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Physica A 378 (2007) 387–398
PHYSICA A
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Statistical properties of German Dax and Chinese indices

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Received 19 June 2006; received in revised form 27 November 2006
Available online 22 December 2006

Abstract

We investigate statistical properties of the German Dax and Chinese indices, including the volatility distribution, autocorrelation function, DFA function and return-volatility correlation function, with both the daily data and minutely data. At the minutely time scale, the Chinese indices may show irregular dynamic behavior. At the daily time scale, the volatility distribution, autocorrelation function and DFA function of the Chinese indices are qualitatively similar to those of the German Dax, while the return-volatility correlation function exhibits an anti-leverage effect, different from the leverage effect of the German Dax.

Keywords: Complex system; Social and economic systems

1. Introduction

In recent years, the application of physical concepts and methods in economic and social science has attracted much attention of physicists. Based on large amounts of historical data, the dynamic behavior of financial indices or stock prices, etc. has been analyzed and considerable progress has been achieved in the understanding of the financial markets. Some ‘‘stylized facts’’ such as the ‘‘fat tail’’ in the volatility probability distribution [1,2] are discovered in the empirical study. The long-range volatility correlation (volatility clustering) [3,4] is quantified by calculating the volatility autocorrelation function, and is confirmed by the detrended fluctuation analysis (DFA). The so-called ‘‘leverage effect’’ is quantitatively studied in a recent paper [5], through calculating the return-volatility correlation based on the daily data of a few financial indices of mature markets. Similar studies for different economic systems, such as the relation between the interest rate and interests rate spread of bonds, etc., can be found in even earlier references [6–8]. Meanwhile, different models and theoretical approaches have been also developed, with a certain degree of success, to describe these features [3,9–23].

To some extent, the collective behavior of the financial dynamics is rather robust, independent of particular financial markets, at least within the mature markets in western countries. On the other hand, it is known that

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0378-4371/$ - see front matter
doi:10.1016/j.physa.2006.12.016

the emerging markets may behave differently. Especially, the Chinese financial market is newly set up in 1990 and shares a transiting social and political system. In recent papers, the authors have carefully analyzed the persistence probability distribution of the German Dax and Chinese indices [24–27]. At the daily time scale, the Chinese indices exhibit a universal dynamic behavior, although the exponents are different from those of the mature financial markets. At the minutely time scale, however, the dynamic behavior of the Chinese indices is disturbed by noises from the environment. More importantly, an anti-leverage effect in the return-volatility correlation function is discovered for the Chinese market, in contrast to the leverage effect for the mature markets [28].

In this paper, we present an extended investigation of the statistical properties of the German Dax and Chinese indices. We carefully analyze both the daily and minutely data, and investigate the dynamic behavior at different time scales and with different methods. In the next section, we present the data analysis and volatility probability distribution. In Sections 3 and 4, we analyze the long-range time correlation through calculating the autocorrelation function and the DFA analysis. In Section 5, we compute the return-volatility correlation function and construct a retarded volatility model to describe the leverage and anti-leverage effects. Finally comes the conclusion.

2. Data analysis and volatility probability distribution

The data analysis is based on both the daily data and minutely data of the German Dax of the German market, and the Shanghai Index and Shenzhen Index of the Chinese market. The daily data of the German Dax is recorded from October 1959 to January 1999 with 9837 data points and the minutely data is recorded every minute from December 1993 to July 1997 with 360,000 data points. The daily data of the Shanghai Index are from December 1990 to December 2003 with 3120 data points and the minutely data are recorded every 5 min from January 1998 to July 2003 with 60,430 data points. The daily data of the Shenzhen Index are from April 1991 to December 2003 with 3165 data points and the minutely data are recorded every 5 min from January 1998 to July 2003 with 50,062 data points.

The volatility represents the magnitude of the price fluctuation. Here, we define the volatility $|Z(t')|$ as the absolute value of the logarithmic price change of the index $y(t')$

$$|Z(t')| = |\ln y(t' + \Delta t') - \ln y(t')|, \tag{1}$$

where $\Delta t'$ is the sampling time interval. For the daily data, we take the sampling time interval $\Delta t' = 1$ day. For the minutely data, we investigate two cases. One case is the sampling time interval $\Delta t'$ taken to be the minimum time interval of the data. For the German Dax, the minimum time interval is $\Delta t' = 1$ min and for the Chinese indices, the minimum time interval is $\Delta t' = 5$ min. The other case is the sampling time $\Delta t'$ taken to be about one working day. For the German Dax, the working day is not regular and ranges from 300 to 480 min, and for the Chinese indices, the working day is 240 min. Here, we assume that as an average the working day for the German Dax is about 450 min. So we have $\Delta t' = 450$ min for the German Dax, and $\Delta t' = 240$ min for the Chinese indices.

For the Chinese indices, the daily data are almost the same as the daily closings of the minutely data. Therefore, the subset of the minutely data with $\Delta t' = 240$ min and t' sampled over the last minute of every day is just the daily data. If t' is sampled over all the times, however, we obtain 48 subsets of the minutely data. Each subset looks like the daily data, but not the same. In this paper, we sample t' always over all the times. Our calculations will show that averaging over these 48 subsets of the minutely data, the dynamics behaves indeed similarly as that of the daily data. For the German Dax, it is not clear to us how the daily data are extracted. In addition, the length of the working day of the German market is not fixed. But our results in this paper indicate that the dynamic behavior of the minutely data with $\Delta t' = 450$ is also qualitatively the same as that of the daily data.

