Asset Allocation Strategy Based on Announcements and Machine Learning-- An approach in Chinese Market

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Abstract. Asset allocation strategy is frequently discussed by investors, either based on fundamental or quantitative analysis. This article discusses Announcement based quantitative asset allocation strategy using machine learning models, based on 2018.Q1 to 2022.Q2 Chinese A share market. We initially select and adjust the pool of tickets through announcement signals, then use technical analysis methods with machine learning models to make return predictions. Finally, we construct portfolios using Mean-variance optimization on daily frequency. The result shows that the combination of fundamental analysis and machine learning models can generate satisfactory return. The best model can reach annualized return of 59.4% considering turnover fee, beating the market which has annualized return of 3%. The annual sharpe ratio with turnover fee of the best portfolio is 2.28, which is a satisfactory result for investors. Besides, through combining fundamental analysis with quantitative methods, the interpretability and stability of quantitative models are greatly enhanced, which provides a novel way in synthesizing two separate investment concepts. In sum, this paper can provide investors with a relatively novel investment strategy that based on the impact of announcement information on stock price and the combination of fundamental and technical analysis.

Keywords: Announcement, Machine Learning, Mean-variance, Investment.

1. Introduction

Consumption is replaced by investment and saving while people's living standard rises. An increasing number of people start to put their attention on how to improve efficiency and maximize the return on their investment [1]. Two of the main challenge of finding the best investment strategy is portfolio selection and portfolio optimization.

Portfolio selection is the process of finding the "best" allocation of the assets [2]. During the epidemic, while travel and banking declined sharply, some sectors like electric vehicle, digital payments and online retail sectors gain significant growth [3]. This emphasizes the importance of selecting appropriate ticket pool for the portfolio. The selection of assets is always a challenging task due to the uncertainty of the stock market, thus, different from normal procedures, this research focuses on selecting assets based on a kind of alternative data - the public announcements.

Apart from portfolio selection, portfolio optimization is another complex quantitative Finance problem [2]. Prediction of price is an essential step of portfolio optimization. The prices of stock are non-linear, dynamic, and chaotic time series that is difficult to be predicted [4]. Among the several solutions, Machine Learning is one of the most productive ones that deal with a complex and unstable pattern of data [4]. In order to provide more comprehensive insight, the research combines the fundamental analysis and technical analysis in the Portfolio Optimization approach. Fundamental analysis is making an investment decision by looking at the intrinsic value of the stock and the overall trend in the industry and economy [5]. Different from fundamental analysis, technical analysis instead uses previous data of stock to identify the patterns and trends to predict how the future market will behave [5]. Moreover, the accuracy of machine learning to predict returns depends heavily on the consistency of the sample, so stocks picked from a specific category, such as announcement related, could hopefully bring better prediction outcome.

Through academic history, effect of announcements on stock return has been studied before, but studies combining these signals with quantitative strategies are hardly known. In general, the announcement effect generally refers to the impact of any type of news or public announcement on the stock market [6]. The research on the announcement effect has a profound history and is still a very popular topic nowadays. Xu investigated the short-term announcement effect and the influencing factor of share repurchasing of Chinese listed Companies [7]. Wang got the conclusion that there exist positive effect of ownership incentive announcement on stock [8]. This two research are representative of the study relative to the announcement effect. Most of the studies only focus on the economic effect announcement. In contrast, the topic of this article is very novel, a similar study that not only uses announcements as a stock selection strategy but combines them with machine learning for further portfolio optimization. is hardly ever done.

This paper is structured as follows, Section 2 introduces our data source, and section 3 presents the methods and results of our research. Then, discussion based on results will be presented in Section 4. Finally, our results will be concluded in Section 5.

2. Data

Data of stock return is collected from 10JPKA database http://data.10jqka.com.cn/. The time interval of the stock data in the entire ticket pool is from January 2, 2018, to June 28, 2022, which is also the back-testing period of our models. Simple return is employed to evaluate the performance of portfolios. The price we employ to calculate simple return is time average price during the beginning 60 minutes.

The announcement data is utilized as the standard in selecting the first stage tickets pool. The source of the announcement data is DataYes database https://app.datayes.com/. After evaluation and filtering, stocks that relative to three types of announcements, change in shareholding, equity incentive and buyback are involved in the further modeling in rolling basis. For each announcement, several crucial dates will be treated as signals, like the publish date, the date of the shareholders' meeting, the begin date and so on.

3. Method and results

3.1. Framework

The portfolio construction procedure proposed in this article mainly includes four steps: Stock selection, factor selection, machine learning rolling prediction, and mean variance optimization. The overall framework is shown in Figure 1.

