Research Article

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The Influence of Trading Volume, Market Trend, and Monetary Policy on Characteristics of the Chinese Stock Exchange: An Econophysics Perspective

<https://doi.org/10.1515/phys-2019-0105>

Received Oct 15, 2019; accepted Nov 19, 2019

Abstract: The paper adopts the financial physics approach to investigate influence of trading volume, market trend, as well as monetary policy on characteristics of the Chinese Stock Exchange. Utilizing 1-minute high-frequency data at various time intervals, the study examines the probability distribution density, autocorrelation and multi-fractal of the Shanghai Composite Index. Our study finds that the scale of trading volume, stock market trends, and monetary policy cycles all exert significant influences on micro characteristics of Shanghai Composite Index. More specifically, under the conditions of large trading volumes, loose monetary policies, and downward stock trends, the market possesses better fitting on Levy's distribution, the volatility self-correlation is stronger, and multifractal trait is more salient. We hope our study could provide better guidance for investment decisions, and form the basis for policy formulation aiming for a healthy growth of the financial market.

Keywords: Econophysics; Micro-characteristics; high frequency data; trading volume; monetary policy

PACS: 02.50.-r, 02.50.Cw, 02.50.Ng, 02.60.Gf

1 Introduction

Since Mantegna and Stanley's [1] introduction of the concept of "Econophysics" in 1995, financial physics has gradually developed into a new interdisciplinary field to apply

physics methods to examine research questions on economics and finance. Over the years, scholars in this field have utilized such physics and statistics methods as complex theory, nonlinear dynamics, network science, and statistical mechanics, to analyze characteristics of the financial market and financial data [2]. The main objective of this paper is to follow this strand of burgeoning research to explore micro characteristics of the Chinese stock exchange by utilizing high frequency data of Shanghai Stock Exchange Index, which is made available by the rapid advancement of computing technology and the explosion of computing power and storage space over the past several decades.

Several main findings emerge from extant studies utilizing the financial physics method to examine patterns of financial markets. An early study by Stanley *et al.* [3] on the US market suggests that the probability distribution of the earnings price ratio of the 1-min Standard & Poor's Index was neither a Gaussian distribution nor a Levy distribution, but a truncated Levy flight distribution. The father of fractal theory Mandelbrot [4] proposed that multi-fractals possess broad prospects in financial market research. Many scholars have then confirmed that multi-scale fractal theory is a practical tool to describe the complex volatility in financial markets [5–7]. For example, Wang and Song [8] empirical study of the stock market finds that the truncated Levy distribution can describe the distribution characteristics of experience, and perform better than the Gaussian distribution. Gao *et al.* [9] also shows that China's stock market, as financial markets in developed economies, has a multi-fractal scales hierarchical structure, while it differs from advanced markets in certain characteristics of this hierarchical structure. Parisi *et al.* [10] study on foreign exchange and stock index suggests that there are universally applicable statistical laws such as autocorrelation and multi-fractal in asset price fluctuations. Qiu *et al.* [11] applies the differential network method to examine the stock market pattern, and finds

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that the differential network can effectively describe the industry structure characteristics of the stock market. Tang et al. [12] recently investigates the micro characteristics of China's financial market and documents that Shanghai Stock Exchange Index has the characteristics of fat-tailed and non-Gaussian distributions of the Levy dimension to the incremental sequence. Besides, the fat-tailed features are more obvious when the market is experiencing a downward trend.

Aforementioned studies mainly focus on the statistical laws of financial market variables, especially the scaling law with the universality. However, these studies neglect the underlying differences and principles behind the universality of the stock market. In addition, they fail to consider the impact of key stock market factors such as trading volume and stock market trend as well as macroeconomic conditions on characteristics of the stock market. What are the differences in statistical laws such as probability distribution density, autocorrelation and multiple fractals under various trading volume scales, stock market trends and monetary policy cycles? What is the economic significance? When the stock market is in different trading volume scales, stock market trends and monetary policy cycles, what are the motives and basis for the investors to make decisions? What is the guiding significance of identifying the micro-characteristics of different positions for investment decision-making? These will be the focus of our study.

We also contribute to the literature by exploring differences in statistical laws such as probability distribution density, autocorrelation and multiple fractals under various trading volume scales, stock market trends and monetary policy cycles. This new perspective complements previous econophysics studies and reveals the internal behavioral patterns of the stock market. Moreover, our paper can directly verify the effectiveness of various trading volumes scales, stock market trends and monetary policies cycles, which will not only help to explain investor behaviors and guide investors' investment decisions, but also provide important guidelines for the government to formulate relevant policies. Therefore, our paper also possesses important practical implications.

2 Data selection and methods

2.1 Data selection criteria

This study selects the 1-minute data of the Shanghai Stock Exchange Index. In order to eliminate the influence of sam-

ple size on the research results, the data interval is controlled at the same time length, and the date is postponed in case of non-trading day. The data are obtained from Wind Database.

