Mutual Fund Objective Misclassification

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Mutual funds are usually classified based on their stated objectives. 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. This study classifies funds based on their attributes (characteristics, investment style, and risk/return measures). We find that the stated objectives of more than half the funds differ from their attributes-based objectives, and over one third of the funds are severely misclassified. However, contrary to the reports in the financial press, we do not find that mutual funds are gaming their objectives, i.e., deviating from their stated objectives to earn a higher relative performance ranking. © 2000 Elsevier Science Inc.

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I. Introduction

Mutual funds explain their investment style, strategy, and philosophy in an objective statement, which is distilled into a fund objective category such as growth, income, foreign, etc. Investors, popular press, and academics alike use these objectives as a basis of comparison among funds. Fund objectives are used by investors to assess their investing style and relative risk. While choosing mutual funds, investors first delineate the specific mutual fund objective(s) that suit their needs, and then choose fund(s) that meet the desired objective(s). The Wall Street Journal grades fund performance by comparing the return earned by a fund with the returns of other funds in the same stated objective group. Academic research also uses stated objectives for categorizing funds for various tests.¹ This categorization based on investment objectives implicitly assumes that funds of the same stated objective are alike in their attributes.

¹ Hendricks, Patel and Zeckhauser (1993) limit their sample of mutual funds to those with stated objectives of growth, aggressive growth and growth-income. Grinblatt and Titman (1993) divide their sample of mutual funds into subsamples based on stated investment objectives of aggressive growth, balanced, growth, growth-
If the actual investment activities of funds do not coincide with their stated objectives, comparisons within objective groups may be misleading. For example, if a fund states its objective as growth but pursues an investment style that is more like that of an aggressive growth fund, comparing the performance of this fund with other growth funds would be inappropriate. Similarly, an investor who picks a fund that states its objective to be growth-income but pursues investment strategies similar to the other aggressive-growth funds is being misled.

There are no specific guidelines as to how to declare fund objectives and then how to manage portfolios exactly in pursuance of the declared objectives. Even mutual fund information providers take the fund objectives at face value. For example, Morningstar (1997) says that “[Fund objective] is based on the wording contained in the fund’s prospectus and on the manner in which the fund is marketed. We do not try to outwit fund companies in categorizing funds—if they call it a growth fund, we will put it in the growth category.” Although regulations in the mutual fund industry require mutual funds to adhere to their stated investment objectives, some departures may nevertheless occur, either deliberately or due to insufficient control. Therefore, it is to be expected that funds within an objective group have diverse attributes. Some variation in the attributes may not be critical even within broader fund objective groupings such as income-oriented fund group (asset allocation, balanced, and equity-income funds), growth-oriented fund group (growth and growth-income funds), or aggressive capital appreciation-oriented fund group (aggressive growth and small capitalization funds). However, if growth-oriented funds have attributes of income-oriented funds or vice versa, stated objectives will seriously misinform investors and lead them to wrong investment decisions.

The mutual fund industry has experienced tremendous growth in the last 25 years. According to Investment Company Institute (1996, 1997), there were 452 mutual funds with eight objective categories in 1976. By 1986, the number of mutual funds had grown to 1,840 divided among 16 objectives. At the end of 1996, there were 6,293 mutual funds with 21 objectives. With the proliferation of mutual fund objectives and the number of mutual funds, it has become increasingly difficult to distinguish among funds.

The primary objective of this study is to examine whether funds with the same stated objectives are comparable and whether funds with diverse objectives are indeed different. With increased competition in the mutual fund industry, fund managers strive to attract investors by highlighting the special features of their investment styles to suit investor needs. They are also compelled to provide evidence of superior performance to attract investors. Because true risks of funds are essentially unobservable, some funds may be tempted to deviate from their stated objectives and take higher risks to earn higher returns and consequently a higher performance rank in their stated objective group, even though they may do poorly in the high risk group to which they actually should belong based on their investment activities. The actual investment objectives of the funds are reflected in their attributes. Therefore, it should be possible to determine their true objectives from their attributes.

income, income, special purpose, and venture capital/special situation. Connor and Korajczyk (1991) also divide their mutual fund sample into groups based on stated investment objectives. These studies use performance benchmarks based on the stated objectives of the mutual funds and summarize results by grouping them according to the stated objectives.

2 Section 13 (a), item (3), of Investment Company Act of 1940 states that an investment company, unless authorized by a majority of its shareholders, will not deviate from its investment policy.
Our results show that the stated objective groups are indeed distinct from each other in terms of their attributes, but classification by fund attributes makes the objective groups even more distinct. We find that over 50% of the mutual funds are misclassified, i.e., their stated objectives do not match their attributes-based objectives. Almost 33% of the funds are severely misclassified. We do not find that fund managers are systematically gaming their investment styles towards higher risk objectives to earn higher relative performance measures. Nevertheless, a majority of the funds that deviate into higher risk objectives do earn higher performance rank in their stated objective groups.

