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Application of Momentum Strategy in the Chinese Market

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Abstract: In recent years, momentum trading has been a very mainstream trading strategy. The Chinese market is an emerging market and there are a large number of retail investors. Thus it is characterized by irrational behavior and non-efficient markets. These characteristics are favorable for applying the momentum strategy, which has not been widely used in the Chinese market. In this paper, three tests to examine the non-effectiveness and trend correlation of the market are conducted and a momentum strategy - determining the timing of trades by judging the market trend based on those tests is proposed. The empirical experiments shows that when time interval is small, the strategy achieves good performance on two representative indices of Chinese market, the CSI 300 Index and the CSI 500 Index. It also indicates that in certain cases there are indeed a certain of market inefficiency in China and that momentum is a proper trading strategy to get profit.

1. Introduction

Richard Driehaus took the practice and made it into the strategy he used to run his funds. His philosophy was that more money could be made by "buying high and selling higher" than by buying underpriced stocks and waiting for the market to re-evaluate them.

Driehaus believed in selling the losers and letting the winners ride while reinvesting the money from the losers in other stocks that were beginning to boil. Many of the techniques he used became the basics of what is now called momentum investing.

In 1997, Carhart argued that the study of stock returns should introduce momentum effects into the study by constructing a four-factor model based on Fama and French's three-factor model. This brought momentum officially into the limelight.

Three tests are conducted to investigate the non-effectiveness and trend correlation of the Chinese market to inform the design of quantitative strategies. We then went on to design the quantitative strategy - making 0.85 and 0.15 separate, applying the 0.85 parameter to 0.15 to see the actual returns and comparing them to the benchmark. Finally, we found that our strategy achieved good results.

Although this strategy is popular in places like the UK in the US, there are many scholars studying it. However, the unshortable nature of the Chinese market and T+0 has limited many from doing research about it. Therefore, we would like to study this strategy. It can provide a reference for those

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who are interested in this area to make money by taking advantage of the non-effectiveness and the majority of retail investors in Chinese stocks.

2. Literature Review

How to choose the appropriate strategy in the stock market to maximize the benefits has always been the focus of research.

Alexei Chekhlov argued that stock returns are uncertain, so the choice of a portfolio from assets with uncertain returns amounts to the choice of a particular return distribution [1]. At the same time, a more customized version of portfolio optimization is the aim [2], rather than the idea that a single ' master fund ' may arise from market equilibrium and serve the interests of all investors [3].During this period, many scholars carried out theoretical research on book writing. Grossman S J on Portfolio optimization with drawdown constraints [4]. Both in Asset and Liability Management Tools and Portfolio selection by H. M. Markowitz analyze the optimal risky investment policy for an investor who, at each point in time, wants to lose no more than a fixed percentage of the maximum value of his wealth has achieved up to that time [5]. Pflug G C 's Some remarks on the value-at-risk and the conditional value-at-risk and R.T. Rockafellar Optimization of conditional value-at-risk both summarize the value at risk of the investment market [6][7].

Many scholars will conduct empirical research on Konno H Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market.R. C. Grinold 's Active Portfolio Management and Kemel E point out that propose a new one-parameter family of risk measures, both to solve a real life portfolio allocation problem using the proposed measures [8] [9] [10].

To sum up, the stock investment market research has been more comprehensive, to study the trend of the stock market trading strategy has a rich theoretical basis.

3. Empirical Research

3.1. Data

The foundation of momentum trading derived from the volatility of price of asset, which is like a spring of water in a barren land of traders. The price of asset fluctuates from time to time and results in peak and bottom, from which traders can make benefit by purchasing at the early stages of upstream and leave before the extreme has come. For these reasons, in most of empirical strategies, underlying asset with high liquidity is selected because of its cyclical fluctuation. When the strategies in this article searching for appropriate market in China, the two most widely used indexes that reflect the overall performance of Chinese security market CSI 300 and CSI 500 is used as the research subjects.

The two index is of the properties following. Firstly, high liquidity and thus constant fluctuations occurs since its funded date since they are compromise of the weighted average of the 300/500 stocks with largest market value in Chinese stock exchanges hence continuous trading from time to time. Then representativeness for the performance of Chinese financial market provides a more extensive signals for the usage of momentum strategy in Chinese market. It produces a great proof for whether the strategy is empirical in further specific assets.