Sampling for different t', we obtain a set of $|Z(t')|$, which should follow a certain probability distribution $P(|Z|)$. Fig. 1 shows the volatility probability distributions of both the daily data and minutely data of the German Dax and Shanghai Index, with $\Delta t'$ taken to be one working day as explained above. In about two orders of magnitude of $P(|Z|)$, the curves of the German Dax exhibit a power-law tail,

$$P(|Z|) \sim |Z|^{-\mu}, \tag{2}$$

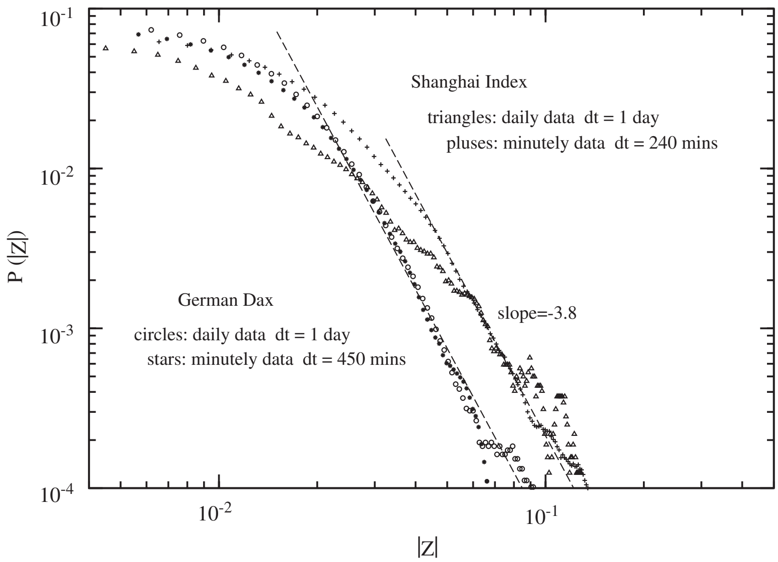

Fig. 1. Volatility probability distributions $P(|Z(t')|)$ plotted on a log–log scale. Circles are for the daily data of the German Dax with $\Delta t' = 1$ day and stars are for the minutely data with $\Delta t' = 450$ min. Triangles are for the daily data of the Shanghai Index with $\Delta t' = 1$ day and pluses are for the minutely data with $\Delta t' = 240$ min. The dashed lines are with a slope $= -3.8$ for guiding the eyes.

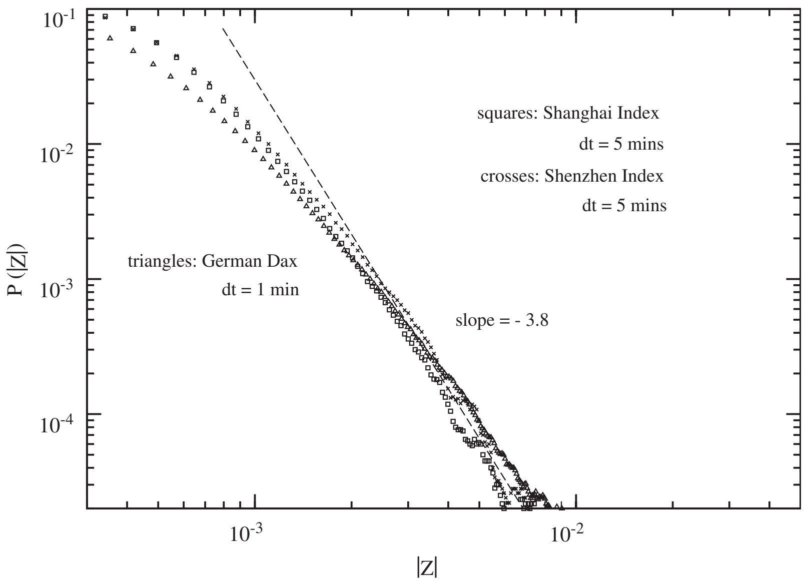

Fig. 2. Volatility probability distributions $P(|Z(t')|)$ of the minutely data of the German Dax with $\Delta t' = 1$ min (circles), and of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min (triangles and crosses).

with the exponent μ close to 3.8, as reported for other financial indices [4,29], well outside $0 < \mu < 2$ of the stable Lèvy distribution. The curves of the Shanghai Index show similar behavior, although the daily data are recorded only for about 10 years and the curve is somewhat fluctuating.

In Fig. 2, the volatility probability distributions of the minutely data are plotted, for the German Dax with $\Delta t' = 1$ min and for the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min. The tails of the curves obey the power law in Eq. (2), and the central part exhibits the shape of the Lèvy distribution as reported in previous studies [29]. In the figure, the dashed line with a slope $= -3.8$ is for guiding the eyes. Briefly speaking, the volatility probability distributions $P(|Z|)$ of both the German Dax and Chinese indices present qualitatively the same behavior for both the daily data and minutely data, although with some fluctuations. In the following sections, we will reveal the long-range volatility correlation, and the return-volatility correlation. Special attention is paid to the possibly different behaviors at the daily and minutely time scales.

