

Journal of Zhejiang University SCIENCE
 ISSN 1009-3095
<http://www.zju.edu.cn/jzus>
 E-mail: jzus@zju.edu.cn



Empirical study on mutual fund objective classification*

JIN Xue-jun (金雪军)[†], YANG Xiao-lan (杨晓兰)

(College of Economics, Zhejiang University, Hangzhou 310027, China)

[†]Email: cec_jxj@zju.edu.cn

Received Apr. 30, 2003; revision accepted Sept. 1, 2003

Abstract: Mutual funds are usually classified on the basis of their objectives. If the activities of mutual funds are consistent with their stated objectives, investors may look at the latter as signals of their risks and incomes. This work analyzes mutual fund objective classification in China by statistical methods of distance analysis and discriminant analysis; and examines whether the stated investment objectives of mutual funds adequately represent their attributes to investors. That is, if mutual funds adhere to their stated objectives, attributes must be heterogeneous between investment objective groups and homogeneous within them. Our conclusion is to some degree, the group of optimized exponential funds is heterogeneous to other groups. As a whole, there exist no significant differences between different objective groups; and 50% of mutual funds are not consistent with their objective groups.

Key words: Mutual funds classification, Distance analysis, Discriminant analysis

Document code: A

CLC number: O212.4

INTRODUCTION

Financial theory and practices suggest that mutual funds can use information advantage and subdivide financial markets according to preferences of investors. They are the reasons for the emergence and tremendous development of the mutual fund industry in recent decades. Mutual funds investors have different risk preference resulting from different levels of income, resources of income and psychological characters. Consequently, they will choose mutual funds to suit their needs. It was reported by Sharpe (1966) that mutual funds select a risk class and then invite investors with similar risk preferences to invest. He stresses that a fund must remain in the same risk class so that investors may arrange portfolio holdings.

Generally, mutual funds should show their characters of 'selecting risk class' or 'subdividing markets' to investors by their investment objectives. Investment objectives are stated in mutual funds' prospectus to explain their investment style, strategy, and philosophy, which is distilled into fund objective category such as growth, income, balanced, etc. Investors can make decisions on the basis of the funds' objectives. That implicitly assumes activities of mutual funds are consistent with their stated objectives. However, if the stated objectives are not the actual objectives the funds pursue, conclusions drawn by investors and researchers based on the stated objectives will be misleading (Kim *et al.*, 2000). For instance, if income-oriented funds have attributes of growth-oriented funds or vice versa, the stated objectives may seriously misinform investors and lead them to wrong investment decisions. For these reasons, regulations in the mutual fund industry require mutual funds to adhere to their stated investment ob-

* Project supported by the National Foundation of Social Sciences (No. O2BJY131) and by the Science and Technology Program of Zhejiang Province (No. 021110168)

jectives^a.

In China, the mutual fund industry has been burgeoning in recent years. Currently, in the securities markets there are more than 40 closed-end mutual funds with different objective categories including aggressive growth, moderate growth, balanced, optimized exponential, and so on. It is meaningful to ask whether those investment objectives can properly convey information to investors. That is, if we classify mutual funds on the basis of their stated objectives; whether it is homogeneous within investment objective groups and heterogeneous between them? This paper will argue such questions using data in the Chinese securities market by statistical methods of distance analysis and discriminant analysis.

There are some researches in this area recently. diBartolomeo and Witkowski (1997) focused on the question of whether funds are misclassified, if the misclassification is random, and if misclassification is a hindrance to investors. They regress a fund's returns against the returns of the various objective indices and then classify the fund as belonging to the objective group whose index provides the best fit. They found that the current classification system is indeed insufficient in classifying funds and that about 40% of funds are misclassified. Brown and Goetzmann (1997) investigated whether fund classifications are useful in providing benchmarks for evaluating historical fund performance and in explaining differences in future returns among funds. They also found that the current classification system is inefficient in answering such questions. Kim *et al.*(2000) classified funds based on their attributes (characteristics, investment style, and risk/return measures). They concluded that the stated objectives of more than half the funds differed from their attributes-based objectives, and over one third of the funds were severely misclassified.

In this paper our methodology consists of

^a The USA Securities and Exchange Commission (SEC) requires that mutual funds disclose risk to potential investors through the prospectus. These investment objectives must be adhered to and may only be changed with approval of the shareholders by a majority vote. Similar regulation has also been made in China by the Chinese Securities Regulatory Commission (CSRC).

analyzing mutual funds based on their actual attributes and measuring the separation between different groups of funds in multidimensional space by Mahalanobis distance. And this idea is original from Kim *et al.*(2000). Our conclusion is that to some degree, the group of optimized exponential funds is heterogeneous to other groups. As a whole, there are no significant differences between different objective groups; and 50% of mutual funds are not consistent with their objective groups.

