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Analysis of Volatility Long Memory and Investment Strategies of China Stock Market Segmentation Index

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Abstract: This paper investigates the volatility and logarithmic return long memory of four representative Chinese stock indexes by using the R/S analysis method. The findings indicate that when specific price changes are selected for research, the fluctuations of the price limit and the logarithmic return both have significant long memory and multifractal characteristics. There is a correlation between the long memory of the price limit fluctuations limit and the logarithmic return. We find that the characteristics of long memory are significantly different at each stage of market development through the 23-year long memory analysis of the Shanghai and Shenzhen stock markets and the 10-year long memory analysis of the four stock markets in the same period. It indicates that the growth of the stock market has an important impact on long memory. The results show that the reasonable use of logarithmic rate of return for long-memory cycle investment can yield higher investment returns.

Keywords: price limit; long memory; fractal theory; R/S analysis; investment strategy.

Nowadays, the stock market has the ”barometer” function of accumulating disperse small funds and using them for social reproduction, distributing social and economic resources to high-efficiency sectors, adjusting the macro economy, and reflecting the operation of the national economy. With the development of global economic integration, more and more factors affect stock price changes. The stock price fluctuates drastically and the risk of stock market investment is increasing. Many scholars are paying attention to the stock market trend and the predictability of stock prices. Regarding this issue, the academic community has not yet reached a consistent conclusion. Different scholars have different opinions, and some are even completely opposite. For example, two theories that won the 2013 Nobel Prize in Economics at the same time gave completely different answers. Efficient Markets Hypothesis [1, 2] believes that stock prices have the characteristics of random walks and cannot predict their short-term and long-term trends. However, ¡°Behavioral Finance and Financial Physics [3] believes that although short-term stock price changes cannot be accurately predicted, the stock market has long memory and its long-term trend is regular. This research status provides a large space for further research. This article explores the predictability of the stock market by analyzing the long memory of the stock market.

The long memory of the stock price refers to the time period of the stock price but still has a certain correlation. The autocorrelation coefficient of stock price time series is continuous, showing a hyperbolic decay, and lasts a long time. When the autocorrelation coefficient is greater than 0, the stock price maintains the original trend; when the autocorrelation coefficient is less than 0, the stock price trend reverses. Long memory analysis of the stock market can be used to judge the effectiveness and maturity of the stock market. The analysis of long memory parameters is conducive to judging the trend of the stock market. Then it provides practical guidance for investors to reduce investment risks and increase investment returns.

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1 literature review

Avoiding systemic risks in economic phenomena and using the long memory of the stock market to increase investment returns have gradually become a research focus. Mandelbrot [4] was the first to use R/S analysis method to study the stock return changes in the U.S. stock market. Henry [5] believes that the stock price trend is predictable through long memory analysis of stock prices. Yuan [6, 7] found that China stock market price sequence, transaction volume sequence itself and the stock market price-volume relationship have significant long memory and multifractal characteristics. Zhang and Yan [8] found that the sample sequence showed biased characteristics such as spikes and fat-tailed in Shanghai and Shenzhen market, which obviously fails to meet the assumption of normal distribution, indicating that the return sequence may have long-range dependence or long memory. Tan [9] used the constructed model to analyze that SSE Composite Index has long memory and find 8 rising or falling trend switching signals, of which 7 signals were proved to be correct in the actual stock market operation.

