

# Research on investment strategy of E-fund Asian Selection QDII Fund

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**Abstract.** The paper optimizes E-fund Asian Selection Hong Kong stock investment strategy using the XGBoost machine learning algorithm and multi-factor stock selection theory, determining stock holding based on Hong Kong stock correlation factors. First, the new investment strategy derived from the XGBoost algorithm has better performance in terms of profitability and risk control compared to the original investment strategy. Second, for Hong Kong stocks, technical and valuation factors are more important in multi-factor quantitative stock selection, which can be a reference for QDII fund managers as well as investors when selecting factors. Thirdly, the XGBoost algorithm classifier is also more capable of classifying Hong Kong stocks, which can improve the rationality and accuracy of investment decisions, thus helping investors to better allocate their investment in Hong Kong stocks and achieve excess returns. Studying strategies investment of the QDII funds can aid fund managers in adjusting their strategies, enhance fund performance.

## 1 E-fund Asian Selection QDII Fund status quo analysis and optimization objectives

### 1.1 E-fund Asian Selection QDII Fund Overview and selection reasons

E Fund Asia selected full name e Fund Asia selected stock securities investment fund, it is a fund management Co., Ltd. issued a QDII fund wealth management products. Established for a long time, is the QDII fund issued in the early stage of the establishment, and survive to the QDII, one of the stock funds, is also one of the long-term issuance of e Fund company funds. This paper mainly studies the investment strategy of QDII funds, so it is necessary to select representative QDII funds. E-fund Asian Selection QDII Fund has a long period of establishment and a large issuance scale. However, its performance is relatively poor compared with similar funds, and both its profitability and risk control ability are far behind similar funds. Its investment strategy has more space for optimization, and it also needs to be optimized.

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## 1.2 E Fund Asia selected QDII fund existing investment strategy analysis and optimization objectives

### 1.2.1 Analysis of the existing investment strategy of the QDII Fund

The initial phase of the fund, namely, the 2010-2013 area configuration was rather decentralized, investing mainly in Hong Kong, Korea, the United States, the UK, Southeast Asia and other countries. In April 2014, the present fund manager began to concentrate funds on the Hong Kong market, and supplemented with the Asian enterprises listed in the US stock market. The risk-free yield rate and the market index are selected according to the annual fixed (pre-tax) yield and the total index of the stock-type fund. The greater the number of indicators of equity selection, the higher the corresponding capacity. The larger the systemic risk factor, the greater is the market risk that the fund bears.

**Table 1.** Stock selection ability and timing ability of E-fund Asian Selection and similar funds.

metric	E-fund Asian Selection	Guangfa Global Selection	ICBC Global Select
Share selection ability	-0.61%	4.53%	2.22%
Time selection ability	2.79	1.23	1.53
system risk	0.77	0.50	0.26

Data source: wind

### 1.2.2 E-fund Asian Selection QDII Fund optimization target

Using the multi-factor stock selection model, explore more effective factors based on the original fund product stock selection strategy, construct the stock selection factor pool, screen the high-quality stocks with large market value, and build the fund stock selection pool. Through the factor effectiveness analysis eliminate the stock selection poor factors, and through the screening factor input machine learning model, using machine learning model of the ability to select high quality stock to optimize investment strategy, in order to obtain relatively higher returns and lower risk for the optimization goal, namely for yield, annualized yield increase at the same time, improve the sharp ratio and reduce the maximum retracement rate.

## 2 Impact factor construction and data preprocessing

### 2.1 Stock and impact factor pool construction

In this paper, 119 stocks of the Hang Seng Composite Index with large market value were selected. Monthly cross-sectional data of the associated factor eigenvalues were collected for each stock from January 2016 to March 2024.

This paper selects the factor data in the wind database, summarizes the previous academic research on the basis of considering the data availability, and finally selects a total of 40 factors. The factors are divided into valuation, growth, leverage, finance, technology, and 5 categories.

## **2.2 Data pre-processing**

This paper uses the MAD method of polar devaluation, which replaces the factor data by using the absolute median data to the range of 3 times the absolute average. At the same time, the Z-score standardization method is used to standardize the data of factors, making the median value zero the standard difference.

