shanghai markets and two Shenzhen markets are all much larger than the critical values for the $\chi^2(m)$ distribution at the 5% level of significance with degrees of freedom varying from 10^0 to 10^3. That is to say, Chinese A-share and B-share markets are strongly cross-correlated.[1]

Fig. 11 provides the log–log plots of $F_q(s)$ versus time scale s for absolute return series of two Shanghai stock markets. The values of q vary from -10 to 10. The situations for two Shenzhen markets are also shown in Fig. 12. We can find that the location of "crossover" is at about $s^* = 2.2$, very similar to the location in Figs. 5 and 6.

We provide the scaling exponents for different time scale intervals in Table 2. For $s < s^*$, the change of scaling exponents depends on the values of q implying the fact of multifractality. Moreover, the scaling exponents are all larger than 0.5 implying the persistent cross-correlated behavior between the volatility of Chinese A-share and B-share markets. Especially for $q < -6$, the scaling exponents are much close to 1 indicating that the cross-correlations of small fluctuations are strongly persistent in the short-term. For $s > s^*$, the cross-correlated behavior between Chinese A-share and B-share markets are also multifractal. Moreover, for $q < 0$, the scaling exponents are larger than 0.5 indicating that the cross-correlations of small fluctuations between A-share and B-share markets are persistent in the long-term. However, for $q = 10$, the scaling exponents are close to 0.5 indicating that the extreme large fluctuations are nearly not cross-correlated in the long-term.

Employing the method of rolling windows, Fig. 13 shows the time-varying scaling exponents for $q = 2$ for the volatility series of Shanghai A-share and B-share markets. The length of each window is also fixed to be 250 business days. We can find that although the scaling exponents seemed to run a downward trend from 1997 to 2003, they kept going around 0.6 after 2003 implying the constant trend of persistent behavior of cross-correlations. That is to say, the volatilities of prices of two markets are still persistently cross-correlated now. The situations for two Shenzhen stock markets are very similar to those for Shanghai markets.[2]

5. Discussion

5.1. On the rolling windows

Although has been employed in previous papers, after the influential work in Cajueiro and Tabak [3], the method of rolling windows began to be widely used to investigate many topics on the financial markets, such as market

[1] To save space, we do not show the figure presentation of the cross-correlation statistics which can be obtained upon request.

[2] To save space, we do not show the graphical representation of the dynamics of the volatility series of two Shenzhen markets. It can be obtained upon request. It is very similar to that of two Shanghai markets.

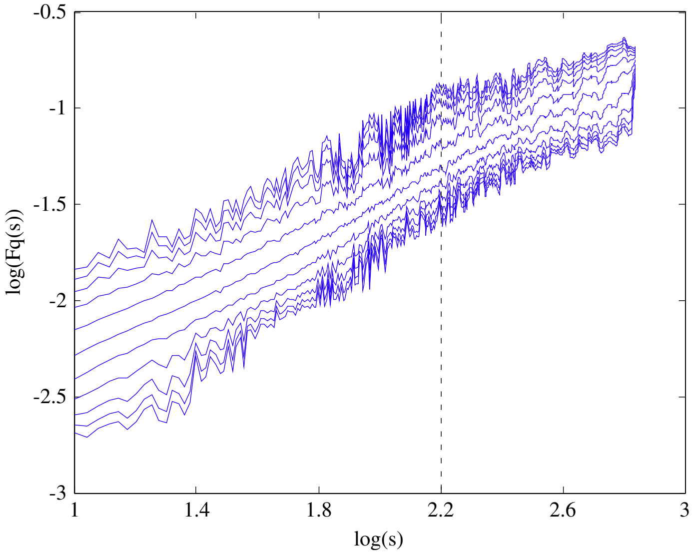

Fig. 12. Log-log plots of $F_q(s)$ versus s for volatilities of Shenzhen A-share and B-share markets.

Table 2
Scaling exponents for volatility series with q varying from -10 to 10.

q	Shanghai A-share and B-share markets		Shenzhen A-share and B-share markets	
	$S < S^*$	$S > S^*$	$S < S^*$	$S > S^*$
−10	1.0419	0.7646	1.0458	0.6535
−8	1.0179	0.7506	1.0201	0.6483
−6	0.9838	0.7403	0.9822	0.6496
−4	0.9402	0.7491	0.9313	0.6719
−2	0.8935	0.8010	0.8825	0.7386
0	0.8450	0.8476	0.8463	0.8020
2	0.8081	0.7964	0.8335	0.7446
4	0.7860	0.6988	0.8404	0.6279
6	0.7609	0.6173	0.8338	0.5408
8	0.7377	0.5616	0.8183	0.4869
10	0.7194	0.5245	0.8028	0.4831

