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Pattern of trends in stock markets as revealed by the renormalization method

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HIGHLIGHTS

- We propose a renormalization model to analyze the pattern of stock price trends.
- The model is able to partition the time series into different scaling of trends.
- We show that the asymmetric phenomena of the trends in American stock market.
- The stronger Herd behavior is discovered in the Chinese stock market.

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ABSTRACT

Predicting the movement of prices is a challenging topic in financial markets. So far, many investigations have been performed to help understand the dynamics of stock prices. In this work, we utilize the renormalization method to analyze the scaling and pattern of stock price trends. According to the analysis of length and changing velocity of the price trends, we find that there exist asymmetric phenomena of the trends in American stock market. In addition, a stronger Herd behavior is also discovered in the Chinese stock market. Since the Chinese (American) stock market is a representative of emerging (mature) market, the study on comparing the markets between these two countries is of potential value, which can leave us a wiser about both the pattern of the markets and the underlying physical mechanisms.

1. Introduction

As a most challenging topic in financial market, predicting the movement of price has inspired many researches by not only market investors but also modern scientists and economists. So far, huge amount of qualitative theories about stock price dynamics [1–4] have been proposed to understand the patterns of stock markets, such as random walk model [5–7], correlation properties [8–10], scaling behavior [11–14], stock market volatility [15,16], distribution of stock price returns [17,18] and derivative pricing research [19]. Meanwhile, numerous methods in different aspects have been developed to predict the price movements. In technical analysis field, Pai et al. applied hybrid ARIMA and support vector machines model in stock price forecasting in 2005 [20]. On the other hand, in fundamental analysis field, Abarbanell and his co-workers investigated how detailed financial statement data (fundamental signals) help the market participants to make investment decisions [21]. Moreover, in marginal information field, Bollen et al. used the Twitter mood to predict the stock market and

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gained the excess return [22]. In addition, agent-based model and network theory which are included in complex system are also used widely to understand the mechanism of stock market [23–25].

A basic theory of classical economics is that investment decisions reflect agents' rational expectations and are made by analyzing all available information in an efficient manner. However, the real market are composed of huge amount of irrational investors. Consequently, behavioral economics are created to study the effects of social, cognitive, and emotional factors on the economic or finance decisions of individuals and institutions and the consequences for market prices, returns, and the resource allocation [26,27]. In addition, the agent based model derived from Ising model is also widely used to study the macro state of the market by researching and simulating the micro mechanism (investors behavior) [28–30]. As significant behavioral phenomena impact the stock market, Herd behavior describes how individuals in a group can act collectively. For example, lots of large stock market trends often begin and end with frenzied buying (bubbles) or selling (crashes). Cont et al. gave an analysis of Herd behavior and aggregate fluctuations in financial markets [31]. Zhao et al. studied herd behavior in complex adaptive system by human dynamic experiment [32]. The price trend is defined as the instrument price in financial markets tending to a particular direction over time. Understanding the pattern and mechanism of price trends can help investors, speculators and researchers analyze the stock markets. Kasa investigated the stochastic trends in equity markets of different countries and found the presence of a single common trend which dominates these countries' stock markets [33]. Zhong et al. investigated the effects of dynamic response in the evolution of collective behavior in an evolving market [34]. Fung et al. presented a system that predicts changes of stock trends by studying the influence of non-quantifiable information [35]. Clearly, all above discoveries are valuable for us. However, the world-wide financial crisis brought a great disaster in 2008. Since then the scholars have paid more attentions to the study of large market fluctuations. In 2009, Yuan and Zhuang used multifractal detrended fluctuation analysis to measure the multifractality of stock price fluctuations and also researched the pattern of price fluctuations [36]. Later, the renormalization method adopted by Wei et al., and Liu et al., are used to analyze the scaling and volatility of breakouts and breakdowns in stock price dynamics [37,38]. In this article, we mainly focus on the statistical properties of stock price trends and attempt to give a quantification analysis. Also, we compare patterns of the price trends in American stock market and Chinese stock market, trying to discover the different regularities between developed and emerging market.

