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OPTIMIZATION OF SHORT-TERM STOCK SELECTION BASED ON VOLUME AND PRICE USING A NON-COOPERATIVE PARALLEL DEA MODEL

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Abstract. This paper presents a novel approach to portfolio optimization in the field of finance, with a specific focus on short-term yield. Existing literature has mainly utilized fundamental data to predict long-term trends in stock prices, but our proposed methodology utilizes technical indicators based on the theory of chasing up. Furthermore, we address the non-cooperative nature of volume and price fluctuation indicators and introduce non-cooperative theory into the short-term volume and price stock selection scheme for the first time. We propose an optimization of short-term stock selection based on volume and price using a non-cooperative parallel Data Envelopment Analysis (DEA) model, which we apply to Chinese main board listed companies. Our empirical results demonstrate the effectiveness of our model in selecting high-yield stocks in the short term. This paper contributes to the ongoing discussion on portfolio optimization and presents a compelling solution for investors seeking to maximize their financial gains. The proposed methodology can be utilized in practical applications and has significant implications for the financial industry.

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1. Introduction

Portfolio performance assessment has been a hot topic in academic and practical area. In an active stock trading market, investors make trading decisions based on the fundamental and technical data of the stock to predict the future trend of the stock [28,36,38,41]. Investors who mainly analyze fundamental data believe that the price of a stock will fluctuate with the intrinsic value of the stock, so they can find stocks with investment value by analyzing the fundamental data of listed companies. The investors who mainly focus on analyzing technical indicators follow the law of "history repeats itself" and expect to discover stocks with potential investment value by analyzing the relevant technical indicators of stocks.

Currently, scholars are adept at using fundamental data to predict long-term trends in stocks. Edirisinghe and Zhang [14] used the generalized DEA model to analyze the financial data of 230 companies in different

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technology industries in the United States to predict the future earnings of stock prices. Dia [10] proposed a four-step method for stock selection based on data envelopment analysis for portfolio optimization. Hwang *et al.* [22] designed a stock classification model based on the fundamental data of listed companies, and combined DEA theory with the stock classification model, thereby verifying the model's excellent ability to predict stock returns. Based on the financial data and market data of listed companies, Gardijan and Krinjari [17] used DEA efficiency scores to rank stocks, so as to help investors choose excellent stocks through scores, and found that the financial data of listed companies is very important in long-term prediction of stock prices. Kuo *et al.* [25] used a two-stage network DEA model to evaluate the performance of China-specific listed companies by leveraging the listed company's financial indicators and stock market data.

It can be found that most of the authors are based on fundamental data for portfolio optimization. Listed companies will regularly release business reports to investors, and the shortest time is one quarter. Therefore, fundamental data has a time lag in stock price analysis. Investors can only predict the long-term trend of stocks using fundamental data, and cannot predict the short-term trend of stocks well. With the increasing frequency of stock trading, investors not only demand high returns when investing in stocks, but also hope to obtain high returns in a shorter period of time. At this time, fundamental analysis cannot meet the needs of investors, and technical analysis that reflects short-term trends becomes more important.

Therefore, this article innovates in this context and proposes an optimization method of short-term stock selection based on volume and price using a non-cooperative parallel DEA model in the financial field. This model is based on technical indicators and focuses on the short-term returns of stocks, which can greatly increase the trading frequency of investors and promote a more dynamic financial market. Secondly, we also introduce non-cooperative game theory into the model to further improve the short-term stock selection returns of the model by studying the non-cooperative nature of trading volume indicators and price volatility indicators.

This rest of this paper is organized as follows. In Section 2, we present the relevant literature review. Section 3 introduces the relevant basic theories. The fourth section presents the optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model. Section **??** applies the model to the Chinese main board market for testing. Section 6 presents the conclusions and the future research directions.

2. Literature review

There are various fundamental and technical indicators for stocks, and it can be challenging to establish a clear correlation between these indicators. As a non-parametric method, Data Envelopment Analysis (DEA) has the advantage that it can analyze multiple input and output indicators that do not need functional relationships [5, 11, 19, 40]. DEA has been applied to many areas [15], such as hospitals [7, 12, 20], banks [44–46], financial institutions [34], environmental protection [16, 48] and so on. Therefore, when evaluating the investment value of stocks, the method of data envelopment analysis is very suitable.

Investors who focus on long-term value investment in stocks usually use different data envelopment analysis models based on the fundamental data of stocks to analyze the investment value of stocks, in order to construct a long-term investment portfolio optimization model. In the field of portfolio optimization by using DEA, Chen [6] adopted data envelopment analysis (DEA) to construct portfolios, and compared their return rates with the market index to examine whether DEA portfolios created superior returns. Ptr, Leivo and Honkapuro [35] proposed a method for enhancement of equity portfolio performance using data envelopment analysis. Lim *et al.* [30] proposed a DEA cross efficiency approach to evaluate portfolio selection and applied its method to the Korean stock market. Zhou *et al.* [50] proposed a new method for evaluating stocks by combining big data with DEA, considering the diversification of stock data. Li *et al.* [27] proposed an envelope method similar to DEA to evaluate the efficiency of stocks. Mills *et al.* [32] proposed a new dynamic SBM-DEA model considering the relationship between company performance and stock returns, and tested it in real estate listed companies.