3.2. Descriptive Statistics

Both CSI 300 and CSI 500 are minute-level data containing opening and closing prices. For the construction and backtesting of the quantitative strategies, the data of CSI 300 and CSI 500 are divided in the ratio of 0.85/0.15 and used as the training set and the test set, respectively. The training set is used to determine the parameters of the quantitative strategy, and the test set is used for backtesting to measure the returns of the actual application of the quantitative strategy in the market.

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Table 1: Descriptive statistics.

	CSI 300			CSI 500		
	Total	**Training set**	**Test set**	**Total**	**Training set**	**Test set**
Sample Size	1008960	857616	151344	906000	770101	135899
Maximum	5929.01	5890.2	5929.01	11615.76	11615.76	7686.36
Minimum	807.86	807.86	3503.58	1488.9	1488.9	4975.38
Standard Deviation	1105.50	985.42	493.22	1473.56	1431.46	543.92

According to the result, both CSI 300 and CSI 500 have large fluctuations in the longitudinal time series, and the maximum and minimum values differ significantly. In the cross-sectional comparison, CSI 500 is more volatile than CSI 300.

3.3. Hypothesis Test

The modern efficient market hypothesis assumes the randomness and unpredictability of the prices of market. The price of stock is a full representativeness of relevant information to the prices which is absolutely unknown when concerning the future. Yet the momentum strategy scratches the potential force that drive up the price in the next few periods from the previous pattern. Therefore, if the market is non-effective and has trend correlation, it is possible to dig for opportunities from market volatility and gain extra profit, which is what the following tests count for.

3.3.1. Counting Test

From now on, two fundamental types of data properties will be induced. One is trend-following (type c), which constitutes subsequent movement towards the same direction, the other is mean-reversal (type r), one that triggers backward movement afterwards. Suppose that the prices of underlying asset follow a discrete-time stochastic process:

$$P(t): t \in T, \quad where\ T \in N$$

A specific price unit $P(i), i \in N$ is a trend-following data if and only if:

$$[p(i+1) - p(i) / p(i)] \times [p(i+2) - p(i+1) / p(i+1)] \geq 0$$

Which suggest the two following units are whether move upward or downward consistently. The term ‘trend following’ simply means that there is a trend followed. By contrast, a specific price unit $P(i^*), i^* \in N$ is a mean-reversal data if and only if:

$$[p(i+1) - p(i) / p(i)] \times [p(i+2) - p(i+1) / p(i+1)] \leq 0$$

noting the difference direction of movement for the two followed price units. Once price increase in one interval, the next will return to a corresponding mean within a range of intervals.

If the market is efficient, the number of Type C should be relatively close to the number of Type R. If the number of Type C is significantly more than the number of Type R, the market is non-efficient and has trend-following characteristics, and if the number of Type C is significantly less than the number of Type R, the market is non-efficient and has mean-reverting characteristics.

In this paper, different time intervals of both high, medium and low frequency are selected to study the trend of return movements of CSI 300 and CSI 500, and the results are as follows

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Table 2: Counting test for CSI 300/CSI 500.

	CSI 300 Index		CSI 500 Index	
interval	Type c	Type r	Type c	Type r
Tau=1	682798	314514	651769	247013
Tau=2	639130	363871	582189	320747
Tau=3	586786	418001	522958	380574
Tau=4	550468	454975	487989	415882
Tau=5	528485	477384	470183	433935
Tau=10	502702	489257	463208	441022
Tau=15	503014	504245	456676	448081
Tau=30	509691	497950	473754	431159
Tau=45	507333	500401	475673	429307
Tau=60	510231	497666	481294	423749

For the CSI 300 and CSI 500 indices, as the time interval gradually increases, both have the characteristics that the number of Type C gradually decreases, while the number of Type R gradually increases and the gap narrows. When the time interval is 1-5 minutes, the number of Type C is significantly larger than the number of Type R. When the time interval is larger, the number of Type C and the number of Type R of CSI 300 index are already very close to each other. They still have some gap for CSI 500, but in general, it is smaller than when the time interval is small. Therefore, further analysis is necessary to find the market non-effective interval and design practical quantitative strategies based on it.

