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Research on Algorithmic Trading and Its Role in Pricing Efficiency in Chinese Stock Market

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Abstract: This paper uses the A-share stock data in 2021 as a sample to study the impact of algorithmic trading activities on pricing efficiency through empirical analysis. Combining with the current market transaction structure and institutional characteristics in China, this study uses the proportion of small transaction volume STR as a proxy variable to measure the intensity of algorithmic trading activities in China. Empirical results show that algorithmic trading can effectively improve the pricing efficiency of Chinese stock market. In addition, an important way for algorithmic trading to improve pricing efficiency is to reduce stock market volatility and reduce investor heterogeneity. Through extended analysis, the findings demonstrate that algorithmic trading has a differential impact on the pricing efficiency of different stocks, with the highest degree of improvement in pricing efficiency for stocks with high market prices; at the same time, algorithmic trading can play a better role under the condition of sufficient market liquidity.

Keywords: algorithmic trading, pricing efficiency, securities market

1. Introduction

The rudimentary theory concerning algorithmic trading can be traced back to America in the early 1980s. The technological changes and destabilized stock market caused by large orders encouraged the application of algorithmic trading in the capital market in 2000. It uses pre-programmed instructions to model and generate the best configurations of orders given different variables. The system aims at reducing risk, enhancing dealing speed and satisfying the demand of investors. It was relatively late for algorithmic trading to be introduced to China markets. Compared with 75% of the US market based on algorithms, China has only about 20% of the total trading volume. The increasing explorations towards algorithms triggered the question whether its engagement is beneficial to the capital allocation efficiency. To further improve the trading system, our study focused on the adjusting speed of prices based on market variation and how well the share prices reflect available information. In this paper, a regression model was built to investigate the relationship between stock pricing efficiency and algorithm trading system.

Algorithmic trading is a new type of trading. As Chen pointed out, previous literature has not conducted systematic research on the impact of algorithmic trading on the overall quality or efficiency

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of capital markets [1]. In China, algorithmic trading is still immature and there is a large gap compared to mature markets, but in developed capital countries such as the EU and the US, it has become a major trading instrument. So, this is an important topic that is worthen studying in the future. Niu asserted that algorithmic trading has obvious advantages in reducing market impact of trading, improving trading efficiency and reducing human interference [2]. In terms of reducing the market impact of trading, Zhou argued that algorithmic trading can help investors reduce market shocks. Chen and Zhou were also elaborated AT can improve trading efficiency and reduce human interference. In the paper of Zhou that algorithmic trading can help fund managers effectively reduce tracking error and transaction costs [3]. Chen believed that the impact of algorithmic trading on the capital market is mainly reflected in the fact that algorithmic trading reduces the impact on the market through large order splitting, thus reducing transaction costs [1]. In addition, trade execution path can be obtained by hiding the trade intention, etc. Niu also pointed out that algorithmic trading can facilitate price discovery. Traders can develop algorithmic trading strategies based on massive amounts of historical and real-time data to correct price deviations that occur in the market [2]. Hendershott's research also showed that algorithmic trading can provide continuous liquidity in times of severe market volatility, increasing market price elasticity and effectively curbing price volatility [4].

Fama presented the theory of market efficiency, also known as the efficient market hypothesis (EMH), defining market efficiency achieved when the stock prices can fully reflect the information available [5]. The practical measurement is focused on the speed of stock price change and the market performance according to the updated information. In the model designed by Fama, the abnormal rate of return which is used as a measure of security performance should equal zero. This assumption, of course, is very limited in reality. Thus, Grossman and Stiglitz revised this idea to allow for slight and inconsistent profits as a result of information imperfection [6]. The premise for both researchers is that individuals interpret information only from security prices regardless of their preferences or education level.

With the foundation of theories and models built, Busse and Green examined the time needed in minutes for price to respond to positive and negative news reports in real time and supported statements above empirically [7]. Additionally, they discovered a similar trend measured in minutes between abnormal return performance and price response. However, the price reaction is found less significant in the Morning period. This can be influenced by individual preferences and decisions. Is the machine going to show the same pattern? Viljoen, Westerholm and Zheng studied SPI 200 futures and found the upheaval of trading and average trade size happens in the morning opening [8]. It shows a pattern surprisingly inversely related to the AT activities. The decisions made by AT traders are usually driven by low transaction costs and low level of information symmetry. These AT traders are defined as informed individuals in Grossman and Stiglitz 's model. They are described as the main contributors promoting market liquidity. AT improves the efficiency of traders and thus contributes to market liquidity [9].