Based on the fractal theory, Zhang [10] applied the modified R/S method to empirically carry out long memory empirical research on his return sequence. He found that the long memory of style assets is significantly different, and the holding strategies used by each style asset are also different under different time scales. By examining the long memory of the Shanghai and Shenzhen stock market returns and their volatility from 1996 to 2004, Luo [11] found that there is no long memory in the Shanghai stock market return sequence, but the Shenzhen stock market return sequence has a certain long memory. Therefore, there is no trend or structural change in the China stock market. Zheng [12] analyzed the data of the Shanghai and Shenzhen stock markets from 1991 to 2006 and found that the short-term yield is biased towards random walks, and price behavior is not easy to predict. Zhao [13] analyzed the Shanghai and Shenzhen stock market from 1998 to 2002 and concluded that there is no long-term correlation between the Shanghai and Shenzhen stock markets, and the efficiency of the China stock market cannot be denied. Kristoufek [14] constructed an efficiency Index based on the concept of long-term memory, short-term memory and fractal dimension measures. Ferreira [15] analyzed the efficiency of African stock markets, using the Hurst exponent to evaluate serial dependence and the results showed the existence of statistically significant serial dependence.S¨ɇnchez-Granero [?] proposed a novel approach to study if Latin America Stock Markets are Efficient. Liu [17] showed that the Hong Kong REITs market has not yet reached weak efficiency. Nguyen [18] found that the volatility of stocks with longer memory is more predictable than stocks with shorter memory. Zebende [19] analyzed the effect of removing pieces in time series with long range memory by DFA method and detrended cross-correlation coefficient.Most of the existing research focus on the long memory of stock index and there aren't too many studies of its application. Xu [20]introduced the multifractal R/S analysis method to the field of fund investment for the first time. Liang [21] used the two measures of stock return correlation and liquidity correlation to construct a negative correlation network between Shanghai and Shenzhen stock markets. Zhuang [22] used the threshold method to construct a complex network model of the China stock market and found that the network clustering coefficient time series has long memory and durability.Shahzad [23] examines the multifractal scaling behavior and weak form market efficiency of clean energy stock indices using an asymmetric MF-DFA and find asymmetric multifractality in the US, European, and global clean energy stock indices.

Based on the existing research, this paper mainly uses the R/S analysis method to deeply explore the long memory law of China stock market. And compared with previous studies, the innovations of this paper are as follows. Firstly, due to the relatively short time span of previous research, this research extends the time span of the research. We analyze the relevant data of China's stock market for 23 years from January 1, 1997 to February 28, 2019, including all the data since the implementation of the rule that the increase or decrease did not exceed 10 % of the previous day's closing price. Secondly, since previous studies rarely subdivide the rise and fall, this article intends to subdivide the rise and fall to study whether the stock market has long memory and the strength of long memory when the rise and fall are different. Lastly, previous research focused on theoretical analysis, but lacked practical application analysis. Therefore, on the basis of theoretical analysis, this research explores ways to improve investment efficiency through the analysis of the logarithmic rate of return long memory cycle, and provides guidance for investors to increase returns and reduce investment risks.

2 R/S analysis method

R/S analysis method is a non-parametric analysis method for processing time series proposed by Hurst based on empirical research.

Let e_u be a certain time series, M_n is the mean value of e_u, S is the standard deviation of the time series e_u and $X_(t,n)$ is the cumulative deviation. The formula is as follows:

$$X(_{t,n}) = \sum_{u=1}^{t}(e_u - M_n) \tag{1}$$

$$R = max(X(_{t,n})) - min(X(_{t,n})) \tag{2}$$

Define the R/S increasing over time as the re-standard range. The formula is as follows:

$$R/S = M * n^H \tag{3}$$

where M is a constant, H is defined as Hurst exponent. Hence, the following correlation formula is got:

$$C = 2^{2H-1} - 1 \tag{4}$$

where C is the relevance measure and represents the current impact on the future. When $H = 0.5$, $C = 0$, the events are not correlated, and the sequence is random; when $0 < H < 0.5$, $C < 0$, the sequence is anti-persistent, also called "Mean Reversion" or reverse state persistence; when $0.5 < H < 1$, the sequence has a continuous trend at this time, that is, the time sequence has a downward trend in the previous period, and there is still a downward trend currently. The trend sequence is a biased random walk or fractional Brownian motion, and the degree of bias is related to the specific degree of Hover 0.5.

Then take the logarithm of equation (3) and use the least squares method to get the following:

$$log(R/S)_n = H * log(n) + log(M) \tag{5}$$

To get an estimate of the period length by using the following statistics:

$$V_n = (R/S)_n/\sqrt{n} \tag{6}$$

If the time series is an independent random process, V_n is a horizontal line under the condition of $log(n)$. When $H > 0.5$, the time series has the characteristics of long memory, and V_n slopes upward under the condition of $log(n)$. When $H < 0.5$, the time series has the characteristics of reverse state persistence, and V_n is downward sloping under the condition of $log(n)$. Therefore, based on the above results, the length of the cycle of V_n can be calculated.