To avoid the influence of the circulation stock for each stock, we adopt the turnover rate as the measure of trading volume [13].

$$g(t) = \begin{cases} 0.5 & \ln To(t) \leq u - e \\ 1 & u - e < \ln To(t) \leq u + e \\ 1.5 & u + e < \ln To(t) \end{cases} \quad (1)$$

$g(t)$ is a piecewise function based on turnover rate, dividing the trading volume into three stages. $To(t)$ is the turnover rate. u is the mean and e is the standard deviation. When the value of $g(t)$ is 0.5, it is a small trading volume stage. When the value of $g(t)$ is 1, it is a medium trading volume stage, and when the value of $g(t)$ is 1.5, it is a large trading volume stage. The interval of the large volume is from Mar 17, 2015 to Jul 17, 2015. The interval of the medium volume is from Jan 17, 2016 to May 17, 2016. The interval of the small volume is from Mar 17, 2014 to Jul 17, 2014.

Since there is no uniform criterion for classifying monetary policy cycles, this study divides policy into three intervals through the monetary policy indicators such as deposit reserve ratio, treasury bond yield and reverse repurchase ratio, namely, loose, steady and tight monetary policy¹ [14, 15]. More specifically, we define the loose monetary policy interval as from Jun 28, 2015 to Oct 28, 2015, the steady monetary policy interval from Mar 28, 2016 to Jul 28, 2016, and the tight monetary policy interval from Dec 21, 2016 to Apr 21, 2017.

We also divide the market based on three types of trends, rising, falling and stationary oscillations through the trend chart of weekly data based on methods applied by Ref. [12, 16]. More specifically, we define the trend as rising if the price increases over 30% from the previous low point. In contrast, the falling range refers to a decline over 30% from the previous high point. Finally, the steady trend indicates that variation rate remains between 5% and 10%. More specifically, the rising period is from Sep 12, 2014 to Jan 12, 2015, the stable period is from Dec 12, 2016 to Apr 12,

¹ Five clear signals of easing were issued in 2015. Since the reduction of the reserve requirement ratio on February 29, 2016, the central bank has not taken any obvious easing measures. More is to supplement market liquidity through open market operations, which means that policy has changed from loose to steady. In August 2016, the 14 day reverse repo was restarted, followed by a 28 day reverse repo, which increased MLF operations, marking the transition of monetary policy from steady to tight.

2017, and the falling period is from Jun 12, 2015 to Oct 12, 2015.

This study selects the logarithmic incremental of stock index, which is calculated as follows:

$$R_k(t) = \ln P(t+k) - \ln P(t) \quad (2)$$

Where k represents the time interval, $P(t)$ means the stock index. Y is defined as a time series, then

$$R_Y = \frac{dY}{dt} \quad (3)$$

$$R_Y^k(t_i) = Y(t_i+k) - Y(t_i) \quad (4)$$

Where $Y = \ln(P)$. Then the absolute return is:

$$|R_Y^k| = |Y(t_i+k) - Y(t_i)| \quad (5)$$

Standard absolute return can be obtained from formula (5) as follows,

$$|\hat{R}_Y^k| = \frac{|R_Y^k|}{(\sum_{t_i}^{N_T-k} |R_Y^k|)/(N_T - k)} \quad (6)$$

Where N_T is the total amount of data in time series Y , the denominator is the arithmetic average of the absolute returns.

2.2 Physical finance method

2.2.1 Probability distribution function

2.2.1.1 Heavy-tailed distribution

In this paper, the hierarchical ordering method is used to describe the fat-tailed distribution of financial asset returns. This method has the advantages of easy implementation, no loss of information and low noise [17, 18].

Considering that the variable x has n observations, $f(x)$ is the true probability density, and then the complementary probability distribution can be expressed as $C(x) = \int_x^\infty f(y)dy$. The n observations are sorted from largest to smallest, and the formula can be obtained as follows.

$$x_1 \geq x_2 \geq \dots \geq x_R \dots \geq x_n \quad (7)$$

R is the level, namely rank. Thus, $nC(x_R)$ is the number of observations no less than x_R , namely,

$$nC(x_R) = R \quad (8)$$

Assuming that the variable x possesses a power law tail distribution, namely $f(x) \sim x^{-(1+\omega)}$, and then $C(x) \sim$

$x^{-\omega}$. The approximation relation of x_R and R can be obtained as follows,

$$x_R \sim R^{-1/\omega} \quad (9)$$

The exact expression of the above formula can be derived from formula (8), namely

$$x_R \sim \left(\frac{\omega n + 1}{\omega R + 1} \right)^{1/\omega} \quad (10)$$