Previous literature has shown that algorithmic trading can have a huge impact on securities markets. Aggarwal addressed the problem of endogeneity bias by using the introduction of co-location, an exogenous event after which algorithmic trading is known to increase. Matching procedures are used to identify a matched set of firms and set of dates that are used in a difference-in-difference regression to estimate causal impact. The results reflected that securities with higher algorithmic trading have lower liquidity costs, order imbalance, and order volatility. Weller measured information price efficiency from a dynamic perspective [10], using price information content as an evaluation factor, using quarterly panel market data of the US stock market to study and found that although algorithmic trading is very important for converting information into prices, it may also hinder information. Capture and reduce the price efficiency of available information [11]. When Boehmer explored the impact of algorithmic trading on market quality from the perspective of the global stock

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market, they took liquidity and volatility into the perspective of measurement, combined with information efficiency to comprehensively judge the impact on the entire market, and found that algorithmic trading will produce a narrower impact. The effective spread improves market liquidity; at the same time, the absolute value of the autocorrelation of intraday returns is relatively small, which improves the information [12]. Wang took the A-share market data from 2016 to 2021 as a sample and found that algorithmic trading has significantly improved the pricing efficiency of my country's stock market. It is also concluded through the mediation effect analysis that algorithmic trading mainly improves the stock market pricing efficiency by slowing down market volatility and investor belief heterogeneity. In addition, the positive impact of algorithmic trading in improving pricing efficiency is more pronounced for high-priced stocks, when market liquidity is plentiful, and when market sentiment is high [13].

In order to have a broader view of AT appliances and performance in the financial market, fifteen quantitative funds with best performance since its inception were selected. The chosen funds according to their different investing strategies have been divided into three groups which are active quantitative fund, enhanced index fund (EIF) and quantitative hedge fund. According to data analyzed by CMFDB, active quantitative funds and EIF accounted for 50% and 44% respectively of total market share. In terms of capital scope, active quantitative funds and EIFs are relatively larger than quantitative hedge funds. Consequently, this analysis will focus on active quantitative funds and EIFs specifically.

2. Method

2.1. Sample and Data

The data in this paper are obtained from the RESSET database of daily and time-of-day stock data for the A-share market for 2021. In addition to deleting missing values of indicators, samples from the financial industry and listed companies that were ST, *ST or PT at the end of the year were also excluded.

Table 1: Descriptive statistics of 52 A-share stocks.

	Minimum	Maximum	Mean	S. D.
Trading Price (¥)	1.130	83.200	12.584	14.017
Trading Deals	1.000	2,760	7.317	27.137
Absolute effective bid-offer spread (¥)	0.000	0.370	0.012	0.011
Relative effective bid-offer spread (¥)	0.000	0.009	0.002	0.001
Amplitude (%)	0.253	19.261	2.861	2.028
Until Now Yield (%)	-9.987	10.022	0.011	0.022

Table 1 shows that the data used in this empirical study has a total of 52 A-share stocks on the Shanghai Stock Exchange, with 18,821 daily trading samples. Summarize the maximum, average and deviation values of trading price, volume, amplitude, etc. The mean of daily until-now-yield is 0.011%, with a minimum of -9.987% and a maximum of 10.022%.

Subsequently, Shanghai composite index was used as a reference standard. The data are obtained from the daily data of Shanghai Stock Exchange A-share market from 2017-2022. The daily opening price, closing price, volume and fall and rise of nearly 50 companies over five years were collected. Removing the samples where the in-sample variables did, a total of 365,000 daily observations of sample data for 50 stocks were obtained. The line graphs were then synthesized with the values of these four variables.

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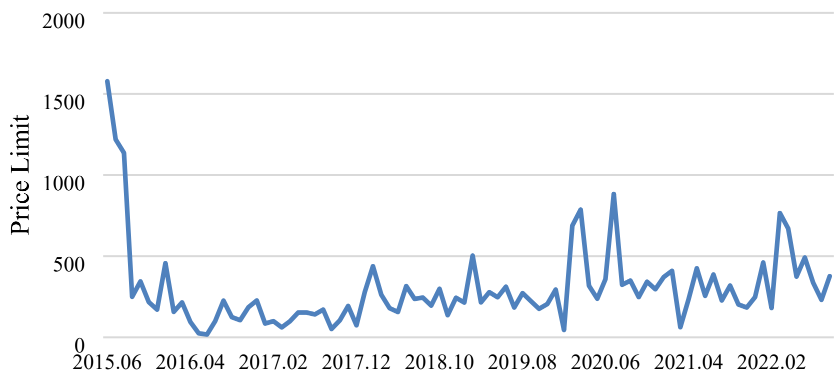

Figure 1: The trend of monthly price limit of Shanghai Composite Index from 2015 to 2022.