The paper is organized as follows: Section II reviews existing literature related to this issue and compares our methodology and results with the other papers. Section III describes the mutual fund sample. Section IV describes the attributes and distinct identities of stated mutual fund objective groups. Section V describes the discriminant analysis process. Section VI provides the evidence related to misclassification of mutual fund objectives. In Section VII we examine the stability of fund objectives over time. Section VIII examines the evidence related to gaming. Section IX concludes the paper.

II. Literature Review

The issue of mutual fund objective misclassification has been examined by two studies recently using methodologies very different from ours with similar conclusions as reached in our paper.

diBartolomeo and Witkowski (1997) investigate 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 classify the fund as belonging to the objective group whose index provides the best fit. The objective group indices are equal weighted returns of all funds in that objective group. The process of fund classification and objective indices calculation is iterated until every objective index consists of funds that are actually classified into that objective group. They determine that the current classification system is indeed insufficient in classifying funds, and find that as many as 40% of funds are misclassified.

Brown and Goetzmann (1997) focus on the questions of whether fund classifications are useful in providing benchmarks for evaluating historical fund performance and in explaining differences in future returns among funds. Like diBartolomeo and Witkowski (1997), they conclude that the current classification system is inefficient in answering these questions. They propose a generalized style classification method, a variation on the switching regression technique, in which funds are assigned to style classes based on the sensitivity of their returns to eight factors (indexes) chosen by the authors.

Both diBartolomeo and Witkowski (1997) and Brown and Goetzmann (1997) use fund returns for classifying individual funds. Our study uses other fund attributes in addition to fund returns. These attributes represent the type of information that investors typically reference when making investment choices. Like diBartolomeo and Witkowski (1997), our study takes the number and types of fund objectives as given, and looks for misclassification with respect to these objectives. Brown and Goetzmann (1997) determine the number of styles using a likelihood ratio test.

We believe that our approach of using attributes in addition to the risk and return measures is more comprehensive than that used by the other papers. Risk-return measures are undoubtedly the most important variables in determining a mutual fund’s investment
style and performance. However, they may not capture all aspects of mutual fund behavior. Returns are affected by the decisions made by the fund managers and advisors. These decisions are manifested immediately in fund characteristics and style. Including characteristic and style variables, therefore, enriches our analysis. Furthermore, risk-return characteristics are estimated using relatively long time series of returns [36 months in our paper, 60 months in diBartolomeo and Witkowski (1997), and 24 months in Brown and Goetzmann (1997)]. This emphasis on historical returns alone may introduce a bias in classification towards historical behavior, which is corrected to some extent in our paper by using other attributes measured using more recent data.

III. Mutual Fund Data

Mutual fund data are collected from the January Morningstar OnDisc databases of 1994, 1995, 1996, and 1997, which contain data as of Decembers of 1993, 1994, 1995, and 1996. We select all funds in the seven objective groups shown in Table 1 that had all the data items we use in this study. The availability of data items necessitates that the funds should have existed for at least three years. Our sample represents four end-of-the year snapshots

\begin{table}
\centering
\begin{tabular}{|l|c|c|c|c|c|}
\hline
\textbf{Stated Objective} & \textbf{Objective Code} & \textbf{Dec 93} & \textbf{Dec 94} & \textbf{Dec 95} & \textbf{Dec 96} & \textbf{Average} \\
\hline
Asset allocation & ASAL & 38 & 57 & 53 & 78 & 57 \\
Balanced & BLNC & 51 & 77 & 125 & 185 & 110 \\
Equity-income & EQIN & 46 & 54 & 65 & 90 & 64 \\
Growth-income & GRIN & 155 & 213 & 252 & 312 & 233 \\
Growth & GRTH & 269 & 344 & 423 & 539 & 394 \\
Small cap & SMCP & 65 & 105 & 159 & 224 & 138 \\
Aggressive growth & AGGR & 36 & 46 & 45 & 65 & 48 \\
Total & & 660 & 896 & 1122 & 1493 & 1044 \\
\hline
\end{tabular}
\caption{Distribution of the Mutual Fund Sample According to Their Stated Objectives at Various Time Points}
\end{table}

Note: The averages have been rounded.