2.2.1.2 Levy distribution

The symmetric stable distribution with an average value of 0 is utilized. For any stock index logarithmic increment $R_k(t) = \ln P(t+k) - \ln P(t)$, If $R_k(t)$ satisfies the symmetrical Levy stationary distribution, then

$$P(R_k) = \frac{1}{\pi} \int_0^\infty e^{-k\gamma|q|^\alpha} \cos(qR_k) dq \quad (11)$$

Where γ is a positive scale factor, α is the parameter of a positive scale distribution and $0 < \alpha \leq 2$. In the data increment, the data of 0 is relatively concentrated and is at the peak of the probability distribution. For the sake of calculation, the data $P(R=0)$ is selected as the basis to fit the data of Levy's distribution. If the distribution possesses the self-similar structure, and then the varied Δt corresponds to the same α . Self-similarity is a significant feature of the stable distribution of Levy, thus, when $R_k = 0$, the above formula can be converted into as follows,

$$P(R_k=0) = \frac{1}{\pi} \int_0^\infty e^{-k\gamma|q|^\alpha} dq = \frac{\Gamma(1/\alpha)}{\pi\alpha\gamma^{1/\alpha}} \quad (12)$$

The following formula can be obtained by taking the logarithm of both sides of the equation.

$$\log P(R_k=0) = \log \left[\frac{\Gamma(1/\alpha)}{\pi\alpha\gamma^{1/\alpha}} \right] - \frac{1}{\alpha} \log k \quad (13)$$

The exponential distribution parameter α of the Levy distribution can be obtained by the above fitting formula.

2.2.2 Autocorrelation function

We next apply the autocorrelation functions to analyze financial time series and signal processing, and express the correlation degree of values at different times in the sequence. In order to analyze the yield time series $R(t)$, the autocorrelation coefficient $C(\tau)$ is defined as follows when the time interval k is given.

$$C_R(t) = \frac{\langle R_k(x)R_k(x+t) \rangle - \langle R_k(x) \rangle \langle R_k(x+t) \rangle}{[\sigma(R_k)]^2} \quad (14)$$

Figure 1: Distributions of complementary probability

In formula (14), when $t = 0$, and then $C_R(t) = 1$. If there is no correlation between logarithmic increments of interval t at the same k level, i.e. $\langle R_k(x)R_k(x+t) \rangle = \langle R_k(x) \rangle \langle R_k(x+t) \rangle$, and then $C_R(t) = 0$.

2.2.3 Multi-fractal

The multi-fractal process is defined by Mandelbrot [19] as follows. $X(t) = \ln[P(t)]$, $X(t)$ is made as the random process with stationary increment $\delta_k X(t)$, namely, $\delta_k X(t) = X(t) - X(t-k)$. Assuming that $E[|\delta_k X(t)|^q]$ exists for all $q \in Q$, in which $Q \rightarrow$ is the suitable set containing the interval $[0, 1]$, and then $c_q = E[|\delta_1 X(t)|^q]$. Furthermore, $\zeta : Q \rightarrow$ defines a differentiable function, T is the positive real value. If all $\tau \in [0, T]$ and all moments $q \in Q$ can meet the formula as follows,

$$M(q, k) = E[|\delta_k X(t)|^q] = c_q k^{\zeta(q)} \quad (15)$$

The process $X(t)$ can be viewed as scale invariance. Taken the absolute moment of the scale invariance process increment in Formula (15) as a sample, the function of interval k presents the power law distribution. We next divide the scale invariance process into two cases as follows: (1) When $\zeta(q)$ is the linearity such as $\zeta(q) = qH$ (H is Hurst index), then the process is single fractal process. (2) When $\zeta(q)$ is the nonlinearity, and then the process is multi-fractal process.

3 Empirical analysis

3.1 Impact of trading volume

3.1.1 Probability distribution function of $|\hat{R}_Y^k|$

We first analyze the influence of trading volume scale on the heavy-tailed distribution of Shanghai Stock Exchange Index. The standardize absolute return sequence $|\hat{R}_Y^k|$ is selected as the study sample to ensure that the sequence of different time intervals is comparable. $k = 1$ and $k = 100$ are respectively selected, and the results are shown in Figure 1.