The price limit of Shanghai composite return was calculated from 2015 June to 2022 September. Since the price limit is positively correlated to the rate of return, price volatility can be used as a prediction of the rate of return. Compared with the quantitative funds above, the tendency of Shanghai composite index monthly price limit in Figure reports basically equal status with some big fluctuations but canceled out later in these seven years since the dramatic index drop happened in 2015.

2.2. Variable Definitions

Core Explanatory Variable: Algorithmic Trading. Separate identification of orders generated by algorithmic trading has not yet been implemented in Chinese exchanges. Thus, it is not possible to directly observe whether a particular order is generated by a computer algorithm. Measuring the activity of algorithmic trading needs to rely on relevant proxy variables. Given that high-frequency conditions are not yet available for algorithmic trading in China, the frequency of trading and the degree of trade automation are still somewhat different from those in mature securities markets. Therefore, in terms of variable selection, it is not feasible to refer to some foreign literature on algorithmic trading due to the lack of data sources.

Based on the institutional framework and investor level restrictions, most of the current algorithmic trading in China are basic algorithmic trading types, such as Stop Loss Orders, Call Orders, Strike Orders, Volume Weighted Average Price (VWAP), Time Weighted Average Price (TWAP), etc. The main characteristics of such standardized algorithmic orders are: splitting of larger parent orders and trading sub orders according to different benchmark price strategies on a time and volume basis. The existing literature suggests that a higher ratio of small orders traded indicates more algorithmic trading and that the proportion of small orders traded is proportional to the intensity of algorithmic trading. Therefore, the small order volume ratio STR is used as a proxy variable for algorithmic trading. The small order volume ratio STR, which characterizes the proportion of small order volume to total volume, is calculated as:

$$STR_{i,t,1} = \frac{Vol\_B_{i,t,0}+Vol\_S_{i,t,0}}{\sum_{m=0}^{1}(Vol\_B_{i,t,m}+Vol\_S_{i,t,m})} \tag{1}$$

$Vol\_B_{i,t,m}$ and $Vol\_S_{i,t,m}$ are the main buy volume (shares) and main sell volume (shares) of stock i in the m th tranche of the sell order on trading day t, respectively, with $m = 0$ for a single transaction amount less than ￥50,000 and $m = 1$ for a single transaction amount greater than or equal to ￥50,000; $STR_{i,t,0}$ denotes the proportion of the volume of stocks with a single transaction amount less than ￥50,000 of stock i in trading day t to the total volume of that day. The larger the value, the higher the proportion of small orders in the day's volume of the stock and the stronger the algorithmic trading activity.

Table 2 shows the results of STR calculation for 52 stocks. By finding the buying and trading volume of these 52 stocks and determining whether their single transaction amount is greater than or equal to ￥5,000, or less than ￥5,000. Later, the above data were calculated. From the chart, it is obvious that some stocks have smaller STR, such as code 600010. Indicating their weaker algorithmic trading activity. Some stocks have larger STR, such as code 600007. Indicating stronger algorithmic trading activity.

Table 2: Descriptive Statistics of 52 A-share stocks.

Code	STR	Code	STR	Code	STR	Code	STR
600000	0.080	600033	0.041	600019	0.098	600056	0.295
600004	0.362	600035	0.063	600020	0.048	600057	0.249
600006	0.152	600036	0.404	600021	0.241	600058	0.470
600007	0.498	600037	0.319	600022	0.009	600059	0.383
600008	0.031	600038	0.715	600023	0.036	600060	0.402
600009	0.577	600039	0.212	600025	0.157	600061	0.186
600010	0.003	600048	0.225	600026	0.117	600062	0.318
600011	0.152	600050	0.015	600027	0.073	600063	0.132
600012	0.407	600051	0.404	600028	0.017	600064	0.202
600015	0.040	600052	0.320	600029	0.109	600066	0.329
600016	0.003	600053	0.766	600030	0.199	600067	0.185
600017	0.016	600054	0.586	600031	0.172	600068	0.047
600018	0.074	600055	0.576	600032	0.408	600070	0.423