3 In a recent paper, Chan, Chen, and Lakonishok (1999) classify funds based on their size and book-to-market ratios calculated as a weighted averages of the size and book-to-market of the component stocks. Both these characteristics are included in our paper.
4 In an earlier version of the paper we included foreign funds as the eighth objective. These funds were clearly distinct from the rest of the funds and were identified as being a distinct group by the discriminant analysis process.
5 Requiring that the funds in our sample should have existed for at least three years may induce survivorship bias. Survivorship bias arises from the fact that of the funds that take high risks, those that are successful in earning high returns survive while those that suffer losses cease to exist. If the non-surviving funds are not included in the analysis, the average return of the sample will be an upward biased estimate of the true population average return. Grinblatt and Titman (1989) and Brown, Goetzmann, Ibbotson and Ross (1992) report that
of the mutual fund industry. The four cross-sections, however, are not independent because the risk/return measures are estimated using 3 years of data which overlap for cross-sections that are less than 3 years apart. Only two cross-sections, December 1993 and December 1996, are truly independent of each other.

Our methodology consists of classifying mutual funds based on their observable attributes. Although Morningstar database provides a multitude of variables, we limit our choice of fund characteristic and investment style variables to those we consider most relevant. We divide fund attributes into three categories: characteristics, investment style, and risk/return.

The fund characteristic variables we use are: (1) net assets; (2) fund inception date; (3) fund manager tenure; (4) minimum initial purchase; (5) turnover; (6) expense ratio; and (7) maximum sales charge. Net assets represent the most recently reported total net assets of the fund, in millions of dollars. Fund inception is the date the fund began operations. The fund inception date is used to calculate the fund age in months. Fund manager tenure refers to the length of time the most recent manager has been at the fund. Minimum initial purchase is the minimum amount necessary to invest in the fund. Turnover measures the fund’s trading activity. Based on an SEC formula, it is calculated by dividing the lesser of purchases or sales for all securities with maturities greater than one year by average monthly assets. A turnover ratio of 100%, although indicating high trading activity, does not necessarily mean that all of the securities in the portfolio have been traded. The expense ratio represents the percentage of fund assets that is paid for operating expenses, management fees, and 12b-1 fee costs. This ratio excludes sales charges (loads). Maximum sales charge is the maximum amount of front and back loads charged by the fund.

The investment style variables are: (1) percent cash; (2) percent stock; (3) percent foreign stock; (4) debt as a percent of total capitalization; (5) median market capitalization; (6) price to earnings ratio; (7) price to book ratio; and (8) income ratio. Percent cash indicates the fund’s cash and money market security holdings. Percent stock is the percentage of the fund’s holdings that are held as nonpreferred equity securities. Percent foreign stock indicates holdings in foreign company equities. Debt as a percentage of total capitalization measures the average amount of capital derived from long term debt for each company within the fund’s portfolio of investments. Median market capitalization is a measure of the size of the firms in which the fund invests, expressed in millions of dollars. Price to earnings ratio is a weighted average of the price to earnings ratios of the stocks within the portfolio. Similarly, price to book is a weighted average of the price to book ratios of the stocks within each portfolio. Income ratio is the ratio of fund’s income return to its total return.

The risk/return variables consist of: (1) average return; (2) standard deviation; (3) alpha; (4) beta, and (5) R-square. Standard deviation is a measure of the total risk of a fund. Alpha measures a fund’s risk-adjusted return performance. It represents the difference between a fund’s actual return and expected return given its level of beta risk. Beta is a measure of the systematic risk for a fund. The R-square measures fund diversification.
We have a total of 20 fund attributes: seven characteristic variables, eight investment style variables, and five risk-return variables. Because we do not have prior knowledge about the most important variables, we performed principal factor analysis on these variables and identified the following ten as the most significant variables (listed in order of importance): standard deviation of returns ($\sigma$), income ratio (Inc), beta ($\beta$), R-square ($R^2$), price to earnings ratio (PE), price to book ratio (PB), % stocks (% Stk), debt as a percent of total capitalization (D%C), market capitalization (MktCap), and average return ($\bar{r}$). All results reported in the paper are based on these 10 variables.

In principle, our methodology can be applied at any point of time as long as the attributes for mutual funds are available. We apply the methodology at four time points: Decembers of 1993, 1994, 1995, and 1996. In the paper, we report the average results from four separate analyses: for Decembers of 1993, 1994, 1995, and 1996. The tables are the averages of four identical tables from these analyses. These average results are an accurate representation of the results for the individual results for the four years since there is very little variation in results from year to year. The results for the individual years are available from the authors upon request.