Figure 1 compares the probability density distributions of the standardized returns of the Shanghai Composite Index with various trading volume scales when $k = 1$ and $k = 100$. This indicates that the distribution function possesses obvious heavy tail characteristics. Besides, the estimation results of KS also indicate that there is a significant difference between the heavy-tailed distributions. When $k = 1$, the tailed distribution of the return sequence spreads with the increase of the trading volume, that is, the increase of the trading volume increases the possibility of extreme events. Due to the increase of trading volume, the information content in stock trading increases, the non-linearity or lagged response of investors to the information causes the investors' flock behavior, and consequently results in fluctuation agglomeration of return rate series. Besides, the same trading leads to greater volatility of stock price. When $k = 100$, the distribution of the

Figure 2: Situation in large volume, medium volume and small volume log-log plot of the probability $P(R = 0)$ versus k

(a) with $k = 1$

(b) with $k = 100$

Figure 3: Autocorrelation functions of volatility

yield rate is more suitable for Gaussian distribution. Figure 1 suggests that the probability distribution converges to a normal distribution as the interval k increases. This is related to the noise impact on the closing price of stock per minute (a large amount of trading cause discontinuity in short time). However, noise can be filtered out with the increase of k . Thus, the return sequence at $k = 100$ is more convergent to the normal distribution than the return sequence at $k = 1$, where the fitting positive distribution of probability distribution for large volume states is better, and it has more predictive value for investors' investment decisions.

The following chart adopts the stable distribution of Levy to fit the distribution of returns. We first analyze the probability distribution function of $R_k(t)$. When respectively taking $k = 1, 3, 10, 32, 100, 316, 1000$ min, the probability distribution function of $R_k(t)$ in different trading volume states can be obtained. We then fit the exponential distribution parameter α of Levy distribution according to equation (13). The result is showed in Figure 2.

In Figure 2, data points fit well in a straight line, which shows that the assumption of the above-mentioned Levy distribution is reasonable. Through the least square method, the slope $(-1/\alpha)$ of the fitting straight-line under the state of big volume, medium volume and small volume can be obtained as $-0.6264, -0.60207, -0.55726$, the corresponding distribution parameters α are respectively $1.5964, 1.6609, 1.7945$. It shows that the truncated Levy flight can describe the sharp fat-tailed features of return sequence. Meanwhile, the goodness-of-fit R^2 are respectively $0.9955, 0.9701$ and 0.9888 , they are all greater than 95%. Therefore, the parameter estimation is reliable. It further shows that the fitting effect of truncated Levi flight is good, moreover, the fitting effect of Levy distribution is better the stock market is under big trading volume.

3.1.2 Autocorrelation analysis of volatility $|R_Y^k|$

$|R_Y^k|$ is taken as the volatility to study the volatility autocorrelation of the Shanghai Stock Exchange Index at different trading volume stages, $k = 1$ and $k = 100$ are respectively adopted. The result is showed in Figure 3.

Figure 3 shows the autocorrelation functions of three trading volume with $k = 1$ and $k = 100$. It can be seen that there is a clear autocorrelation for the volatility. In addition, the autocorrelation of volatility series increases with the increase of trading volume. For the mean value and peak value, when $k = 1$, the autocorrelation in the large trading volume stage is the strongest, the average

Figure 4: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$

value tends to 0.1, while the average value tends to 0.47 when the lag period $t = 240$. The autocorrelation in the medium trading volume stage is in the medium, the average value tends to 0.05, while the mean value tends to 0.3 at $t = 240$. The autocorrelation in the small trading volume stage is weakest, the mean value tends to 0, while the mean value tends to 0.18 at $t = 240$. This rule also applies when $k = 100$. For the period characteristics, the volatility shows an obvious periodicity of $T = 240$. When $k = 1$, the volatility curve appears alternately with low correlation and high correlation with a period of $T = 120$, and a significant large peak appears at $t = 240, 480$ and 960 . When $t = 120, 360, 600$ and 840 , a wavelet peak appears in the volatility autocorrelation curve under the big trading volume and the medium trading volume stage, while a wavelet trough appears in the volatility autocorrelation curve under the small trading volume stage. When $K = 100$, the autocorrelation function of volatility is positively correlated at $t = 240, 480$ and 960 , and a wavelet peak appears in both medium and small trading volumes, while large trading volumes is a wavelet trough. When $t = 120, 360, 600$ and 840 , the volatility autocorrelation curves of the medium trading volume and the small trading volume present a wavelet trough, while the volatility autocorrelation curves of the small trading volume present a wavelet peak.

In the field of market microstructure research, the relation between trading volume and the volatility of financial assets has always been the focus of research. This study finds that the volatility in the three stages of big trading volume, medium trading volume and small trading volume all present obvious autocorrelation, and the autocorrelation is stronger when the trading volume scale is bigger.

Meanwhile, the study also finds that the volatility has an obvious periodicity when $k = 1$ and $k = 100$. With $T = 240$ as a period, this may be mainly due to the influence of the intraday model (calendar effect), but it is not merely the intraday model. It shows that the volatility possesses a long memory, so investors can apply more historical information to improve the prediction of volatility.