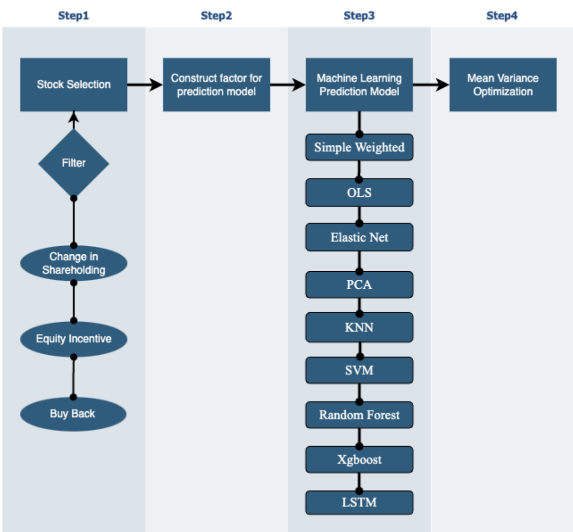

Figure 1. Framework

3.2. Stock pool formation

As we mentioned above, we apply several criteria to filter announcements. In this section, we will discuss our criterion and their rationale.

3.2.1 Change in shareholding

First and foremost, this paper filters the announcements of change in shareholding based on their incentives. In general terms, an increase in holdings is a positive signal compared to decrease in holdings, and an incentive of believing in the company's future is better than personal financial needs. In order to study further, we use "reasons of change" to identify shareholders' incentives. Thus, announcements about behaviors of executives and small shareholders are screened out. Besides, we use the changing reason — "Company's future" as the second filter, and positive shareholding change as the last filter.

Using the filtered data, we calculate the mean cumulative return of both original and filtered data 20 days before and after the event and show it in Figure 2. In the graph, we also calculate the standard deviation of cumulative return to represent risk in investing this incident, and we show the number of signals in the legend.

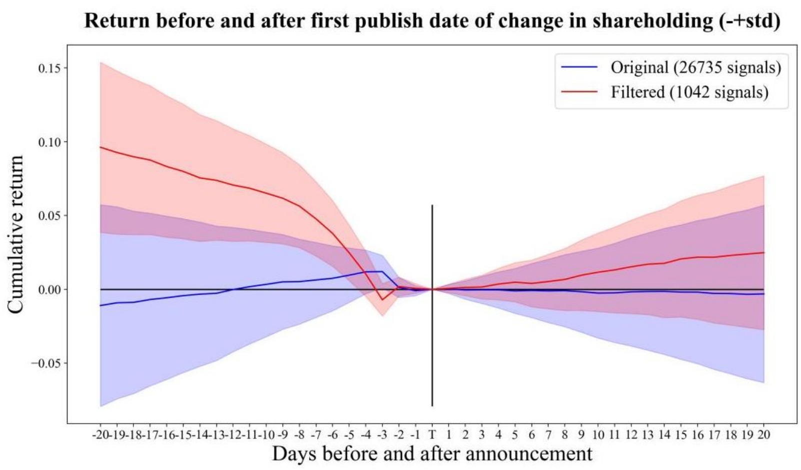

Figure 2. Return before and after first publish date of change in shareholding

From the result, we can see that filtered data can provide better return than original one. Besides, increase in return has already begun before the announcement, meaning that announcement signals suffer slightly time lag.

3.2.2 Equity incentive

This paper filters the announcement of equity incentive based on its subject and mode. The two main categories of subject are option and stock. Referring to the theory of liquidation, options cannot be liquidated immediately to gain income, so stocks will be timelier in comparison. Therefore, we include stock incentive as positive investment signal. Besides, we filter the incidents according to their modes. The three types of modes are Buyback, Handover and Private placement. Handover is the transfer between shareholders within the company, which most likely happens when the strong shareholder sacrifices his own interests to transfer shares toward some executives. Therefore, we keep the announcements related to handover for the follow-up study. Consequently, we keep all announcements of stock incentive, alongside with announcements of option incentives related to Handover for the follow-up study. The results are shown in Figure 3.

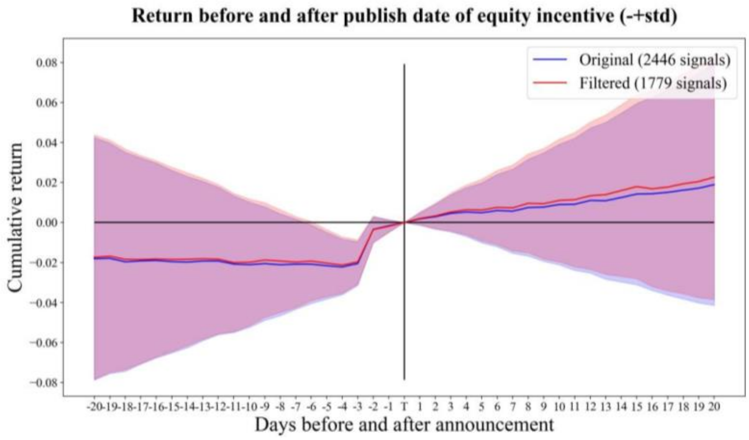

Figure 3. Return before and after publish date of equity incentive

3.2.3 Buyback

Finally, we filter the announcements of buyback based on the incentive of company. Buyback refers to six kinds of mode, which are shown in the following graph. We consider buybacks aiming at market value management and the implementation of convertible bonds as investment signals. This is because these two incentives usually signify positive information. Market value management means buying back some shares to increase market value, which could happen when the company believes that there are profit compensations in the future. Similarly, as a financial tool to raise fund, the implementation of convertible bonds signifies that the company may gain higher earnings from new projects. Consequently, we filter out announcements of buyback aiming at market value management and the implementation of convertible bonds. The results are in Figure 4. We can see that filtering is essential and this signal also suffer a bit from time lag.