It can be found that different data envelopment analysis models combined with fundamental data of stocks to construct long-term value investment models have excellent results. In order to improve the short-term trading efficiency of stocks, investors should pay more attention to technical indicators and further use different data envelopment analysis models to analyze the investment value of stocks, in order to construct a short-term investment portfolio optimization model. Neely *et al.* [33] shows that combining technical and macroeconomic indicators can significantly improve risk premium forecasts for stocks. Dai *et al.* [9] propose a new technical indicator for stock picking that can significantly improve stock returns. Qin *et al.* [37] used technical indicators to design regression models and neural network models to more accurately predict stock price changes. Silva [41] combines financial data and technical indicators of stocks to select stocks to build portfolios.

It can be found that few scholars combine data envelopment analysis with stock technical indicators when constructing portfolio optimization. This article is based on technical indicators and combines the parallel DEA model based on Stackelberg game with stock technical indicators to construct a short-term investment portfolio model.

In reality, the two most important types of analysis indicators in technical analysis are volume indicators and price volatility indicators. We can regard these two types of indicators as two parallel systems in technical indicators [18], and it is more effective to evaluate parallel systems than traditional black box systems [3,23,24]. The parallel system usually has the feature that one sub-system dominates the other. For example, a university usually has two major missions-teaching and research [2], which can be deemed as two parallel sub-systems, *i.e.*, teaching department and research department. In reality, some sub-systems in parallel systems are not of equally important. The kind of parallel systems usually has the feature that one process dominates the other. For example, in research-oriented universities, research is always more important than teaching, thus research is in the leading position; and in teaching-oriented universities, teaching is more important than teaching and is in the leading position. The importance of these two indicators in short-term stock selection can be analyzed by using game theory [43]. Thus, in the efficiency evaluation of such systems, the leader and follower relationship should be considered [29].

In previous literature, some scholars have proposed to model this kind of leader and follower relationship in DEA models by introducing Stackelberg game theory when evaluating efficiencies [31, 49]. Since Liang *et al.* [29] considered the leader-follower relationship in two stages and introduced Stackelberg game theory into the two-stage tandem DEA model and proposed a non-cooperative game model, DEA theory considering game relationship has been developed in most fields. Tavana [42] used Stackelberg game theory to optimize the efficiency score of decision-making units, and proposed an effective two-stage fuzzy DEA model for the two-stage performance evaluation problem in the banking industry. Du *et al.* [13] further combined Stackelberg game theory with parallel systems and proposed a non-cooperative parallel DEA model. Wu *et al.* [47] used game theory to improve the two-stage network DEA model and evaluate the manufacturing performance of my countrys iron and steel enterprises. Shi [39] proposed a new non-cooperative two-stage DEA model to evaluate the efficiency of industrial production systems considering the non-cooperativeness between the production subsystem and the pollutant treatment subsystem.

It could be found that the Stackelberg game theory combined with data envelopment analysis theory is widely used in industrial systems, but it is less used in the field of portfolio optimization. This paper intends to combine parallel DEA model based on Stackelberg game theory with stock technical indicators to construct investment portfolios to fill the gap in the combination of network DEA model based on Stackelberg game theory in the field of portfolio optimization. It expands the application of game data envelopment theory in short-term investment portfolio optimization.

3. Background

3.1. Short-term volume and price stock selection theory

The technical investors believe in "history repeats itself", and they infer the future direction of stock prices by analyzing their previous movements [21]. Therefore, technical investors are good at using fractal theory, trend theory and other methods to predict the future trend of stocks.

One of the most widely used technical methods is called chase after go up kill drop [8]. Investors believe that when a listed company is stimulated by good news, the stock price will rise, and this rise will accompany the trend for a period of time in the short term until the good news is fully reflected in the stock price. Investors buy stocks early in an uptrend in the hope that they can profit from the uptrend that follows, a behavior known as bull chasing. Conversely, when a listed company is stimulated by bad news, the stock price will fall, and this decline will continue with the trend for a period of time in the short term until the bad news is fully reflected in the stock price. Investors sell stocks early in a downtrend to avoid losing money in the following downtrend, a behavior known as a sell-off.

Here, we give the description of common technical indicators: moving average, trading volume, turnover, change, Moving Average Convergence and Divergence (MACD) , etc.

(1) The moving average is a curve formed by the average value calculated according to the closing price of a stock in a specific period of time, which can reflect the trend of the stock price. It is generally believed that when the short-term moving average crosses the long-term moving average from bottom to top, the market outlook is bullish. When the short-term moving average crosses the long-term moving average from top to bottom, the market outlook is bearish.
(2) Volume refers to the number of shares traded in a specific time period. In general, a rise in stock prices is accompanied by an increase in trading volume.
(3) Turnover refers to the turnover rate of a stock over a period of time. The higher the turnover, the more active the stock turnover. The lower the turnover, the duller the stock turnover.
(4) Change is the percentage change in a stock price relative to the previous days closing price over a specified period of time. A positive value means the stock price has risen, and a negative value means the stock price has fallen.
(5) MACD reflects the moving trend of the moving average. When the MACD changes from a negative value to a positive value, we think it is a signal that the stock price trend is turning more, and we can appropriately carry out the operation of chasing up. When the MACD changes from a positive value to a negative value, we think it is a signal that the stock price trend has turned bearish, and we should carry out the sell-down operation in time.