3. Volatility autocorrelation function

It has been well known that the volatility is long-range correlated in time, i.e., the autocorrelation function decays by a power law, in spite of the absence of the time correlation of the return itself. The volatility autocorrelation function is defined as

$$A(t) = [\langle |Z(t')||Z(t+t')|\rangle - \langle |Z(t')|\rangle^2]/\sigma. \tag{3}$$

Here $\sigma = \langle |Z(t')|^2\rangle - \langle |Z(t')|\rangle^2$ and $\langle \cdots \rangle$ is the average over t'.

Fig. 3 shows the volatility autocorrelation functions $A(t)$ of the daily data with $\Delta t' = 1$ day for the German Dax, Shanghai Index and Shenzhen Index. We find that $A(t)$ obeys a power law [30–36],

$$A(t) \sim t^{-\beta}, \tag{4}$$

although the curves are somewhat fluctuating after 50 days. Fitting the curves to the power-law behavior in Eq. (4), one estimates $\beta = 0.39$ for the German Dax and $\beta = 0.34$ for the Chinese indices. The dynamics of the Chinese indices seems slightly slower than that of the German Dax.

To further illustrate the long-range volatility correlation, we now compute the autocorrelation function $A(t)$ with the minutely data. Because of the gathering of information, traders are more active around the opening and closing times in a trading day. This leads to an intra-day pattern [30–32,37], which strongly affects the dynamic behavior. In Fig. 4, $A(t)$ of the minutely data of the German Dax, Shanghai Index and Shenzhen Index are displayed. Periodic oscillations are observed. The period is just a working day, which is 240 min in the Chinese market, and about 450 min in the German market. The effect of the lunch break can be also detected for the Chinese market, although it is not visible for the German market probably due to the somewhat noisy background and the unfixed length of the working day. Such a kind of intra-day pattern should be removed. Here, we follow the manner in Ref. [4]. The intra-day pattern $D(t'_{day})$ is defined as

$$D(t'_{day}) = \frac{1}{N}\sum_{j=1}^{N} |Z_j(t'_{day})|, \tag{5}$$

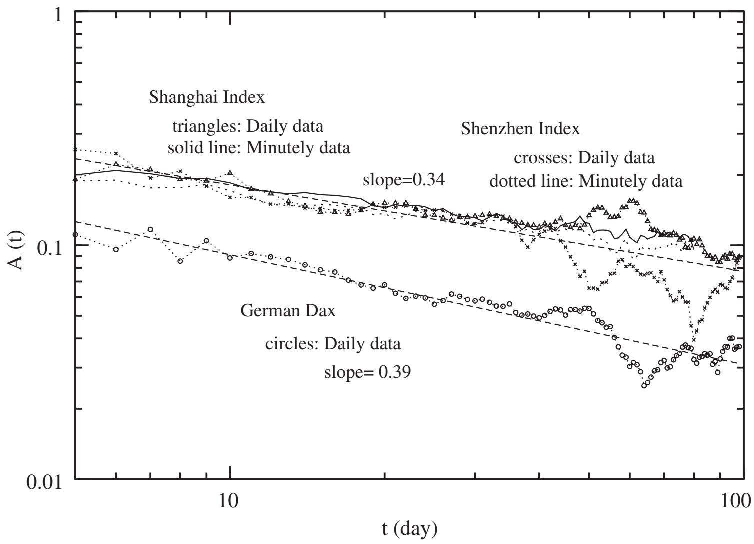

Fig. 3. The volatility autocorrelation functions plotted on a log–log scale. Circles, triangles and crosses are for the daily data of the German Dax, Shanghai Index and Shenzhen Index with $\Delta t' = 1$ day, respectively. The solid line and the dotted line are for the minutely data of the Shanghai Index and Shenzhen Index with $\Delta t' = 240$ min.

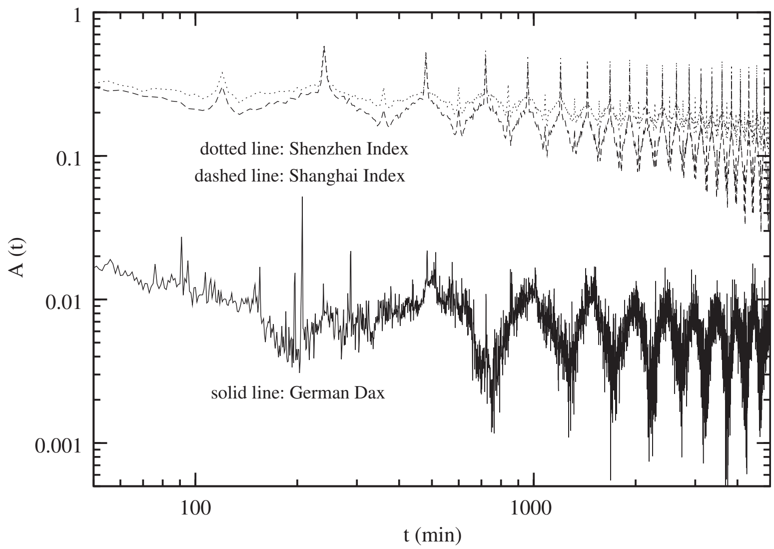

Fig. 4. The volatility autocorrelation functions $A(t)$ of the minutely data of the German Dax with $\Delta t' = 1$ min, of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min plotted on a log–log scale. The intra-day patterns have not been removed.