### IV. Attributes of Stated Objectives

The attributes of the stated fund objective groups are shown in Panel A of Table 2. Asset allocation and balanced funds invest much lower percent of their portfolios in stocks than

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6 Average return, alpha, and beta are not independent of each other in the sense that alpha is calculated as the average return minus the beta times the average market return which is fixed across securities. Using all three variables makes the covariance matrix of fund attributes singular. So, we dropped alpha from our analysis. This left us with 19 variables.

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**Table 2. Attributes of Stated Objective Groups**

<table>
<thead>
<tr>
<th>Objective</th>
<th>% Stk</th>
<th>D%C</th>
<th>MktCap</th>
<th>PE</th>
<th>PB</th>
<th>Inc</th>
<th>$\bar{r}$</th>
<th>$\sigma$</th>
<th>$R^2$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASAL</td>
<td>42.78</td>
<td>30.10</td>
<td>7552.05</td>
<td>23.36</td>
<td>3.51</td>
<td>2.54</td>
<td>10.38</td>
<td>6.86</td>
<td>55.51</td>
<td>0.55</td>
</tr>
<tr>
<td>BLNC</td>
<td>53.99</td>
<td>29.58</td>
<td>8930.36</td>
<td>20.49</td>
<td>3.55</td>
<td>3.20</td>
<td>10.69</td>
<td>6.88</td>
<td>80.61</td>
<td>0.68</td>
</tr>
<tr>
<td>EQIN</td>
<td>82.03</td>
<td>34.83</td>
<td>7481.35</td>
<td>19.27</td>
<td>3.02</td>
<td>3.32</td>
<td>12.77</td>
<td>8.29</td>
<td>73.09</td>
<td>0.77</td>
</tr>
<tr>
<td>GRIN</td>
<td>91.57</td>
<td>29.52</td>
<td>11410.15</td>
<td>20.14</td>
<td>3.57</td>
<td>1.81</td>
<td>12.89</td>
<td>8.94</td>
<td>86.60</td>
<td>0.92</td>
</tr>
<tr>
<td>GRTH</td>
<td>90.76</td>
<td>27.46</td>
<td>6211.62</td>
<td>22.64</td>
<td>4.09</td>
<td>0.58</td>
<td>12.56</td>
<td>10.79</td>
<td>68.03</td>
<td>0.98</td>
</tr>
<tr>
<td>SMCP</td>
<td>90.22</td>
<td>24.72</td>
<td>908.40</td>
<td>23.40</td>
<td>3.45</td>
<td>0.19</td>
<td>16.65</td>
<td>12.50</td>
<td>39.61</td>
<td>0.85</td>
</tr>
<tr>
<td>AGGR</td>
<td>89.86</td>
<td>23.84</td>
<td>1711.38</td>
<td>30.63</td>
<td>5.35</td>
<td>−0.34</td>
<td>14.61</td>
<td>16.00</td>
<td>42.97</td>
<td>1.14</td>
</tr>
<tr>
<td>Overall</td>
<td>82.85</td>
<td>28.27</td>
<td>6846.85</td>
<td>22.45</td>
<td>3.82</td>
<td>1.38</td>
<td>12.97</td>
<td>10.17</td>
<td>67.47</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Panel B: Mahalanobis distances between attributes-based objective groups

<table>
<thead>
<tr>
<th></th>
<th>ASAL</th>
<th>BLNC</th>
<th>EQIN</th>
<th>GRIN</th>
<th>GRTH</th>
<th>SMCP</th>
<th>AGGR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASAL</td>
<td>0.00</td>
<td>11.54</td>
<td>23.17</td>
<td>32.53</td>
<td>33.93</td>
<td>48.84</td>
<td>55.23</td>
</tr>
<tr>
<td>BLNC</td>
<td>11.54</td>
<td>0.00</td>
<td>13.21</td>
<td>19.08</td>
<td>31.72</td>
<td>56.51</td>
<td>62.96</td>
</tr>
<tr>
<td>EQIN</td>
<td>23.17</td>
<td>13.21</td>
<td>0.00</td>
<td>6.09</td>
<td>14.18</td>
<td>33.42</td>
<td>41.93</td>
</tr>
<tr>
<td>GRIN</td>
<td>32.53</td>
<td>19.08</td>
<td>6.09</td>
<td>0.00</td>
<td>7.48</td>
<td>28.04</td>
<td>35.50</td>
</tr>
<tr>
<td>GRTH</td>
<td>33.93</td>
<td>31.72</td>
<td>14.18</td>
<td>7.48</td>
<td>0.00</td>
<td>11.99</td>
<td>14.41</td>
</tr>
<tr>
<td>SMCP</td>
<td>48.84</td>
<td>56.51</td>
<td>33.42</td>
<td>28.04</td>
<td>11.99</td>
<td>0.00</td>
<td>10.38</td>
</tr>
<tr>
<td>AGGR</td>
<td>55.23</td>
<td>62.96</td>
<td>41.93</td>
<td>35.50</td>
<td>14.41</td>
<td>10.38</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: All Mahalanobis distances are significant at 1% level.
other funds. Small capitalization and aggressive growth funds clearly stand out as investing in much smaller size companies than the other funds. The price to earning and price to book ratios are higher for aggressive growth funds than for other funds. Growth, small capitalization and aggressive growth funds derive much smaller portions of their returns from income than asset allocation, balanced, equity-income or growth-income funds. The group means for the risk/return variables show an expected pattern: The higher average return funds have higher risks as measured by the standard deviations and betas of their returns.