2. Method

The upward trends are composed by several increasing prices while the downward trends are a series of decreasing prices. The regularities of the trends are very important factors which are studied by huge amount of investors and researchers. In general, the short-term investors will pay more attention to the trends of short time scales, while the long-term investors may focus more on the trends of long time scales. In our study, the trends of the stock price are analyzed through the renormalization method [39,40].

Denote the price at time t as $P(t)$, where $t = 1, 2, 3, \ldots, N$. A local maximum price, $P_{\max(i)}$, of $\triangle t (\triangle t = 1, 2, 3, \ldots)$ can be defined if there is no higher price existing in the time interval $(t - \triangle t, t + \triangle t)$. By this way, all the local maximum $P_{\max(i)}$, $(i = 1, 2, 3, \ldots)$ can be found by a given $\triangle t$ in price series [3]. Thus, the local minimum $P_{\min(i)}$ can be just determined through searching the minimum point between two local maximums, $P_{\max(i)}$ and $P_{\max(i+1)}$. It can be easily noticed that one can connect the $P_{\max(i)}$ and the $P_{\min(i)}$ to determine a downward trend. Accordingly, by connecting $P_{\min(i)}$ with $P_{\max(i+1)}$, one can determine an upward trend as shown in Fig. 1(a). With different $\triangle t$, the trends with different time scales can be found to satisfy various investors as shown in Fig. 1(b).

After finding all the trends with different $\triangle t$, we define the trend return, $R_u(i)$, to describe the return rate of the ith upward trend as

$$R_u(i) = \ln\left(\frac{P_{\max(i+1)}}{P_{\min(i)}}\right). \tag{1}$$

Similarly, we define $R_d(i)$ to describe the rate of return of the ith downward trend and it can be expressed as

$$R_d(i) = \ln\left(\frac{P_{\min(\mathrm{i})}}{P_{\max(\mathrm{i})}}\right). \tag{2}$$

For the sake of quantifying how quickly a trend transform, we also perform a changing velocity analysis for stock trends in the two stock markets. We define the time span, $t_u(i)$, to describe the duration of ith upward trend, and $t_d(i)$ to describe the duration of ith downward trend. Therefore, we can calculate the changing velocity of ith upward trend according to

$$V_u(i) = \frac{R_u(i)}{t_u(i)}, \tag{3}$$

and the changing velocity of ith downward trend can be derived according to

$$V_d(i) = \frac{R_d(i)}{t_d(i)}. \tag{4}$$

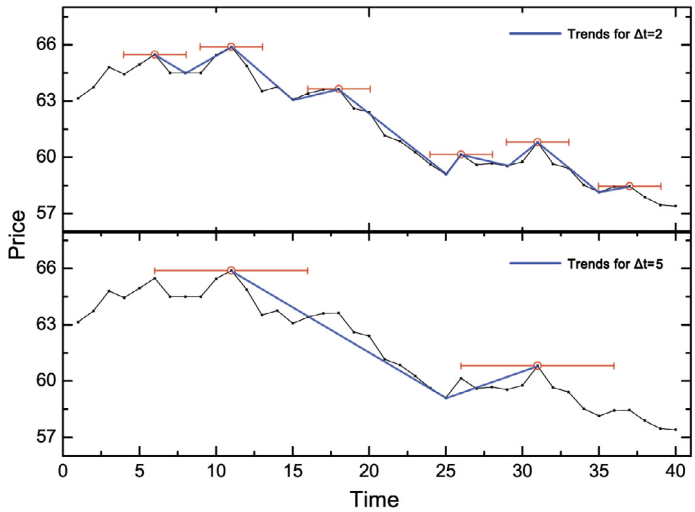

Fig. 1. Schematic graphs of (a) local maximum and trends where $\triangle t = 2$, (b) $\triangle t = 5$.