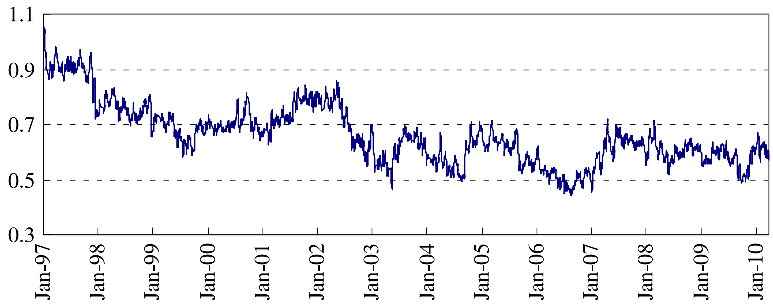

Fig. 13. Scaling exponents for $q = 2$ for two Shanghai markets with window moving. The length of each window is fixed to be 250 days.

efficiency [3,4,9,10,12,13], the prediction of crash in financial markets [28,29] and risk measurement [30], etc. For different purposes, the lengths of the time-window are various. Obviously, as made in Cajueiro and Tabak [3–5], and Tabak and Cajueiro [4], for analyzing the evolution of long-term correlations, the length should be several years. To investigate the dynamics of short-term correlations, as argued in Grech and Mazur [28], if the length of rolling window is too large, the calculated exponent may lose its locality. For example, if the length is larger than a year, the seasonal cycling in financial markets may cover the short-term properties and induce to the poor predictability. However, if the length is too small, the evolution of the local exponents may be too fierce which can result in the fact that it is hard to observe the trend of local exponents. Grech and Mazur [28] also argued that the local exponent at a given time t depends on the time-window length. Thus, for different purposes, the selection of the length of rolling window should be careful. In this paper, we choose two different lengths of rolling window, 250 and 175 business days to investigate the dynamics of short-term cross-correlations. The results are very similar implying the robustness.

5.2. Some implications

We have investigated the cross-correlations between Chinese A-share and B-share markets. The results show that the return series were weakly cross-correlated in the short-term. Moreover, short-term cross-correlations displayed high complexity (multifractality) indicating that the cross-correlations were easily to be affected by large and small fluctuations. The results from rolling windows also show that the short-term cross-correlations were lower and lower. That is to say, it is nearly impossible to predict the future prices based on the history of the other markets. However, the long-term cross-correlations displayed high degrees and low complexity indicating that the markets were predictable in the long-term. For the volatility series, they were strongly cross-correlated both in the short-term and in the long-term implying the high predictability. With time varying, the short-term cross-correlations between volatility series changed largely indicating that the optimal portfolio varied over time. Investors should not hold the portfolio with fixed weight of each asset.

Our results also have important modeling implications for Chinese stock markets. Firstly, the cross-correlated behavior between the return series of A-share and B-share markets were nonlinear (multifractal) implying that conventional linear models such as vector auto-regression models (VAR) could not be used to describe the dynamics of the cross-correlations between Chinese stock markets. Nonlinear methods are appealing. Secondly, the short-term cross-correlated behavior was different from long-term situations implying that modeling the cross-correlations between stock markets should consider the different term and period cycling. Thirdly, the cross-correlations were easy to be affected by events such as the reforms indicating that using nonlinear model to analyze the cross-correlations between stock markets should consider the structural changes caused by the shock of events. On the volatility, the high degrees of cross-correlations which changed over time indicating that the linear bivariate GARCH models such as BEKK-GARCH cannot well capture the cross-correlations between the volatility of Chinese stock markets.

As an emerging market, Chinese stock markets which have experienced some essential reforms became more and more efficient over time. However, they are still not mature markets. They are easily to be affected by market external factors, such as many regulated policies imposed by the government, financial crisis and some political factors. Recently, the cross-correlations between Chinese stock markets seemed to be larger than 0.5. This was caused by the recent global crisis and some unreasonable fiscal and monetary policies implemented by the government to weaken the effects of crisis. To improve the market efficiency and weaken the cross-correlations between stock markets, the government needs to do much more work in the future operation.

6. Conclusion

In this article, we investigate the cross-correlations between the return series of Chinese A-share and B-share markets. Based on the analysis of the significance of a statistic, we find that the cross-correlations were overall significant. Employing the method of DCCA, we find that the cross-correlations were strongly multifractal in the short-term but weakly multifractal in the long-term. Moreover, the cross-correlations of small fluctuations were persistent and those of large fluctuations were anti-persistent in the short-term while the cross-correlations of all kinds of fluctuations were persistent in the long-term. We also analyze the situations for volatility series and find the cross-correlations were much stronger both in the short-term and in the long-term.

Using the method of rolling windows, we find that the short-term cross-correlations between return series were gradually close to 0.5 over time while those between volatility series still kept the high degrees. At last, we also show some discussions on the method of rolling windows and implications for modeling and practical operations.

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