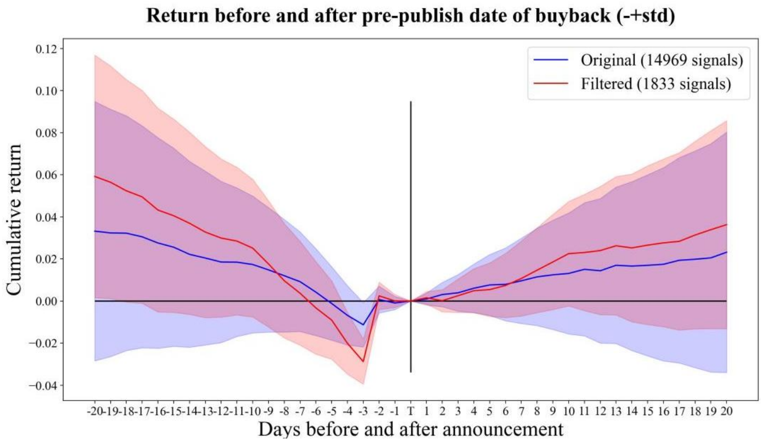

Figure 4. Return before and after pre-publish date of buyback

3.2.4 Generate investment signals

When an announcement signal is triggered, we include these stocks into our stock pool and hold for 20 days before selling them out. By executing this procedure, we can generate a stock pool that changes according to announcements of companies. The weights of each stock held each day are determined by quantitative models which will be discussed later. From Figure 5, we can see that the average number of eligible stocks recorded per day is approximately 50 and can reach up to 200. Accordingly, the sample size is relatively stable and sufficient.

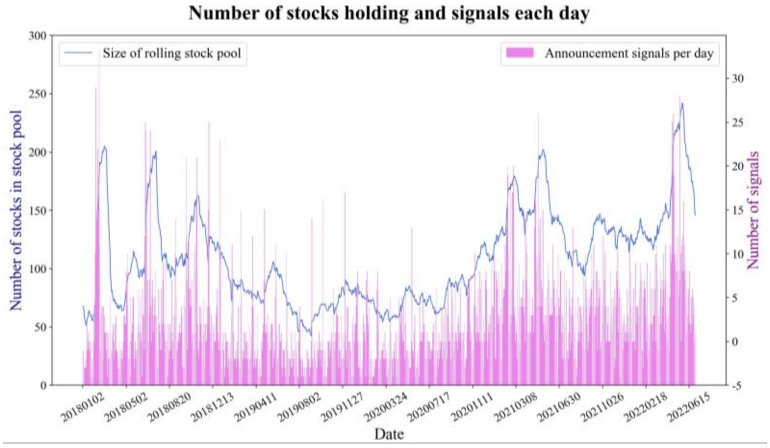

Figure 5. Number of stocks holding, and signals triggered each day

3.3. Factor construction

To determine the weights of stocks in our rolling stock pool, we need to firstly make predictions of stock return based on factors. The theory of factor model originates from CAPM model and Fama French three-factor model. In practice, we define stock and time specific indicators that have correlation with future stock return as factors and use them to make return predictions [9].

In our research, we use only technical analysis indicators as factors since stocks that are experiencing announcements may have similar fundamental properties, rendering fundamental analysis indicators less effective. To be more specific, we construct 42 technical analysis indicators based on 7 categories: MACD, RSI, KDJ, Bollinger band, High moment features, Return features and Trade volume [10]. These include all major aspects of classic technical analysis, including trend, volatility, volume, momentum and so on. We construct 6 factors for each category.

To test the effectiveness of our factors, we calculate the IC (daily correlation between factor and next-day's return) time series of each factor and present it in figure 6. The higher IC the factor has, the more effective the factor is. Results are shown in figure 6.