The paper is organized as follows: Section II describes the mutual fund sample. Section III describes the method of distance analysis and discriminant analysis. Section IV describes the analysis process and results. Section V provides discussion and conclusion.

MUTUAL FUND DATA

In this research, we chose 22 samples of closed-end mutual funds, which were all founded before 2000. Mutual fund data were collected from their annual financial reports in 2000. Some data were obtained from websites such as www.p5w.net and www.homeway.com.cn.

Our research began with analyzing the actual attributes of funds in different groups. Firstly, we needed a market benchmark. However in the Chinese market there are two stock exchanges, which have their respective indexes: Shanghai's index and Shenzhen's index. So we calculated the growth rate of incorporated index by the average growth rate of these two indexes as follows:

$$INDEX = \ln \frac{\frac{INDEXH_{t+1}}{INDEXH_t} + \frac{INDEXS_{t+1}}{INDEXS_t}}{2} \quad (1)$$

INDEX: logarithm growth rate of incorporated index; *INDEXH_t*, *INDEXH_{t+1}*: Shanghai's index of period *t* and *t+1*; *INDEXS_t*, *INDEXS_{t+1}*: Shenzhen's index of period *t* and *t+1*.

Then, we regarded the 28 days national debt repurchase interest rate of the Shanghai exchange as risk-free rate and got its logarithm.

And then, in order to describe the actual activities of funds, we use the following characteristic variables of fund: (1) percent stock; (2) concentricity of stock; (3) average return for month; (4) standard deviation; (5) beta; and (6) R-square.

Percent stock is the percentage of the fund's holdings held as stock, which represents the structure of its asset allocation. Concentricity is calculated as the ratio of the first ten stocks in a fund's portfolio to its amount of stock asset. Concentricity shows whether the investment style of the fund is relatively more concentrated or more dispersed. Standard deviation is a measure of the total risk of a fund. Beta is a measure of the systematic risk for a fund. The R-square measures fund diversification^b.

RESEARCH METHOD

The main objective of this study is to examine whether funds with the same stated objectives are similar and whether funds with diverse objectives are indeed different. We assume that if mutual funds adhere to their stated objectives, attributes must be heterogeneous between investment objective groups and homogeneous within them. Our methods are designed to test this assumption. Distance analysis is used to measure the difference of diverse groups. Furthermore, discriminant analysis determines whether one fund should be classified into its stated objective group on the basis of its actual characters.

Distance analysis

We classify the mutual fund samples into groups on the basis of their stated objectives. Then each group can be regarded as a population with dimensions of $n \times m$ (that means each group includes n mutual funds and each fund can be characterized by m variables). If funds with the same stated objectives have similar attributes, and these attributes differ from the funds in other objective groups,

^b The R-squared measures the explanatory power of the market index relative to the fund behavior. If the market index used had a small number of members, a high R-squared would not necessarily indicate a diversified portfolio. We use R-square here to measure fund diversification, because Shanghai's index and Shenzhen's index both have large number of members.

funds will cluster by their stated objectives, and will be distinct from the clusters of other fund objectives. The separation between these clusters in multidimensional space is measured by Mahalanobis distance.

There are two populations: mutual fund groups G_1 and G_2 . Each group has n mutual funds; and each mutual fund is described by m characteristic variables. Our null hypothesis H_0 is that these two groups have identical average values. If the null hypothesis H_0 is rejected, that means G_1 , G_2 are really diverse. If H_0 cannot be rejected, that suggests the difference between average values of G_1 and G_2 is not significant.

We assume mutual fund group G_i , $G_i \sim N(\mu^{(i)}, \Sigma_i)$ ($i=1, 2$), vector of average values $\mu = (\mu_1, \mu_2, \dots, \mu_m)'$, covariance matrix $\Sigma = (\sigma_{ij})_{m \times m}$ and mutual fund sample $X = (x_1, x_2, \dots, x_m)'$. For the purpose of testing $H_0: \mu^{(1)} = \mu^{(2)}$, we calculate the Mahalanobis distance $d^2(1,2)$ between these groups:

$$d^2(1,2) = (\bar{X}^{(1)} - \bar{X}^{(2)})' S^{-1} (\bar{X}^{(1)} - \bar{X}^{(2)}), \quad (2)$$

Where, S is covariance matrix of incorporated samples.