3.1.3 Multi-fractal analysis

Figure 4 shows the trend chart of return ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$ for time interval k under various trading volume scales [20], where q takes 1.5, 2, 2.5 and 3, the time interval k is 5 min. Figure 4 reveals that the scale functions corresponding to varied q values depict the fractal features at different time points. With the change of time scale, we can observe the price fluctuation information under different time scales. The trend of the yield ratio is non-linearity under these three types of trading volumes. It indicates that the Shanghai Stock Exchange Index possesses multi-fractal characteristics in varied trading volume scales. Moreover, the bigger the q value, the more obvious the change of the return ratio. When $q = 3$, the linear slope of the yield ratio curve under the big trading volume is the largest, which shows that the big trading volume has stronger multi-fractals compared with the small and medium trading volumes, and the market is more complex.

We draw Figure 4 based on the various q values to describe the multi-fractal structure of the stock market by the scale characteristics of the time-incremental moments. We

Figure 5: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$ with $q = 3$

next use the yield ratio curve of $q = 3$ to measure the multifractal characteristics of the stock market, and to analyze the fluctuation trend of the return ratio under the three trading volume scales. These results are plotted in Figure 5.

Figure 5 selects the yield ratio curve of $q = 3$ to measure the multi-fractal characteristics of the Shanghai Composite Index. All yield ratio curves in the figure show a downward trend. It indicates that the Shanghai Stock Exchange Index possesses long memory characteristics under various trading volume scales. The difference lies in the speed of decay. Among them, the decay speed of the return series in the big trading volume is the fastest, followed by the medium trading volume, while the decay speed of the return series in the small trading volume is the most stable. Trading volume is a measure of market liquidity and represents the willingness of investors to buy and sell stocks. If the trading volume is high, then the investors' willingness to buy and sell stocks increases. At this time, investors believe that the market is relatively active, which may easily lead to investors' aggressive investment and the phenomenon of going with the tide. That is, the higher the trading volume, the stronger the liquidity of the market. However, the high liquidity tends to cause the large price fluctuation of the market. Therefore, the yield rate series of yield ratio data under high trading volume decays fastest. Conversely, the market liquidity is low under small trading volume. Inactive markets often possess relatively conservative investments, the investors think they will possess little opportunities to achieve profits in short-term period and reduce their investment. Thus, the decay speed of the return series in the small trading volume is the most stable.

3.2 The impact of monetary policy

3.2.1 Probability distribution function of $|\hat{R}_Y^k|$

As can be seen from Figure 6, the distribution functions of the standard absolute return sequence under three major monetary policies show the thick-tailed phenomenon. Besides, the KS estimation results show that there is a significant difference between the thick-tailed distributions. When $k = 1$, the tail of the loose monetary policy stance deviates furthest from the standard normal distribution curve, i.e. compared with the periods of steady and tight monetary policy, the tail characteristics are more obvious under the loose monetary policy period, and the extreme risks are even more salient. Loose policy will encourage people to invest surplus funds in stocks and other financial assets, making a large number of monetary assets flow into the stock market, and then the stock market begins to boost. Affected by the appearance of false prosperity, a large number of investors choose to purchase stocks, that is, irrational investments, this can easily lead to stock price bubbles. The money supply increases and the liquidity of the stock market increase accordingly, resulting in extreme risks to the stock market. Comparing the two graphs, we can see that as k increases, the noise can be filtered out. The return sequence with $k = 100$ is more convergent to the normal distribution than with $k = 1$, and the thick tailed characteristics become weak. When $k = 100$, the tailed distribution under the tight monetary policy is more fitting for normal distribution compared with the tail distribution of the loose and steady monetary policies. This feature shows the asymmetry of the impact of China's monetary policy on the stock market. It is mainly influenced by the economic subject's anticipation and behavioral asymmetry as well as the stickiness theory of market price.

We next utilize the stable distribution of Levy to fit the distribution of returns.

As can be seen in Figure 7, the data points fit well on a straight line, it shows that the assumption of the above-mentioned Levy distribution is reasonable. The least square method is applied to fit the slopes $(-1/\alpha)$ of the fitting straight line under the loose policy, the stable policy and the tight policy. The slopes are -0.58687 , -0.52916 , -0.55154 , while the corresponding distribution parameters are respectively 1.7039 , 1.8898 and 1.8131 . It shows that the truncated Levy flight can characterize the peak heavy tailed features for the return sequence. Meanwhile, the goodness of fit R^2 is respectively 0.99 , 0.9641 and 0.9876 , and they are all greater than 95% . Therefore, the parameter estimation is reliable, thus it further shows that the fitting effect of the truncated Levy flight is good, and

(a) with $k = 1$ (b) with $k = 100$

Figure 6: Distributions of complementary probability

Figure 7: Situation in loose policy, steady policy and tight policy log-log plot of the probability $P(R = 0)$ versus k

the stock market possesses better fitting effect of Levy distribution under loose policy.

3.2.2 Autocorrelation analysis of volatility $|R_Y^k|$

$|R_Y^k|$ is taken as the volatility to study the volatility autocorrelation under different monetary policies respectively with $k = 1$ and $k = 100$. The results are shown in Figure 8.