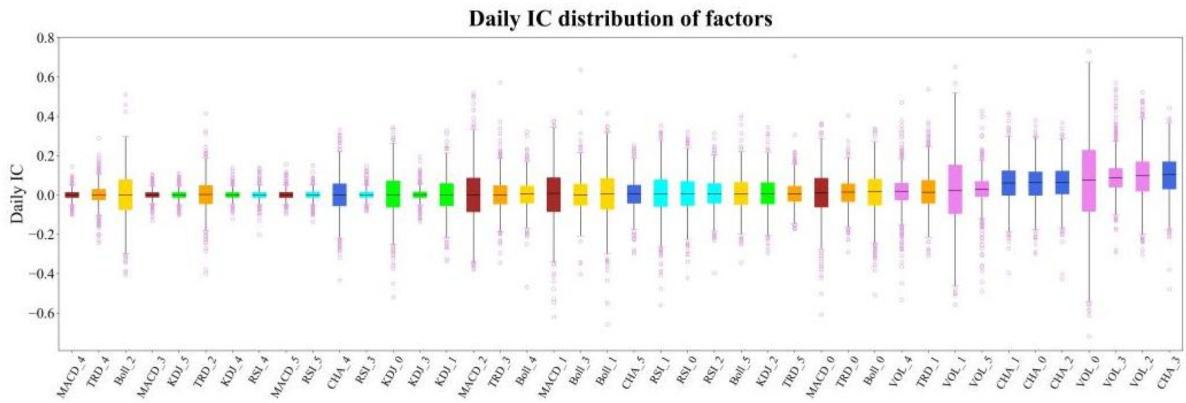

Figure 6. Daily IC distribution of factors

3.4. Prediction using machine learning models

3.4.1 Introduction of machine learning models

To combine the prediction power of our factors, we apply machine learning methods to predict stock return. We use past 60 days as training set to make next day's return prediction. Since our stock pool alters daily, machine learning model is trained on daily basis, using the past 60 days data of the stocks whose return is to be predicted as training set. As for parameters, we apply rather modest parameters based on experience for each model and remain constant throughout the back-testing period to alleviate over-fitting.

Before training, we process our factors to eliminate data noise and outliers. For each factor, we use it to rank our stocks daily and map the ranking to the range between -0.5 and 0.5. The result is used to substitute the original factor. For the stock return in our training set, we linearly map it to the range between -0.5 and 0.5. By doing this, we not only unify the units, but we also relieve the problem of data noise, making our model more robust.

To compare the prediction power of different machine learning models, we applied 8 types of models in our research. They are simple weighted model (EW), ordinary least squares (OLS), principal component analysis (PCA), K-nearest-neighbor (KNN), support vector machine (SVM), random forest (RF), Xgboost (XGB) and long-short term memory (LSTM).

3.4.2 Results of machine learning models

(1) Prediction power of models

To compare the prediction power of our models, we apply the Diebold and Mariano test between pairs of models [9]. This test is based on the comparison of squared residual, where the model with larger squared residual is inferior. To be more specific, we define the test statistic DM [10], where:

$$DM_{12} = \frac{Mean(d_{12,t+1})}{Std(d_{12,t+1})} \tag{1}$$

$$d_{12,t} = \frac{1}{n_{3,t+1}} \sum_{i=1}^{n_{3,t+1}} ((e_{i,t+1}^{(1)})^2 - \left(e_{i,t+1}^{(1)}\right)^2) \tag{2}$$

$e_{i,t+1}^{(1)}$ denotes the prediction error of a model (1) for stock return i at time t, and $d_{12,t+1}$ denotes the error difference between two models 1 and 2 at time t. Therefore, DM_{12} obeys standard t distribution and we can provide p value for our comparison tests. If DM_{12} is significantly lower than zero, than model 1 is significantly superior to model 2. The comparison matrix is shown in table 1.

Table 1. Comparison matrix of machine learning models

	PCA	SVM	KNN	EN	XGB	RF	EW	LSTM
OLS	-7.543***	5.821***	-3.109***	1.159	1.441	3.062***	-6.237***	-0.949
PCA		12.639***	5.877***	7.645***	8.246***	9.673***	1.844*	7.246***
SVM			-10.983***	-5.007***	-4.232***	-3.13***	-10.858***	-5.759***
KNN				3.41***	4.383***	5.81***	-4.012***	2.144**
EN					0.919	2.722***	-6.538***	-1.434
XGB						1.342	-6.949***	-1.994**
RF							-8.655***	-3.426***
EW								9.212***

To elaborate our result, we sort the models based on DM test, and define the DM_{ij} statistic as the gain from model j to model i. On this basis, we plot the cumulative gain of sorted models, with the band representing standard deviation of DM statistic.

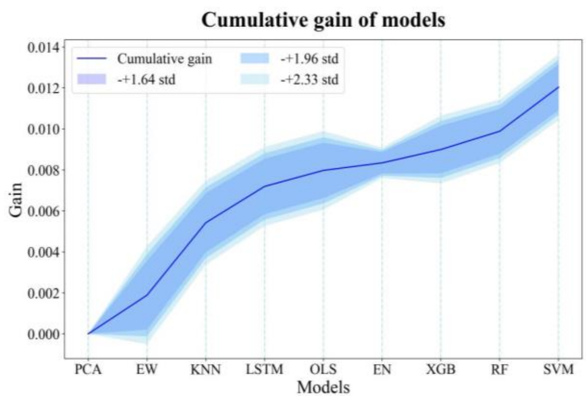

Figure 7. Cumulative gain of models based on DM test

From the result shown in figure 7, we can see that most machine learning models significantly outperforms equal weight benchmark, except unsupervised learning (PCA). Besides, LSTM and OLS has nearly the same prediction power, both inferior to tree models (Xgboost and RandomForest). Finally, SVM is significantly better than any of other models.

This result is not very apparent since sophisticated models like LSTM or Xgboost are not significantly better, even inferior to classic models like OLS and SVM. This is mainly due to over-fitting problem, where sophisticated models may rely too much on distribution of training data set and cannot extrapolate efficiently. However, we need to make clear that good prediction power does not necessarily guarantee good portfolio return, more criterion, like volatility and stability need to be taken into consideration.