3.3.2. Ratio Test

The previous result from counting two types of data provides a base for further insight. When going through the selected data, two types of variables can be calculated, which are theoretical ratio of data type and the actual ratio of data type. The latter one is simply examining each price unit one by one and the ratio is computed by:

$$Ratio\ c = Number\ of\ type\ c\ /\ Number\ of\ total\ data$$

$$Ratio\ r = Number\ of\ type\ r\ /\ Number\ of\ total\ data$$

While the actual one suggest the valid proportion of two types of data in whole data set, the theoretical ratio is computed from probability of two type of data, delivering a proportion in theory-----How much times should each type occurs ? Suppose that for a discrete-time stochastic process $P(t)$,

Probability of increases is:

$$p\ =\ P[return\ \geq 0]\ =\ \sum_{i}^{T} P(i)\{[P(i+1)-P(i)\ /\ P(i)] \geq 0\}\Big/T$$

Probability of decreases is:

$$q\ =\ P[return\ \leq 0]\ =\ \sum_{i}^{T} P(i)\{[P(i+1)-P(i)\ /\ P(i)] \leq 0\}\Big/T$$

By the definition of type c and type r, the theoretical ratio is computed by:

$$Ratio\ c = P[return\ i\ \geq 0\ and\ return\ i+1 \geq 0] + P[return\ i\ \leq 0\ and\ return\ i+1 \leq 0]$$
$$= p^2 + q^2$$

$$Ratio\ r = P[return\ i\ \geq 0\ and\ return\ i+1 \leq 0] + P[return\ i\ \leq 0\ and\ return\ i+1 \geq 0]$$
$$= 2pq$$

Given the two types of variables, the ratio test statistics then computed by:

$$Actual\ type\ /\ theoretical\ type$$

If the statistic is larger than one, that means the actual data is more like to be the specific type comparing to theoretical inference, which further suggests that there is non-effectiveness for given market, and there is opportunity for profit digging.

Furthermore, by selecting data of different time interval τ (says, $\tau = 10$ means that we select data for each 10 minutes) and plotted them graphically, it's more perceptual to see which time interval generates more space for speculating. Figure 1 shows the pattern for CSI300 and CSI500 index at intervals from 1 to 60.

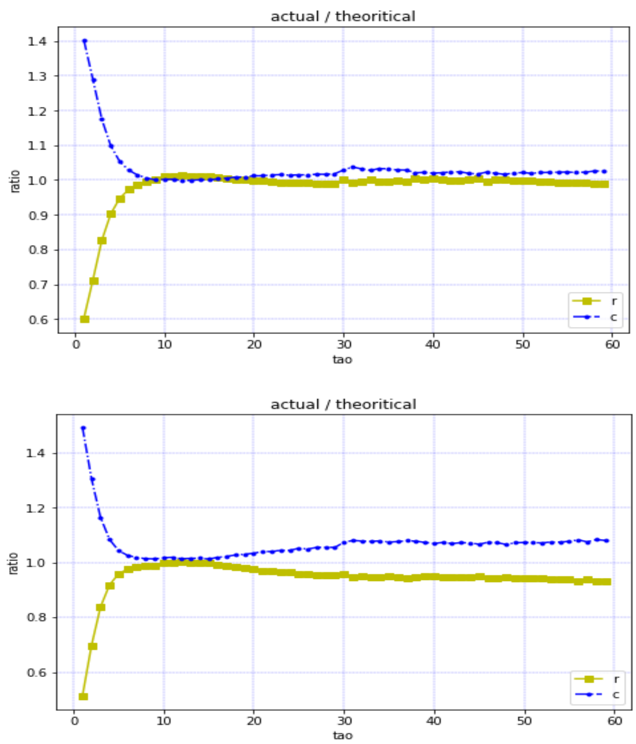

Figure 1: Ratio test.

Both of the index data shows a pattern that the ratio of Actual type over theoretical type is highest at the beginning to the level of 1.4, which means that the occurrence of type c in actual is around 40% more likely than that in theory. As the interval become greater, the ratio begins diminishing to 1 at period 10 and shows little variations as the interval become further greater. The brief inference is that at small intervals, the data is more likely to have a trend effect that todays' increase of decrease in

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price follows increase or decrease in tomorrow's price. Yet in a greater interval, this pattern shows little. The outcome of the ratio test provides a preview of market inefficiency and possible pattern. Still, a more precise and academic test should be conducted to confirm the statement.