Figure 8 reveals that the volatility has obvious autocorrelation characteristics. When $k = 1$, the volatility autocorrelation function under the partially loose monetary policy is positive, that is, there is a significant positive autocorrelation characteristic. In terms of the mean value and the peak value, the autocorrelation function of the par-

tial loose monetary policy shows strong autocorrelation. The mean value of the autocorrelation coefficient tends to 0.1, and it tends to 0.45 at the lag time $t = 240$. The autocorrelation coefficient tends to 0 under the steady and tight policies, while it approaches 0.25 at $t = 240$. When $k = 100$, the volatility autocorrelation under the loose monetary policy is also stronger than the volatility autocorrelation under the steady and tight policies. In the periodic characteristic, when $k = 1$, the wavelet peak appears in the autocorrelation function at the lag time $t = 120$ and appears in a period of $T = 240$. a large peak appears in the autocorrelation function at the lag time $t = 240$ and also presented in a period of $T = 240$. That is, the high correlation and low correlation of the volatility curves are exchanged periodically with $T = 240$. However, this periodical law is only utilized in the autocorrelation function under the partially loose monetary policy with $k = 100$, and the periodicity of the autocorrelation functions under steady and tight monetary policies are not significant.

The volatility of the Shanghai Composite Index under the three monetary policies shows significant autocorrelation. This significant positive autocorrelation may originate from the market's non-synchronous trading. Due to the asymmetry and market frictions of market information transmission, the public and private information that should have responded immediately is often lagging and persistent, thus the stocks that constitute the Shanghai Composite Index possess varied information feedback speed, resulting in autocorrelation of the volatility sequence. The autocorrelation curve possesses a significant

Figure 8: Autocorrelation functions of volatility

periodicity of $T = 240$, this is consistent with the research results of scholar Zhou *et al.* (2009). Meanwhile, it also finds that the monetary policy affects the strength of volatility autocorrelation, in which the autocorrelation is the strongest under the loose monetary policy period. It is likely that the stock demand increases with the increase of monetary assets in the stock market, which also increases investor confidence, and results in obvious investors' momentum trading behaviors in the market. Thus, the trend of "chasing after go up kill drop" and "pursuing trend" are even more salient.

3.2.3 Multi-fractal analysis

Figure 9 shows that the trend of the yield ratio is non-linear under three types of monetary policies. It indicates that the Shanghai Stock Exchange Index has multi-fractal characteristics in varied policies. Moreover, the bigger the q value, the more obvious the change of the return ratio. When $q = 3$, the linear slope of the yield ratio curve under the loose policy is the largest. It shows that the multi-fractal features of the loose monetary policy is stronger compared with the steady and tight policies, and its market is more complex.

The yield ratio curve with $q = 3$ is selected to measure the multi-fractal characteristics of the stock market in the following. Besides, the fluctuation trends of the yield ratio under these three policies are analyzed respectively. Figure 10 shows the results when the value of k is 5 min.

By comparing the charts of the yield ratios of monetary policies with $q = 3$, Figure 10 suggests that all yield curves in the chart show a down trailing trend, it indicates that the Shanghai Stock Exchange Index possesses obvious long memory characteristics under different monetary policies. Among them, the decline rate of the loose policy is the fastest. This may be due to the central bank's several reductions in the reserve requirement ratio and the release of loose policy signals. It prompts a considerable portion of incremental funds to flow into the capital market as funds of entering stock market or "hot money". As a result, the cost of capital has reduced accordingly. As investors reduce the level of risk aversion, the market liquidity significantly increases, which consequently causes large price fluctuations. Under the tight monetary policy, when the signal of tight policy appears in the short term, the investor's capital cost increases, the investment decisions of investor are more rational, and the market liquidity is reduced accordingly. When tight policy is undergoing for a long period of time, the government may continue implementing reverse repurchases, and rising the yield ratio and SLF interest rates of national debt. This will lead to pessimistic expectation of investors and cause substantially panic selling, and finally lead to large fluctuations in the stock market. During the period of steady monetary policy, the stock market has the weakest long-term memory characteristics, and the trend of stock price variation is also the most difficult to capture.