3.5. Holding strategy based on prediction

3.5.1 Introduction of portfolio optimization

After machine learning prediction, the Mean-Variance Model is applied to finish the portfolio weight optimization. Mean-variance model is proposed by Markowitz in 1952 to find the best stock portfolio weight that maximize the return on investment and reduce risks. It is a single-period theory provide the optimal trade-off between the mean and variance, which is also the trade-off between the measure of profit and the measure of risk. The following are the relative formula:

$$\sum_i Weight_i = 1 \tag{3}$$

The $Weight_i$ means the weight of assets in the portfolio.

$$\mathrm{E(RP)} = \sum_{i=1}^{n} w_i\, r_i \tag{4}$$

Where Rp is the portfolio return, w_i is the Weight in last formula, r_i is the compound return of the asset data.

$$Variance\ of\ Portfolio = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i\, w_j Cov(r_i, r_j) \tag{5}$$

Where w_i is the weight of asset i, w_j is the weight of asset j, and $Cov(r_i, r_j)$ is the denotes the covariance between the return of the asset I and asset j.

$$\text{Sharpe ratio} = \frac{\mathrm{E}(R_P) - R_f}{\sigma_P} \tag{6}$$

Where R_f is the risk-free rate and σ_P is standard deviation.

3.5.2 Portfolio evaluation

We construct prediction models and compare them with two benchmarks, Index and equal weight model. Index is the equal-weight average of CSI300 index, CSI500 index and CSI 1000 index. We use the mean of three indexes instead of a single index because the former is free of market value style and more stable. Equal weight model means using the mean of factors as prediction of return to construct portfolio. If we can beat the Index which suggests the trend of market, that means our strategy is worth investing. If we can beat equal weight model which is theoretically most ineffective, our strategy is at least working well statistically.

To make thorough comparison, we generate the return and alpha return (return minus index return) both with and without turnover fee. Turnover fee is set 0.05% per trade, based on regulations of Chinese market. The results are as shown in Figure 8-9. We calculate the cumulative return under both scenarios with and without turnover fee.

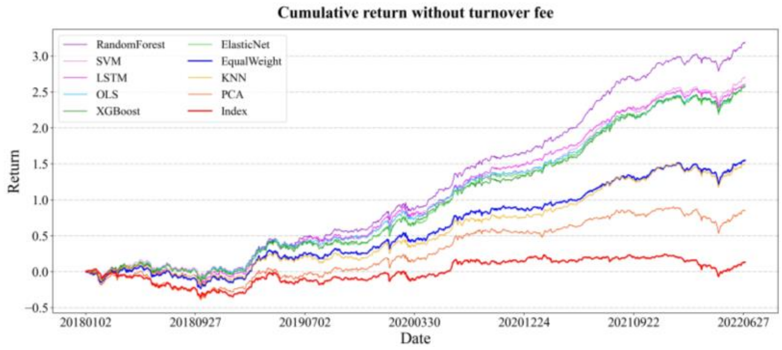

Figure 8. Cumulative return without turnover fee

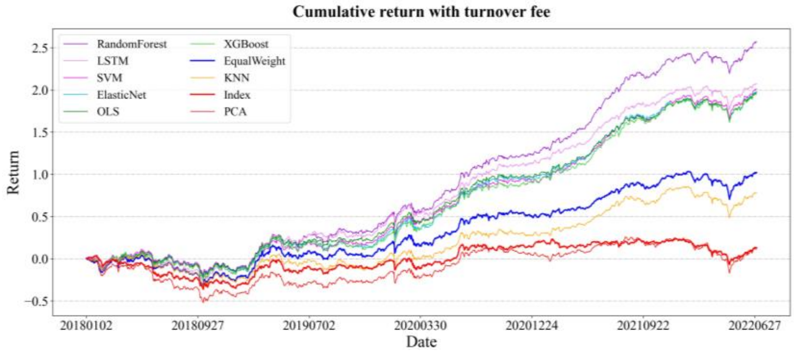

Figure 9. Cumulative return with turnover fee

From the results above, we can conclude that Random Forest model provides the best strategy, outperforming SVM which seems better considering prediction power. Besides, LSTM, OLS, SVM and Elastic Net all performs similar, far better than KNN and equal weight, meaning that machine learning models are effective. Finally, PCA provides the worst strategy unsurprisingly, since it isn't supervised, but it still outperforms benchmark index.