Through the introduction of the above R/S analysis method, it can be seen that it is a nonlinear non-parametric analysis method, which belongs to the fractal theory method and is very suitable for studying the distribution of stock market data. Therefore, this paper uses the R/S analysis method and takes the range of stock market price fluctuations as the research object to explore the occurrence of stock market price fluctuations and the long memory of time intervals, which has a certain guiding effect on the prediction of stock market risks.

3 Long memory analysis

3.1 Sample selection and data analysis

Beginning on December 16, 1996, the Shanghai and Shenzhen Stock Exchanges imposed restrictions on the volatility of stock prices on two adjacent opening days, and implemented a rule that the increase or decrease should not exceed 10% of the previous day¡¯s closing price. Therefore, the starting point of the data selected in this article is January 1, 1997, and the deadline is February 28, 2019. China's stock market opened 5367 days. The data comes from https://www.yucezhe.com. This paper makes a detailed classification of price limit on the basis that price limit of the stock market does not exceed 10% of the previous day¡¯s closing price. Using

Table 1: Statistics of changes in China's Shanghai and Shenzhen A shares

Price limit	Total shares	Advancing shares	Falling shares	Proportion of advancing stocks
Unlimited	9370168	4809132	4561036	51.32%
0.01	5797928	2950424	2847504	50.89%
0.02	3521814	1805293	1716521	51.26%
0.03	2154883	1116443	1038440	51.81%
0.04	1359941	711834	648107	52.34%
0.05	877049	465085	411964	53.03%
0.06	591780	315827	275953	53.37%
0.07	434523	234898	199625	54.06%
0.08	336294	186048	150246	55.32%
0.09	271597	156442	115155	57.60%

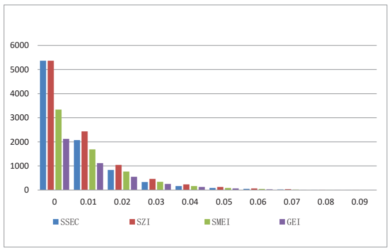

Figure 1: The number of days when different indices reached different levels of price limit

different price limit as the subdivision criteria, analyze the long memory changes of the stock market under the circumstances of refined price limit, and then compare the long memory changes of the stock market that appear at different price limit, and explore the laws of stock market operation. The purpose of adopting this subdivision analysis method is to realize the analysis of vital data, reduce the interference of other data, reduce the difficulty of calculation, and make it easier to capture the essential laws of the stock market.

table 1 is a statistical table of the changes in China¡¯s Shanghai and Shenzhen A shares. The statistics are classified according to the daily closing price of all Shanghai and Shenzhen A shares and the data span the period from January 1, 1997 to February 28, 2019. The stock price fluctuation can be divided into 10 groups, so as to avoid the effect of too dense or too sparse grouping on the nuance of the results. It can be seen that the China stock market has closed daily, and the share of stocks accounted for more than 50%, and the stock market has shown an upward trend in the past 23 years.

The stock price index can reflect the social, political, and economic immediate changes of the country (or region) where the market is located. It can make corresponding changes with the average price of the stock through specific technical arrangements. Therefore, this paper selects representative Shanghai Stock Exchange Composite Index£¨SSEC£©, Shenzhen Stock Exchange Component Index£¨SZI£©, Small and Medium Enterprise Board Index£¨SMEI£©, and Growth Enterprise Index £¨GEI£© as representatives of China stock market to analyze the relationship between them.

The price limit is the most common stock market indicator. Breaking down the price limit is helpful to discover the characteristics of changes in the stock market. The breakdown of the price limit refers to the limitation of the price limit above a certain amount, which includes both data where the stock index rises more than this amount and data that the stock index falls more than this amount. It can be seen from Fig. 1 that as the price limit increases, the number of days the corresponding index occurs is nonlinearly reduced. When the price limit is selected at [0.08,0.1], the corresponding index occurs in fewer days; when the price limit is selected at [0.09,0.1], the stock data is less and not statistically significant. Therefore, this paper will no longer analyze the data restricted above 0.09.

Then the JB statistic test is performed on the four index data to test whether the four index samples come from a normal population.JB test results in Table 2 reveals that it can be seen that when the fluctuation range is [0.08,0.1], $h = 0$, indicating that the four stock indexes obey a normal distribution. P is the probability of accepting the hypothesis, when $h = 1$, $p < 0.05$, $p \to 0$, then reject the null hypothesis of normal distribution.