Core Explained Variable: Pricing efficiency. Hou et al. (2005) proposed to use the delay of stock price to information to describe the severity of the friction affecting the stock market. This method has been adopted by many scholars [14]. If the market cannot reflect the information into the stock price in a timely and sufficient manner, then the information will be absorbed in the subsequent time, resulting in a lag in the price response. The lag of this price response can be obtained by a regression model with lagged market returns. The stronger the explanatory power of the lagged variable, the longer the price response time to information. Referring to the above research, this paper uses the degree of explanation of lagging market returns on individual stocks as a proxy variable for pricing efficiency, and constructs $D1$ and $D2$ indicators. The specific calculation method is as follows:

$$r_{i,t} = \alpha_i + \beta_i \times r_{m,t} + \sum_{n=1}^{4} \delta_{i,n} \times r_{m,t-n} + \varepsilon_{i,t} \tag{2}$$

Among them, $r_{i,t}$ represents the rate of return of stock i at time t; $r_{m,t}$ represents the market rate of return at time t; $r_{m,t-n}$ represents the market rate of return with a lag n period; $\varepsilon_{i,t}$ is the random error term.

First, estimate the model (2) to obtain the regression coefficient of determination R^2 of the original model; then, set the coefficient of the lagging market return to zero, estimate the regression equation, and obtain the regression coefficient of determination R'^2 of the restricted model. Based on the above calculations, the first price lag reaction indicator can be obtained:

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$$D1_i = 1 - \frac{R'^2}{R^2} \tag{3}$$

Similar to the F-test, this measure captures the proportion of individual asset returns explained by lagged market returns. The smaller the value of $D1$, the lower the dependence of the asset return on past market information, the shorter the time required for assets to absorb market information, and the higher the pricing efficiency.

In addition to the coefficient of determination of the regression equation, we can also use the parameter size of the explanatory variables in the regression equation to measure the dependence of the return of a single asset on the lagged market return, and obtain the second lagged response indicator:

$$D2_i = \frac{\sum_{n=1}^{4} |\delta_{i,n}|}{|\beta_i| + \sum_{n=1}^{4} |\delta_{i,n}|} \tag{4}$$

$D2$ captures the proportion of the regression coefficient of lagged market returns in all regression coefficients in Equation (2). The smaller the value, the higher the pricing efficiency.

In order to keep the above construction method consistent with the positiveness of pricing efficiency, this paper revises the above indicators, and defines the first pricing efficiency indicator of individual stock i as:

$$E1_i = ln\left(\frac{1}{D1_i}\right) = ln\,(R^2 - R'^2) \tag{5}$$

$$E2_I = \frac{1}{D2_i} = \frac{|\beta_i| + \sum_{n=1}^{4} |\delta_{i,n}|}{\sum_{n=1}^{4} |\delta_{i,n}|} \tag{6}$$

It can be seen from equations (5) and (6) that the main difference between the pricing efficiency indicators $E1$ and $E2$ and the information response lag indicators $D1$ and $D2$ is that the former is the reciprocal of the latter, which ensures that the economic significance between the two remains consistent. The larger the index $E1$, the higher the pricing efficiency of the stock; the larger the index $E2$, the higher the pricing efficiency of the stock.

Table 3: Variable definitions.

Types	variable name	specific calculation method
Explained variables	E1	Explanation degree of spot price as a percentage of lag period
	E2	The ratio of the spot price regression coefficient to the lag period
Explanatory variables	STR	Small order volume/total volume

The definitions of all variables in this paper are shown in Table 1. The core explanatory variables are STR and the explained variables are E1 and E2. E1 is an explanation degree of spot price as a percentage of lag period and E2 is the ratio of the spot price regression coefficient to the lag period.

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3. Results and Discussion

3.1. Results

The results in Table 1 show that the regression coefficients of the algorithmic trading strength STR on the two efficiency indicators E1 and E2 are 2.19 and 2.772, respectively, and the coefficients of and are significant at the 5% confidence level. That is to say, there is a positive correlation between algorithmic trading intensity and pricing efficiency. The higher the intensity of algorithmic trading in trading, the higher the pricing efficiency.

