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A clustering-based portfolio strategy incorporating momentum effect and market trend prediction☆

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ABSTRACT

The hierarchical clustering algorithm has been proved useful in portfolio investment, which is one of the hottest issues in finance. In our new portfolio strategy, central, peripheral and dispersed portfolios constructed from clusters detected using unweighted and weighted modularity are compared according to their past performances, and the optimal portfolio is used in the investment period only if the market index return predicted by the LR, WMA or BP models is positive to avoid losses when the market drops. Our strategy is tested using the daily data of Chinese A-share market from January 4, 2008 and December 31, 2016, and the average investment return during different moving investment periods and 200 repeated runs is calculated. We find that although incorporating dispersed portfolio into our strategy has no significant effect in raising the investment return, it shows a similar performance as the peripheral portfolio, and the strategy constructed using unweighted modularity generally outperforms its counterpart by using weighted modularity. In addition, the market trend prediction can refine the investment return of our strategy. In brief, the strategy constructed using the BP model and unweighted modularity has the best investment return, which also outperforms the Markowitz portfolio.

1. Introduction

A great number of studies have focused on the analysis of portfolio optimization due to its important application value in portfolio investment. Scholars have put forward many theories and frameworks of optimizing portfolios with the purpose of raising profits and reducing risks. The framework of Markowitz portfolio optimization theory is one of the milestones in modern finance theory for optimal portfolio construction, weight allocation and asset diversification [1]. The research on the application of this framework has subsequently encountered many restrictions such as the influence of noise on covariance estimation [2,3], constraints including short selling, cardinality and bounding [4–6], and requirement of a set of pre-selected stocks [7,8]. Many methods and approaches, for example, the random matrix theory (RMT) and the filtering method [9,10], artificial neutral networks [5], and the genetic algorithm [11], the K-means algorithm [7], and the network clustering method [8,12–14] have been put forward to solve these restrictions respectively. In most of these studies, the stocks selected from clusters or communities detected by specific classification methods are used to build portfolios.

The clusters or communities detected by the hierarchical clustering analysis of the correlation-based network of the stock market can provide useful information about the correlations among stocks, for instance, industry classification [12,15,16], regional classification [17], and financial risk [18–20]. Previous studies have proposed many efficient ways of selecting portfolios from classified clusters or communities based on their locations in the network, and many of them have been proved to be successful. The research of the minimum spanning tree (MST) [21] conducted by Onnela et al.has shown from the aspect of diversification that, the stocks in the optimal Markowitz portfolio are always located on the outer leaves of the tree [12,22]. Similarly, using the filtered graphs like MST and planar maximally filtered graphs (PMFG), Pozzi et al.found that the portfolios compromising a selection of peripheral stocks were most successful in diversifying, having both lower risks and higher returns than portfolios made up of a selec-

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tion of central stocks. To identify the central or peripheral stocks, the hybrid centrality indices grouping together common centrality/peripherality measures have been used [13]. Taking market trends into account, it has also been found that the optimal choice varies between central portfolios and peripheral portfolios under different market conditions [23].

Apart from these studies, some novel methods have been integrated to build portfolios from single clusters with higher returns and lower risks. Choudhury et al. proposed a novel Self-Organizing Maps (SOM) based on hybrid clustering method, which was proved to be efficient for the selection of optimized portfolios that investors can use for risk reduction and profit earning [24]. Chen and Huang performed a cluster analysis to categorize 122 Taiwan equity mutual funds into four clusters, among which aggressive funds and good performance funds dominated inferior performance funds and stable funds, and therefore were included in the portfolio selection model [25]. After a series of studies on the internal structures of the complex networks in stock markets [26,27], Boginski et al.introduced a new network-based data mining approach to select diversified portfolios by finding the maximum-weight s-plexes in the resulted networks [28].

Additionally, the idea of building portfolios from a selection of stocks from each cluster has also been widely used in portfolio selection. On the one hand, a cluster generally corresponds to a group of nodes that have more internal connections than external connections [29,30], therefore, the diversity of the portfolio [8,31] can be guaranteed by selecting stocks from each cluster. On the other hand, this idea can be used to obtain a meaningful selection of portfolio comprising a fixed number of stocks, so as to tackle the cardinality constraint [32,33].

Portfolios selected from clusters detected in stock networks may vary greatly according to different detecting methods. Among the methods for detecting clusters, a hierarchical clustering [34,35] algorithm proposed by Newman et al. is one of the most efficient methods. The original Girvan–Newman algorithm [29,36] proposed by Girvan and Newman is not suitable for large networks due to its low computational capacity. Newman later proposed a new fast algorithm [37], which can be applied to the analysis of large networks. This agglomerative hierarchical clustering algorithm repeatedly joins communities together in pairs, choosing at each step the link that results in the greatest increase (or smallest decrease) in modularity, which could be interpreted as a measure index of community structure. A higher value of the modularity represents a more meaningful community division.

It has been shown that the performances of selected portfolios are closely related to their historical returns known as the momentum effect, based on which a new momentum strategy was proposed [38]. Jegadeesh and Titman [39] found that the winner portfolio over the past three to twelve months outperformed the loser portfolio by 1% per month during the next three to twelve months. Other studies have also shown evidence that rising stocks will continue to rise and falling stocks will continue to fall [39–41], which further provides the basis for the construction of momentum strategy. The momentum effect has also been demonstrated in the Chinese stock market [42,43], and therefore it would be interesting to study the portfolio strategy in the Chinese stock market after incorporating this momentum effect.

It should be noted that a portfolio which has been proved historically efficient may suffer losses when the market is in drawdown periods [23,24,44,45]. Therefore, a growing number of studies use the market trend as a significant basis for trading strategy. Choudhury et al. proposed a novel Self-Organizing Maps (SOM) based hybrid clustering technique to build portfolios, and the predictions of stock prices and volatilities were incorporated into the trading strategy [24]. Chen et al. used a probabilistic neural network (PNN) to forecast the direction of index return, and found that the PNN-based investment strategies can obtain higher returns than other investment strategies [44]. Ren et al. used the empirical data to identify the market trend, and chose the optimal portfolio under a specific market condition in their strategy [23]. Given short sale is not allowed for individual stocks in the Chinese stock market, it is necessary to make predictions for the market trend upon which to decide whether to use the optimal portfolio in bear market in order to avoid losses.

In this paper, we propose a new dynamic portfolio strategy based on the clusters detected in the filtered networks of the Chinese stock market. Compared with the existing studies, the innovation of our work lies in three aspects. First, most studies build only a single portfolio based on the clusters detected in the networks, but the portfolio may not always be optimal under different conditions [13]. We consider three types of portfolios, namely, central portfolio, peripheral portfolio and dispersed portfolio, and choose the optimal portfolio by evaluating their performances in different periods. Second, the past performance of the portfolio, far or near, may influence its future performance at different levels. Following the idea of momentum effect, each portfolio is endowed with a score which is determined by its historical returns and refined with a time weight, so as to find out the optimal portfolio with the highest score. Finally, the market trend is predicted in our strategy, and it is further used to decide whether or not to adopt the optimal portfolio for reducing risks in drawdown periods.

The rest of this paper is organized as follows: Section 2 describes the data and methods used to construct our dynamic portfolio strategy. The results of our portfolio strategies are presented in Section 3. We summarize our conclusions in Section 4.

2. Data and methods

2.1. Data

Our data include the daily closing prices of stocks listed on the Chinese A-Share market over a period of 9 years from January 1, 2008 to December 31, 2016. We use the China Securities Index (CSI) 300 over the same period as the benchmark index for comparison, and it includes 300 of the largest, high liquidity and most representative stocks listed in the Chinese A-Share market. All data are obtained from Bloomberg.

A moving window is used in our dynamic portfolio strategy to search for the optimal portfolios in different temporal windows. Each window contains two periods: observation period and investment period. In the observation period, we first build the network and select portfolios from the detected clusters. We then evaluate the performances of selected portfolios based on their historical returns to identify the optimal portfolio. In the investment period, we determine whether to use the optimal portfolio according to the predicted market trend using data in the observation period. The length of the investment period is set to be 1 month, which is an appropriate length that one not only has a sufficient number of investment periods but it also ensures the sustainability of investment in a long enough period. Considering that the performance of the portfolio is measured by a time-weighted average of the monthly returns in the observation period, comparable to the return in the following month of investment period, the length of the observation period should be multiples of 1 month. The length of the observation period is chosen to be 6 months, to make sure we have an appropriate length of the moving window which should not be too long. The interval between two consecutive windows is 1 month, and there are a total 102 moving windows in our study.

The data filtering process is conducted to ensure the continuity and integrity of data in the observation period. We first filter out those stocks which are once suspended from the market for more than 10 trading days. We then select 100 stocks that are most