Our ranking of fund objectives from Asset Allocation (ASAL) to Aggressive Growth (AGGR) is intended to be in the increasing order of risk. This ordering is consistent with the anecdotal assessment of risk of these fund objectives. The ordering is also borne out by the examination of total risk (\(\sigma\)) and systematic risk (\(\beta\)). The total risks of these funds are in strictly increasing order as we go from ASAL to AGGR. The systematic risks are also in the increasing order, with the exception of small capitalization funds.

A mutual fund’s objective represents the goals the fund is trying to achieve. Therefore, it is natural to expect that funds of identical objectives should be similar in their attributes and funds of different objectives should differ. Imagine positioning the mutual funds in a multidimensional space of their attributes. Funds that are alike will be spatially closer to each other. If funds with the same stated objectives have similar attributes, and these attributes differ from the funds in other objective groups, 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. Panel B of Table 2 shows the Mahalanobis distances between stated objective groups. The Mahalanobis distances between similar objective groups are smaller while those between objective groups of very different objectives are much larger.

Morrison (1983) shows that if the \(p\) attributes used as discriminating variables have a multivariate normal distribution, then under the null hypothesis that funds in two groups are from the same population, the variate

\[
\frac{(n_1 + n_2 - p - 1)}{p(n_1 + n_2 - 2)} \cdot \frac{n_1 n_2}{n_1 + n_2} \cdot D^2
\]

has an \(F(p, n_1 + n_2 - p - 1)\) distribution where \(n_1\) and \(n_2\) are the number of funds in the two groups, and \(D^2\) is the Mahalanobis distance. In all cases, the \(F\)-statistics are significant at 1% level. This shows that the centroids of the stated objective groups are indeed away from each other suggesting that the stated objective groups are distinct from each other.

V. Discriminant Analysis

The closeness of a fund to an objective group may be assessed through the use of confidence intervals (multidimensional ellipsoids) about the mean of each objective group. Based on this principle, a fund may be classified into the objective group closest to it; this may or may not be the fund’s stated objective. This approach is implemented through discriminant analysis. Discriminant analysis is concerned with separating several groups, based upon measurements of multiple attributes (discriminating variables) for the members in the groups. Discriminant analysis maximizes the Mahalanobis distance—a measure of separation between two groups—by assigning observations to groups.
Allocation of individual observations to groups is done through a discriminant function estimated using the discriminating variables. The discriminant function may be linear or use cross product and squared terms, leading to linear discriminant analysis (LDA) or quadratic discriminant analysis (QDA).

Suppose we have \( m \) fund objective groups and there are \( n_1, n_2, \ldots, n_m \) funds in these groups. On each of the funds we have measurements for \( p \) discriminating variables (fund attributes) \( x_1, x_2, \ldots, x_p \). Let \( \mu_i \) and \( V_i \) denote the \( p \times 1 \) mean vector and \( p \times p \) variance-covariance matrix of the discriminating variables for group \( i \). Furthermore, let \( V \) denote the \( p \times p \) pooled variance-covariance matrix of the discriminating variables. The Mahalanobis distance between two groups is the difference between the means of the discriminating variables weighted by the inverse of the pooled covariance matrix (in LDA) or covariance matrix for one of the two groups (in QDA):

\[
D_{ij}^2 = \begin{cases} 
    (\mu_i - \mu_j)'V^{-1}(\mu_i - \mu_j) & \text{(LDA)} \\
    (\mu_i - \mu_j)'V_i^{-1}(\mu_i - \mu_j) & \text{(QDA)}
\end{cases}
\]  

(2)

To ensure that the choice of discriminant analysis method is not affecting our results, we use both the LDA and the QDA procedures.\(^7\) The results using the two procedures are qualitatively very similar. In the paper we report the LDA results and will provide the QDA results upon request.