Table 2: JB test results of SSEC

Price limit	h	p	JBSTAT	CV
Unlimited	1	0.001	5227.7196	5.9817
0.01	1	0.001	30.4074	5.9646
0.02	1	0.001	29.0106	5.9131
0.03	1	0.001	28.7051	5.7912
0.04	1	0.0029	19.8155	5.619
0.05	1	0.0091	13.0995	5.3614
0.06	1	0.0235	7.8219	4.9697
0.07	1	0.048	4.3817	4.2601
0.08	0	0.0805	2.3096	3.1726

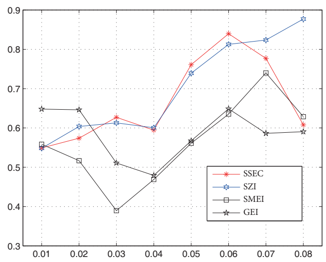

Figure 2: Distribution of Hurst index in four index sub-divisions

With the price limit of the selection, the JB statistics gradually become smaller. It can be seen from the results in Table 2 that various stock indexes are not normally distributed in most cases, and it is not suitable to use linear regression methods for analysis. Therefore, other nonlinear methods must be used for research. It can also be seen from the table that if you do not limit the rise and fall, the value of JBSTAT is very large. If only the selected fluctuations are removed to [0,0.01], the JBSTAT value will be significantly smaller, the amount of calculation will be significantly reduced, and the data will still show a non-normal distribution. Therefore, this article will focus on analyzing the characteristics of sample data with a range of [0.01, 0.08]. The table shows the JB test results of the Shanghai Composite Index. The results of the other three index JB tests are similar, and are not presented in the table due to space reasons.

3.2 Long memory analysis of four stock indexes

In subsection 3.1, the overall sample selection and data processing of China stock market are analyzed and the rise and fall of the feasibility of subdivision analysis is illustrated. In the following part, the long memory of the ups and downs of the four stock indexes and the memory of the logarithmic rate of return will be analyzed. The laws of the two kinds of long memory in the case of the ups and downs are explored. Finally, the relationship between the two types of long memory is analyzed.

3.2.1 Four kinds of stock index rise and fall their own long-term memory analysis

Price fluctuation is the most obvious characteristic of stock market change, and the fluctuation is the index reflecting the degree of price fluctuation. Therefore, it is very important to carry out long-term memory analysis on the fluctuation itself. Hence, this paper will analyze the rise and fall of the four indexes from three aspects: the long memory cycle, the long memory cycle determined by Hurst index, and the correlation between the Hurst index of the four indexes in the case of segmented rise and fall.

As can be seen from Fig. 2, SSEC and SZI all show long memory in the case of sub-divided rise and fall. The rise and fall of the selected index are the smallest in [0.04,0.1], but it still shows the characteristics of long memory. SMEI and GEI show long memory in most cases, but the characteristics of long memory disappears when the fluctuation is in [0.04,0.1]. From the whole perspective, the four indexes show long memory in most

Table 3: The long-term memory cycle distribution of the four indexes in the case of sub-division

Price limit	SSEC	SZI	SMEI	GEI
0.01	53	55	47	27
0.02	98	83	30	74
0.03	223	223	5	74
0.04	83	535	83	93
0.05	761	761	731	535
0.06	120	761	658	658
0.07	1772	1867	107	1373
0.08	1784	4518	2158	514

Table 4: Statistical table of correlation coefficients of four indexes¡¯ own Hurst index in the case of sub-divided price limit

Price limit	SSEC	SZI	SMEI	GEI
SSEC	1	0.6636	0.5611	0.1358
SZI		1	0.7479	0.1622
SMEI			1	0.5131
GEI				1

cases, with the increase and decrease in the range of [0.03,0.1], [0.04,0.1] and [0.05,0.1] the characteristics of long memory is lower or even disappeared.