Table 4: STR and efficiency regression results.

Var		Coeffi-cient	Std.err.	t	P>|t|	[95%conf.	interval]
E1	STR	2.190	0.213	9.90	0.000	1.680	2.536
	cons	11.441	0.694	19.64	0.000	9.834	13.952
E2	STR	0.772	0.031	12.03	0.000	0.709	0.935
	cons	0.605	1.251	0.41	0.686	-1.813	3.203

3.2. Discussion

According to the result, algorithmic trading has improved the efficiency of stock market pricing. However, in order to evaluate the long-term benefits of greater intensity of algorithmic trading, we also observe and discuss how the returns of five active quantitative funds have fared in the investment market in recent years in response to the growth of AT, based on the long-term volatility of trading markets.

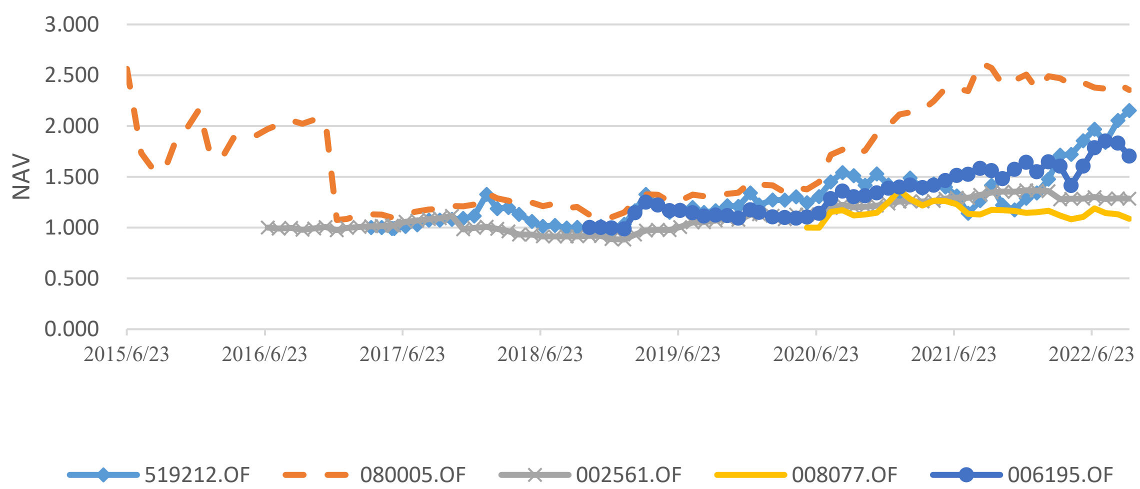

Figure 2: The trend of net value of active quantitative funds from 2015 to 2022.

With different dates of establishments, Figure 2 illustrates all five active quantitative funds have shown a stable increasing trend on yield rate. The earliest one was built in 2015 June. Non-significant increment in terms of long run but positive rate of return was maintained. The performance of EIFs demonstrates a larger fluctuation and bigger overall rise reported in Figure 3. This results in relatively higher risk since the yield rate had frequently reached negative in the process of holding. This EIFs established in recent years also reflects better performance in investment market with the evolution of AT.