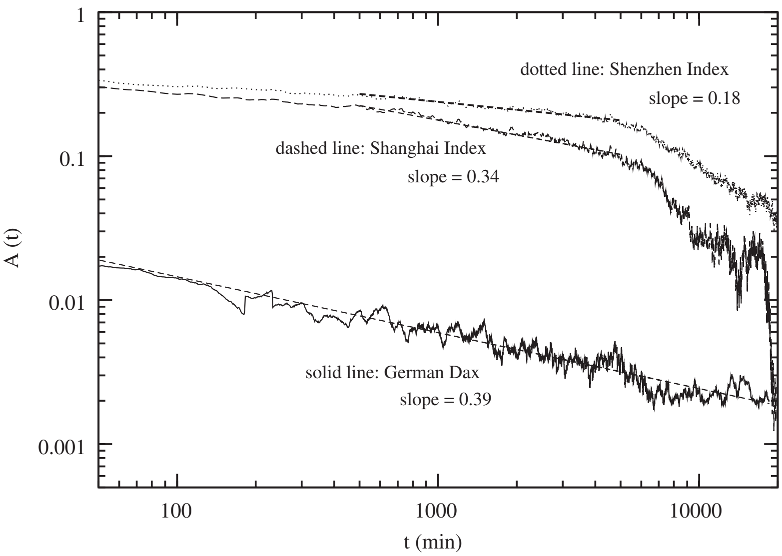

Fig. 5. The volatility autocorrelation functions $A(t)$ of the minutely data of the German Dax with $\Delta t' = 1$ min, of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min plotted on a log–log scale. The intra-day patterns have been removed.

where j runs over all the trading days N, and t'_{day} is the time in a trading day. To remove this intra-day pattern, we normalize the volatility at time $t' = t'_{day}$ as

$$g(t'_{day}) = |Z(t'_{day})|/D(t'_{day}). \tag{6}$$

The volatility autocorrelation function is then defined as

$$A(t) = [\langle g(t')g(t+t')\rangle - \langle g(t')\rangle^2]/\sigma, \tag{7}$$

here $\sigma = \langle g(t')^2\rangle - \langle g(t')\rangle^2$, and $\langle \cdots \rangle$ is the average over t'.

In Fig. 5, the autocorrelation functions $A(t)$ of the German Dax with $\Delta t' = 1$ min, of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min are displayed. Obviously, the curve of the German Dax follows a power law, with an exponent $\beta = 0.39$. This β value is the same as that obtained with the daily data. For the Chinese indices, however, the curves do not show a clean power-law behavior, different from the case of the daily data. For the Shenzhen Index, for example, the curve decays slowly with an exponent β much smaller than $\beta = 0.39$ of the German Dax in the first 5000 min, then drops relatively fast afterwards. Qualitatively, $A(t)$ of the minutely data still indicates a long-range time correlation for the dynamics of the Chinese indices, but the dynamic behavior at the minutely time scale is affected by irregular noises from the environment. Such a phenomenon is also observed in the measurements of the persistence probability distribution [26].

To emphasize that the noises do not change the dynamic behavior at the daily time scale, we investigate $A(t)$ of the minutely data with $\Delta t' = 240$ min for the Chinese indices. For comparison with the curves of the daily data, the autocorrelation functions of the minutely data are also plotted with $\Delta t' = 240$ min for the Shanghai Index and Shenzhen Index in Fig. 3. The curves exhibit a nice power-law behavior with an exponent β close to but slightly smaller than that of the daily data. This also supports that the dynamics of the Chinese indices is somewhat slower than that of the German Dax.

4. Detrended fluctuation analysis

To further quantify the time correlation of the volatility, we apply the DFA method. The DFA method was proposed a decade ago [38,39], and has been successfully applied to detect the long-range time correlations in various physical systems.

Let us first introduce the DFA algorithm [38,39]. For a fluctuating dynamic series $B(t')$, we construct

$$C(t') = \sum_{t''=1}^{t'} [B(t'') - B_{ave}]. \tag{8}$$

Here B_{ave} is the average of $B(t')$ in the total time interval $[1, T]$. Then we uniformly divide the interval $[1, T]$ into windows with a size of t, and fit $C(t')$ to a *linear* function $C_t(t')$ in each window. Finally, we calculate the DFA function

$$F(t) = \sqrt{\frac{1}{T}\sum_{t'=1}^{T} [C(t') - C_t(t')]^2}. \tag{9}$$

In general, $F(t)$ will increase with the window size t and obeys a power-law behavior

$$F(t) \sim t^{\theta}. \tag{10}$$

If $0.5 < \theta < 1.0$, $B(t')$ is long-range correlated in time; if $0 < \theta < 0.5$, $B(t')$ is temporally anti-correlated; $\theta = 0.5$ corresponds to the Gaussian white noise, while $\theta = 1.0$ indicates the $1/f$ noise. If θ is bigger than 1.0, the time series is considered to be unstable. The exponent θ in the DFA function is related to the exponent β in the autocorrelation function by the scaling relation $\beta = 2 - 2\theta$.