The two most important types of technical indicators are volume indicators and price volatility indicators. We combine these two types of indicators with the chasing theory in trend theory, and design a short-term volume-price stock selection model under the constraints of common technical indicators.

The prevailing belief is that a company's stock price tends to remain stable without significant price fluctuations during normal operations. We call this period the incubation period of the stock price. When a listed company is stimulated by good news, the stock price will immediately respond to a rise. This is called the stock price response, and the first day when the stock price rises sharply after breaking through the early incubation period is called the breakthrough day. Some stocks will also rise sharply on the breakout day without being stimulated by good news. Hence, this is a market deception, and there will be no upward trend in the later period. In order to avoid this risk, we propose another concept confirmation day: the confirmation day is the day after the breakout day, and the stock price still obeys the upward trend and shows a good upward trend. The larger the confirmation days rise, the greater the probability of a rising market outlook. If it is confirmed that the daily increase is small or even declines, then the market on the breakout day is a deception and will not perform a buying operation next. If the confirmation day has a large increase or even a daily limit, then the increase in these two days is the signal of the next uptrend, and we will implement chasing buy strategy on the trading day (the day after the confirmation day).

Based on the above technical principles, we propose the following assumptions for the short-term volume-price stock selection model:

Assumption 3.1. We use the short-term moving average group most commonly used by investors, which is also the default short-term moving average group used by Wind Database. Break through the daily short-term moving average long arrangement (5^{th}, 10^{th}, 20^{th}, 30^{th}).

Assumption 3.2. Break through the golden cross on the daily MACD curve.

Assumption 3.3. The cumulative increase on the breakthrough day and confirmation day are greater than 10%.

Assumption 3.4. The increase range of the incubation period within one natural year before the breakthrough date is 0%∼100%.

Assumption 3.5. Remove Special Treatment shares.

Assumption 3.6. The smaller the relative volatility of the stock price during the monthly incubation period before the breakout date, the better, and the smaller the trading volume, the better. On the breakthrough day and confirmation day, the larger the positive volatility of the stock price, the better, and the larger the trading volume, the better.

From a technical standpoint, we believe that stocks meeting the above criteria hold significant potential for short-term growth. For Assumption 3.1 to 3.5, we can directly implement it using conventional computer software. For Assumption 3.6, due to the diversity of its indicators, the complexity of the data, we decided to use the non-cooperative parallel DEA theory to deal with it.

3.2. Data Envelopment Analysis

Charnes *et al.* [4] proposed a new method of relative efficiency analysis based on the assumption that returns to scale are constant. To commemorate their great achievements, the first DEA model was named after them as the CCR model.

In an evaluation system, it is assumed that there are n decision-making units, each with m input indicators and s output indicators. The input indicator is represented as x_{ij} $(i = 1, ..., m)$ and the output indicator is represented as y_{rj} $(r = 1, ..., s)$. When evaluating the efficiency of decision-making units, the goal is either to achieve the maximum output under constant input conditions or to achieve the minimum input under constant output conditions.

Under the input orientation, the CCR model can be expressed as:

$$\begin{aligned}
&\max \sum_{r=1}^{s} u_r y_{r0} \\
&\text{S.t.} \ \sum_{i=1}^{m} v_i x_{i0} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \forall j \\
&u_r, v_i \geq 0, \forall r, i.
\end{aligned} \tag{1}$$

Where the optimal objective value θ_0^* is the efficiency score of DMU_0. When the relative efficiency of the decision unit is evaluated from the perspective of output, the CCR model can be expressed as:

$$\begin{aligned}
&\min \sum_{i=1}^{s} v_i x_{i0} \\
&\text{S.t.} \ \sum_{r=1}^{s} u_r y_{r0} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \forall j \\
&u_r, v_i \geq 0, \forall r, i.
\end{aligned} \tag{2}$$

To evaluate the relative efficiency of the decision unit when scale reward is variable, the BCC model was proposed by Banker [1]. Under the input orientation, the BCC model can be expressed as follows:

$$\begin{aligned}
&\max \sum_{r=1}^{s} u_r y_{r0} + w \\
&\text{S.t. } \sum_{i=1}^{m} v_i x_{i0} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + w \leq 0, \forall j \\
&u_r, v_i \geq 0, \forall r, i.
\end{aligned} \tag{3}$$

When the relative efficiency of the decision unit is evaluated from the perspective of output, the BCC model can be expressed as:

$$\begin{aligned}
&\min \sum_{i=1}^{s} v_i x_{i0} - w \\
&\text{S.t. } \sum_{r=1}^{s} u_r y_{r0} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + w \leq 0, \forall j \\
&u_r, v_i \geq 0, \forall r, i.
\end{aligned} \tag{4}$$

4. Optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model

The CCR model and BCC model regard the decision-making unit as a black box and evaluate the efficiency of the decision-making unit. If the decision-making unit is composed of multiple subsystems, and the importance of the multiple subsystems is not the same, we can use the non-cooperative parallel DEA theory to evaluate the decision-making unit. Compared with the traditional data envelopment analysis method, the non-cooperative parallel data envelopment analysis method can consider the primary and secondary degrees between subsystems more accurately. Thus, more invalid decision-making units and obtaining more accurate evaluation results could be identified.