3.3.3. Variance Ratio Test

When it comes to efficient market and security prices, one empirical test for market efficiency is variance ratio test. If the security price obeys random walking, the market is generally considered to be weak form efficient. Andrew W. Lo and A. Craig MacKinlay proposed the variance ratio test in 1988 to test for random walking [11]. The advantage of the variance ratio test is that it can test the case under the assumptions of both independent identical and non-independent identical distribution of the disturbance terms, and the Monte Carlo simulation by Lo and MacKinlay in 1989 showed that the variance ratio test is more effective than the traditional Dickey-Fuller test [12].

Let P_t denote the security price at moment t. Define $X_t = lnP_t$ to denote the logarithmic price process, and assume that the security price obeys random wandering, then we have

$$X_t = \mu + X_{t-1} + \varepsilon_t$$

$$\mathrm{VR(q)} = \frac{VAR(X_t - X_{t-q})}{qVAR(X_t - X_{t-1})}$$

If ε_t is the independent identical distribution, q is the sampling interval, and nq+1 is the total number of samples, the variance ratio formula is constructed as

$$\overline{M_r(q)} = \overline{\sigma_c^2}/\overline{\sigma_a^2} - 1$$

Of which

$$\hat{\mu} = \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1}) = \frac{1}{nq}(X_{nq} - X_0)$$

$$\overline{\sigma_a^2} = \frac{1}{nq-1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2$$

$$\overline{\sigma_c^2} = \frac{1}{m}\sum_{k=q}^{nq}(X_k - X_{k-q} - q\hat{\mu})^2$$

$$\mathrm{m} \equiv \mathrm{q(nq - q + 1)}(1 - \frac{q}{nq})$$

At this point the statistic

$$\sqrt{nq}\overline{M_r(q)} \sim N\left(0, \frac{2(2q-1)(q-1)}{3q}\right)$$

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Constructing statistic

$$\mathrm{Z(q)} = \frac{\sqrt{nq}\overline{M_r(q)}}{\sqrt{\frac{2(2q-1)(q-1)}{3q}}} \sim \mathrm{N}(0,1)$$

If ε_t is not independently and identically distributed, the statistic is adjusted to

$$\mathrm{Z}^*(q) = \frac{\sqrt{nq}\overline{M_r(q)}}{\sqrt{\hat{\theta}}}$$

Of which

$$\hat{\theta} = \sum_{j=1}^{q-1} \left(\frac{2(q-j)}{q}\right)^2 \widehat{\delta(j)}$$

$$\widehat{\delta(j)} = \frac{\sum_{k=j+1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2 (X_{k-j} - X_{k-j-1} - \hat{\mu})^2}{\left[\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2\right]^2}$$

The results of the variance ratio test for CSI 300 and CSI 500 under the two hypotheses of independent identical distribution and non-independent identical distribution by taking time intervals of 2, 4, 6, 8 and 10, respectively, are as follows.

Table 3: Variance ratio test for CSI 300/CSI 500.

CSI 300 index (CSI 500 index)				
Interval	I.I.D	Z Statistics	Random Walk	VR(q)
2	Yes	344.18*** (394.50)***	No (No)	1.342 (1.4145)
4	Yes	348.31*** (392.80)***	No (No)	1.648 (1.772)
6	Yes	278.47*** (299.41)***	No (No)	1.685 (1.7776)
8	Yes	221.17*** (231.03)***	No (No)	1.651 (1.718)
10	Yes	186.31*** (195.38)***	No (No)	1.626 (1.6931)

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Table 3: (continued).