Here we apply the DFA method to the analysis of the time series $B(t') = |Z(t')| = |\ln y(t' + \Delta t') - \ln y(t')|$. In Fig. 6, the solid, dashed and dotted lines show the DFA functions of the daily data of the German Dax, Shanghai Index and Shenzhen Index with $\Delta t' = 1$ day. A nice power-law behavior is observed for all the three indices, and an exponent $\theta = 0.81$ is estimated for the German Dax and $\theta = 0.83$ for the Chinese indices. Then, one calculates $\beta = 2 - 2\theta = 0.38$ and 0.34 for the German Dax and Chinese indices, respectively, which are close to $\beta = 0.39$ and 0.34 obtained from the autocorrelation functions of the daily data.

To understand the dynamic fluctuations at the minutely time scale, we have also calculated the DFA function with the minutely data. In this case, the intra-day pattern does not affect the results so much. In Fig. 7, the DFA functions after removing the intra-day pattern are shown for the minutely data of the German Dax with $\Delta t' = 1$ min, of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min. A two-stage scaling behavior is observed, and there is a crossover phenomenon in between. For the German Dax, the exponent θ takes the values

$$\theta = 0.67 \quad \text{for } t < t_c, \tag{11}$$

$$\theta = 0.92 \quad \text{for } t > t_c, \tag{12}$$

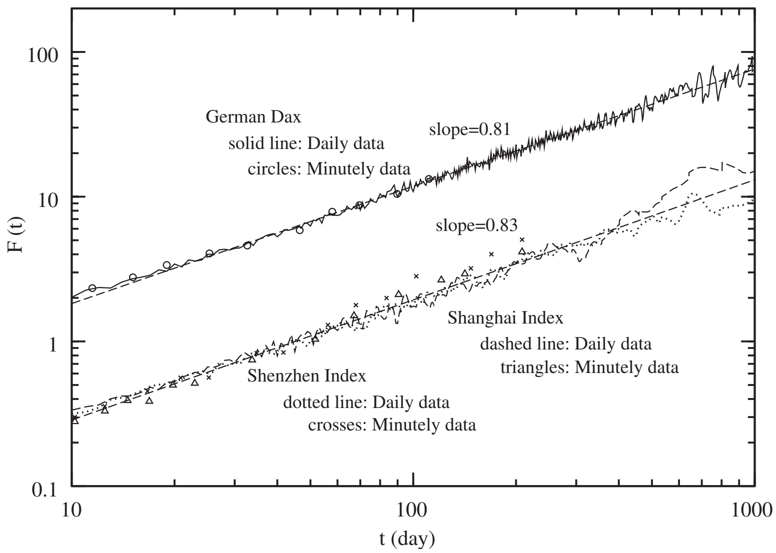

Fig. 6. DFA functions plotted on a log–log scale. The solid line is for the daily data of the German Dax with $\Delta t' = 1$ day, and circles are for the minutely data with $\Delta t' = 450$ min. Dashed and dotted lines are for the daily data of the Shanghai Index and Shenzhen Index with $\Delta t' = 1$ day, triangles and crosses are for the minutely data with $\Delta t' = 240$ min.

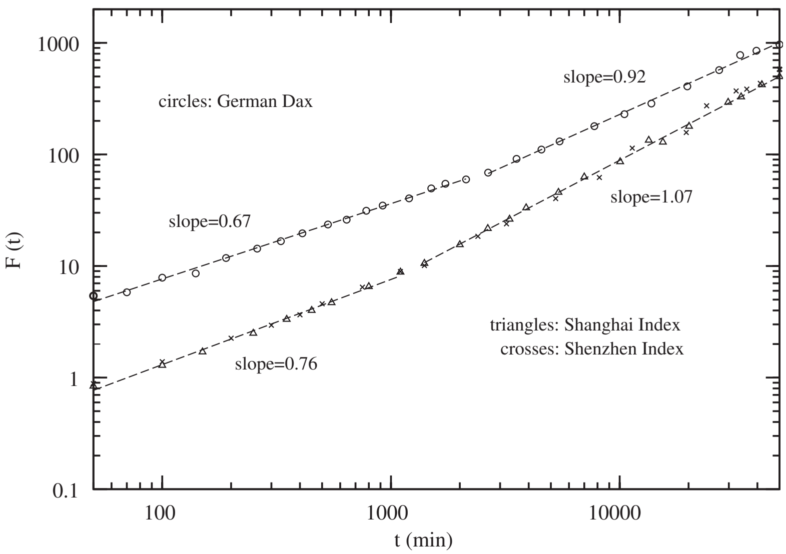

Fig. 7. DFA functions of the minutely data of the German Dax with $\Delta t' = 1$ min, of the Shanghai Index and Shenzhen Index with $\Delta t' = 5$ min plotted on a log–log scale.

where the crossover time $t_c \sim 2300$ min, about 5 days. For the Shanghai Index and Shenzhen Index,

$$\theta = 0.76 \quad \text{for } t < t_c, \tag{13}$$

$$\theta = 1.07 \quad \text{for } t > t_c, \tag{14}$$

with the crossover time $t_c \sim 1200$ min, also about 5 days. For both the German and Chinese financial markets, the DFA functions of the time series $|Z(t')| = |\ln\ y(t' + \Delta t') - \ln y(t')|$ do not show a clean scaling behavior, and the Chinese market is more fluctuating and even tends to be unstable.