In the short-term evaluation of stocks, we mainly consider the technical indicators of stocks. The two most important types of technical indicators are volume indicators and price volatility indicators. The whole technical indicators could be regarded as the total system. The stock selection system of volume indicators and the stock selection system of price fluctuation indicators could be regarded as two subsystems of the total system. And the importance of these two subsystems in the whole technical indicators is different.

Whether the trading volume or the price of the stock, their size in different time periods is not necessarily related. Therefore, when we take the trading volume or price in different time periods as an index to evaluate the stock, we can regard the decision unit as the state of constant scale reward.

Then the non-cooperative parallel DEA is applied to short-term volume-price stock selection to select high-efficiency decision-making units to build a stock pool.

We can divide technical indicators into two categories: volume index and price volatility index, which are used as system 1 and system 2 of the model, as shown in Figure 2:

For the entire stock selection system, the total input is x_{ij}, and the total output is y_{rj} $(i = 1, ..., m;\ r = 1, ..., s;\ j = 1, ..., n)$. The input of the trading volume index stock selection system is recorded as x^1_{ij}. The output of the trading volume index stock selection system is recorded as y^1_{rj}. The input of the price volatility index stock selection system is recorded as x_{ij}^2. The output of the price index stock selection system is recorded as y_{rj}^2. The above satisfies the relation: $x_{ij} = x_{ij}^1 + x_{ij}^2, y_{rj} = y_{rj}^1 + y_{rj}^2$.

Based on the non-cooperative parallel DEA theory proposed by Du *et al.* [13], we combine the non-cooperative parallel DEA theory with our short-term volume-price stock selection model, and formulate different short-term stock selection schemes through the game relationship between trading volume index and price volatility index. This can help investors choose stocks with better performance in the short term.

Assuming that the volume index stock selection system is dominant in the entire evaluation system, we first evaluate the efficiency of the volume index stock selection system, and then use the efficiency result of the volume index stock selection system as a constraint to evaluate the price volatility index stock selection system. Finally, its total efficiency is calculated. In order to obtain high-quality stocks with better performance in the short term [26].

The efficiency calculation model of the trading volume index stock selection system is as follows:

$$\begin{aligned} & E_k^1 = \max \sum_{r=1}^{s} u_r y_{rk}^1 \\ & \text{s.t. } \sum_{i=1}^{m} v_i x_{ik}^1 = 1 \\ & \sum_{r=1}^{s} u_r y_{rj}^1 - \sum_{i=1}^{m} v_i x_{ij}^1 \leq 0, j = 1, \ldots, n \\ & u_r \geq \varepsilon, r = 1, \ldots, s \& v_i \geq \varepsilon, i = 1, \ldots, m. \end{aligned} \tag{5}$$

Through model (5), we can obtain the optimal efficiency value E_k^{1*} of the volume index stock selection system. In order to reflect the dominant position of the volume index stock selection system, it is necessary to take $E_k^1 = E_k^{1*}$ as a constraint condition when evaluating the price volatility index stock selection system. The efficiency calculation model of the price volatility index stock selection system is as follows:

$$\begin{aligned} & E_k^2 = \max \sum_{r=1}^{s} u_r y_{rk}^2 / \sum_{i=1}^{m} v_i x_{ik}^2 \\ & \text{s.t. } \sum_{r=1}^{s} u_r y_{rj}^2 / \sum_{i=1}^{m} v_i x_{ij}^2 \leq 1, j = 1, \ldots, n \\ & \sum_{r=1}^{s} u_r y_{rj}^1 / \sum_{i=1}^{m} v_i x_{ij}^1 \leq 1, j = 1, \ldots, n \\ & \sum_{r=1}^{s} u_r y_{rk}^1 / \sum_{i=1}^{m} v_i x_{ik}^1 = E_k^{1*} \\ & u_r \geq \varepsilon, r = 1, \ldots, s \& v_i \geq \varepsilon, i = 1, \ldots, m. \end{aligned} \tag{6}$$

The above model can be converted to a linear structure using the Charnes-Cooper [4] transformation:

$$\begin{aligned} & E_k^2 = \max \sum_{r=1}^{s} u_r y_{rk}^2 \\ & \text{s.t. } \sum_{i=1}^{m} v_i x_{ik}^2 = 1 \\ & \sum_{r=1}^{s} u_r y_{rj}^2 - \sum_{i=1}^{m} v_i x_{ij}^2 \leq 0, j = 1, \ldots, n \end{aligned} \tag{7}$$

$$\sum_{r=1}^{m} u_r y_{rj}^1 - \sum_{i=1}^{m} v_i x_{ij}^1 \leq 0, j = 1, \ldots, n$$
$$\sum_{r=1}^{s} u_r y_{rk}^1 = E_k^{1*} \sum_{i=1}^{m} v_i x_{ik}^1$$
$$u_r \geq \varepsilon, r = 1, \ldots, s \& v_i \geq \varepsilon, i = 1, \ldots, m.$$

Where u_r and v_i are weights attached to outputs and inputs, respectively. The optimal solution of model (7) is E_k^{2*}, *i.e.* the efficiency E_k^2 of system 2.

$$\begin{aligned} E_k &= w_1 E_k^1 + w_2 E_k^2 \\ w_1 &= \sum_{i=1}^{m} v_i x_{ik}^1 / \left(\sum_{i=1}^{m} v_i x_{ik}^1 + \sum_{i=1}^{m} v_i x_{ik}^2 \right) \\ w_2 &= \sum_{i=1}^{m} v_i x_{ik}^2 / \left(\sum_{i=1}^{m} v_i x_{ik}^1 + \sum_{i=1}^{m} v_i x_{ik}^2 \right). \end{aligned} \tag{8}$$

Through the model (8), the total efficiency of the system when the trading volume index stock selection system is in the dominant position is obtained.