As can be seen from Table 3, when the selected rise or fall is between [0.01,0.1] and [0.02,0.1], the cycle length of the four indexes is between 27 and 98 days. With the increase of price limit, the cycle length has an nonlinear increasing trend. For example, when the price limit is [0.04,0.1], the cycle length of the SSEC decreases with respect to the price limit in [0.03,0.1]. Similarly, when the price limit of the selected index of SMEI is [0.02,0.1], the cycle length is also smaller compared with that of the selected Index when the price limit is [0.02,0.1]. When the price limit is [0.07,0.1] and [0.08,0.1], the cycle length of the four indexes is between 514 and 4518 days, and the price limit has a smaller long memory and tends to be random.

It can be noticed from Table 4, the correlation coefficients of the four indexes are all positively correlated, but the degree of correlation varies greatly. The correlation coefficient between SSEC and SZI is 0.6636, showing a great correlation. The correlation coefficient between SZI and SMEI is 0.7479, which showing a greater correlation. GEI has a small correlation with the CSI index, however, it has a large correlation with the Sme Board Index, which is supported by the fact that GEI has been established for a short time and is still growing.

3.2.2 Long memory analysis of four exponential logarithmic returns

In the following part, the price limit of the four indexes from three aspects will be analyzed: the long memory cycle determined by Hurst index, the cycle of long memory and the correlation between Hurst index of the four indexes under the condition of sub-dividing the price limit.

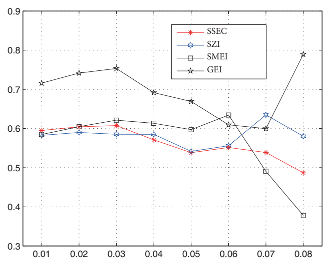

Figure 3: Distribution of Hurst index logarithmic returns of the four indices under the condition of sub-dividing

Table 5: The long memory cycle distribution of four exponential logarithmic returns under the condition of sub-division price limit

Price limit	SSEC	SZI	SMEI	GEI
0.01	65	67	56	56
0.02	143	129	62	87
0.03	727	626	208	74
0.04	759	658	223	166
0.05	759	759	759	535
0.06	140	671	746	658
0.07	237	1802	33	33
0.08	1784	1772	1874	131

Table 6: Statistical tables of correlation coefficients of four kinds of exponential logarithmic return under the condition of sub-dividing price limit of Hurst index

Price limit	SSEC	SZI	SMEI	GEI
SSEC	1	0.0838	0.7762	0.0982
SZI		1	-0.3609	-0.1064
SMEI			1	-0.2889
GEI				1

As shown in Fig. 9, when the price limit of the four indexes are [0.01,0.1], the Hurst index of all four indexes are all above 0.5, so all of them have long memory. The long memory characteristic last until the price limit of the four indexes are [0.06,0.1]. SZI and GEI as a whole show strong long memory. However, when the price limit is above 0.08, SSEC loses its long memory. When the price limit of the index is [0.07,0.1], the index of SMEI loses its long memory, which indicates that SMEI has great uncertainty and the risk increases.

As can be seen from Table 5, when the price limit of the selected index is [0.01,0.1], the cycle length of the four indexes are between 56 and 67 days. With the increase of the price limit, the cycle length shows a nonlinear increase trend. For example, when the price limit of SSEC changes from [0.05,0.1] to [0.06,0.1], the cycle length decreases. Similarly, when the price limit of the selected index of SMEI ranges from [0.06,0.1] to [0.07,0.1], the length of the cycle becomes smaller when the price limit is [0.05,0.1], especially when the price limit is [0.07,0.1], the length of the cycle is only 33 days. When the price limit of the index is [0.08,0.1], the length of the cycle is mostly between 1700 and 1900 days. However, when the price limit of GEI is [0.07,0.1], the length of the cycle relative to the price limit of the index is also smaller, especially when the price limit is [0.07,0.1], the length of the cycle is only 33 days, moreover, when the price limit is [0.08,0.1], the length of the cycle is 131 days. The reason for the above situation is that the Shenzhen Stock Exchange officially compiled and released GEI on June 1, 2010, so the law reflected in the long memory is not consistent with the first three indexes.

As can be seen from Table 6, SSEC is positively correlated with other indexes, among which the correlation coefficient with SMEI reaches 0.7762, which has a strong correlation, but the correlation coefficient with GEI and SZI is small. SZI is negatively correlated with GEI and SMEI, while SMEI is negatively correlated with GEI (expressed in another form or deleted: the correlation regularity of the four indexes is relatively small).