Table 1 shows that the number of funds in each objective group is quite different. In order to avoid discrimination bias due to some objectives having far greater number of funds than others, the prior probabilities for assignment to various objectives are set equal.

A final consideration in discriminant analysis is that of classification method. Given our sample size, dividing it into two groups—one for estimation of the discriminant function and another for classification—would not be practical. To achieve unbiased classification, the leave-out-one method is employed. In this method, the discriminant function is calculated based on the entire sample except for the observation to be classified. This method maintains sample size without biasing the classification process.

Following the example of diBartolomeo and Witkowski (1997), we iterated the discriminant analysis process until we were able to classify at least 99% of the funds into the objective in which they were classified before that iteration. On an average this took 16 iterations and we achieved classification consistency of 99.24%.

The attributes of the objective groups resulting from the iterative discriminant analysis based on the attributes are shown in Panel A of Table 3. By comparing this table with Panel A of Table 2 we see that shuffling of funds to increase the separation among the groups results in the mean attributes that are different in many ways from the attributes of stated objective groups. For example, % Stk was reduced from 42.78% to 32.86% for asset allocation group, a change of 23%. Similarly, MktCap for growth-income funds was changed from 11410.15 to 14651.12, a change of 28%.

Due to the multidimensional nature of the attributes, it is difficult to get an intuitive grasp of the changes in the attributes. For example, the average market capitalization of small capitalization funds increases from 908.40 to 1359.46 whereas that of aggressive growth funds decreases from 1711.38 to 1411.67, making the two funds closer along this

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\(^7\) LDA, while simpler in nature, requires the assumptions that the population covariance matrices are equal across groups. Other factors, such as the group size, dimensionality of the covariance matrix, and departures from normality also affect the choice of method. See Bayne, Beauchamp, Kane and McCabe (1983), and Seber (1984) for a discussion of the related issues.
attribute dimension. However, in terms of PE, PB, Inc and σ, the separation between the two groups increased.

The Mahalanobis distances are shown in Panel B of Table 3. Comparing this table with Panel B of Table 2, we see that the attributes-based objective groups are much more distinct than the stated fund objective groups. The Mahalanobis distances for the nearest neighbor objective groups are always higher for the attributes-based objectives than for stated objectives groups. Examining aggressive growth and small capitalization funds, we see that the Mahalanobis distance between these neighboring groups increases from 10.38 to 28.31.

VI. Misclassification

The null hypothesis tested in this paper is:

Funds within a stated objective group are homogeneous in terms of their attributes (fund characteristics, investment styles, and risk-return measure), and are distinct from the funds in other objective groups.

Table 4 provides evidence to test this hypothesis. This table shows how funds of various stated objectives are classified into the attributes-based objectives. If the fund objectives are unique with respect to their attributes and most funds follow their stated objectives, we should see very high values along the diagonal in the classification table. Large values off the diagonal would suggest that the funds do not follow their stated objectives.

On average, the attributes-based objectives of 46% (484 out of 1,043) funds are the same as their stated objectives. The worst consistency is for funds with the stated objective of asset allocation where only 22% (13 out of 57) are classified as asset allocation based
on their attributes, and the best consistency is for balanced funds where 83% of the funds are classified as balanced.

For every fund except the asset allocation funds the classification table has the highest percentages along the diagonal. Nevertheless, a significant number of funds are off the diagonal. The $\chi^2$ statistic for the null hypothesis that the classification table is diagonal is 2799, which is significant at the 1% level. Therefore, we reject the null hypothesis that the funds within a stated objective group are homogeneous, and distinct from the funds in other stated objective groups. In other words, some funds in the stated objective groups have attributes distinct from the majority of the funds in their objective groups.

Table 4 also shows that the attributes-based objectives of a significant number of funds are far away from their stated objectives. For example, seven out of 57 (12%) asset allocation funds are classified into growth-income, growth or small capitalization funds, and four out of 48 (8%) of the aggressive growth funds are classified into asset allocation, balanced and equity income groups based on their attributes. To get an idea of the extent of this severe misclassification, consider the three broad fund groups: income-oriented fund group (asset allocation, balance, and equity income funds), growth-oriented fund group (growth and growth-income funds), and aggressive capital appreciation-oriented fund group (aggressive growth and small capitalization funds). A misclassification outside of these broad fund groups may be considered severe. Panel B of Table 4 shows that 353 out of 1,043 (34%) funds are severely misclassified. This degree of severe misclassification casts serious doubt on the current fund objective classification system. The $\chi^2$ statistic for the diagonality of classification table in Panel B of Table 4 is 1,718, which is also
significant at 1% level, again leading to rejection of the null hypothesis that mutual funds in even these three aggregated objective classes are homogeneous in their attributes. This degree of disagreement between the stated and attributes-based objectives is a genuine cause for concern.