Through the above model, we can get the high-quality stocks selected from each trading day when the trading volume index stock selection system is the dominant system.

5. Application of Optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model

In this section, we will verify the effectiveness of our proposed non-cooperative parallel DEA short-term volume-price stock selection model in the Chinese A-share market. First we need to define variables and set the model.

5.1. Variables selection

In the current literature, most authors use financial indicators as input and output variables in the model when selecting stocks. Due to the time lag of financial data, they cannot well reflect the short-term trend of stock prices in the future. In the face of increasingly frequent short-term transactions, stock selection schemes based on financial data cannot meet the needs of investors. We use technical indicators to design a optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model. It could help investors choose stocks with high yields in the short term.

Consider the case of Chinese A-share market, for ease of presentation, let's assume that the stock trades normally 22 days in a month. According to Figure 1, we set the trading day as the t-th day, then the $t-1$ day represents the day before the trading day, and so on, the confirmation day is $t-1$ day, the breakthrough day is $t-2$ day, and the last day of the incubation period is $t-3$ days, the penultimate day of the incubation period was $t-4$ days, and the first day of the monthly incubation period was recorded as t-24days. The specific input indicators and output indicators are shown in Table 1.

In the trading volume index stock selection system, we choose the cumulative turnover rate of the last two days of the incubation period (model 9) as our input indicator, and the cumulative turnover rate of the breakthrough day and confirmation day (model 10) as our output indicator. It should be noted here that for the trading volume index stock selection system, we did not directly use the trading volume of the stock as an indicator in the model, but chose the turnover rate indicator to replace it. The reason for this is that the trading volume of the stock is an absolute number and will be disturbed by the share capital. A company with a large share capital will have a large trading volume, and a company with a small share capital will have a small trading

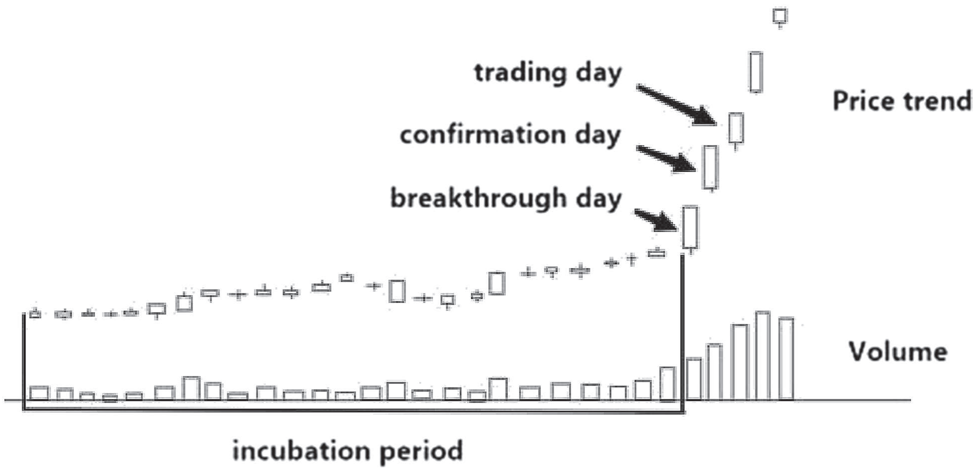

FIGURE 1. The short-term volume-price stock selection model.

FIGURE 2. Short-term stock selection based on volume and price using a non-cooperative parallel DEA model.

TABLE 1. Input indicator and Output indicator.

Input indicator	Meaning
$Cumulative\ turnover\ rate_{t-4,t-3}$	The cumulative turnover rate of the last two days of the incubation period
$Cumulative\ gain_{t-4,t-3}$	The cumulative increase in the last two days of the incubation period
$Cumulative\ gain_{t-24,t-3}$	The cumulative increase in the monthly incubation period
Output indicator	Meaning
$Cumulative\ turnover\ rate_{t-2,t-1}$	The cumulative turnover rate of the breakthrough day and confirmation day
$Cumulative\ gain_{t-2,t-1}$	The two-day cumulative increase on the breakthrough day and the confirmation day
$Gain_{t-1}$	The increase on the confirmation day

volume. Values that are too large or too small are unreasonable for DEA processing. The turnover rate is a ratio value that is not disturbed by the share capital, so that this effect can be excluded.

$$Cumulative\ turnover\ rate_{t-4,t-3} = \frac{Cumulative\ volume_{t-4,t-3}}{Total\ number\ of\ outstanding\ shares} \tag{9}$$

$$Cumulative\ turnover\ rate_{t-2,t-1} = \frac{Cumulative\ volume_{t-2,t-1}}{Total\ number\ of\ outstanding\ shares}. \tag{10}$$