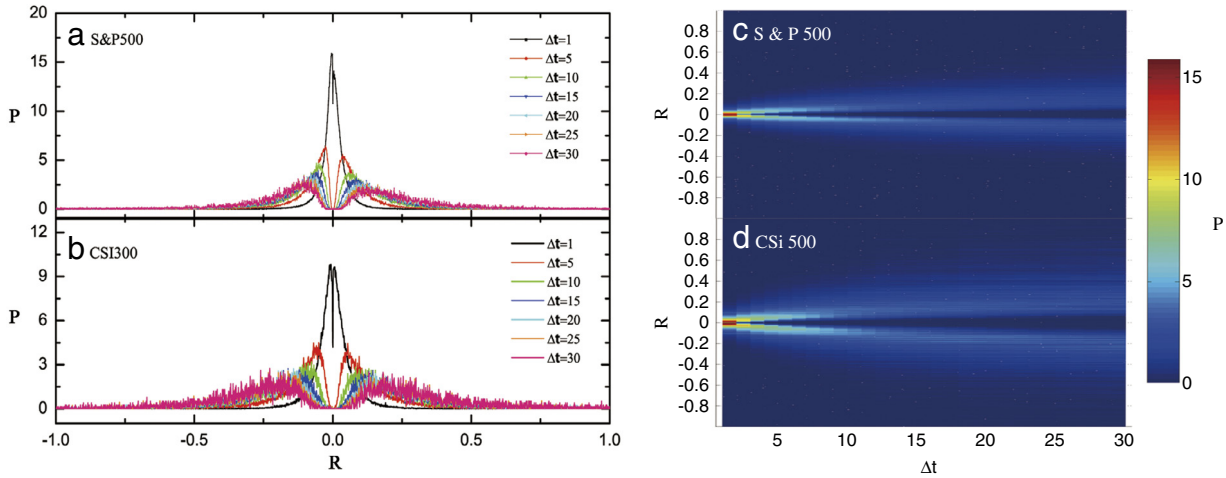

Fig. 2. (a) The PDF curves of trend return in S&P 500 where $\triangle t = 1, 5, 10, 15, 25, 30$. (b) The PDF curves of trend return in CSI 300 where $\triangle t = 1, 5, 10, 15, 25, 30$. (c) The three-dimensional graphs showing PDF curves of trend return in S&P 500 where $\triangle t = 1, 2, \ldots, 30$. The color bar shows the values of the corresponding probability.(d) The three-dimensional graphs showing PDF curves of trends return in CSI 300 where $\triangle t = 1, 2, \ldots, 30$. The color bar shows the values of the corresponding probability.

3. Results

To study the patterns of stock trends, we analyze time series of daily closing prices of all 500 components in the S&P 500 index from 2004-1-2 to 2012-4-20 as the symbol of American stock market. As a comparison, we also study the patterns of trends in Chinese stock market. We choose the time series of daily closing prices of all 300 components in the CSI 300 index during the same period. All of these series have been adjusted for dividends and splits.

Then, we divide the price series of one stock into several upward and downward trends. As shown in Fig. 2(a, b), to gain probability density functions (PDFs), which depict the trend return in various stock markets as $\triangle t$ varies from 1 to 30, a summary about trend return of all the component stocks should be given. It can be distinctly seen that each PDF has two peaks, one presents the results of upward trends and the other shows the results of downward trends. All the peaks in these graphs mean in which trend return that the trends have maximum probability to reverse. Meanwhile, the maximum probability position is increasing for upward trends and decreasing for downward trends when $\triangle t$ is increasing since the larger $\triangle t$ captures the longer length of trends as presented in Fig. 2(c, d).