Further, F-statistics is calculated as follows:

$$F = \frac{(n_1 + n_2 - m - 1)n_1 n_2}{m(n_1 + n_2)(n_1 + n_2 - 2)} d^2(1,2) \quad (3)$$

In Eq.(3), n_1 and n_2 are the number of funds in the two groups. Under the null hypothesis that funds in two groups have the same average values, F is characterized by F distribution with numerator's degree of freedom m and denominator's degree of freedom $(n_1 + n_2 - m - 1)$. Further, we can calculate the p -value. If p -value is less than the given significant level α , the null hypothesis H_0 is rejected. That is, these two fund groups are significantly different from each other. While, if p -value is greater than α , H_0 cannot be rejected. That means although these two groups have diverse investment objectives, they do not show significantly different attributes in operation. Each of

them does not have its own particular investment style and relative risk and income.

Discriminant analysis

Discriminant analysis is used to determine into which group a fund should be classified on the basis of their attributes. Our principle is that we classify a fund into the group closest to it. This approach is concerned with separating several groups, based on measurements of multiple attributes (discriminating variables) for the members in the groups. Discriminant analysis is based on maximizing the Mahalanobis distance, which is a measure of separation between two groups.

We have fund $X = (x_1, x_2, \dots, x_m)'$. The Mahalanobis distance between X and an objective group G_i can be defined as:

$$d^2(X, G_i) = (X - \mu)' \Sigma^{-1} (X - \mu) \quad (4)$$

As to fund X , we set the following discriminant function:

$$\text{If } d^2(X, G_1) < d^2(X, G_2), X \in G_1 \quad (5)$$

$$\text{If } d^2(X, G_1) \geq d^2(X, G_2), X \in G_2 \quad (6)$$

That is, we classify a fund into a group which is closest to it.

EMPIRICAL RESEARCH RESULTS

The 22 mutual funds are classified into 6 groups on the basis of their investment objective: moderate growth, assets restructuring, optimized exponential^c, balanced, middle and small enterprise growth, aggressive growth^d. We measure the degree of diversity between each other. Each fund is described by 6 variables including percent stock, concentricity of stock, and average return for month, standard deviation, beta and R-square. Distance analysis and discriminant analysis are implemented by software SAS.

Results of distance analysis

Table 1 shows the Mahalanobis distances between stated objective groups in multidimensional space. F -statistics and p -value are listed in Table 2 and Table 3. The above results suggest that if α is given as 0.05, no couples of funds can pass the significance test (each p is greater than 0.05). That means the stated objective groups are not distinct from each other. When α is given as 0.1, optimized exponential and moderate growth, optimized exponential and balanced, optimized exponential and aggressive growth, balanced and assets restructuring, balanced and middle and small enterprise growth pass the test. Hence, those couples are diverse at significance level 0.1. As we can see, in those

Table 1 Squared distance to group

From group	Moderate growth	Assets restructuring	Optimized exponential	Balanced	Middle and small enterprise growth	Aggressive growth
Moderate growth	0	10.66441	10.98309	5.14556	8.22608	2.39935
Assets restructuring	10.66441	0	14.08073	18.68796	6.93418	4.03729
Optimized exponential	10.98309	14.08073	0	22.12258	7.89869	11.78212
Balanced	5.14556	18.68796	22.12258	0	19.79169	6.86633
Middle and small enterprise growth	8.22608	6.93418	7.89869	19.79169	0	5.40004
Aggressive growth	2.39935	4.03729	11.78212	6.86633	5.40004	0

^c Optimized exponential fund in China is similar to index fund in US and other countries. Optimized exponential fund put 30% of its portfolio in positive investment. And this is the difference between optimized exponential and index fund holding totally passive investment style.

^d In our country, managers of funds frequently state inconsistent investment objectives. In this paper we mainly investigate the prospectus of funds and partly refer to Quanjing website (2002).

Table 2 F-Statistics, NDF=6, DDF=11 for squared distance to group

From group	Moderate growth	Assets restructuring	Optimized exponential	Balanced	Middle and small enterprise growth	Aggressive growth
Moderate growth	0	1.83294	3.02035	1.17919	1.41386	0.74980
Assets restructuring	1.83294	0	2.15122	2.56960	0.79454	0.66087
Optimized exponential	3.02035	2.15122	0	4.34551	1.20674	3.00008
Balanced	1.17919	2.56960	4.34551	0	2.72136	1.47519
Middle and small enterprise growth	1.41386	0.79454	1.20674	2.72136	0	0.88394
Aggressive growth	0.74980	0.66087	3.00008	1.47519	0.88394	0

Table 3 Prob>Mahalanobis distance for squared distance to group

From group	Moderate growth	Assets restructuring	Optimized exponential	Balanced	Middle and small enterprise growth	Aggressive growth
Moderate growth	1.0000	0.1817	0.0536	0.3837	0.2924	0.6224
Assets restructuring	0.1817	1.0000	0.1284	0.0832	0.5932	0.6829
Optimized exponential	0.0536	0.1284	1.0000	0.0172	0.3716	0.0546
Balanced	0.3837	0.0832	0.0172	1.0000	0.0715	0.2725
Middle and small enterprise growth	0.2924	0.5932	0.3716	0.0715	1.0000	0.5375
Aggressive growth	0.6224	0.6829	0.0546	0.2725	0.5375	1.0000

6 groups, optimized exponential fund group is distinct from other groups more significantly. However, moderate growth, aggressive growth and middle and small enterprise growth are very close, which suggests similarity in investment characters.