In the price volatility index stock selection system, we choose the cumulative increase in the last two days of the incubation period (model11) and the cumulative increase in the monthly incubation period (model12) as the input indicators of the system. The two-day cumulative increase on the breakthrough day and the confirmation day (model13) and the increase on the confirmation day (model14) are selected as the output indicators.

$$Cumulative\ gain_{t-4,t-3} = \frac{Closing\ price_{t-3} - Closing\ price_{t-5}}{Closing\ price_{t-5}} \tag{11}$$

$$Cumulative\ gain_{t-24,t-3} = \frac{Closing\ price_{t-3} - Closing\ price_{t-25}}{Closing\ price_{t-25}} \tag{12}$$

$$Cumulative\ gain_{t-2,t-1} = \frac{Closing\ price_{t-1}}{Closing\ price_{t-3}} \tag{13}$$

$$Gain_{t-1} = \frac{Closing\ price_{t-1}}{Closing\ price_{t-2}}. \tag{14}$$

In the same way, in this system, we choose the indicator as the cumulative stock price increase rather than the actual change of the stock price. It is also to exclude the interference of the factor of share capital. In order to make the sample data more reasonable, we add two more assumptions:

Assumption 5.1. Exclude stocks with a one-character board on any one of the two days after the incubation period, the breakthrough day, and the confirmation day. When stocks exhibit a one-character board pattern, their turnover rate and price fluctuations can be very abnormal compared to normal values, and one-character board stocks generally cannot be traded normally. To ensure the normal operation of the model, the model does not consider one-character board stocks.

Assumption 5.2. The values of the selected indicators are all greater than 0.

Wind Database is currently one of the most powerful databases in China's financial field. It can provide investors with relatively complete historical trading data of stocks. The data used in this article comes from the daily historical trading data of stocks in the Wind Database. The data we use is from August 2020 to September 2021 and the trading range is set from August 1 to August 31, 2021. In each trading day, the optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model is applied to select high-quality stocks, and count the highest returns of high-quality stocks in the next 20 trading days to verify the effectiveness of the model in short-term stock selection. After screening through 8 constraints, if the number of stocks to be evaluated on that day is less than twice the sum of the input index and the output index, then the number of decision-making units to be evaluated on the trading day is too small to be suitable for evaluation, and the trading day will be excluded. After screening, the eligible trading days are August 6, 12, 13, 16, 17, 24, 25, 26, 27, 30, and 31, 2021. A total of 11 trading days.

For 11 trading days that meet the requirements. We implement the following plans for stock selection on each trading day:

Option 1: Take the trading volume index stock selection system in the model as the dominant position, and the price volatility index stock selection system as the subordinate position for short-term stock selection.

Option 2: Take the price volatility index stock selection system in the model as the dominant position, and the trading volume index stock selection system as the subordinate position for short-term stock selection.

Set the fundamental indicator stock selection as the control group. For the control group, we selected the constituent stocks of the Shanghai Stock Exchange 180 Index as the original stock pool, and the sample stocks were carefully selected from all the A-share markets and were representative. We use two common fundamental indicators, dynamic ROE and operating income year-over-year growth rate, for stock selection. For each trading day, based on the 2021 semi-annual financial report, select a single stock with the highest indicator above as a high-quality stock selected based on fundamental data.

TABLE 2. High-quality stocks selected by each option and the control group.

Option 1		Option 2		Control group	
Trading day	Stock code	Trading day	Stock code	Trading day	Stock code
6-Aug	600438	6-Aug	603897	6-Aug	600309
	002518	12-Aug	000400		600779
12-Aug	000400	13-Aug	601678	12-Aug	600309
	002549	16-Aug	002516		600779
	600218	17-Aug	600516	13-Aug	600309
13-Aug	601678	24-Aug	000922		600779
16-Aug	002516	26-Aug	002079	16-Aug	600309
	002741	31-Aug	600281		600779
17-Aug	600277			17-Aug	600309
	600516				600779
24-Aug	000922			24-Aug	600132
	600787				603392
25-Aug	601101			25-Aug	600132
26-Aug	002865				603392
	600213			26-Aug	600132
	601101				603392
27-Aug	600213			27-Aug	600132
	600358				603392
	600428			30-Aug	600132
30-Aug	600331				600061
31-Aug	002057			31-Aug	600132
	002218				600061
	600165				
	601777				

5.2. Empirical Analysis

The stocks with an efficiency of 1 after the evaluation of Option 1 and Option 2 and the stocks selected by the control group were recorded as our selected high-quality stocks. The high-quality stocks selected by each scheme within the trading range are listed in Table 2.

Assuming that investors have two strategies when buying stocks. One is to evenly allocate their assets to various high-quality stocks for trading, which we call the strategy of asset-to-share allocation strategy. The other is to distribute its assets evenly on each trading day for trading, which we call the asset daily average distribution strategy.

As for the first trading strategy, we assume that the investor allocates his assets equally to each stock to buy the above stocks, then his highest stock yield in the next 20 days is shown in Table 3.