2	No	104.69*** (102.10)***	No (No)	1.342 (1.4145)
4	No	109.09*** (108.80)***	No (No)	1.648 (1.772)
6	No	91.69*** (87.81)***	No (No)	1.685 (1.7776)
8	No	76.26*** (71.17)***	No (No)	1.651 (1.718)
10	No	66.83*** (62.81)***	No (No)	1.626 (1.6931)

***: significant at 99% level

According to the results, under the assumptions of independent identical and non-independent identical distributions, the original hypothesis that the stock price return series obeys random wandering is rejected for all intervals of the CSI 300 and CSI 500 indices, which indicate that they are non-effective and trend-relevant for time intervals from 1 minute to 10 minutes. Moreover, the result shows that all VR(q) are greater than 1. Therefore, the trend correlation of the Chinese market is trend-following rather than mean-reverting.

3.4. Adaptive Strategies and Results

Through the above test, when time interval τ is 1-10 minutes, the Chinese market has trend-following trend, we design quantitative strategy based on this feature and backtest.

If the opening price of the current period is greater than or equal to the maximum value of the closing price of the past L periods multiplied by $(1-\alpha)$, the security has entered the upward phase based on the trend-following characteristics of the Chinese market, i.e., the security has risen and will continue to rise for some time in the future, so the security is long. Similarly, if the opening price of the current period is less than or equal to the minimum of the closing price of the past L periods multiplied by $(1+\alpha)$, then the security has entered a downward phase and the security is short.

When the position in hand is positive, record the long price and the highest value of the closing price of each time node so far, if the current closing price is less than or equal to the highest value multiplied by $(1-\beta)$ which indicates that the trend has reversed and the securities have entered the downward phase, the position will be closed at the opening of the next time node.

When the position in hand is negative, record the shorting price and the lowest value in the closing price of each time node so far, if the current closing price has been greater than or equal to the lowest value multiplied by $(1+\beta)$ which indicates that the trend reverses and the securities have entered the upward phase, the position will be closed at the opening of the next time node.

In particular, the strategy requires that $\beta > \alpha$ and that β is at a certain distance from α. This avoids the loss of going long again when the security is still in the down phase after the trend reverses and the holding is sold, and also avoids the loss of going short again when the security is still in the up phase after the trend reverses and the shorted security is bought.

In the actual design of the quantitative strategy, the commission per trade is set to 0.0002 and the share is set to 100. The parameters are determined by optimization in the training set. For different τ, the parameters L, α, β are searched to find the one that maximizes the average value of the total return obtained by applying the quantitative strategy at the beginning of each minute of a time interval as parameters. The search range of L is from 5 to 40 in steps of 5, the search range of α is from 0.01

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to 0.1 in steps of 0.01, and the search range of β is from α+0.1 to 0.3 in steps of 0.01. Afterwards, backtesting is performed in the test set using the identified parameters, and the indicators and total returns are recorded and compared with the benchmark. The benchmark is a simple strategy that buys at the beginning of the test set and sells at the end. The results are stated as Table 6, Table 7, Figure 2 and Figure 3.

Table 4: Results of applying quantitative strategies on CSI 300.

Tau	1	2	3	4	5	6	7	8	9	10	Benchmark
L	20	30	20	5	5	5	5	5	5	5	
α	0.001	0.001	0.002	0.001	0.003	0.002	0.002	0.003	0.003	0.003	
β	0.011	0.027	0.027	0.015	0.018	0.014	0.012	0.013	0.015	0.013	
Trade times	507	105	102	281	212	299	357	321	242	292	1
Win times	194	43	45	99	72	110	139	119	95	111	1
Loss number	313	62	57	182	140	189	218	202	147	181	0
Max profit rate	0.1378	0.1933	0.1966	0.1755	0.1581	0.1736	0.1534	0.1855	0.1821	0.1827	0.0704
Max loss rate	-0.0280	-0.0354	-0.0317	-0.0275	-0.0282	-0.0282	-0.0276	-0.0276	-0.0278	-0.0300	0
Average profit rate	0.0144	0.0293	0.0286	0.0207	0.0231	0.0193	0.0166	0.0186	0.0212	0.0188	0.0704
Average loss rate	-0.0078	-0.0163	-0.0169	-0.0110	-0.0129	-0.0104	-0.0093	-0.0100	-0.0115	-0.0105	0
Average return	0.0007	0.0024	0.0032	0.0002	-0.0007	0.0005	0.0007	0.0006	0.0013	0.0006	0.0704
Standard variance	0.0153	0.0324	0.0331	0.0210	0.0232	0.0197	0.0175	0.0197	0.0228	0.0202	
Sharp ratio	0.0434	0.0746	0.0957	0.0077	-0.0303	0.0259	0.0426	0.0310	0.0582	0.0307	
Total profit	159663.4	103432.2	138847.4	23246.33	-81648.92	71119.22	120493.5	81537.09	136999.4	87761.86	27863.41