Actually, the crossover behavior of the minutely data shown in Fig. 7 is typical for the financial dynamics. In Ref. [40], for example, such a crossover behavior is observed for both the volatility fluctuations of stock prices and the fluctuations in the intervals between consecutive trades. A possible explanation may be that at short time scales within minutes and hours the traders take less informed decisions, and thus the dynamic behavior is less correlated, for the market-relevant information reaches them at longer time scales.

Here it is also interesting to note that the autocorrelation function of the minutely data of the German Dax shows a relatively clean power-law behavior, while the DFA function does not. For the Chinese indices, both the autocorrelation function and DFA function of the minutely data do not obey a pure power law. At each stage of the two-stage crossover scaling behavior, the scaling relation $\beta = 2 - 2\theta$ does not hold. As shown in Ref. [41], this is because the autocorrelation function has strong limitations in properly quantifying signals with a long memory, and even worse when the signals are not stationary.

At time scales above a trading day, it is as expected that both the minutely data and daily data exhibit a similar scaling behavior. For example, we compute $|Z(t')|$ of the minutely data with $\Delta t' = 450$ min for the German Dax and $\Delta t' = 240$ min for the Shanghai Index and Shenzhen Index. Fig. 6 shows the corresponding DFA functions. It is observed that for all the indices, the DFA functions of both the minutely data and daily data with $\Delta t'$ taken to be one working day look very similar, and exhibit a universal scaling behavior.

Finally, we have also performed the DFA analysis to higher orders [42]. For example, we now fit the data $C(t')$ in each window with a size of t to a *quadratic* function $C_t(t')$ rather than a linear function in the previous calculations, and compute the DFA function in Eq. (8). The results qualitatively remain the same. For further analysis with the DFA methods and improved techniques one may follow, for example, Refs. [42–45]. Since this paper is already somewhat lengthy, we will not continue in this direction here.

5. Leverage correlation function

5.1. Phenomenological analysis

Recently, Bouchaud et al. [5] have quantitatively studied the so-called ‘‘leverage effect’’ by calculating the return-volatility correlation function with the daily data of a few financial markets. Such a phenomenon indicates how the volatility is affected by the return in the past times. Here we investigate the return-volatility correlation functions of the German Dax and Chinese indices with both the daily data and minutely data.

The return-volatility correlation function is defined as

$$L(t) = \frac{1}{M}(\langle Z(t')[Z(t'+t)]^2\rangle - \langle Z(t')\rangle\langle [Z(t')]^2\rangle), \tag{15}$$

which measures the correlation between the price change at time t' and the square volatility at time $t'+t$. Here $\langle \cdots \rangle$ is the average over t'. The coefficient M is a normalization constant, and here is set to be $M = \langle Z(t')^2\rangle^2$ according to Ref. [5]. A negative $L(t)$ indicates that a price drop at t' will induce a higher volatility at $t'+t$, and a price increase will lead to a stable stock price. This phenomenon (a negative $L(t)$) is the so-called ‘‘leverage effect’’ [46–49].

Fig. 8 shows the return-volatility correlation functions of the daily data of the German Dax, Shanghai Index and Shenzhen Index. It is clearly observed that the correlation $L(t)$ of the German Dax shows negative values within 20 days, i.e., the leverage effect [5,46–49]. On the other hand, the correlation $L(t)$ takes positive values for the Shanghai Index and Shenzhen Index within 10 days. We name such a phenomenon the ‘‘anti-leverage effect’’.

Usually, the leverage effect is considered to be a phenomenon at the daily time scale, and therefore only computed with the daily data. To further confirm our findings with the daily data, we also analyze the minutely data. The minutely data of both the German Dax and Chinese indices are taken only for a few years. If the findings from the daily data may also be found with the minutely data, we can conclude that the leverage and anti-leverage effects are indeed the features of the German Dax and Chinese indices, respectively.