In Table 3, we take each stock as a measure, and list the highest rate of return of the effective decision-making units obtained by each stock based on the above scheme in the next 20 days. As shown in Table 3, the mean rate of return of scheme 1 over the entire test period was 22.04%, the mean rate of return of scheme 2 over the entire test period was 17.54%, and the mean rate of return of the control group over the entire test period was 4.61%. The rate of return of Scheme 1 and Scheme 2 is much higher than that of the control group. It can be seen from this that optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model has a much higher rate of return on the selected stocks in the short term than the rate of return of the stocks selected by the control group represented by fundamentals. This also shows that in short-term stock selection, the stock selection model we propose is far superior to the common fundamental-based stock selection strategy. Secondly, the rate of return of option 1 is higher than that of option 2, which shows that the

Table 3. The short-term maximum return under the asset-to-share allocation strategy.

Option 1		Option 2		Control group	
Stock code	Rate of return	Stock code	Rate of return	Stock code	Rate of return
600438	20.73%	603897	13.86%	600309	−0.99%
002518	29.31%	000400	22.63%	600779	21.62%
000400	22.63%	601678	23.62%	600309	1.78%
002549	6.96%	002516	−6.55%	600779	7.90%
600218	42.67%	600516	25.72%	600309	4.11%
601678	23.62%	000922	32.15%	600779	10.94%
002516	−6.55%	002079	16.46%	600309	−2.19%
002741	15.10%	600281	12.40%	600779	8.94%
600277	19.28%			600309	0.93%
600516	25.72%			600779	8.61%
000922	32.15%			600132	7.37%
600787	17.50%			603392	8.18%
601101	67.74%			600132	−1.87%
002865	10.63%			603392	1.77%
600213	2.49%			600132	−1.90%
601101	61.91%			603392	−3.67%
600213	−3.76%			600132	2.09%
600358	19.55%			603392	−0.60%
600428	18.07%			600132	0.30%
600331	45.76%			600061	10.40%
002057	4.22%			600132	3.37%
002218	10.44%			600061	14.27%
600165	30.78%				
601777	12.12%				
Mean	22.04%	mean	17.54%	mean	4.61%

stock selection program dominated by the trading volume index stock selection system is better than the stock selection program dominated by the price volatility index. Remind short-term investors to pay more attention to trading volume indicators when making stock selections.

When the investor's investment strategy no longer focuses on individual stocks, but is measured by the trading day, and trades with the same amount of assets on each trading day, the rate of return is shown in Table 4:

It can be found from Table 4 that when investors implement the daily average asset allocation strategy, the average rate of return of scheme 1 during the entire test period is 26.23%, the average rate of return of scheme 2 during the entire test period is 17.54%, and the average rate of return of the control group throughout the test period is 4.61%. It can be seen that the rate of return of scheme 1 is higher than that of scheme 2, which is much higher than that of the control group. On the one hand, it can prove the superiority of our proposed optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model represented by technical indicators in short-term stock selection, and on the other hand, it can also prove the importance of trading volume indicators in technical indicators.

It can be found that no matter the investor's trading style focuses on the perspective of individual stocks or the perspective of trading days, the rate of return of the scheme 1, which is dominated by the stock selection system based on trading volume indicators, is higher than that of the scheme 2 dominated by the stock selection system based on price fluctuation indicators. This shows that it is necessary for us to conduct a game analysis of volume indicators and price indicators. Hence, it can be concluded that when using technical indicators to make short-term forecasts of stock prices, volume indicators are more important than price volatility indicators.

TABLE 4. The short-term maximum return under the daily average asset allocation strategy.

Trading day	Option 1	Option 2	Control group
6-Aug	25.02%	13.86%	10.32%
12-Aug	24.09%	22.63%	4.84%
13-Aug	23.62%	23.62%	7.53%
16-Aug	4.28%	−6.55%	3.38%
17-Aug	22.50%	25.72%	4.77%
24-Aug	24.83%	32.15%	7.78%
25-Aug	67.74%		−0.05%
26-Aug	25.01%	16.46%	−2.79%
27-Aug	11.29%		0.75%
30-Aug	45.76%		5.35%
31-Aug	14.39%	12.40%	8.82%
Mean	26.23%	17.54%	4.61%

5.3. Robustness test

To further verify the effectiveness of our proposed model, we selected data from September 2020 to October 2021 for further validation. We set September 1st to September 30th, 2021 as the trading range. After screening the conditions in the trading range, the trading days that meet the requirements are September 1, 3, 6, 7, 8, 9, 10, 13, 14, 16, 17, 23, and 24, 2021. A total of 13 trading days. For 13 trading days that meet the requirements of the model, we processed the optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model and obtained high-quality stocks as shown in Table 5.

Similarly, we assume that investors still adopt the asset stock allocation strategy and asset daily allocation strategy when purchasing stocks.

Firstly, let's take a look at the asset stock allocation strategy. Assuming that investors distribute their assets equally among stocks to purchase the above stocks, their highest stock returns over the next 20 days are shown in Table 6.

We can find that under the asset stock allocation strategy, the average return of Scheme 1 during the entire testing period is 13.75%, the average return of Scheme 2 during the entire testing period is 8.64%, and the average return of the control group during the entire testing period is 2.56%.The return rates of Scheme 1 and Scheme 2 are still higher than those of the control group. And the return rate of Scheme 1 is still much higher than that of Scheme 2. This further proves the effectiveness of our proposed optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model. In terms of short-term stock selection, the stock selection ability of our proposed model is much greater than that of stock selection methods based on fundamental indicators.

Let's take a look at the daily average asset allocation strategy again. Assuming that investors allocate assets evenly across trading days for trading. So his highest stock yield in the next 20 days is shown in Table 7.