In terms of logarithmic rate of return (Large scale liquidity is good in front of the echo, considering the introduction of the four indicators indicated), on the one hand, in the large scale, good liquidity of the stock market and the majority of the stock market, including SMEI and GEI in the yield change difference. On the other hand, the proportion of large and liquid stocks in the stock market is still small, which is also a direction for the healthy development of China¡¯s stock market.

3.2.3 Correlation analysis between the two types of long memory

Table 7 shows the calculation results of correlation coefficient of Hurst indexes in Fig.2 and Fig.3. The correlation coefficient of SSEC changes from positive correlation to negative correlation. SZI changed from positive correlation to negative correlation when the correlation coefficients is 0.01-0.06, and be positive correlation when

Table 7: Correlation analysis table of two kinds of long memory Hurst index

Correlation coefficients	SSEC	SZI	SMEI	GEI
0.01∼0.03	0.8877	0.6833	-0.9431	-0.7477
0.01∼0.04	0.1226	0.6344	-0.9301	0.2614
0.01∼0.05	-0.7961	-0.895	-0.9169	0.1948
0.01∼0.06	-0.8005	-0.8433	-0.0429	-0.2376
0.01∼0.07	-0.834	0.0319	-0.6954	-0.1987
0.01∼0.08	-0.3949	0.012	-0.5525	-0.1443

Table 8: Statistical table of correlation analysis of two kinds of long memory cycles in the case of sub-division Correlation coefficients

Correlation coefficients	SSEC	SZI	SMEI	GEI
0.01∼0.03	0.2975	0.7707	-0.8398	-1
0.01∼0.04	0.3198	0.8192	-0.5048	-0.2294
0.01∼0.05	0.2749	0.8392	-0.5465	-0.0036
0.01∼0.06	0.2216	0.8403	-0.5339	0.0396
0.01∼0.07	-0.0117	0.4346	-0.0822	0.1221
0.01∼0.08	0.0121	0.3572	-0.2992	0.1458

the correlation coefficients is 0.01-0.07 and 0.01-0.08, though the positive correlation coefficient was very small and the correlation was very weak. SMEI is all negatively correlated. GEI performance is negative correlation in most cases.

Table 8 is the calculation result of the correlation coefficient between the two cycle values in Table 5 and Table 5. It can be seen that the cycles of the price limit in SSEC are mostly positively correlated with the cycles of logarithmic return rate. The correlation between the cycles of SZI¡¯s price limit and the cycles of the logarithmic return rate is larger, and the correlation is positive; the index of SMEI is all negative correlated; GEI from negative correlation gradually change into positive correlation, and the correlation coefficient also gradually increased.

4 Empirical Analysis

The previous part analyzes the price limit of the China stock market itself, the long-term memory of logarithmic return and the relationship between them. The following part applies the analysis results of the previous part to the China stock market, conducts actual investment research, and further tests the practical guidance of the research results to the China stock market. The stock market risk exists and accumulates constantly. When the stock price rises continuously, the risk also increases continuously. The stock price reaches the peak of the stage when the risk also reaches the maximum. Similarly, when the stock price falls continuously, the risk is released gradually. The stock price reaches the valley value of the stage when the risk is also minimized. The optimal investment strategy is to buy the stock when it falls to the lowest point and sell it when it rises to the highest point, only in this way the maximum return can be obtained. However, it is only a kind of ideal condition, because how to determine extreme value point is very difficult. The data of Shanghai and Shenzhen A-share stocks during the 23-year period from January 1, 1997 to February 28, 2019 were calculated in stages, and the results of each long memory cycle were used to predict the occurrence time of the extreme point in the next stage, and dynamic adjustments were made, so as to predict the volatility of China's stock market.