Fig. 9(a) shows the return-volatility correlation functions of the minutely data with different $\Delta t'$ for the German Dax. Obviously, the results are rather noisy for the curves containing high-frequency fluctuations. The smaller the $\Delta t'$, the more fluctuating is the curve. In order to extract the dynamic behavior of the slow

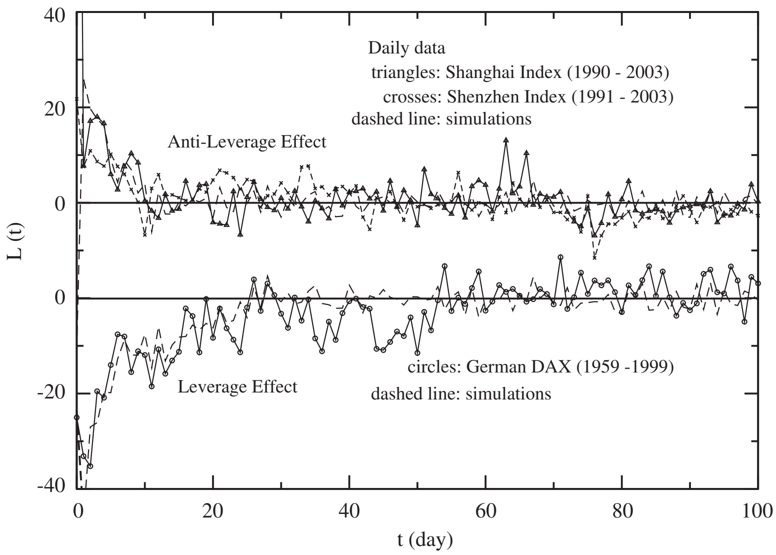

Fig. 8. Return-volatility correlations of the daily data of the German Dax, Shanghai Index and Shenzhen Index with $\Delta t' = 1$ day are plotted with circles, triangles and crosses, respectively. The dashed lines are from numerical simulations.

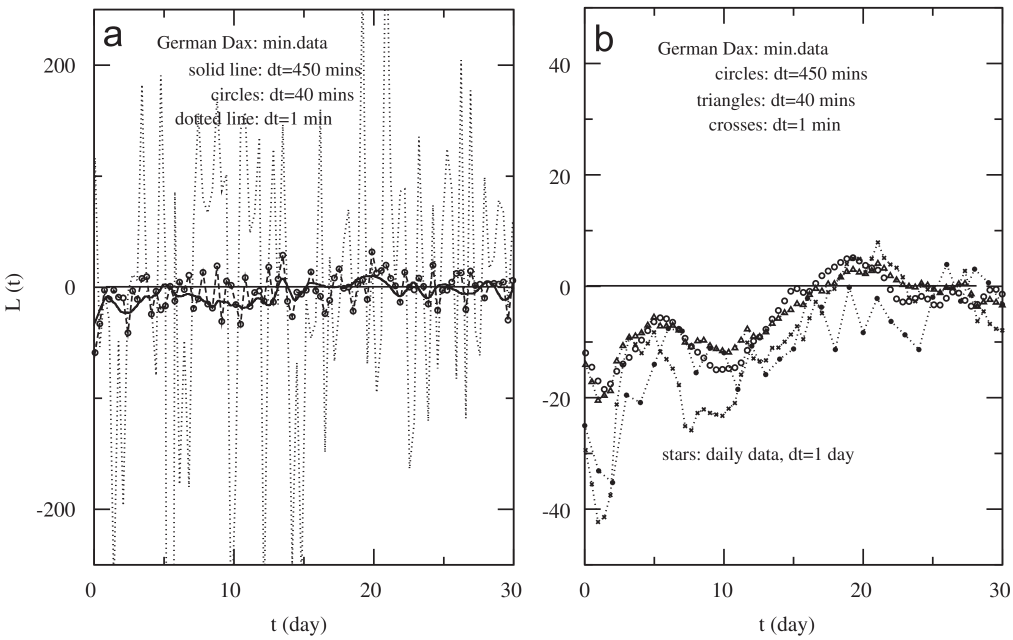

Fig. 9. (a) Return-volatility correlations of the minutely data of the German Dax with $\Delta t' = 1$, 40, 400 min are plotted. (b) The same curves as in (a), but after performing an average within a 4-day window.

mode, we then perform an average within a 4-day window. This is shown in Fig. 9(b). It is rather interesting that we clearly observe negative return-volatility correlations, i.e., the leverage effect, after performing the averaging. For comparison, the curve of the daily data is also displayed in the figure. We find that the minutely data with different $\Delta t'$ and daily data exhibit qualitatively the same leverage effect. In Fig. 10, similar analysis is performed for the Shenzhen Index. The anti-leverage effect is confirmed. The Shanghai Index behaves similarly. Our procedure to remove the high-frequency fluctuations seems to be remarkable in uncovering the leverage and anti-leverage effects.