## **2.3 Factor validity test**

Rank-IC was selected for factor validity testing. The mean value of the Rank-IC value during the sample period was obtained as the Rank-IC value, and the IR value was calculated. Where the mean of the Rank-IC value is recorded as `ic_mean`, the standard deviation as `ic_std`, IR, and the value as `ic_ir`. In this paper, the factors with the absolute value of Rank-IC greater than 0.02 were regarded as screened and arranged in descending order according to the absolute value of Rank-IC. There were 17 factors passed through the screening, and the factors of five major categories were selected. Factor codes are `bias`, `rsi`, `wr`, `lncaptial`, `cfc`, `profit`, `kdj`, `macd`, `npm`, `diff`, `quickratio`, `volume`, `cashflow`, `ocfc` Yoyeps and `pe`.

# **3 Model construction and investment strategy optimization research**

## **3.1 Model training**

### *3.1.1 Model training*

Rolling training is to use the data for four years from January 2016 to December 2019 for training modeling, predict data for the first half of 2020, evaluate accurateness to join the training set, then use the 2016 to 2020 first half for the second half of the year for predicting data, so push to the latest data, only the last training is using 9 months of data from July 2023 to March 24, 2019, a total of 8 training sessions.

### *3.1.2 Parameter tuning*

In this paper, the grid search method is selected for parameter adjustment. Considering the characteristics of the grid search method, each addition of a parameter increases a large number of possible parameter combinations, combined with the parameter importance. The optimal parameter combination obtained by the grid search method is: `colsample_bytree=0.8`, `gamma=0`, `learning_rate=0.1`, `max_depth=3`, `n_estimators=800`, `subsample=1`.

## **3.2 Investment strategy optimization**

The code of this paper is based on the Python language. The backtest interval selected in this paper is the sample, using the rolling prediction method, and the rolling mode is rolling every six months from 2020 except for the last training. Select the stocks with the larger market value of the Hang Seng Composite Index in Hong Kong stocks as the stock pool, and the strategic return comparison benchmark is the original fund and the yield.

The strategy takes the net asset value of the fund recorded in the annual report of 2019, that is, the net asset value of the fund at the end of 2019 as the initial capital, and calculates

the net value of the fund shares. Invest at a rate of 94% of stocks, 3% of demand deposits and 3% of one-year time deposits. The stock part is adjusted once a month, and the stock rate is the top 30 stocks in the stock pool until the end of this period, and the return rate is calculated after deducting the stamp duty of Hong Kong shares; the deposit part is held for a long time. At the end of each period, add the returns of all investment methods and calculate the net value of the fund shares in the current period.

### 3.3 Retest of the optimized investment strategy

#### 3.3.1 Retest of the investment strategy after optimization

Through the above predicted stock selection results, and using the investment strategy designed by the previous backtest, and compared with the net value of E Fund Asia Select, the backtest results are shown in Figure 1.



**Fig. 1.** Results of backtesting.

As can be seen in Fig, overall, XGBoost, the net performance of the optimized investment strategy is better than E Fund Asia Select, achieved the purpose of optimizing the stock selection ability of E Fund Asia Select Fund. The detailed back-test indicators are shown in Table 2.

**Table 2.** Back-test indicators.

List of strategies	gross rate	annualized rate of return	Sharp ratio	Maximum retraction rate
Original investment strategy	-4.64%	-1.58%	-0.296	51.58%
Optimize the investment strategy	62.45%	21.29%	2.953	48.56%

### 3.4 Analysis of the advantage of the optimized investment strategy

In this paper, XGBoost uses the algorithm to make multi-factor quantitative investment in stock selection. On the premise of fully respecting the original investment strategy and investment philosophy of the fund, the optimized investment strategy has a great advantage in terms of profit.

The optimized investment strategy offers advantages in terms of risk, with a high maximum retracement rate and a 3.02% reduction in the Sharpe ratio compared to the original strategy. The strategy's income obtained by taking unit risk is significantly improved, thus enhancing the investment value of the fund.

## 4 Conclusion and suggestion

### 4.1 Conclusion

The paper evaluates investment strategies based on return and risk dimensions, finding the XGBoost algorithm's new strategy improves profitability and risk control. The optimization strategy achieves the original investment style's purpose. The equity model is suitable for domestic stock markets outside Hong Kong, but investors still use less important strategies due to stock agency calculators. The QDII strategy is highly effective in combination with stock market options.

### 4.2 Propose

The XGBoost algorithm can be used in decision-making for multi-factor quantitative selection, assisting fund managers in identifying factors with longer periods and better yield capability. Technical and valuation factors can be considered in factor pool construction, with stronger predictive ability for sharing yields and the ability to form new factors.

When choosing an investment fund, focus on its annual report, strategy, risk control, and manager experience. Professional investors can use quantitative investment guidance, multi-factor equity selection, and machine learning algorithms to build a portfolio and form their own investment style.

## References

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