VII. Objective Stability and Consistency

Mutual funds change their investment style and attributes over time because of the change in management philosophy. This may or may not be accompanied by an explicitly stated change in the fund’s objective since the way in which the objective statements are written in the prospectus gives the fund management a lot of flexibility to change the investment philosophy of the fund without explicitly changing its stated objective. Furthermore, an explicit change in the stated objective requires approval from the shareholders, and may be quite tedious and time consuming. An explicit change in the stated objective of the fund is not a desirable business strategy because it may force some existing investors to close their accounts and take their business elsewhere. For these reasons the stated objective of a fund is changed very rarely. A fund’s investment philosophy and style changes quite frequently. The discriminant analysis process should be able to pick up these changes because of the resulting changes in the fund attributes. As a result, we should find the stated objectives to be much more stable over time than attributes-based objectives.

In this section, we study the stability of stated and classified objectives, and consistency between stated and attributes-based objectives using the two independent samples: December 1993 and December 1996. Our December 1993 sample has 660 funds. By December 1996, 144 of these funds disappeared from the sample either because the fund itself ceased to exist or because the Morningstar database did not have some item needed for our analysis. Table 5 shows the results from the remaining 516 funds.

On the whole, 7.95% of the funds changed their stated objectives between December 1993 and December 1996. The highest frequencies of objective change are for the small capitalization and aggressive growth funds. In contrast, the attributes-based objectives changed in almost half (54.46%) the cases. The highest frequencies of objective changes are for equity-income, growth-income, and growth funds. Our finding is consistent with Indro, Jiang, Hu and Lee (1998) who find that over the period of 1993 through 1995, 57%
of the funds changed their investment styles (investment orientation or median market capitalization).

The last column of Table 5 shows the degree of consistency between the stated and attributes-based objectives for these 516 funds. 26.94% of the funds had identical stated and attributes-based objectives in December 1993 and December 1996. From Table 4 we know that only about 46% of the funds have the same stated objectives as their attributes-based objectives. This agreement between stated and attributes-based objectives deteriorates as we examine the consistency at multiple time periods.

VIII. Objective Gaming

Several stories in the popular business publications suggest that some funds may be taking on too much risk by leveraging or including derivatives and riskier securities in their portfolios [see, for example, Herzfeld (1991), Stone (1994), Simon (1994) and Schwimmer (1994)]. In an article in The Wall Street Journal, Clements (1994) reports that the Oppenheimer Main Street Income & Growth Fund is classified as growth-income by both Morningstar and Lipper Analytical Services, “But it turns out that the Oppenheimer fund is really a small-company stock fund in disguise. Its holdings have a tiny average market value of just $380 million. ‘It’s certainly not your conventional growth-and-income fund,’ concedes Jon Fossel, chairman of Oppenheimer Management, which manages the fund.” Hector (1995) concludes that “a growing number of funds operate according to a Wall Street axiom: ‘The best way to win a contest for largest tomato is to paint a cantaloupe red.’” Clements (1994) also cites, ‘There’s a dramatic variation in the risk level among funds,’ says Dreyfus’s Mr. Hoey. ‘There are some funds that are running much higher levels than their shareholders may be aware of.’” In a story about equity-income funds, Stone (1994) notes that “The trick to investing in this group is understanding that despite their common classification, the funds have widely varying strategies. . . . ‘The only thing equity-income about some of the funds is the name,’ says Roger Newell, who is portfolio manager of the more traditional Vanguard Equity-Income Fund.”

Anecdotal evidence cited above suggests that some funds may be gaming their objectives by stating their objectives to be in lower risk classes than the risks they actually pursue. Using this strategy, the fund managers may be expecting to perform better in relation to the funds in their stated objective groups by earning higher returns consistent with the objectives they actually pursue. The actual objectives can be determined from their attributes. If our sample of mutual funds engage in objective gaming discussed above, we should find that among the funds that deviate from their stated objectives, more deviate into higher risk objectives, as judged by their attributes, than into lower risk objectives.

Using the numbers shown in Table 4 we find that, 238 (22.8%) funds have lower risks while 325 (312%) have higher risks than their stated objectives. A similar pattern (more funds deviating to lower risk objectives than higher risk objectives) holds for individual fund objective groups as well (except for the two edge objective groups—asset allocation and aggressive growth—where such a deviation is possible only in one direction). This

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8 Stated objectives of the funds above the diagonal in Table have lower risks than their attributes-based objective. If we add up the numbers above the diagonal, we get $34 + 4 + 3 + 2 + 2 + 0 + 4 + 2 + 2 + 2 + 18 + 1 + 2 + 19 + 9 + 44 + 37 + 53 = 238$. Similarly, the numbers below the diagonal add up to 325.
pattern of departure from their true (attributes-based) objectives does not corroborate the anecdotal evidence on gaming.