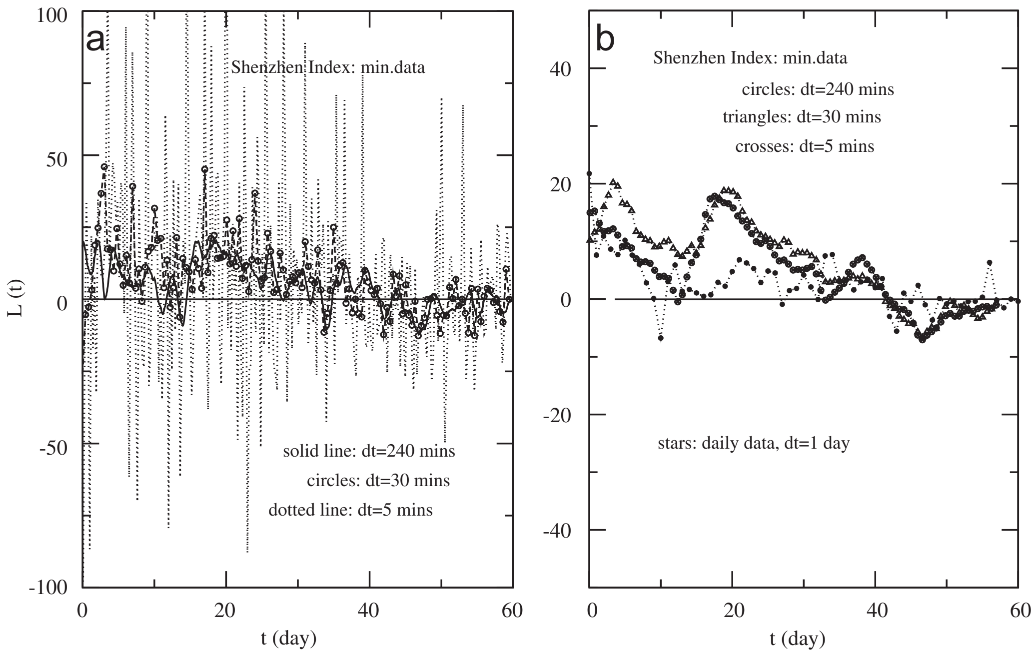

Fig. 10. (a) Return-volatility correlations of the minutely data of the Shenzhen Index with $\Delta t' = 5, 30, 240$ min are plotted. (b) The same curves as in (a), but after performing an average within a 4-day window.

According to the previous reports [5], the German Dax and other financial indices typically in western countries show a standard leverage effect, which is rather robust. Our study, however, indicates that the Chinese indices behave differently, and exhibit an anti-leverage effect for both the daily data and minutely data.

An explanation is that people in western markets show risk aversion and would expect a stock market like a bank. If there is a price drop, the market will become more volatile, and therefore it leads to the standard leverage effect. The situation is quite different in China, and there is a "rebound" after a price drop, i.e., the observed anti-leverage effect. One reason may be that people in China are excessively speculative in a stock market. If the price increases, the market will be more volatile. If there is a price drop, people would wait until the price climbs up again, and thus it leads to the anti-leverage effect.

Actually, a similar anti-leverage effect is also observed in other economic systems [6–8]. For example, before an economic crash in the 19th century, both the interest rate and interest rate spread of bonds increase simultaneously. This phenomenon and the anti-leverage effect in the Chinese financial markets might originate from a common mechanism.

5.2. Modeling return-volatility correlation

A "retarded" volatility model is introduced in Ref. [5] to explain the leverage effect. The model reasonably assumes a lagged response to the price changes based on the traditional volatility model, and can properly interpret the negative return-volatility correlation. Analytical calculations have been given in Ref. [5]. In order to account for the anti-leverage effect and leverage effect observed in this article, we construct a new version of the retarded volatility model, and solve it numerically. Following the idea in Ref. [5], we simply write down

$$Z(t') = \left[1 - \sum_{t=1}^{\infty} K(t)\, Z(t'-t)\right] \sigma(t')\varepsilon(t'), \tag{16}$$

where $\sigma(t')$ is the volatility, which may be generated in a certain way, for example, by the interacting EZ herding model [14]. $K(t)$ is a kernel which represents the retarded effect of the returns in the past times.

Analytical computations give $L(t) = -2K(t)$ if $\sigma(t')$ is the order of 1. Such computations are straightforward following the procedure in Ref. [5]. Taking $K(t) = c\exp(-t/\tau)$, a positive c results in a leverage effect, while a negative c leads to an anti-leverage effect. We perform numerical simulations based on Eq. (16) and measure $L(t)$, and the results are shown in Fig. 8 with dashed lines. Indeed, we observe the leverage and anti-leverage effects, in good agreement with the phenomenological results.

6. Conclusion

We present a comparative study of the dynamic behavior of the German Dax and Chinese indices. From the volatility distributions, autocorrelation functions and the DFA functions of the daily data, we find that the German Dax and Chinese indices exhibit a similar dynamic behavior at the daily time scale. The exponent $\beta = 0.34$ of the autocorrelation function of the Chinese indices is slightly smaller than $\beta = 0.39$ of the German Dax. Measurements of the exponent θ of the DFA functions confirm the scaling relation $\beta = 2 - 2\theta$. At the minutely time scale, the autocorrelation function of the Chinese indices behaves differently from that of the German Dax, and does not show a clean power-law behavior due to irregular noises from the environment. If we take $\Delta t'$ to be a working day in calculating the volatility of the minutely data, however, the power-law behavior is recovered and in agreement with that of the daily data.

We carefully study the return-volatility correlation functions of the German Dax and Chinese indices. With the daily data, we demonstrate that the German Dax shows a standard leverage effect, while the Chinese indices present an anti-leverage effect. Carefully removing the high-frequency fluctuations, we find that the minutely data lead to the same conclusion. The leverage and anti-leverage effects are indeed the features of the German Dax and Chinese indices, respectively.

Acknowledgments

This work was supported in part by NNSF (China) under Grant Nos. 10325520 and 70371069, DFG (Germany) under Grant No. TR300/3–4.

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