In order to compare the patterns of downward and upward trends easily, we just take the trend return of downward trend into their absolute value. So the PDF curves of downward trends are overturned to the same side as upward trends shown in Fig. 3. From Fig. 3, one can easily notice that the shapes of PDF curves are almost the same in component stocks of CSI 300 with different $\triangle t$, which shows that the patterns of downward and upward trends in Chinese stock market are analogous. Meanwhile, it is obviously that the patterns of downward and upward trends in American stock market are

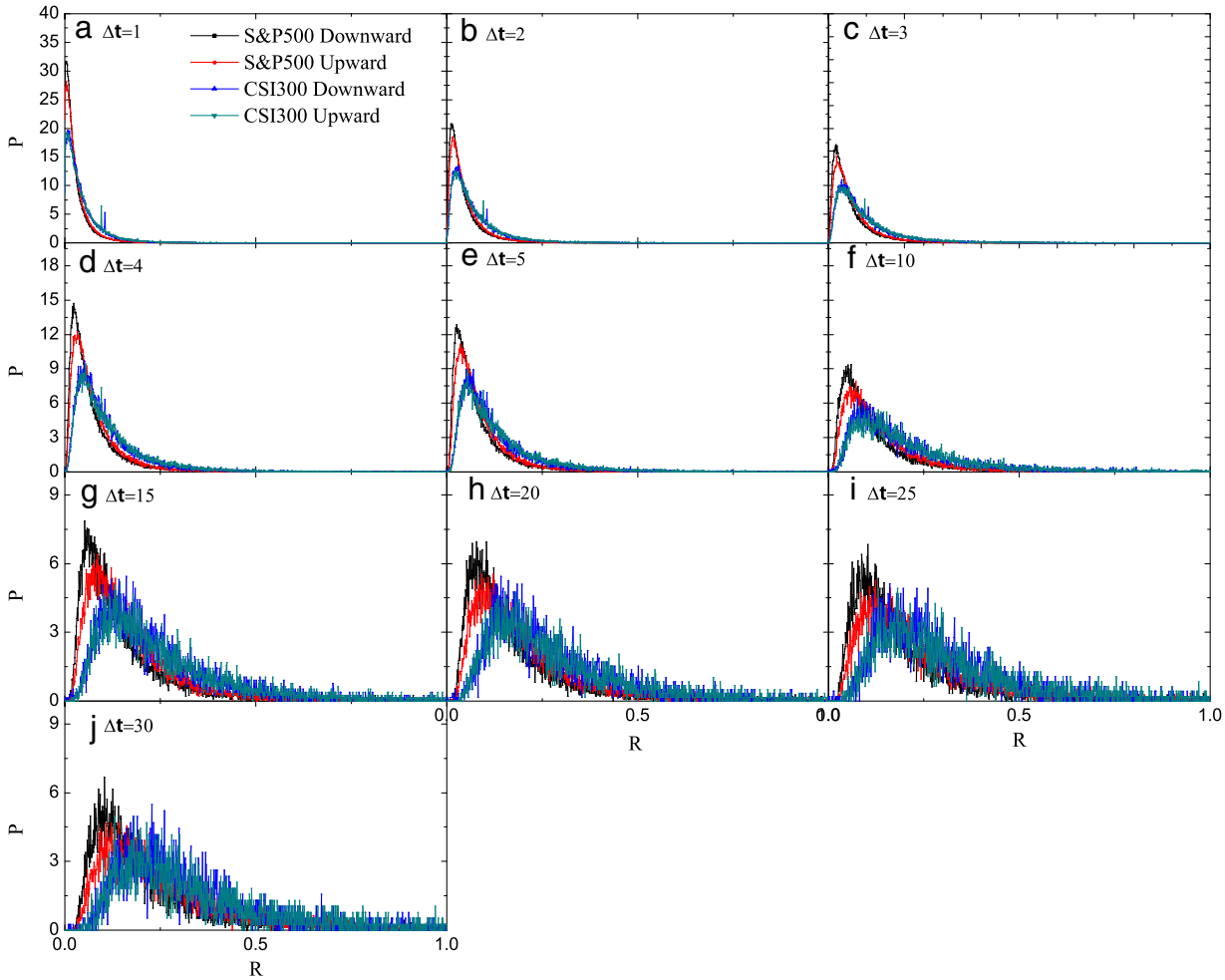

Fig. 3. The PDF curves of absolute trend return of downward and upward trends in two stock markets (USA&CHN) with different $\triangle t$.