Figure 9: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$

Figure 10: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$ with $q = 3$

3.3 Influence of Stock Market Trend

3.3.1 Probability distribution function of $\hat{R}_Y^k$

Comparing the two groups in Figure 11 reveals that the distribution function exhibits a thick-tailed feature. Besides, the KS estimation results show that there is a significant difference between the thick-tailed distributions. As the time interval k increases from 1 to 100, the distribution of the return sequence converges to a normal distribution. When $k = 1$, the stock market's downward trend distribution is more diffuse compared with the upward and stable trends. This feature is consistent with the asymmetry of the stock market information impact. This is in line with the asymmetry of investors' information, government macroe-

conomic regulation as well as the herd behaviors of the individual investors and the lack of stock market short mechanism. Investors' decisions are deeply influenced by investors' sentiment. During the fall of stocks, the contagion effect is even more pronounced. When $k = 100$, the tail of the downward trend is more suitable for the normal distribution compared with the upward and the steady trends. This is mainly caused by social behavioral characteristics of investors, which will directly or indirectly affect individual investment decisions. Once the investors appear a "panic" emotion, it may further exacerbate the spread of market "panic" emotions. Extant study suggests that when the stock market declines, the stock market investment shows higher investment homogeneity, while the return sequence with longer time interval smoothes out the divergence characteristics caused by the noise factors in the short-term time interval.

We next utilize the stable distribution of Levy to fit the distribution of returns.

Figure 12 indicates the data points in the figure are well fitted on a straight line, it indicates that the assumptions of the above-mentioned Levy distribution are reasonable. The slopes ($1/\alpha$) of the fitted straight line in the upward, steady and downward trend states are -0.59952 , -0.58287 and -0.5691 by applying the least-squares fitting, the corresponding distribution parameters are respectively 1.6680, 1.7156 and 1.7571. It indicates that the truncated Levy flight can describe the spike thick-tailed characteristics of the return sequence, and the goodness of fit R^2 are respectively 0.9922, 0.989 and 0.9938, which are greater than 95%. Therefore, the parameter estimation is reliable, and then it further shows that the fitting effect of the truncated Levy

Figure 11: Distributions of complementary probability

Figure 12: Situation in upward trend, steady trend and downward trend log-log plot of the probability $P(R = 0)$ versus k

flight is good. Meanwhile, the stock market has a better fitting effect of the Levy distribution in the downward trend.

3.3.2 Autocorrelation analysis of volatility $|R_Y^k|$

$|R_Y^k|$ is taken as the volatility to study the volatility autocorrelation of the Shanghai Composite Index under different market conditions respectively with $k = 1$ and $k = 100$. The results are shown in Figure 13.

Figure 13 shows that volatility possesses obvious autocorrelation characteristics, and the stock market trend influences the volatility autocorrelation. In terms of the mean value and the peak value, when $k = 1$, the volatility autocorrelation under the rising and falling states are stronger than the volatility autocorrelation under the steady state. Among them, the volatility autocorrelation is

(a) with $k = 1$ (b) with $k = 100$

Figure 13: Autocorrelation functions of volatility

Figure 14: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$

the strongest under the downward trend, the mean value tends to be 0.05, and the autocorrelation coefficient tends to 0.45 at $t = 240$. The mean value of the autocorrelation coefficient tends to 0.15 under the upward trend, and the autocorrelation coefficient tends to 0.3 at $t = 240$. The volatility autocorrelation under the steady trend is the weakest, the mean value of the autocorrelation coefficient tends to 0.02, and the autocorrelation coefficient tends to 0.15 at $t = 240$. For periodic characteristics, the volatility shows a clear periodicity of $T = 240$. When $k = 1$, the volatility curve appears alternatively with low correlation and high correlation in the period of $T = 120$. At $t = 240$, 480 and 960, there is an obvious large peak in the autocorrelation function diagram. A wavelet peak appears at $t = 120, 360, 600$ and 840. This periodic law still exists at $k = 100$.

There is significant autocorrelation in the volatility of the upward, steady and downward trend, which is consistent with the mainstream trend of economists, that is, the volatility of stock price possesses a strong memory. Meanwhile, we found that the volatility autocorrelation curve possesses significant periodicity with $K = 1$ and $k = 100$, that is, there is a high correlation between the daily opening price of China's stock market, which may be due to the existence of the intraday model [21]. However, this study attempts to alter the initial values of the samples and respectively takes 9:27, 10:34, 11:39, 13:51, 14:47 and 15:26 as the initial data. We also found that this periodic pattern remains unchanged. It shows that the one-minute stock price fluctuation is deeply affected by the volatility of the stock price at the same time in the previous period, while it's not just the effect of the intraday model [22–24]. Therefore, the research perspective of investors should not only

be limited to the closing price and open price of the stock market, but should also explore the intrinsic properties of the high-frequency data and make investment decisions with the cyclical law of autocorrelation. In addition, the study also found that the volatility autocorrelation of the downward trend is stronger compared with the upward trend and the steady trend, which further validates the asymmetric nature of information shocks in China's stock market.

3.3.3 Multi-fractal analysis

Figure 14 shows that the trend of the yield ratios under the upward, steady and downward trends are all non-linear, indicating that the Shanghai Stock Exchange Index possesses the multi-fractal characteristics in different stock market conditions. Moreover, the variation of the yield ratio is the most obvious with $q = 3$. The linear slope of the yield ratio curve under the downward trend is the largest, and it shows that the multi-fractals under downward trend is the strongest compared with and upward and steady trends, and the market is more complex.