To investigate the issue of gaming further, we examine the performance of mutual funds relative to their peers. If a majority of funds are successfully able to game their objectives, we should find that the relative performance of funds that successfully game their objectives is systematically higher (or at least not lower) in their stated objective group than their performance in their attributes-based objective group (the group in which they should actually belong).

We use a technique similar to The Wall Street Journal to assign relative performance based grades: We assign an ‘A’ to a fund if its average return ranks in the top 20% in the comparison group, ‘B’ if it ranks in the next 20%, and so on.

In Table 6 we examine the effect of objective gaming on relative performance. To interpret the numbers in this table, let’s examine the funds with stated objective of growth. Of the 394 funds with growth as stated objective, 81 pursued higher risk objectives (small cap or aggressive growth). Twenty-six of these 81 funds received a higher performance ranking in their stated group (growth) than if they had been evaluated in their attributes-based objective group. On the whole, 234 funds pursued objectives with higher risk than their stated objectives. Of these, 69 (29%) benefited in terms of relative performance in their stated objective group, 128 (55%) were unaffected, and 37 (16%) were affected negatively.

<table>
<thead>
<tr>
<th>Risk of attributes-based objective</th>
<th>Higher</th>
<th>Same</th>
<th>Lower</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pos</td>
<td>None</td>
<td>Neg</td>
</tr>
<tr>
<td>ASAL (57)</td>
<td>12</td>
<td>31</td>
<td>2</td>
</tr>
<tr>
<td>BLNC (110)</td>
<td>9</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>EQIN (64)</td>
<td>21</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>GRIN (233)</td>
<td>8</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>GRTH (394)</td>
<td>81</td>
<td>44</td>
<td>12</td>
</tr>
<tr>
<td>SMCP (138)</td>
<td>26</td>
<td>53</td>
<td>18</td>
</tr>
<tr>
<td>AGGR (48)</td>
<td>13</td>
<td>31</td>
<td>8</td>
</tr>
<tr>
<td>Total (1043)</td>
<td>69</td>
<td>128</td>
<td>37</td>
</tr>
</tbody>
</table>

Note: The total number of funds does not add up to the total shown in Table 1 due to rounding.
We conducted a sign test to assess whether there is any statistically significant relationship between the effect on relative performance ranking and deviation of attributes-based objectives from their stated objectives. The null hypotheses is that the median effect of reclassification on relative performance is zero. For the total sample, the only significant effect is for funds whose attributes-based objectives are higher than their stated objectives, and it is in the expected direction: A deviation into higher risk objective does indeed result in a better relative performance in the stated objective group. For individual stated objectives, the results are mixed and often in the direction opposite to that anticipated based on the gaming hypothesis.

IX. Conclusion

Using discriminant analysis we classify mutual funds based on their attributes (characteristics, investment style, and risk/return measures) to see how well their stated objectives conform to the attributes-based objectives. We find that the stated objectives of over 50% of the funds do not match their attributes-based objectives, and the stated objectives of over 33% of the funds depart severely from their stated objectives. Therefore, like Brown and Goetzmann (1997) and diBartolomeo and Witkowski (1997), we conclude that the current system of classifying mutual funds based on their stated objectives has a significant room for improvement. This provides impetus for future research into better fund classification schemes and more careful monitoring of fund investments to ensure that the funds do indeed stay true to their stated objectives.

In a recent article in *The Wall Street Journal*, Boitano (1999) reports that Lipper Analytical Services is considering a new classification system which will place funds into categories based on actual portfolio holdings and riskiness of investment style. This classification method is consistent with the conclusions of our paper.

Funds may deviate from their stated objectives either deliberately or accidentally. Reports in the financial press suggest that funds may be deliberately departing from their stated objectives into higher risk objectives to capture higher returns associated with higher risks. Our findings do not support this conjecture. We find that more funds are deviating into lower risk objectives than into higher risk objectives. Nevertheless, of the funds that diverge into higher risk, more benefit in relative-performance than are hurt. Regardless of the source of the problem, the drift from the stated objective is potentially detrimental to the investor who relies on the manager to carry out the fund’s stated mission. The new Lipper fund classification system reported in Boitano (1999) is intended to adjust relative fund performance assessment by drawing conclusions based on “true” fund objectives.

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