remarkably different. In all $\triangle t$, the peaks of upward trends are on the right side of the peaks of downward trends and the peaks of upward trends are lower. Also, the tails of upward-trend PDF curves are fatter than those of downward trends. These asymmetric phenomena mean that in American stock market, the stocks' (short-term and long-term) upward trends, difficulties in reversing, and their absolute return is inclined to sustain larger compared with (short-term and long-term) downward trends. These characteristics are beneficial to the long position investors in the long run. To compare the results of two stock markets, for all $\triangle t$, the peaks of both downward and upward trends of the stocks in S&P 500 are on the left side of those in CSI 300. Meanwhile, the peaks of the upward and downward trends in S&P 500 are both higher than what in CSI 300. The tails of trends in CSI 300 are fatter than those in S&P 500. Accordingly, comparing with the American stock market, the absolute trend return of stocks in Chinese market generally have higher probability to extend larger. These characteristics are beneficial to the long position investors in the long run. To compare the results of two stock markets, for all $\triangle t$, the peaks of both downward and upward trends of the stocks in S&P 500 are on the left side of those in CSI 300. Meanwhile, the peaks of the upward and downward trends in S&P 500 are both higher than what in CSI 300. The tails of trends in CSI 300 are fatter than those in S&P 500. Accordingly, comparing with the American stock market, the absolute trend return of stocks in Chinese market generally have higher probability to extend larger.

We also find that all absolute trend return follows the lognormal distribution, which is the same distribution as what stock price follows. Fig. 4(a) shows the lognormal fit results of PDF curves of upward-trend return in CSI 300 and S&P 500 where $\triangle t = 5$ as an example. Meanwhile, we fit the PDF curves of $\ln(R)$ by gauss distribution where $\triangle t = 5$ and show the results in Fig. 4(b). Because of the monotonicity of $\ln(x)$ function, just by comparing the mean value and sigma of the $\ln(R)$ distribution, it can be obviously seen that the trend return in Chinese stock market have higher probability to extend larger than those in American stock market.

The similar methods are used to analyze the changing velocities of stock trends. Fig. 5 shows the PDF curves of the absolute changing velocities of trends with different $\triangle t$. When $\triangle t < 15$, one can see that the PDF of changing velocities of upward trends are similar to those of downward trends. In addition, the peaks of the curve from the American market are higher