Results of discriminant analysis

Through discriminant analysis we can classify funds based on their actual attributes. While, the categories of objective groups are based on their stated objectives. Comparing the results of discriminant analysis with the objective groups, we can conclude which fund is heterogeneous within its own group and should be classified into another group on the basis of its attributes. Error Count Estimates for group shown in Table 4 suggests the percentage of misclassified funds in one group. The

higher error count suggests the greater mutual distinction within an objective group. However, the lower error count suggests funds from this group are more homogeneous in attributes.

Our results showed only 11 funds could be classified into their stated groups through discriminant analysis. And the others were misclassified. Among those groups, optimized exponential group had the lowest error count, while balanced had the highest. Reclassification results can be seen in the appendix.

CONCLUSION

This work examines whether the stated investment objectives of mutual funds adequately re-

Table 4 Error count estimates for group

Group	Moderate growth	Assets restructuring	Optimized exponential	Balanced	Middle and small enterprise growth	Aggressive growth
Rate	0.5000	0.5000	0.2500	0.6667	0.5000	0.6000

present their attributes to investors. This is extremely important if an investor attempts to compare risks and returns to choose investment within an investment objective group.

Results from this study revealed that different fund groups were not really distinct from each other on the whole. Therefore, stated investment objectives of mutual funds fail to completely capture attributes. In addition, we conclude that the optimized exponential fund group showed some investment characters in some degree is different from funds in other groups.

Although regulations in the mutual fund industry require mutual funds to adhere to their stated investment objectives, some departures may still occur. Najand and Prather (1999) concluded that this phenomenon might be explained by the intense competition in the mutual fund industry, imperfect monitoring by the SEC and investors, and portfolio manager compensation contracting. The above argument may be also applicable in China. While in our stock market, fund managers, investors and even sup-

ervisors have not attached importance to fund's objective. There are no specific guidelines as to how to declare fund objectives and how to manage portfolios exactly in pursuance of the declared objectives. From our point of view, objective groups may play a relatively important role in the development of the whole mutual fund market.

References

- Brown, S.J., Goetzmann, W.N., 1997. Mutual fund styles. *Journal of Financial Economics*, **43**(3):373-399.
- diBartolomeo, D., Witkowski, E., 1997. Mutual fund misclassification: evidence based on style analysis. *Financial Analysts Journal*, **53**(5):32-43.
- Kim, M., Shukla, R., Tomas, M., 2000. Mutual fund objective misclassification. *Journal of Economics and Business*, **52**:209-203.
- Najand, M., Prather, L.J., 1999. The risk level discriminatory power of mutual fund investment objectives: additional evidence. *Journal of Financial Markets*, **2**: 307-328.
- Sharpe, W.F., 1966. Mutual fund performance. *Journal of Business*, **39**:119-138.

APPENDIX: Discriminant result

Fund name	Objective classifications (from group)	Discriminant results (into group)
An Shun	Moderate growth	Moderate growth
Tong Sheng	Moderate growth	Moderate growth
Tong Yi	Moderate growth	Moderate growth
Xing hua*	Moderate growth	Assets restructuring
Jin xin*	Moderate growth	Optimized exponential
Jing Hong*	Moderate growth	Middle and small enterprise growth
Yu Yuan	Assets restructuring	Assets restructuring
Yu Yuang*	Assets restructuring	Aggressive growth
Xing He	Optimized exponential	Optimized exponential
Pu Feng	Optimized exponential	Optimized exponential
Tian Yuan*	Optimized exponential	Assets restructuring
Jing Fu	Optimized exponential	Optimized exponential
Jin Tai	Balanced	Balanced
Tai He*	Balanced	Optimized exponential
Han Xing*	Balanced	Middle and small enterprise growth
Jing Bo	Middle and small enterprise growth	Middle and small enterprise growth
Jing Yang*	Middle and small enterprise growth	Aggressive growth
Han Sheng	Aggressive growth	Aggressive growth
An Xin*	Aggressive growth	Assets restructuring
Pu Hui*	Aggressive growth	Balanced
Kai Yuan*	Aggressive growth	Assets restructuring
Yu Long	Aggressive growth	Aggressive growth

'Objective Classifications' are initial categories that funds declare to investors. 'Discriminant results' are obtained from reclassification according to fund's performance. Funds with marks are misclassified. That is, they cannot be classified into their stated groups through discriminant analysis