However, when taking turnover fee into consideration, we discover that most strategies provided by machine learning models are hindered. Therefore, turnover rate is crucial when judging machine learning models. To better evaluate strategy performance, we calculate a series of indicators which can reflect the strategy's efficiency from different aspects. The results are shown in table 2 and table 3:

Table 2. Portfolio performance without turnover fee

	OLS	**PCA**	**SVM**	**KNN**	**EN**	**XGB**	**RF**	**EW**	**LSTM**	**Index**
Return	0.597	0.197	0.625	0.347	0.596	0.597	**0.737**	0.358	0.603	0.03
Standard deviation	0.257	**0.236**	0.245	0.24	0.259	0.261	0.26	0.244	0.254	0.199
Sharpe	2.322	0.835	2.557	1.443	2.301	2.283	**2.832**	1.466	2.37	0.152
Max drawdown	0.196	0.171	0.179	0.179	0.195	0.188	0.175	0.186	0.203	**0.162**
IC-IR	0.1	0	0.115	0.052	0.109	0.106	**0.161**	0.048	0.094	-
Turnover rate	1.125	1.352	1.275	1.319	1.092	1.147	1.137	**0.969**	0.978	-

Table 3. Portfolio performance with turnover fee

	OLS	**PCA**	**SVM**	**KNN**	**EN**	**XGB**	**RF**	**EW**	**LSTM**	**Index**
Return	0.455	0.026	0.465	0.18	0.458	0.452	**0.594**	0.236	0.48	0.03
Standard deviation	0.257	0.236	0.245	0.24	0.259	0.261	0.26	0.244	0.254	**0.199**
Sharpe	1.771	0.112	1.901	0.751	1.77	1.73	**2.283**	0.966	1.886	0.152
Max drawdown	0.319	0.535	0.327	0.393	0.313	0.336	0.273	0.364	0.36	**0.162**
IC-IR	0.1	0	0.115	0.052	0.109	0.106	**0.161**	0.048	0.094	-
Turnover rate	1.125	1.352	1.275	1.319	1.092	1.147	1.137	**0.969**	0.978	-

We discover that although strategy constructed by Random Forest has the best return, SVM provides smaller strategy variance and draw-down. Therefore, if investors prefer strategy that is less volatile, SVM may be a better choice than tree models and neural networks. We regard it due to SVM's higher prediction power. This is especially important to portfolio managers since customers normally prefer smoother strategies to volatile ones. However, SVM has higher turnover rate than tree models and linear models, which can be regarded as the trade-off for better prediction power. As a comparison, although LSTM has rather modest prediction power and strategy return, it provides the lowest turnover rate, enabling it to outperform other models when considering high turnover fee.

To sum up, tree models generally outperforms linear models, especially the model Random Forest, which performs best on the whole in. Besides, if investor expect strategies that are less volatile, SVM is recommended since it provides less volatility and smaller draw-down. However, the turnover rate of SVM is rather high, investors better choose LSTM which can generate more balanced results when turnover is hard to perform.

4. Discussion

In this section, we will analyze our result and provide investors recommendations on combining fundamental analysis with technical analysis. We will offer insights in usage of technical analysis and fundamental analysis and delve deeper into factor importance and stock holding pattern of our strategies.

4.1. Feature importance

To analyze the efficiency of technical analysis, we calculated feature importance of different models. Since all of our models are trained on daily basis, the feature importance of a particular feature is calculated by the following method:

$$\text{Feature\_importance}_{\text{i}} = \text{mean}(\text{Feature\_importance}_{\text{it}}) \tag{7}$$

Due to the fact that models have different definitions on feature importance, we apply z-score standardization to each model to clean the scale. The heat-map in figure 10 shows our result:

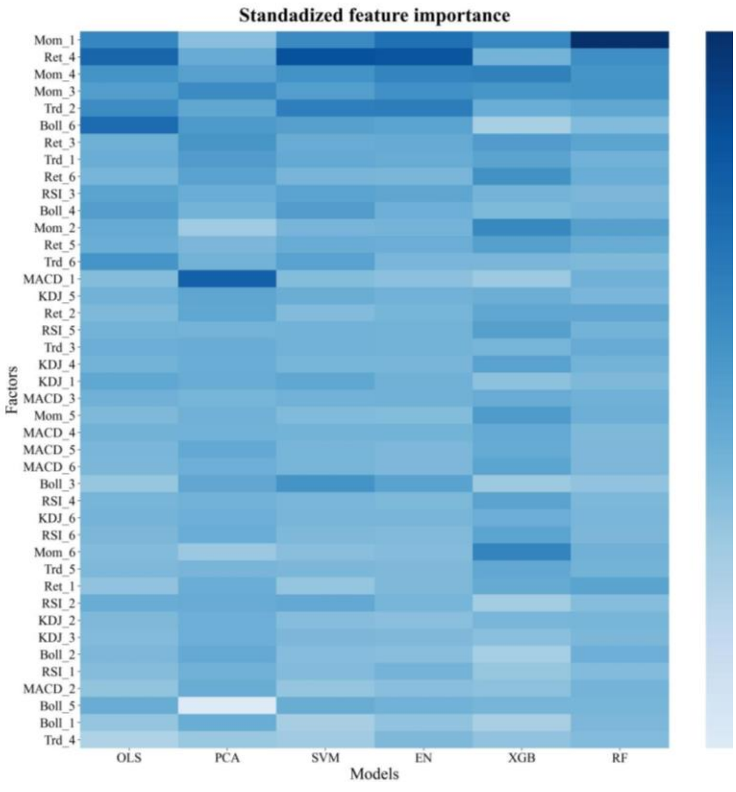

Figure 10. Feature importance

From the result, we can see that high moment features and return features are normally given higher importance, whereas MACD, KDJ, RSI cannot guarantee to be taken seriously. On one hand, this may because of the fact that our indicators are overly simple, therefore cannot provide us much prediction power. On the other hand, it indicates that characteristic of high moment like skewness or kurtosis of return have greater possibility in containing signals that can generate alpha return. Investors can pay extra attention to these features.