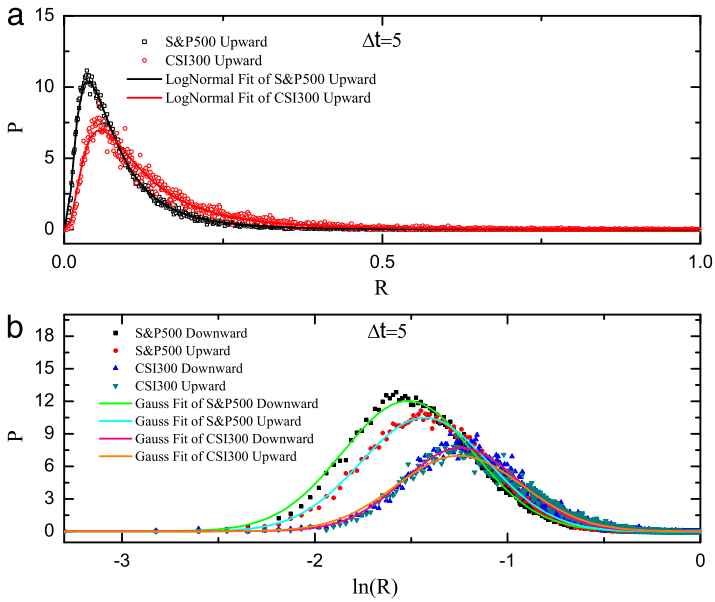

Fig. 4. (a) Lognormal fit of PDF curves of upward trend in S&P 500 and CSI 300 where $\triangle t = 5$. The accordingly adjusted R^2 is 0.997 and 0.983. (b) Gauss fit of PDF curves of $\ln(R)$ in two stock markets with $\triangle t = 5$. The $\ln(R)$ of downward trends in S&P 500 follows $N(-1.517, 0.115)$ distribution, and its adjusted R^2 is 0.996. The $\ln(R)$ of upward trends in S&P 500 follows $N(-1.431, 0.111)$ distribution, and its adjusted R^2 is 0.997. The $\ln(R)$ of downward trends in CSI 300 follows $N(-1.242, 0.89)$ distribution, and its adjusted R^2 is 0.986. The $\ln(R)$ of upward trends in CSI 300 follows $N(-1.250, 0.107)$ distribution, and its adjusted R^2 is 0.983.

than what from Chinese one and the tails in Chinese market are fatter than what in American one. If $\triangle t \geq 20$, it can be found that heights of the peaks follow the rule: $H[v_u(USA)] > H[v_d(USA)] > H[v_d(CHN)] > H[v_u(CHN)]$, and the pattern of tails obey the opposite relation. This rule shows that in Chinese market, the price of stock tends to increase quicker than decreasing, however, the American stock market presents contrary regularity. Above characteristics are obviously showed in last year's steep fall of Chinese stock market. Overall, the stock price trends have more probability to change in high speed in Chinese market than in American market, which means that the momentum is higher in Chinese stock market over the long run.

Above all, the absolute trend return tends to extend larger in Chinese stock market, and the changing velocities of the trends also follow the same law. These two patterns come from the stronger momentum effect and weaker reversal effect. It is well known that the Chinese market are dominated by individual investors, which means concentration degree of fund is much lower in Chinese market. In this background, the strong momentum is mainly caused by huge amounts of irrationally individual investors who follow the trends blindly in China.

4. Conclusion

In this article, based on the renormalization method, we compare the patterns of trends in Chinese with American stock market, and find that the asymmetric phenomena existing in the trend return of American stock market. What is more, the phenomena are also occurred in the changing velocities' cases of the long-term trends in both markets. These phenomena are beneficial to the American long position investors in the long run. In general, with the development of economy, the fundamental value of the great majority corporations should increase and push the stock price forward. Therefore, a stock market whose upward trend return are larger than the downward trend return during a long period of time should be of value to invest. Obviously, the Chinese stock market is a speculative market because even the economy develops swiftly during the period chosen, the long position investors still cannot earn more than speculators.

We find that the absolute trend return follows the lognormal distribution like stock price, which is an important feature for analyzing the trend pattern and describing the underlying physical mechanisms. In addition, we also notice that the absolute trend return in the Chinese stock market tends to extend larger than those in American stock market and the changing velocities of trends in Chinese stock market are higher than those in American stock market as well. It is well known that the American stock market is one of the most developed markets in the world, and the proportion of the institutional investors are really higher than that in Chinese. In general, the institutional investors have much stronger power to steer the stock price than the individual investors so that the momentum should be stronger in these stock markets. However, we obtain the results that in Chinese market the momentum effect is stronger and reversal effect is weaker. These phenomena are mainly caused by huge amounts of irrationally individual investors who follow the trends blindly in China. Consequently, by the analysis of trends pattern, vigorous evidences are gained to prove a stronger Herd behavior in emerging

