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Temporal variations of serial correlations of trading volume in the US stock market

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ABSTRACT

Serial correlations in the trading volume of the US stock market are investigated in this paper. The use of the detrended fluctuation analysis implemented within a rolling window indicated that, for the period 1929–2011, the strength of correlations exhibits important temporal variations with a trend shift by the 1990s, and 4-year and 21-year cycles. These empirical findings are compared to those obtained for mature international stock markets (FTSE-100 and Nikkei) and discussed in terms of potential economic and financial implications.

1. Introduction

The application of methods from statistical physics to the study of financial markets has provided valuable information on the structure and dynamics of such complex systems. Analyses of returns of individual stocks [1,2] and stock indices [3,4] have indicated that the cumulative distribution of returns is well fitted by a power-law asymptotic behavior. This pioneering work motivated a plethora of studies oriented to characterize distinctive features of financial and commodity markets. Just for illustration, results included the presence of serial correlations in stock returns [5,6], the role of multifractality in the complexity of stock markets [7], the temporal changes of fractality in stock indices [8], the characterization of market dynamics in the vicinity of crashes [9] and many more.

The stock return is the most used signal to characterize the dynamics of financial markets. In fact, how the price fluctuation responds to the demand has been widely discussed to understand the origin of large fluctuations of markets [10]. On the other hand, the dynamics of transaction volumes reflect the strength of a market activity as it is related to the excess demand of a specific stock. Studies in this line have focused mainly on establishing the relation between trading volume and volatility/price fluctuations [11–15]. Only recently, some work has been oriented to the characterization of the tail statistics of the distribution of volume, which is important in evaluating the validity of different models of market microstructure [16]. It has been found that the number of shares exchanged in a given time interval meets a power-law distribution [17]. High levels of serial correlation in trading volume have also been documented [18–20] and attributed to information flow in the market [21,22], institutional herding [23] and stealth trading by informed investors [24]. Power-law distribution and serial correlations were also found for the Chinese stock market [25]. Evidence of autocorrelation in daily short volume, which is not explained by liquidity or short-sale constraints, has been found [26]. Based on a proper modification of the DFA [27], cross-correlations between volume change and price change have also been documented for 14 daily recordings of the S&P-500 index over the 59-year period, finding power-law cross-correlations between the absolute volume growth and the absolute price return [28].

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In the present study, the scaling properties of trading volume of the US stock market are investigated. By implementing the detrended fluctuation analysis [29] within a rolling window framework, the temporal variations of the scaling exponent are estimated. Serial correlations of the daily trading volume are confirmed and large temporal variations of the correlation strength are found. The presence of structural breaks and 4-year and 21-year cycles in the trading volume correlations are discussed. Comparison with correlations for trading volume of mature international stock markets is performed, suggesting the synchronization of the different stock markets due to, e.g., global trading.

The paper is organized as follows. Section 2 provides a brief description of the detrended fluctuation analysis. Section 3 describes and discusses the empirical findings. Section 4 closes the paper with some conclusions.

2. Detrended fluctuation analysis

Serial auto-correlation is a property that is commonly found in time series. Traditionally, the auto-correlation function $C(s)$ is used for quantifying the strength of persistence in time. In this form, if the elements of a time series x_k are not correlated, the function $C(s)$ should be zero for all time-scales s, which means that future information is not related to past information. It is expected that correlations exist only up to a certain number of days s^*, which implies that the correlation function vanishes for time-scale s^*. For long-term correlations, the function $C(s)$ exhibits a power-law decay $C(s) = \langle x_k x_{k+s} \rangle \approx s^{-\gamma}$. On the other hand, for large values of s, a direct calculation of the function $C(s)$ can be masked by the data noise and non-stationarities. Under the assumption that the time series is stationary, standard spectral analysis techniques can be used to calculate the power spectrum $E(f)$ of the time series in terms of the frequency f. For long-term correlated data, one finds that $E(f) \approx f^{\beta}$, where $\beta = 1 - \gamma$. If the time series is non-stationary, the detrended fluctuation analysis (DFA) is an alternative approach for calculating the correlation exponent [29]. In this approach, the time series x_k, $k = 1, \ldots, N$, is first integrated

$$Y_k = \sum_{j=1}^{k} \left(x_j - \langle x_k \rangle \right), \quad k = 1, \ldots, N$$

where

$$\langle x_k \rangle = \frac{1}{N} \sum_{j=1}^{N} x_j$$

is the time-series mean. After dividing Y_k into $N_s = [N/s]$ not-overlapping segments of equal length s, a piecewise polynomial trend $Y_{s,k}$ is estimated within each segment and the detrended series is calculated as $\tilde{Y}_k = Y_k - Y_{s,k}$. The degree of the polynomial can be varied in order to eliminate linear, quadratic or higher order trends of the integrated time series. In general, linear fitting suffices for detrending. In the next step, the fluctuation function is computed as

$$F(s) = \left(\frac{1}{sN_s} \sum_{j=1}^{sN_s} \tilde{Y}_k^2 \right)^{1/2}.$$

The integrated time series is self-similar if the fluctuation function $F(s)$ scales as a power-law with the segment size s. The segment size s can be seen as the number of strides in a segment of observation or the time-scale. For typical sequences, $F(s)$ increases with segment size s. A linear relationship on a double log graph indicates that $F(s) \approx s^{\alpha}$, where the scaling exponent or self-similarity parameter α is determined by calculating the slope of the line relating $\log F(s)$ to $\log s$. For stochastic processes where the value at one step is completely uncorrelated with any previous values (as in white noise), one has $\alpha = 0.5$. In contrast, long-range persistent correlations are found if $\alpha > 0.5$. Scaling exponent values with $\alpha < 0.5$ indicate anti-persistent correlations where a large stride interval is more likely to be followed by a small one and vice versa over different time-scales. The scaling exponent α is related to the correlation and spectral exponents by $\alpha = 1 - \gamma/2 = (1 + \beta)/2$.

3. Results and discussion

The daily trading volume, as extracted from www.finance.yahoo.com, for the Dow Jones Industrial Average (DJIA) was considered in this work for investigating serial correlations in the US stock market. Fig. 1 shows the evolution of the DJIA trading volume for the period from 1929 to 2011. In the aftermath of the 1929 Great Depression, the trading volume decreased from about 0.002 trillion to about 0.00025 trillion by 1941. Starting in 1942, the trading volume has shown a sustained growth to achieve a peak of about 8.5 trillion in 2009. This impressive growth can be described on average by an exponential growth with a time constant of about 18 years. The exponential growth suggests using the logarithmic trading volume for estimating serial correlations.

The DFA was implemented in a rolling window [30,31] of 530 observations (about 2 calendar years) and the scaling exponent was computed for scales from 10 to 65 business days. In this way, the estimated scaling exponent is a measure of the correlation strength for scales up to a quarter. Fig. 2(a) presents the temporal variations of the scaling exponent for the logarithmic trading volume $\log(V_t)$. The following features can be commented: