行政院國家科學委員會補助專題研究計畫成果報告

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※ **以類神經網路研究證券成長風格與價值風格之分類、辨識** ※

※Equity Style Classification, Identification and Investing Strategy with Artificial Neural※

※ Networks and Discriminant Analysis ※

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計畫類別：□**個別型計畫** □**整合型計畫**

計畫編號：NSC 89-2416-H-004-036

執行期間：88 **年** 08 **月** 01 **日至** 89 **年** 07 **月** 31 **日**

計畫主持人：蔡瑞煌

共同主持人：

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□**國際合作研究計畫國外研究報告書一份**

執行單位：國立政治大學資訊管理學系

中 華 民 國 89 **年** 8 **月** 16 **日**

行政院國家科學委員會專題研究計畫成果報告

以類神經網路研究證券成長風格與價值風格之分類、辨識

Equity Style Classification, Identification and Investing Strategy with Artificial Neural Networks and Discriminant Analysis

計畫編號：NSC 89-2416-H-004-036
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主持人：蔡瑞煌　　國立政治大學資訊管理學系
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一、中文摘要

本研究應用類神經網路在股票風格投資方面之分類、辨識。類神經網路在樣本內與樣本外的分類正確率皆優於區別分析，而且類神經網路在樣本內的訓練範例中達成了百分之百的分類正確率。此外，我們也解決了傳統方法無法展示股票風格動態的問題。檢視各種風格投資策略在台灣股票市場的績效表現之後，我們以類神經網路為基礎，提出一個簡單而容易實行的投資策略。由這個策略的表現可以說明，即使在考慮了風險因素之後，積極的風格投資策略的確可以增加投資組合的績效表現。

關鍵詞：類神經網路；風格投資分析

Abstract

This paper investigates whether or not the classifications of stock styles can enhance profit. A newly developed method, which is called RNBP (reasoning neural network with backward propagation), is employed in this paper to classify the Taiwan stocks into growth and value stocks. RNBP, though stemming from artificial neural network, has improved the weaknesses of conventional artificial neural networks substantially. To make a comparison, the conventional style classification method, the discriminant analysis (DA), is also examined. Classification accuracy is first compared, and then the style investment strategies are performed. Our results show that RNBP outperforms DA in both in-sample and out-sample classification accuracies. The style investment strategies based on RNBP are also significantly superior to those of DA.

Keywords: Artificial Neural Networks, Style analysis, Growth stock, Value stock

二、緣由與目的

The classification of the style of stocks has recently received a great attention. Stocks with similar characteristics may tend to perform as a group over several economic and business cycles, and constitute equity market segments (Berstein, 1995). Two typical styles, the value style and the growth style, are often discussed in the literature. Value style stocks are stocks with lower prices/earning (P/E) ratio, or price/book (P/B) ratio, whereas growth style stocks are those have above-average growth prospect. Sharpe (1992), who had analyzed almost 400 mutual equity funds, found that 90 to 95 percent of their performances could be attributed to the style allocation. Jacobs and Levy (1996) found that accurate style allocations yielded superior realized returns.

Although the choice of a portfolio style is considered as an important step in the investment decision making process, the methods of classifying the styles remain variable. Gallo & Lockwood (1997) mentioned that there were three approaches to style classification for actively managed portfolios. The first approach was to classify the style on the basis of interview with professionals. The second was the return-based approach, which computed the correlation between the return of the mutual funds and the returns of a number of selected indexes. The third was the characteristic-based approach, where the manager assigns the style for stocks based on the security information including factors such as P/E, P/B and dividend payout ratios (Ramaswami, 1994).

Though the first approach had it own merits, it had been criticized to be subjective. This subjective assessment has made the classification more art than science. With

respect to the second approach, Christopherson (1995) argued that the computed correlation might lead to misclassification because historical correlations were noisy forecasts of the future correlation. Furthermore, the rigid classification, which separated the stocks into either growth or value stocks, ignores the intermediate cases. The third approach utilized the discriminant analysis method (DA), which overcame the above defects by considering the time-varying weight of each stock. For instance, a stock is a mixture of the two styles with a weight of 80% to the first style and a weight of 20% to the second style. Accordingly, the third approach may be more appropriate than the first two in classifying the stocks.