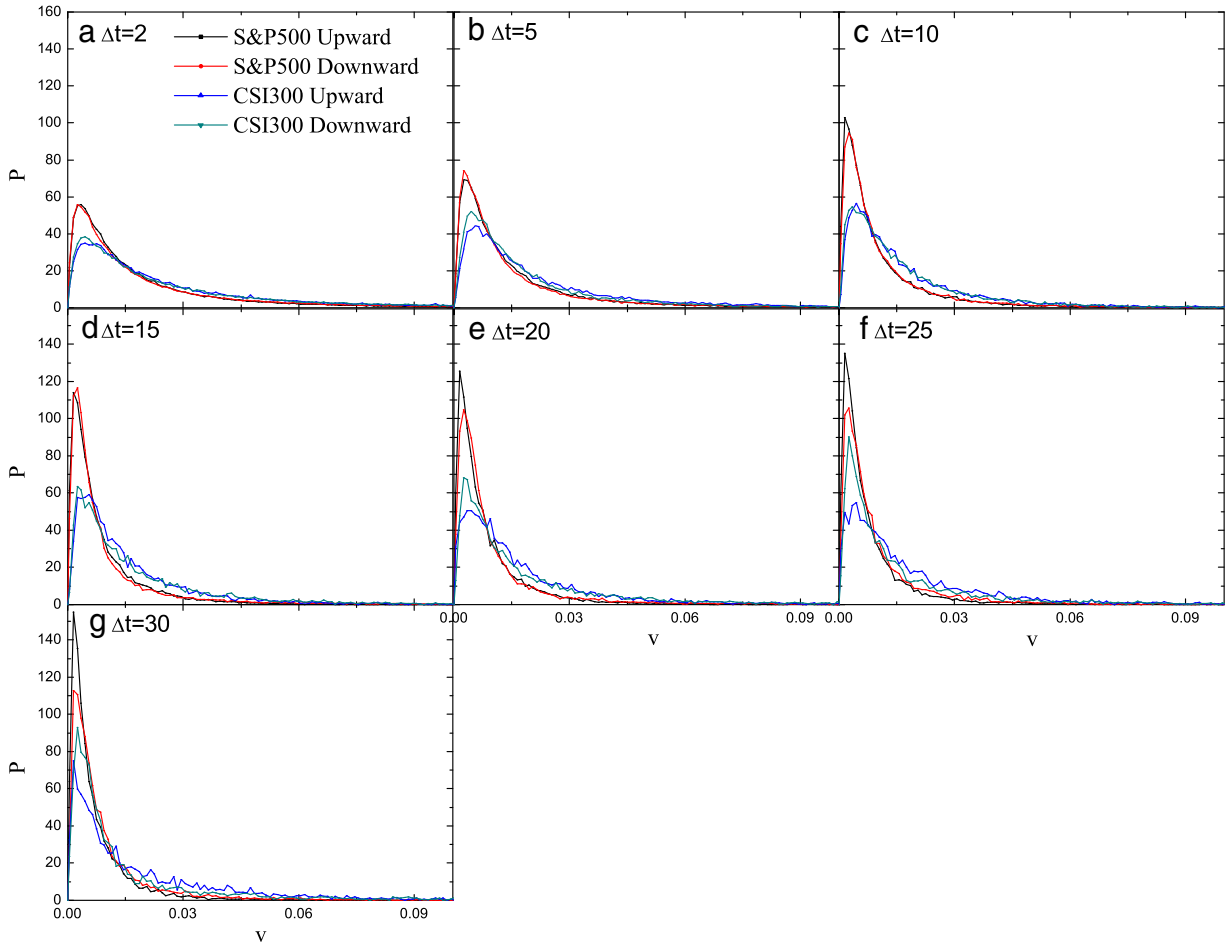

Fig. 5. The PDF curves of absolute changing velocities of downward and upward trends in two stock markets (USA&CHN) with different $\triangle t$.

stock market. Our findings could provide a comprehensive understanding of volatilities related to the trends in stock prices. The methodology presented in this work also offers a way to quantify the patterns of trends in stock price dynamics.

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