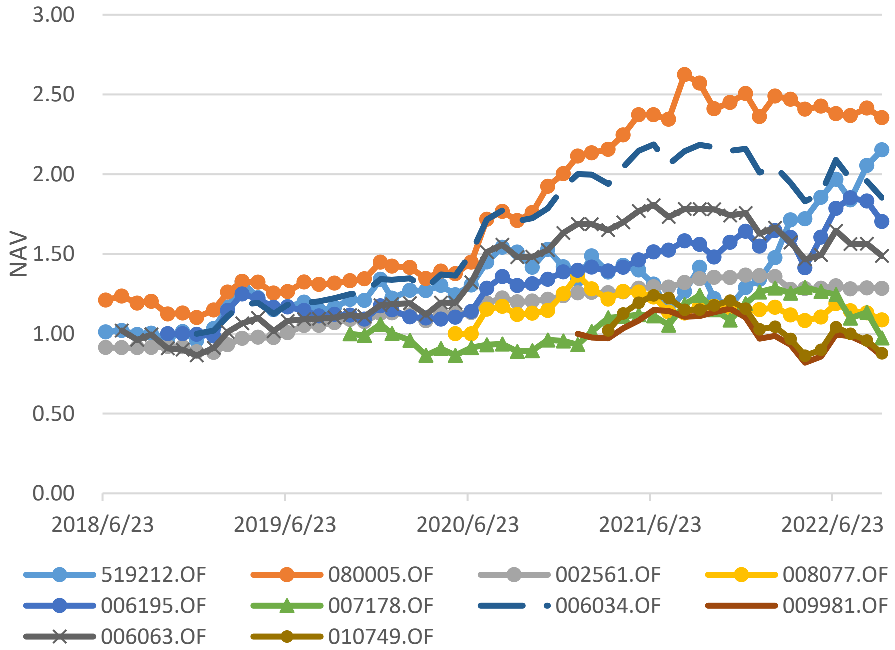

Figure 3: The trend of net value of EIFs from 2018 to 2022.

The development of algorithmic trading along with generated quantitative funds is overwhelming in the last ten years. Increasing number of market entities especially private funds enhanced the concentration of financial market. With the graduating perfection on the algorithm, more types of products are adopted in China stock market. However, the preference of third-party agencies is still focus on the market neutral strategies, also known as Alpha strategies. Concerning the high uncertainty of China market, the current algorithm progress is not enough to support popularization among A-share market. This requires computer to capture the change of market information immediately and adjust correspondingly. These adjustments are dependent on the stored factors analyzed previously. Large-scale quantitative solutions need generous history data and powerful algorithm. It is mentioned at the beginning of the paper that China is a late adopter of algorithmic trading and lacks referable examples. According to our results, algorithm indeed improves the efficiency of stock price-setting, in a broader way saying, market efficiency. This is not omitting the risks and bad consequences brought by inducing algorithm. Moreover, more fails reflect the inefficiencies of quantitative strategies instead of stock markets. For example, the black swan event of Alpha hedge fund happened in 2014 lessoned analysts to rethink the combination of alpha strategy on how to adapt China stock market. Most of the risks are ignored by agencies on the way pursuing revenues. The regulations regarding opaqueness funds especially hedge funds on employing algorithm requires further strengthening.

The A-share market has a large number of individual investors, a growing team of analysts, constantly regulated information disclosure, and complete online data. These are opportunities for quantitative and algorithmic trading due to the availability of relatively independent and timely data compared with traditional volume and price and financial data. The research and use of alternative data such as sentiment metrics, business flow metrics, reporting metrics, and sensor metrics was spawned. As an investment application, domestic alternative data started later, and it is far from mature overseas market applications. At present, domestic alternative data is still in its infancy, and the market has not yet formed a unified understanding.

4. Conclusion

This paper takes the data of some A-share stocks in 2021 as a sample, combines the current market transaction structure and institutional characteristics in China, uses the proportion of small order trading volume as a proxy variable to measure the strength of algorithmic trading in my country, and empirically analyzes the impact of algorithmic trading activities on pricing efficiency. The empirical results show that algorithmic trading can effectively improve the pricing efficiency of my country's stock market.

Regarding the future development trend of quantitative investment in China, the "China Private Equity Investment Fund Industry Development Report 2021" summarizes six aspects: Firstly, the industry has huge space and will maintain stable or fast development in the future. The second is that the position of private equity funds in the large capital management industry is expected to increase. Third, foreign capital will remain stable development, and it is difficult to pose a challenge to people in the short term. Fourth, the investor structure is expected to be optimized. Fifth, the proportion of equity and quantitative strategy products is expected to continue to rise. Sixth, the industry concentration is expected to further increase. This research report also investigates the general trend of the industry. Market institutions believe that quantification will develop in the direction of standardization, mainstreaming, platform, internationalization, intelligence, and strategizing. Among them, the strongest perception is for standardization. The challenges can be understood brought by foreign investment and artificial intelligence are more controversial directions for each market body. The controversy of artificial intelligence is reflected in the fact that all quantitative practitioners are actively learning artificial intelligence on a large scale, but do not feel strongly about its trend. This may be due to the fact that in the specific use, on the one hand, institutions are in the pioneering period for new algorithms, and on the other hand, there are doubts about its interpretability, so the use is more cautious. Data show that the application of artificial intelligence, fundamental quantification, high-frequency data, and high-frequency factor are the three most concerned about the direction of the market. After research and comparison, the report found that AI strategies outperformed other hedge fund strategies in the long term, with the highest annualized rate and Sharpe ratio.

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