We next select the yield ratio curve of $q = 3$ to measure the multi-fractal characteristics, and respectively analyze the fluctuation trends of the yield ratio under three market conditions. Among them, the value of k is 5 min. The results are shown in Figure 15.

When $q = 3$, the stock market under all market conditions in the figure possess a downward-sloping feature, and it reflects the overall stability of the sequence, and indicating that the Shanghai Composite Index possesses stronger long-term memory under varied market condi-

Figure 15: Multifractal curves of ratio $\langle |R^k|^q \rangle / \langle |R^k| \rangle^q$ with $q = 3$

tions. However, the sequence of the yield ratio under the upward and downward trends declines at a faster rate and possesses more significant variation trend in the short term. This indicates that the distribution of the yield ratio series is affected by the variation trend of the yield ratio data to a certain extent [25]. Among them, the variation of the yield ratio under the upward trend causes greater price volatility. This is mainly due to the optimistic expectation and confidence of investors when the stock market is rising, and forms a “band car effect”, which makes the liquidity of assets excess and can easily create an asset price bubble. On the contrary, when the stock market is in a downward trend during the short term, the stock market is in a downturn, the investors will seek investment opportunities with more cautious attitudes, so the market liquidity is low, and inactive markets often lead to relatively small price fluctuations [26]. Thus, the decay rate of fluctuation trend is relatively stable. For long-term investors, when the stock market is at a low price for a long time, they can enter at a low price and seek opportunities to obtain higher returns in the future. Therefore, when the market recovers from the insufficient liquidity to the previous level of liquidity, the price fluctuation range is more pronounced than the upward trend. However, in terms of the yield ratio data under steady trend, the long-term memory of the stock market is the weakest [27]. With the variation of time scale, the price variations show irregular oscillatory fluctuations. This phenomenon is also consistent with the existing research results. When the stock market is stable, it is the most difficult to capture the trend of stock prices.

4 Conclusion

This study analyzes the effects of trading volume, stock market trend, and monetary policy on the probability distribution density, autocorrelation and multi-fractal of the Shanghai Stock Exchange Index using 1-min data at different time intervals. We find that the scale of trading volume significantly influences micro characteristics of the Shanghai Stock Exchange Index. With the increase of trading volume, the thick-tailed characteristics is also increasing, the autocorrelation of the volatility raises gradually, and the multi-fractals traits become more and more salient. High trading volume also means high liquidity and high market participation, which increases the complexity of the stock market as well as the possibility of extreme events. As a result, investors shall invest more cautiously under the conditions of high trading volumes.

In addition, monetary policy also affects characteristics of the Shanghai Stock Exchange Index. More specifically, we find that the probability distribution of the yield ratio shows the thick-tailed feature. With the increase of time interval, the distribution tends to be a Gaussian distribution. While the tail fits the Gaussian distribution better under the tight monetary policy period. Meanwhile, the distributions of all three monetary policy cycles can well describe the logarithmic incremental sequence by Levy distribution. Besides, the fitting effect of Levy distribution under the loose policy period is the best. In addition, the volatility shows strong memory and periodic characteristics, and the autocorrelation is the strongest under the loose policy. Finally, the Shanghai Composite Index possesses strong long-term memory under different policies, while the stock market is more complex and the multi-fractals are more salient under the loose policy. This result also confirms that the asymmetry impact of China’s monetary policy on the stock market, which is mainly affected by the asymmetry between the expectations of economic agents and investment behaviors as well as the stickiness of market prices.

Finally, characteristics of the Shanghai Stock Exchange Index is subject to the upward, steady and downward market trends. Like the mature stock market, the return sequence converges to a normal distribution with the increase of the time interval. In the downward trend, the tail converges to the normal distribution faster, and the Levy distribution possesses a better fitting effect. In the analysis of autocorrelation function, we find that the volatility possesses strong memory, and the autocorrelation of volatility possesses obvious periodic characteristics and has the highest correlation in the downward trend.

In the analysis of multi-fractal structures, we document that the Shanghai Composite Index possesses strong and long memory under varied fluctuation trends. However, due to short-term and long-term impacts of investment decisions and liquidity, there are short-term and long-term differences on the fluctuations of yield ratio under three market conditions.

In summary, this study adopts the financial physics approach to investigate influence of trading volume, market trend, and monetary policy on characteristics of the Chinese Stock Exchange. We hope our paper can offer additional insights for research on financial risk management, provide better guidance for investor decisions, and form the basis for policy formulation aiming for a healthy growth of the financial market in China and beyond.

Acknowledgement: This work is supported by the National Natural Science Foundation of China (Grant Nos. 71573042, 71973028).

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