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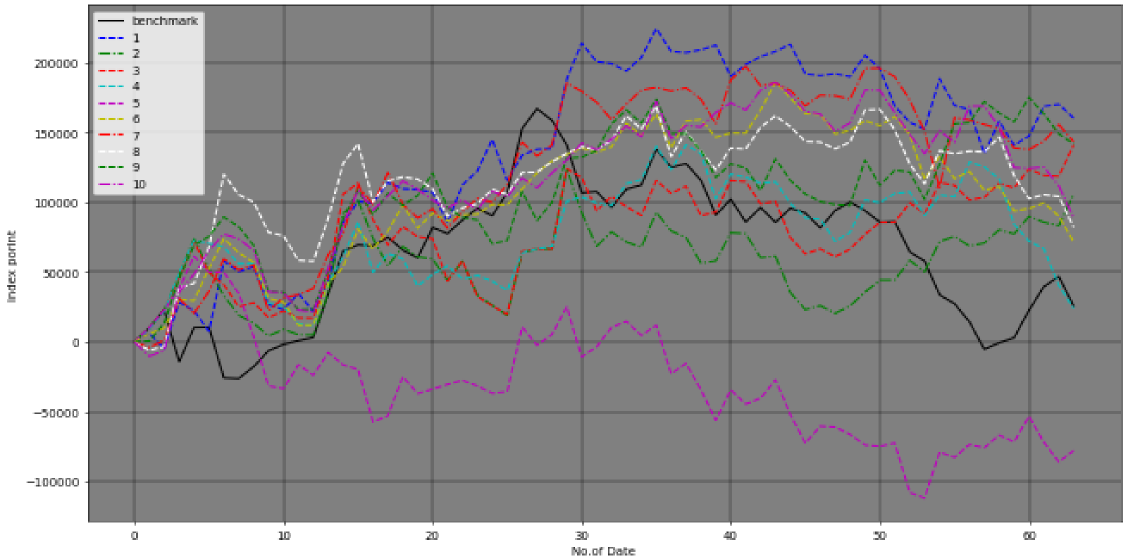

Figure 2: Performance in CSI 300.

Table 5: Results of applying quantitative strategies on CSI 500.

Tau	1	2	3	4	5	6	7	8	9	10	Bench mark
L	40	30	5	5	5	5	5	5	5	5	
α	0.001	0.001	0.001	0.002	0.002	0.002	0.001	0.001	0.002	0.001	
β	0.011	0.02	0.012	0.012	0.012	0.012	0.011	0.011	0.012	0.011	
Trade times	457	163	362	353	333	328	357	337	295	332	1
Win times	180	59	139	130	138	130	132	138	119	126	1
Loss number	277	104	223	223	195	198	225	199	176	206	0
Maximum profit rate	0.0716	0.2096	0.0886	0.0967	0.0967	0.0960	0.1022	0.1025	0.1155	0.1026	0.2544
Minimum loss rate	-0.0245	-0.0315	-0.0300	-0.0301	-0.0258	-0.0234	-0.0261	-0.0306	-0.0339	-0.0336	0
Average profit rate	0.0130	0.0237	0.0156	0.0161	0.0152	0.0154	0.0156	0.0147	0.0164	0.0160	0.2544
Average loss rate	-0.0075	-0.0134	-0.0086	-0.0088	-0.0087	-0.0087	-0.0080	-0.0086	-0.0091	-0.0085	0
Average return	0.0006	0.00003	0.0007	0.0004	0.0012	0.0008	0.0007	0.0010	0.0011	0.0008	0.2544
Standard variance	0.0131	0.0252	0.0153	0.0153	0.0156	0.0157	0.0149	0.0153	0.0165	0.0156	

Table 5: (continued).