Then, we will analyze feature importance given by each model in details. To simplify our analysis, we group the indicators based on 7 categories. Each category's importance is the mean feature importance of its members. We can also get the standard deviation of category's importance, which signifies the consistency of this category. We draw the cumulative feature importance of 7 categories in figure 11, based on OLS and Random Forest model.

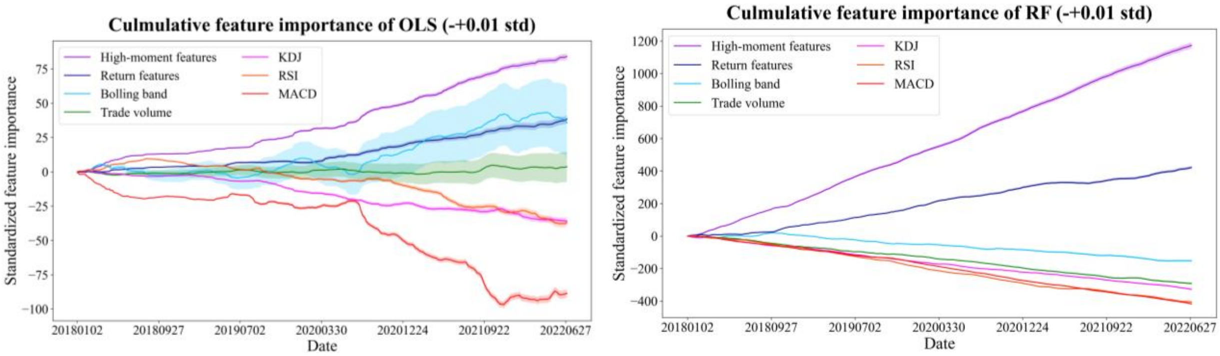

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Figure 11. Grouped feature importance by models

We can conclude that high moment features and return features are indeed taken into serious consideration by most models, whereas other technical analysis indicators pale in importance. Moreover, tree models and elastic net have higher categorical consistency than OLS and PCA models, judging from the bandwidth of feature importance. It means that they tend to assign similar importance to members in the same category, which helps to guarantee the stability and robustness of these models.

To sum up, if investors would like to make return predictions based on technical analysis, they would better use indicators containing high moment information of return. Moreover, tree models are usually more consistent in assigning feature importance, which are suitable for combining technical analysis indicators.

4.2. Actual stock holding

To analyze the real stock holding behavior of our strategies, we calculate the sum of weights of each announcement type for each strategy. Due to the fact that scale varies among different types of announcements, we use the criteria Relative Weight to represent a strategy's inclination on certain announcement. Relative weight is the sum or weight of a particular type of announcement signal in portfolio divided by the sum of weight of this signal.

$$\text{Relative Weight} = \frac{\text{sum(weights of this announcement)}}{\text{percentage(announcement)}} \tag{8}$$

To get a general understanding of the picture, we aggregate the results by calculating the daily mean Relative weight of all models. By doing this, we can also get the standard deviation of Relative weight, signifying the consistency among different models. The more lucrative an event is, the more importance our strategy will attach to this event, which manifests itself in assigning larger weights for relevant stocks. Besides, if the standard deviation of a type of announcement is high, it means that our models don't agree on its benefit, which generally leads to the fact that this particular announcement is not that lucrative. The results are as shown in figure 12:

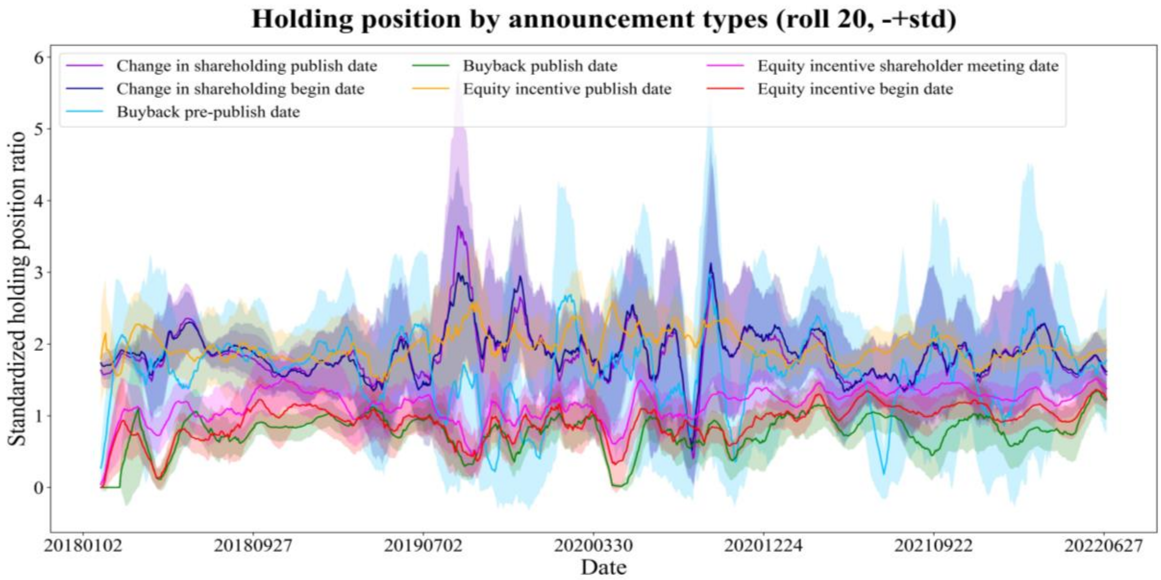

Figure 12. Holding position by models

From the graph above, we can derive the following conclusions: Firstly, our strategies tend to focus more on publish dates than others. It is due to the fact that benefit of announcement will gradually wear off as time goes by, therefore, the return predicted will drop if the model is correct, ending up in less shareholding after initial announcement. This hypothesis can be supported by announcement return description in Section 3.

Secondly, the effect of change in shareholding last longer than other announcements, since change publish date and the following begin date both bear great importance, with little sign of expiring. This may be attributed to the strong incentive behind change in shareholding, which is mostly because of confidence in company's future according to our analysis. Conversely, announcements like buyback and equity incentive have rather opaque incentives.

Thirdly, quality of initial stock pool affects the stability of machine learning models. Pre-publish date of buyback and change in shareholding has high volatility, meaning that the effects of these announcements are not agreed consistently among models. Therefore, benefit in investing these incidents is not guaranteed, which is true according to the inferior initial quality of these announcements. Equity incentive, on the other hand, has better return at the beginning, and machine learning models appear to be more stable when making predictions. Therefore, we reach a conclusion that quality of stock pool can enhance interpretability and stability of quantitative models.

To sum up, announcements of equity incentives are more promising than others, and buyback announcements cannot guarantee benefits. Moreover, the effect generated from change in shareholding can normally last longer due to the strong incentive behind it. Finally, the likelihood of bringing benefit is correlated with the stability of machine learning models. In other words, models are more likely to reach consensus and produce stable strategies if the original stock pool is able to produce considerable benefits.

5. Conclusion

In summary, this paper investigate the possibility of combining announcement signals and quantitative strategies to make investment decisions. Different from previous study of portfolio management, our research focuses on distinctive type of companies who has just launched an announcement, which has strong financial logic and can be directly utilized by investors. Moreover, combining announcement signals with machine learning prediction and portfolio optimization also provides insights on a new way of investment, which is fundamental analysis based quantitative investment.

From our result, we can derive the following three conclusions. Firstly, by selecting announcements through the inner incentives of companies, we are able to construct a rolling stock pool that can provide us considerable benefit alone. It is necessary to point out that the criterion we selected are simple and based on strong financial logic rather than results of data mining.

Moreover, technical analysis and machine learning based portfolio optimization can significantly enhance return of our strategy, but different models have unique characteristics which need to be judged by preference of investors. In details, for selecting technical indicators, high moment features normally contain considerable alpha benefits. For choosing machine learning models, random forest behaves best in this scenario, meanwhile SVM can provide better prediction and generate less volatile portfolio. However, SVM and tree models all have high turnover rate when construction strategies, whereas LSTM can generate strategies with less turnover rate, more suitable for scenarios with high trading fee. Investors can choose indicators and models according to their own preference.

Finally, fundamental analysis based quantitative strategy can generate satisfactory results. We discover that the stability of quantitative analysis is correlated with the initial quality of the stock pool, which is determined by the effect of announcements. Therefore, combining fundamental analysis with quantitative investment can not only enhance the interoperability of strategy, but can also ameliorate prediction power and stability of machine learning models, which is a considerable improvement on purely black-box quantitative investment strategy. As a result, creating initial stock pool with stocks that have similar characteristics using fundamental analysis can effectively enhance the power of quantitative investment, which can be applied to other scenarios other than announcements in real world investment.

Our research can benefit scholars and investors from the following aspects. Firstly, this is a study focusing on Chinese stock market using unique incidents and newest data, an area scarcely discussed by previous studies. Besides, our results not only provide effective investment strategy for investors, but also thoroughly discuss the effects of multiple models and its outcomes, making the conclusion more convincing. Finally, our study discusses the possibility of combining fundamental analysis with quantitative analysis, which has long been two separated areas with little connection.

Admittedly, there exist space for further research. For instance, the announcements we used in this research isn't complete. Other announcements like analyst reports and rankings published by research institutions can also be taken into consideration. Moreover, we didn't discuss every major quantitative method in this paper, which needs further research to elaborate and improve. Apart from these drawbacks, this paper provides an intuitive way of asset allocation, which can yield satisfactory results.

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