We can find that under the asset stock allocation strategy, the average return of Scheme 1 during the entire testing period is 11.63%, Scheme 2 during the entire testing period is 8.64%, and the average return of the control group during the entire testing period is 2.48%. The return rates of Scheme 1 and Scheme 2 are still higher than those of the control group. And the return rate of Scheme 1 is still much higher than that of Scheme 2. Once again, it proves that our model can select stocks with higher returns in the short term in the future.

To summarize, our proposed optimization of short-term stock selection based on volume and price, using a non-cooperative parallel DEA model, can potentially yield higher short-term returns when compared to stock selection methods based solely on fundamental data. Furthermore, in short-term stock selection, strategies emphasizing trading volume indicators outperform those based on price indicators.

TABLE 5. High-quality stocks selected by each option and the control group.

Option 1		Option 2		Control group	
Trading day	Stock code	Trading day	Stock code	Trading day	Stock code
1-Sep	601088	1-Sep	600500	1-Sep	600132
	601255	3-Sep	601390		688185
	601666	6-Sep	000791	3-Sep	600132
3-Sep	601390	8-Sep	002053		688185
	000591	9-Sep	600186	6-Sep	600132
	600163	16-Sep	002866		688185
6-Sep	000791	17-Sep	603002	7-Sep	600132
	600163	23-Sep	600795		688185
	600166	24-Sep	000692	8-Sep	600132
	601222				688185
7-Sep	601177			9-Sep	600132
8-Sep	002911				688185
	600052			10-Sep	600132
	601717				688185
9-Sep	002597			13-Sep	600132
	600186				688185
	600982			14-Sep	600132
10-Sep	000932				688185
	002068			16-Sep	600132
13-Sep	000630				688185
14-Sep	600259			17-Sep	600132
	603010				688185
16-Sep	000631			23-Sep	600132
17-Sep	603002				688185
	603968			24-Sep	600132
23-Sep	600759				688185
24-Sep	000692				

6. Conclusion and direction for future works

The stock selection strategy based on fundamental indicators can only predict the future long-term trend of the stock, and cannot accurately reflect the short-term trend of the stock price. This article uses technical indicators to predict short-term trends in stock prices. Using technical indicators and non-cooperative parallel DEA theory, a optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model is proposed for short-term stock selection. The study found that in predicting short-term rate of returns, the short-term rate of returns of stocks selected based on the model are far superior to short-term rate of returns of stocks selected based on fundamental data. This proves the validity of the model. Secondly, considering the non-cooperative nature of trading volume indicators and price indicators, paying more attention to trading volume indicators during short-term stock selection can further improve the short-term return of stocks. Our proposed the optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model has shown superior short-term stock selection effects, but this article only selected one year of data to test the effectiveness of the model. Due to the dynamic nature of the short-term stock trading market, the sustainability of the optimization of short-term stock selection based on volume and price using a non-cooperative parallel DEA model can be verified in future work by extending research time and increasing data size.

TABLE 6. The short-term maximum return under the asset-to-share allocation strategy.

Option 1		Option 2		Control group	
Stock code	Rate of return	Stock code	Rate of return	Stock code	Rate of return
601088	19.95%	600500	8.36%	600132	2.34%
601255	18.53%	601390	3.96%	688185	−0.97%
601666	28.16%	000791	32.01%	600132	5.46%
601390	3.96%	002053	5.18%	688185	2.64%
000591	45.82%	600186	3.62%	600132	8.17%
600163	57.57%	002866	0.48%	688185	3.38%
000791	32.01%	603002	13.77%	600132	−2.14%
600163	43.33%	600795	6.44%	688185	−1.05%
600166	1.26%	000692	3.95%	600132	−1.45%
601222	2.99%			688185	−2.85%
601177	5.25%			600132	2.45%
002911	7.53%			688185	0.12%
600052	14.90%			600132	3.17%
601717	−3.80%			688185	−1.85%
002597	2.87%			600132	1.33%
600186	3.62%			688185	−5.03%
600982	10.59%			600132	4.96%
000932	−3.47%			688185	−2.99%
002068	−0.85%			600132	10.17%
000630	9.05%			688185	2.95%
600259	1.36%			600132	13.52%
603010	24.74%			688185	4.94%
000631	15.96%			600132	6.92%
603002	13.77%			688185	1.48%
603968	5.86%			600132	9.34%
600759	6.44%			688185	1.47%
000692	3.95%				
Mean	13.75%	mean	8.64%	mean	2.56%

TABLE 7. The short-term maximum return under the daily average asset allocation strategy.

Trading day	Option 1	Option 2	Control group
1-Sep	22.21%	8.36%	0.69%
3-Sep	35.78%	3.96%	4.05%
6-Sep	19.90%	32.01%	5.78%
7-Sep	5.25%		−1.60%
8-Sep	6.21%	5.18%	−2.15%
9-Sep	5.69%	3.62%	1.29%
10-Sep	−2.16%		0.66%
13-Sep	9.05%		−2.85%
14-Sep	13.05%		0.99%
16-Sep	15.96%	0.48%	6.56%
17-Sep	9.81%	13.77%	9.23%
23-Sep	6.44%	6.44%	4.20%
24-Sep	3.95%	3.95%	5.41%
Mean	11.63%	8.64%	2.48%

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