Sharp ratio	0.0425	0.0012	0.0469	0.0240	0.0783	0.0528	0.0480	0.0635	0.0694	0.0512	
Total profit	165255.5	-13679.7	152084.0	63382.16	248187.6	157624.0	153423.1	198655.1	187882.2	147154.7	127542.3

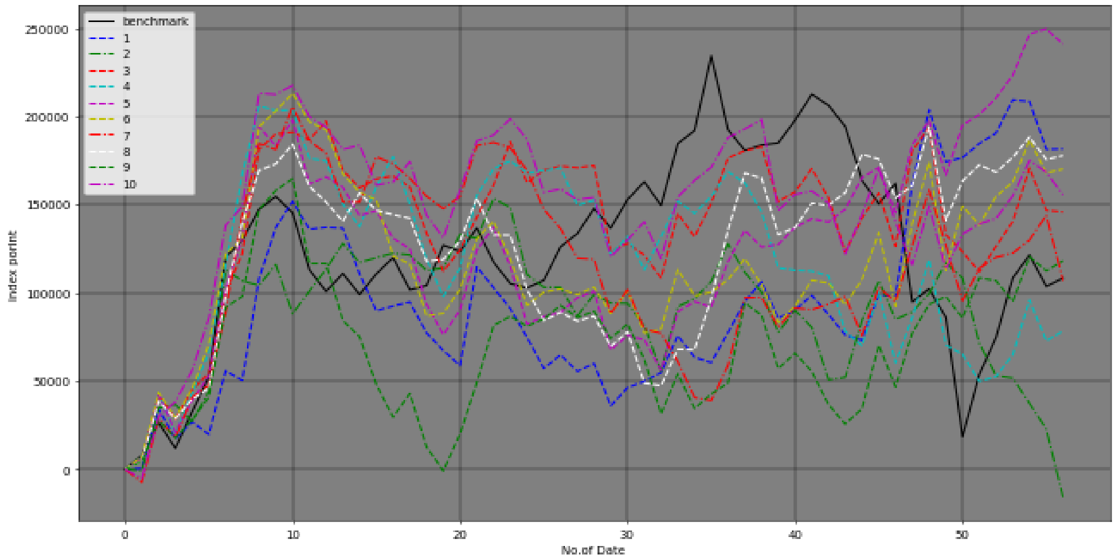

Figure 3: Performance in CSI 500.

For the CSI 300 Index, all time intervals exceeded the benchmark return, except for the return at time interval of 4 minutes and that at time interval of 5 minutes, and most of them exceeded the benchmark return by more. The number of trades at different time intervals fluctuates somewhat, ranging from 102 at time interval of 3 to 507 at time interval of 1, but most of them are around 300. The average profit rate is all greater than the absolute value of the average loss rate, which is about twice as high. For CSI 500, the return characteristics of applying this quantitative strategy are similar to CSI 300, which did not exceed the benchmark return at time interval of 2 and 4 minutes, and the number of trades is different, and the average profit rate is greater than the absolute value of the average loss rate, which is about twice of it. However, the CSI 500 performed slightly worse compared to the CSI 300, and did not exceed the benchmark by much for the rest of the time interval except for 2 and 4 minutes. Overall, this quantitative strategy is effective, with most of the time intervals outperforming the benchmark by a large margin, and the Sharpe ratio is high enough to earn profits according to the trend-following characteristics of the Chinese market.

4. Conclusion

In this paper, from the characteristics of China market as an emerging market and more retail investors, 3 tests, Counting Test, Ratio Test and Variance Ratio Test, were done to verify the non-effectiveness and trend correlation of CSI 300 and CSI 500, and the results show that when the time interval is from 1 minute to 10 minutes, the 2 indices have trend- following characteristics. So, based on this, we designed a quantitative strategy, using 0.85 of the entire data as the training set to determine the three parameters L, a, and b for each time interval, and backtesting in 0.15 as the test set to obtain various measures such as total return. The CSI 300 and CSI 500 had returns that exceeded the benchmark for most of the time intervals, and with a high Sharp ratio, this strategy has a good

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performance. So this quantitative strategy can be a reference for those who want to make profit based on the trend correlation characteristics of the Chinese market.

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Yi Zhang and Yu Mo contributed equally to this work and should be considered co-first authors.
Rui Liu and Ziyu Dai contributed equally to this work and should be considered co-second authors.

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