While the characteristic approach appears better than the other two, the use of DA in separating the stocks also has one weakness. DA is a linear classification method, which separates the stocks by a linear regression line. While this linear separation is easy to apply, it serves only as an approximation to the complexity of the real world. For example, if stock styles indeed exist, but can be separated only on the basis of an S-shaped plane, then the linear separating line may result in misclassification. Hence, a nonlinear separation method, which contains the spirit of DA on one hand and can accommodate the nonlinear relations between variables on the other, should be the most appropriate.

Artificial Neural Networks (ANN) is an ideal tool for this nonlinear separation requirement. The merit of ANN is that it is data driven and model free[1]. In addition, it has powerful pattern classification capabilities, surpassing other techniques in many applications (Altman, 1994; Brockett, 1994; Trippi & Turban, 1996). Furthermore, the ANN model is not subject to DA's constraining assumptions, such as linear separability and independence of the classifying variables.

One of the most popular ANN is the layered feedforward network with the back propagation learning algorithm (BP) (Rumelhart, Hinton and Williams, 1986). However, BP contains some undesirable predicaments, including the proper number of hidden nodes being unknown, the relatively optimal learning results and the sluggish learning process (Tsaih, 1993). To remedy these shortcomings, various modifications are proposed; however, a generalized solution has not been found. Tsaih (1997, 1998) has recently developed a reasoning neutral network (RN), which adopts a learning procedure that ensures an optimal solution. The merit of RN is that it can deal with not only conventional binary output patterns but also non-binary output ones. However, computing time of RN is nontrivial owing to the increasing “nodes” it creates. Combining the merits of BP and RN to overcome their weaknesses, Tsaih, Chen and Lin (1998) presented reasoning neutral networks with back propagation learning algorithm (hereafter, RNBP). From the evaluation of the training and testing samples, RNBP outperforms BP. Accordingly, using RNBP to classify the stock styles seems the ideal step to pursue.

The purpose of this paper is to use artificial neural network to re-assess the equity style investment strategies. To the best of our knowledge, this is the first study of employing artificial neutral network to classify and identify the equity styles. We examine whether or not the RNBP can outperform the DA method, which serves as our benchmark. Taiwan stock market data from 1987:Q1 to 1997:Q3 are used for illustration. Since the

[1] In the context of traditional statistical methods, ANN can be considered as a multivariate nonlinear non-parametric inference technique that is data driven and model free. Multivariate implies that the ANN inputs comprise many different variables whose interdependencies and causative influences are exploited. Nonparametric, model free, means there are no presumptions regarding the relation between input and output variables. Data driven implies that the weights of ANN are estimated from the (given) training data.

use of RNBP and DA requires the sample to be split into training samples and evaluation samples, which are close to the conventional in-samples and out-samples, respectively, we first separate the stock data into these two types of samples using date of 1996:Q1. The training samples are the data used to build up the "relation pattern" between the styles and input variables[2]. Once this relation pattern is built up (learned), it is used to classify the evaluation samples. The classification performance of both training and evaluation samples are compared.

三、結果與討論

Our results are fruitful. First, with respect to the classification accuracy, the RNBP achieves the 100% classification accuracy for the in-sample evaluation and 97% accuracy in out-sample data. Both ratios are significantly higher than those of DA. It seems that if stock styles indeed exist, it shall be separated on the basis of a non-linear separation surface. The proposed style investment strategy is then implemented by constructing portfolios based on a style dynamics, which is the style changing pattern. Portfolio returns are computed. Results show that the style strategies based on RNBP enhance profit regardless of risk adjustment, whereas results do not lend support to style investment strategies based on DA. Although this study uses data from Taiwan, the proposed model can be applied to other countries immediately.

四、計畫成果自評

就目前所知，應用類神經網路在股票風格投資方面的研究不多。本研究是少數之一。研究內容與原計畫相符程度很高，而研究成果的學術價值亦有。不過，離預期目標仍有一段距離。會嘗試在學術期刊發表。

[2] The input variables are P/E, P/B, P/S, and SGR.

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