Trading Strategy Based Portfolio Selection for Actionable Trading Agents

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Abstract. Trading agents are very useful for supporting investors in making decisions in financial markets, but the existing trading agent research focuses on simulation on artificial data. This leads to limitations in its usefulness. As for investors, how trading agents help them manipulate their assets according to their risk appetite and thus obtain a higher return is a big issue. Portfolio optimization is an approach used by many researchers to resolve this issue, but the focus is mainly on developing more accurate mathematical estimation methods, and overlooks an important factor: trading strategy. Since the global financial crisis added uncertainty to financial markets, there is an increasing demand for trading agents to be more active in providing trading strategies that will better capture trading opportunities. In this paper, we propose a new approach, namely trading strategy based portfolio selection, by which trading agents combine assets and their corresponding trading strategies to construct new portfolios, following which, trading agents can help investors to obtain the optimal weights for their portfolios according to their risk appetite. We use historical data to test our approach, the results show that it can help investors make more profit according to their risk tolerance by selecting the best portfolio in real financial markets.

Keywords: Trading Strategy, Portfolio Selection, Trading Agent.

1 Introduction

Trading in electronic markets is increasingly recognized as a promising domain for agent technology within the artificial intelligence field. Trading agents play a significant role in evaluating programmed trading techniques and developing automated strategies in electronic financial markets [15,17], and consequently, the development of trading agent competition [4] (for example, design tradeoffs [12]) has received increasing attention.

Most of the current trading agent research focuses on problems designed in an artificial marketplace with simulated data [3,14]; little attention has been paid to problems in real financial markets, which leads to the lack of practical application for business people, who have their own business preferences. How

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trading agents help investors to manipulate their assets according to their risk appetite and then obtain greater return is a big issue.

Many researchers and market participants may choose the right portfolio to resolve the above issue. Because the application of a right portfolio is a very powerful tool in risk control [11], that is to say investors can mitigate risk by allocating capital to various assets with different weights. Portfolio theory was first introduced by Harry Markowitz in [5] and it has attracted significant attention in practice and in the academic field. The principal rule is to maximize the expected return for a given level of risk, or to minimize the risk based on expected return. With the continuous effort of various researchers, Markowitz's work has been widely extended, but most of the literatures focuses on how to find a better mathematic method to estimate corresponding parameters and gain an optimal return which is closer to the theoretical optimal return. Trading strategy as an important factor that is often ignored in the literature to date.

Trading strategies have been proposed in financial literatures and trading houses to support trading investment decisions. The right trading strategies can assist trading agents in determining the right actions at the right time at the right price [3], so if we import trading strategy into the portfolio optimization problem, we can capture more profitable trading opportunities. Secondly, in practical financial markets, investors always use trading strategies to conduct transactions, so it is not reasonable if we ignore the trading strategies that have been used in the portfolio selection process. In addition, from the view of trading strategy independently, different trading strategies will generate different signals (buy, sell, hold) for one asset, which will lead to different returns. It is not available to choose the profitable one for every investor for their different risk appetite. A trading strategy which produce more return at a period may mean more volatility, namely a higher risk is accompanied when compared to other trading strategies. From this point, the demand for trading agents to be more actionable to provide more proper trading strategies is increasing.

From the above we can see that real financial markets are full of uncertainty, it is not enough to select right portfolios to obtain more profit only through improved mathematical methods. Trading strategy as an important factor also need to be accounted. As for trading strategies, since the global financial crisis in 2007 adds the uncertainty in financial markets, there is increasing demand for trading agents to be more actionable to provide trading strategies for better trading opportunities in financial markets. All of these lead to our concern on how to combine trading strategies and portfolio selection process. In this paper, we develop a new approach to select the right portfolio for trading agents, namely trading strategy based portfolio selection. The system works as follows: for given trading strategies and assets at a time window, firstly we combine every asset and every trading strategy, then we compare the performance of corresponding combinations for each asset; after this we delete the combinations with bad performance. In addition, we use an improved estimation method to obtain the optimal weights for the selected combinations.

The rest of the paper is organized as follows. Section 2 reviews the work related to this paper: trading strategy, portfolio theory and related estimation methods. The framework of our trading agent is illustrated in Section 3. Empirical experiments and evaluation are illustrated in Section 4. We draw conclusions in Section 5.

2 Background

2.1 Trading Strategy

Trading strategies are widely used by financial market traders to assist them in determining their investment or speculative decisions [2], in which way they can make higher profit with lesser risk. A trading strategy indicates when a trading agent can take what trading actions under certain market situation. It is governed by a set of rules that do not deviate. Herein, an example is given: a general Moving Average (MA) based trading strategy.

Example (MA trading strategy) An MA trading strategy is simply an average of current and past prices over a specified period of time. An MA of length l at time t is calculated as

$$M_t(l) = \frac{1}{l}\sum_{i=0}^{l-1} P_{t-i} \tag{1}$$

where p_{t-i} is the price at time $t-i$. Many kinds of trading strategies can be formulated based on MA. A filtered MA strategy (denoted by $\mathrm{MA}(l,\theta)$) compares the current price p_t to its MA value M_t, if p_t rises above M_t by more than a certain percent θ, the security is bought and held until the price falls below MA more than θ percent at which the security is sold. Such trading signals s_t are generated according to Equation (2).

$$s_t = \begin{cases} -1 & \begin{array}{l} if\, P_t > (1+\theta)M_t(l)\, and\, P_{t-u} < M_{t-u}(l) \\ and\, M_{t-i}(l) \le P_{t-i} \le (1+\theta)M_{t-i}(l), \\ \forall i \in \{1,\cdots,u-1\} \end{array} \\ \\ 1 & \begin{array}{l} if\, P_t < (1-\theta)M_t(l)\, and\, P_{t-v} > M_{t-v}(l) \\ and\, M_{t-i}(l) \ge P_{t-i} \ge (1-\theta)M_{t-i}(l), \\ \forall i \in \{1,\cdots,v-1\} \end{array} \\ \\ 0 & otherwise \end{cases} \tag{2}$$

where u and v are arbitrary positive integers, -1 means 'buy', 1 means 'sell' and 0 means 'hold' or 'no action'. In real life trading, trading strategies can be categorized into different classes and a trading strategy class can further be instantiated into different types of trading strategies by different constraint filters. For instance, Moving Average MA discussed above is a common trading strategy, it can be instantiated into several types by different applications of θ. If

$\theta = 0$, it is shrinks to a simple MA. Investors can obtain various results through changing parameters l and θ according to their own risk appetite.

Another three classes of trading strategies: Filter Rules, Support and Resistance and Stochastic Oscillator strategies [13,16] are applied in the experiments in Section 4 which are described below briefly.

Filter Rules (denoted by $FR(l, \theta)$) indicates that if the daily closing price of a particular security moves up at least θ percent, buy and hold until its price moves down at least θ percent from a subsequent high, at which time sell and go short, the short position is maintained until the daily closing price rises at least θ percent above a subsequent low at which time one covers and buys. A high/low can be defined as the most recent closing price that is greater/less than the l previous closing prices.

Support and Resistance (denoted by $SR(l)$) suggests to buy/sell when the closing price exceeds the maximum/minimum price over the previous l days.

Stochastic Oscillator strategies (denoted by $K/D(x, y)$) generate a buy/sell signal when $\%K$ line crosses a $\%D$ line in an upward/downward direction. x, y here are the numbers of periods used to compute the $\%K$ and $\%D$.

2.2 Portfolio Theory

Every investor who wants to get more return subject to a given risk through allocating his capital among different assets within a market will face asset portfolio problem. Markowitz is the father of portfolio theory, he introduced the theory in [5] and then won the Nobel Prize in Economic Sciences for the theory. According to this theory, investors respond to the uncertainty of the market by minimizing risk subject to a given level of expected return, or equivalently maximizing expected return for a given level of risk. These two principles led to the formulation of an efficient frontier from which an investor could choose his or her preferred portfolios, depending on individual risk tolerance. This is done by choosing the quantities of various assets cautiously and taking mainly into consideration the way in which the price of each asset changes in comparison to that of every other asset in the portfolio. In other words, the theory uses mathematical models to construct an ideal portfolio for an investor that gives maximum return depending on his or her risk appetite by taking into consideration the relationship between risk and return.

The mean-variance (MV) model introduced by Markowitz plays an important role in the portfolio problem. It is a bi-criteria optimization problem in which the expectation of return and risk are combined. It has triggered a large amount of research activities in the field of finance for optimal portfolio choice, but it is fraught with practical problems. The main problem is that the estimation error exists in computing the expected returns and the covariance matrix of asset returns. So far researchers (for example, [8,1]) all believe that the reason of the estimation error is the "optimal" return is formed by a combination of returns from an extremely large number of assets, this will lead to over-prediction. In recent years, many attempts have been undertaken to ease the amplification of the estimation error. In [9], authors suggested that imposing the nonnegativity constraint on portfolio weights can make the process more intuitive. Authors in [1] developed new bootstrap-corrected estimations for the optimal return and its asset allocation and proved these estimates are proportionally consistent with their theoretic counterpart.

In our paper, we use a new and improved estimation method introduced by [10] to compute our trading strategies based portfolios. Authors in [11] pointed out and analyzed the limitation of estimators proposed by [1]. Based on this, they presented a new and improved estimator for the optimal portfolio return which can circumvent the limitation. They proved that the new and improved estimated return is consistent when sample size $n \to \infty$ and the dimension to sample size ratio $c/n \to z \in (0, 1)$. They also illustrated that their estimators dramatically outperformed than traditional estimators through their simulation, especially when c/n is close to 1. This is very useful for our issue, because when combined different trading strategies to assets, the sample size c will become much larger than the number in the situation only consider allocation of assets.

3 Modeling Framework

3.1 Trading Agent Framework

The working mechanism of trading agents is represented in Fig.1.

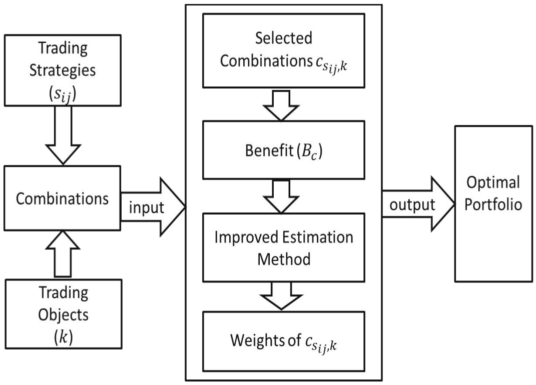

Fig. 1. Framework of actionable trading agents

The working mechanism of actionable trading agents is as follows:

Step 1. For given trading strategies, the agents combine every trading object with every trading strategy. A combination $C_{s_{ij},k}$ indicates the state that an trading agent uses the $s_{ij}th$ trading strategy on kth trading object. s_{ij} represents the jth trading strategy taken from trading strategy class i. Fig.2 is an example of the combinations of two trading objects and four trading strategies from two trading strategy classes. The combinations are inputs in the process.

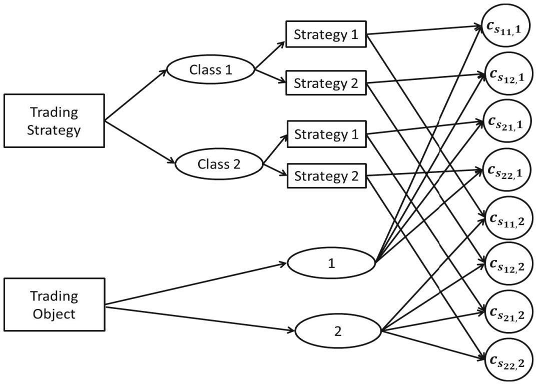

Fig. 2. An example of combination

Step 2. In this step, we do a selection of the combinations obtained from Step 1. For each trading object, we delete those corresponding combinations with bad performance, and leave the remaining for trading agents. Here we use two variables to test the applicability of the obtained combinations, namely return R and volatility σ. For a trading object, we need to compute the return and volatility with the corresponding combinations; then we compared each combination with others to decide which combinations can be abandoned.

For example, there are four combinations $C_{s_{11},1}$, $C_{s_{12},1}$, $C_{s_{21},1}$ and $C_{s_{22},1}$ for trading object 1, the selection process is listed in Fig.3. $\exists C_{m,1}, C_{n,1},\ m,n \in \{s_{11}, s_{12}, s_{21}, s_{22}\}$, if $R_{m,1} < R_{n,1}$ and $\sigma_{m,1} > \sigma_{n,1}$, then $C_{m,1}$ should be deleted.

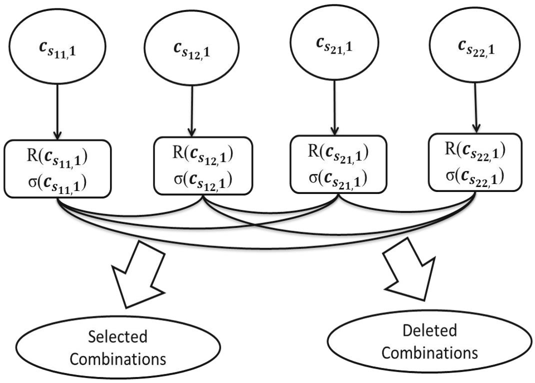

Fig. 3. An example of selection

Step 3. We calculate the benefit of the combinations obtained in Step 2. Here we use the log return to generate the benefit B_C according to signals produced by the corresponding trading strategies. A trading strategy s_{ij} may produce three trading signals in transactions: $\{-1, 0, 1\}$, where -1 indicates a buy signal, 1 indicates a sell signal and 0 means hold or no action. In our process, for example, the benefit for a combination at time t is computed as $B_{C_t} = \log p_t - \log p_{t-1}$ from the generation of a buy signal to that of a sell signal. The benefit for the trading object is 0 in a interval from a sell signal is generated to a buy sinal is generated. Because at this period the object was sold, so the money did not have any change. In addition, in order to simplify the complexity in calculation and make it easier to compare, the volume here equals to 1.

Step 4. Based on the benefit obtained from Step 3, in this step we put these benefits into an improved estimation method to calculate the optimal weights for the selected combinations with a given level of risk. A brief introduction of the method was put in Section 3.2. According to the optimal weights, the trading agent can obtain the optimal portfolio which lead to optimal return.

3.2 Improved Estimation on Markowitz Mean-Variance Analysis

Suppose that there exist c assets in a portfolio, $p = (p_1, p_2, ..., p_c)^T$, and the return denoted by $B = (b_1, b_2, ..., b_c)^T$ follows a multivariate normal distribution with mean $\mu = (\mu_1, \mu_2, ..., \mu_c)^T$ and covariance matrix Σ. According to Markowitz's mean-variance model, an investor who invests capital M on the assets wants to maximize her/his return subject to a given risk, namely try to find an optimal weight $W = (w_1, w_2, ..., w_c)^T$ to maximize portfolio return while keeping the risk level under a specific level σ_0^2. The above maximization problem can be formulated below:

$$R = max\, w^T \mu \text{ subject to } w^T \Sigma w \leq \sigma_0^2 \text{ and } w^T \mathbf{1} \leq 1 \tag{3}$$

where $\mathbf{1}$ represents a c dimensional vector of ones and σ_0^2 indicates the risk level that an investor can suffer. Here we assume that the total portfolio weight $\sum_{i=1}^{c} w_i \leq 1$ for without of generality. Hence, the goal is to find R and W that satisfied the above equation.

From [6,7,1] we can obtain the analytical solution to the problem stated in Equation (3) as follows:

$$w = \begin{cases} \frac{\sigma_0}{\sqrt{\mu^T \Sigma^{-1} \mu}} \Sigma^{-1} \mu, & if \frac{\mathbf{1}^T \Sigma^{-1} \mu}{\sqrt{\mu^T \Sigma^{-1} \mu}} \sigma_0 < 1 \\ \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} + d[\Sigma^{-1} \mu - \frac{\mathbf{1}^T \Sigma^{-1} \mu}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \Sigma^{-1} \mathbf{1}], & otherwise \end{cases} \tag{4}$$

where $d = \sqrt{\frac{(\mathbf{1}^T \Sigma^{-1} \mathbf{1}) \sigma_0^2 - 1}{(\mu^T \Sigma^{-1} \mu)(\mathbf{1}^T \Sigma^{-1} \mathbf{1}) - (\mathbf{1}^T \Sigma^{-1} \mu)^2}}$

Equation (4) provides the solution, and the critical issue here is how to estimate μ and Σ because they are unknown in practical applications. A simple and natural way is to use the corresponding sample mean $\bar{X}$ and sample covariance matrix S, respectively. This type of estimation has been proved to be a very poor estimate method in [1] for its over-prediction problem, namely the expected return using this method is always larger than the theoretic optimal return.

Instead of using the above sample estimates, in this paper we use another estimate method developed by [10], they propose the unbiased estimators to construct the efficient estimators of the optimal return. The expectation properties of these estimators are as follows:

$$\begin{cases} E[\frac{n-c-2}{n-1}S^{-1}] = \Sigma^{-1} \\ E[\frac{n-c-2}{n-1}\mathbf{1}^T S^{-1}\bar{X}] = \mathbf{1}^T\Sigma^{-1}\mu \\ E[\frac{n-c-2}{n-1}\mathbf{1}^T S^{-1}\mathbf{1}] = \mathbf{1}^T\Sigma^{-1}\mathbf{1} \\ E[\frac{n-c-2}{n-1}\bar{X}^T S^{-1}\bar{X} - \frac{c}{n}] = \mu^T\Sigma^{-1}\mu \end{cases} \tag{5}$$

where n is the number of sample from $N_c(\mu, \Sigma)$ distribution, $\bar{X}$ and S are sample mean and sample covariance matrix, respectively. We assume $n - c - 2 > 0$ here.

The above unbiased estimation can be used to correct the corresponding return and weight in the optimization issue, and the improved estimators can be obtained as follows:

$$w_I = \begin{cases} \frac{\sigma_0 f S^{-1}\bar{X}}{\sqrt{f(\bar{X}^T S^{-1}\bar{X}) - \frac{c}{n}}}, \; if \frac{f(\mathbf{1}^T S^{-1}\bar{X})}{\sqrt{f(\bar{X}^T S^{-1}\bar{X}) - \frac{c}{n}}}\sigma_0 < 1 \\ \\ \frac{S^{-1}\mathbf{1}}{\mathbf{1}^T S^{-1}\mathbf{1}} + f d_I[S^{-1}\bar{X} - \frac{\mathbf{1}^T S^{-1}\bar{X}}{\mathbf{1}^T S^{-1}\mathbf{1}} S^{-1}\mathbf{1}], otherwise \end{cases} \tag{6}$$

where $d_I = \sqrt{\frac{f(\mathbf{1}^T S^{-1}\mathbf{1})\sigma_0^2 - 1}{[f(\bar{X}^T S^{-1}\bar{X}) - \frac{c}{n}](f\mathbf{1}^T S^{-1}\mathbf{1}) - (f\mathbf{1}^T S^{-1}\bar{X})^2}}$ and $f = \frac{n-c-2}{n-1}$.

The correspondingly improved estimator for the optimal return can be estimated by $R_I = w_I^T \bar{X}$.

4 Empirical Experiments and Evaluation

In order to verify the performance of our approach, we conduct two experiments which explore different aspects of the problem. We compare our approach with two other approaches in the experiments: Approach 1: portfolios of 12 indexes produced by the improved estimation method illustrated in Section 3; Approach 2: portfolios of 12 indexes with equal weights. From the comparison with Approach 1 which does not consider trading strategies, we can test the usefulness of trading strategies, we can see to what extent our approach performs better than the movements of all indexes through the comparison with Approach 2.

In the first experiment, in order to test the performance of our approach in forecasting, the data is divided into four time periods. Each period consists of one year of data to estimate the optimal weights for corresponding portfolios.

The following month of data is used to compute the return of our approach and two other approaches. Thereafter, their performance is compared.

In the second experiment, we compare the performance of our approach with that of two other approaches in the whole period.

4.1 Data Description

In this paper, we illustrate the applicability of this trading strategy based portfolio selection approach on the investment of stock market indexes in 12 European Countries. As shown in Table 1, all these indexes are taken as price indices. We use daily closing prices of the component indexes listed in Table 1 from January 2006 to January 2012. The data is obtained from yahoo finance (http://finance.yahoo.com) in our experiments. Because different countries own different holidays and then lead to differences on trading days among the 12 countries, we delete the days that some countries are missing and only choose the trading days that all countries have trading. The method of computing the daily benefit for each index is listed in Section 3. We select two trading strategies from each of the four trading strategy classes for our application: Moving Average (MA(10,0.001), MA(50,0.005)), Filter Rules (FR(5,0.005), FR(10,0.001)), Support and Resistance (SR(5),SR(10)) and Stochastic Oscillator strategies (K/Dfast(7,7), K/Dslow(7,7)), the total number of trading strategies is eight.

Table 1. Trading Countries and Indexes

Country	Index	Country	Index	Country	Index
France	^FCHI	Austria	^ATX	Sweden	^OMXSPI
U.K.	^FTSE	Germany	^GDAXI	Portugal	GERAL.NX
Switzerland	^SSMI	Spain	^SMSI	Netherlands	^AEX
Norway	^OSEAX	Ireland	^ISEQ	Belgium	^BFX

4.2 Experimental Results

A. Testing for Forecasting

In this section the data is divided into four time periods for estimation and forecasting. These four periods are given in Table 2 [1]. Each period consists of one year of data for estimation. Here we use data beginning and ending at the middle of the year to avoid possible effect of the end of the calendar year. The benefit of the following month is then used to compute return of our approach (R_O), compared with that of Approach 1 (R_1) and Approach 2 (R_2).

In order to compute the optimal weights, we need to specify the maximum risk level σ_0 in each period. Here we use the standard deviation of the average of all the index benefit of each period to give us an approximate risk level. Suppose

[1] The number of the trading days of an index is too few from 09/09 to 12/09 and from 02/10 to 04/10, so here we delete the test from 07/09 to 06/10.

the standard deviation is $s(t), t = \{1, 2, 3, 4\}$, in this test we set $\sigma_0(t) = \frac{1}{5} \times s(t)$ to calculate the weights and then generate the corresponding return. The final results are shown in Table 2.

Table 2. The return of three approaches

Data	Test	R_O	R_1	R_2
07/06-06/07	07/07	-0.0028	-0.0361	-0.0345
07/07-06/08	07/08	-0.0352	-0.0229	-0.0432
07/08-06/09	07/09	0.1236	0.0325	0.0778
07/10-06/11	07/11	-0.0034	-0.0338	-0.0402
mean		0.0206	-0.0151	-0.0100

The means of the returns are displayed in the last row. From Table 2 we can see when compared with Approaches 1 and 2, our approach performs better. Specifically, our approach can generate more profit when financial markets go up and decrease loss when go down.

B. Backtesting

In this section, we mainly test the performance of our approach through the entire period from January 2006 to January 2012. There was a big change in financial markets during the period, namely financial crisis. The financial market was bull market before 2007 and investors can obtain profit easily, but the stock market experienced a big crash when encountered with the global financial crisis originated by the United States subprime mortgage market in 2007, after which the stock market was in oscillation. We want to see the performance of our approach under the fluctuant environment, when compared with two other approaches. The risk level is $\sigma_p = \frac{1}{5} \times s$, s here is the standard deviation of the average of all the index benefits of the entire period. The results of performance are shown in Fig.4.

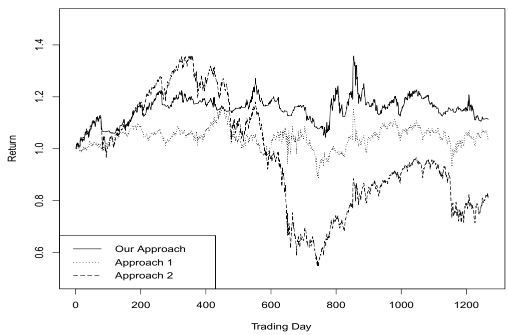

Fig. 4. The performance of three approaches

From Fig.4 we can see that our approach can help investors get a more stable return than other two approaches through the whole period. Investors who use our approach can avoid the big loss in the big crash created by the crisis. The results illustrate the practicality of our approach.

In addition, return volatility is an important factor that investors need to pay attention to. For securities, the higher the return volatility means a greater chance of a shortfall when selling the security in a future date, namely the investor need to face more risk. So here we compare the return volatility of our approach (risk level here is $\frac{1}{5}$) and two other approaches. The results are shown in Fig.5.

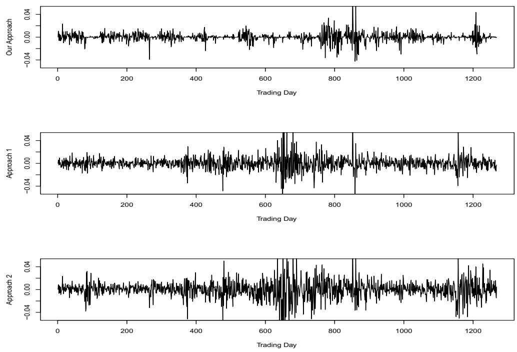

Fig. 5. The return volatility of three approaches

It is clear from Fig.5 that our approach own smaller return volatility than two other approaches. It means that when investors use our approach to make decision, the possibility of losing money is smaller.

A large amount of tests in index data of 12 countries have shown that our approach can lead to higher profit with lower risk when compared with two other approaches. From which we can see the usefulness of importing trading strategies and the superiority of our approach when compared with equally weighted indexes.

5 Conclusion

The marriage of trading strategy with portfolio is expected to greatly enhance the actionability of trading agents, while this has not been explored. This paper has proposed an approach for trading strategy based portfolio selection for trading agents by considering investor risk preference. This approach can enable trading agents to select optimal portfolios which best match investor's risk appetite based on recommended trading strategies. Six years of 12 individual markets data has been used for backtesting. The empirical results have indicated that our approach leads to effective increase of investment return for give risk, and thus strengthen the actionable capability of trading agents in the market.

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