Next, the sliding time window technique is adopted to determine the starting point and extreme value point of the actual long memory cycle in the stock market operation, as shown in Fig. ??. For example, in the Shanghai composite index logarithm yield for extreme value point, the cycle length of long memory analysis serves as scale in table 4 and table 6, from one trading day began to get the entire cycle of the daily closing price values, cycle length to width, the corresponding period of the index values of the high value of a rectangular window, this window there is a low and high. By the same analogy, a series of lowest points and highest points can be obtained through continuous sliding, and the highest points or lowest points that appear more frequently

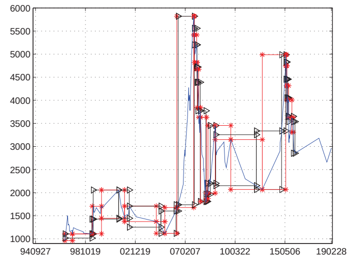

Figure 4: Schematic diagram of the Shanghai Composite index logarithmic return cycle vertex acquisition

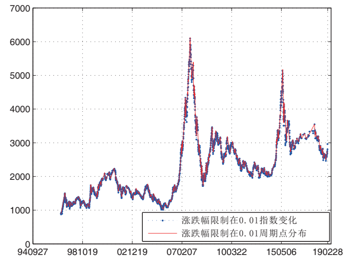

Figure 5: Chart of trend and cycle inflection point when SSEC rises or falls at [0.01,0.1]

in each window in the period can be obtained through comparison, that is, the extremum point of the period. After determining the period point, the current complete stock market cycle can be gotten. This period point is also an inflection point, which is both the end point of the current cycle and the starting point of the next cycle. The extreme value point of the next cycle cannot be accurately predicted, but it may be estimated through the last cycle.

The following is still SSEC as an example for detailed analysis.When the price limit is [0.01,0.1], as shown in Fig. 5, there are 262 periodic inflection points between the fluctuation and decline trend of SSEC from the trading day of January 6, 1997 to the fluctuation and rise trend of the trading day of February 18, 2019. When the price limit is [0.04,0.1], as shown in Fig. 6, SSEC has 14 periodic inflection points from the fluctuating downward trend starting on the trading day of February 19, 1997 to the fluctuating upward trend on the trading day of February 9, 2018. As can be seen from Fig. 5 and Fig. 6, when the price limit is at [0.04,0.1], the overall trend of the stock market is not hidden, but the data volume is greatly reduced, which brings great convenience to long-term capital investment in the stock market. It is also observed in Fig. 6 that the periodic point is less than the maximum point, which belongs to noise and has little impact on the overall stock market.

The unit length of grid line on the horizontal axis in fig. 7 is the cycle length when SSEC breaks the upper or lower bound of [0.04,0.1]. The width of the window in the figure is fixed from the height of the unit length

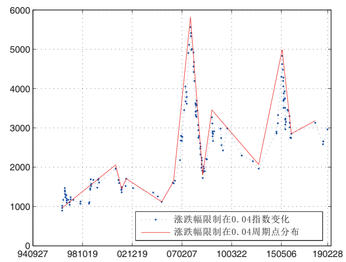

Figure 6: Change trend and cycle inflection point chart of SSEC when rise or fall in [0.04,0.1]

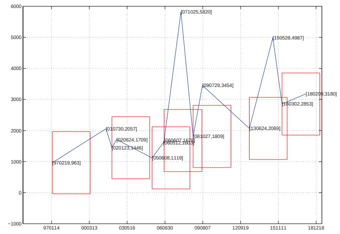

Figure 7: Schematic diagram of comparison between inflection point window and cycle length when SSEC price limit at [0.04,0.1]

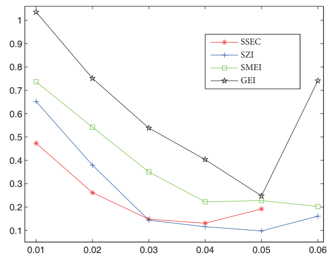

Figure 8: Simulated investment annual return chart of Shanghai and Shenzhen stock index from 1997 to 2019

box of grid line marked from the valley point. It can be seen that in most cases, the actual cycle of the stock market always changes near the theoretical cycle length, so it is not difficult to understand that in most cases, the cycle length can be used to simply predict the upcoming trend, but it cannot be accurate to the specific trading day. It can be seen that it is feasible to use the long-term memory cycle of the stock market to guide investment. In the next part, the maximum return of this method will be simulated and calculated.

According to the cycle inflection point calculated above, the simulated investment of RMB 1 million is an ideal state by buying at the lowest value of the cycle and selling at the highest value of the cycle. Considering the frequency difference of transactions, the transaction taxes and fees of the Shanghai and Shenzhen stock markets are taken into account, and the deduction of taxes and fees is calculated according to the current rules. As can be seen from fig. 8, by comparing the investment returns of Shanghai and Shenzhen, the leading stock markets in China over the past 23 years, it can be found that the returns of purchasing SZI are generally higher than those of purchasing Shanghai Composite Index. When the limit rise and fall gradually increases, the yield difference between the two markets becomes smaller.

Fig. 9 shows the 10-year simulated investment annualized return chart from 2010 to the end of February 2019 for the four indexes after the gem market opened. It can be seen that in the comparison of the simultaneous periods, the return of GEI is greater than that of SMEI, and the return rate of the Shanghai and Shenzhen

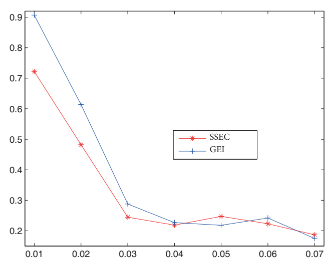

Figure 9: Distribution of Hurst index logarithmic returns of the four indices under the condition of sub-dividing

stock indexes is the lowest. From the perspective of the characteristics of each index, compared with Small and Medium Enterprise Board and the Shanghai and Shenzhen Index of GEI, the stocks contained in the index are comprehensive, with wide investment choices. SMEI and GEI with high returns are listed late, develop rapidly, and the range of stock price changes is larger, so the opportunities for investment income are also greater. In July 2020, the ceiling on stock price bidding on the GEM was adjusted to 20 percent. Things like speculating on concepts will be more risky in the future.

5 Conclusion and Outlook

In this paper,R/S analysis method is used to deeply discuss the law of long memory in China stock market and its investment application. The long memory of the price limit of the four most representative indexes in China stock market and the logarithmic rate of return are calculated, and then the long memory cycle length is used for the empirical analysis of investment returns. The following conclusions: 1)According to the calculation of Hurst index, it is found that the four indexes show long-term memory in most cases. When the rise and fall are above 0.03 and above 0.05, the long-term memory is low and even disappears. Through the calculation of logarithmic return Hurst index, it is found that SZI and GEI show strong long memory on the whole. When the fluctuation limit is above 0.07, SMEI loses its long memory, indicating that SMEI has great uncertainty and the risk increases. However, when the fluctuation limit is above 0.08, SSEC will lose its long memory, which is at greater risk, but this kind of situation occurs less frequently. 2)By comparing the price limit of GEI with the other three indexes, it can be seen that the characteristics of long memory are obviously different at different stages of market development, and the growth of the stock market has an important impact on the long memory. The long memory of yield is obvious when the limit is not high, but not when the limit is high. The long memory of fluctuation itself is not obvious when the fluctuation limit is not high, but it is obvious when the limit is high. 3)Through empirical analysis, we find that under the same investment period and the same cost, the return of investing in Shenzhen stock market is generally higher than that of investing in Shanghai stock market. When the limit rise and fall gradually increased, the income difference between the two markets became smaller, and the overall return from investing in Growth Enterprise stock market was higher than that from investing in the Shanghai and Shenzhen stock markets in the same period. 4)The fundamental reason for the existence of long memory in the stock market is that the China stock market is still in the development stage, with complicated investment structure, too much market noise, too much information feedback, and insufficient securities trading regulations and financial supervision, etc., which lead to the biased random walk of stock prices. The healthy development of the stock market is an important manifestation of the steady development of the economy. Therefore, we should attach importance to the development of the stock market, and promote the healthy development of the stock market by strengthening the cooperation in all aspects, improving the level of legislation, enhancing the governance ability of managers, and enhancing the risk prevention awareness of investors. Although this paper has carried out some exploration and innovation, there are inevitably limitations. In the future, the long memory on the stock market is needed for further theoretical analysis and empirical study, expand the long memory calculation method and the influence factors of the analysis of the principle of long memory exist, to discuss the possibility of the existence of long memory other factors, to strengthen the research of the stock market trends, the risk probability of subdivided market changes, so as to reduce the risk of investing in the stock market to provide more information and guidance.

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