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FUND MISCLASSIFICATION AND THE LIMITATIONS AND APPLICATIONS OF RETURN-BASED STYLE ANALYSIS

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ABSTRACT
Due to misclassification, the determination of the investment objective and policy of a mutual fund is not straightforward. Return-based style analysis, as first introduced by Sharpe (1988, 1992) makes it possible to find out the fund's actual investment policy. The method is, however, not without caveats. In this paper, we first discuss the methodology and limitations of return-based style analysis. Afterwards, an overview is presented of the empirical evidence on mutual fund misclassification and other main applications of return-based style analysis.

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1. Introduction

Since first introduced by Sharpe (1988, 1992) as a method to determine the effective asset mix of a mutual fund, return-based style analysis (RBSA hereafter) has become a popular tool in analyzing mutual fund returns and investment objectives. The interest in style analysis stems from problems faced by investors and the management of companies distributing funds, in determining the actual mutual fund investment objective and investment behavior. We refer to mutual fund misclassification if the actual investment objective and policy of a mutual fund is in conflict with the stated objective in the prospectus, the self-declared style or the one drawn up by a data vendor.

Knowing the actual investment policy is of importance because wrong inferences about the fund's actual investment policy lead to sub-optimal portfolios and unwarranted risk exposures. Suppose we want to hold a diversified portfolio made up of equity and bonds, and hold a portfolio of mutual funds with equity and bond investment objectives. If in reality, the bond funds are all highly exposed to equity, the portfolio will be less diversified than presumed and risk will be more highly concentrated. The same problem arises when we have mixed portfolios of mutual funds and other assets (stocks, bond, real estate, …) Although this example will probably oversimplify the overall portfolio management faced in reality, it makes clear that we need a tool to assess the true mutual fund exposures. RBSA can be used as a kind of auditing tool by the management of companies distributing funds. The assessment of the historical exposures of the various managers can give insight in the possible deviant behavior of individual funds and the impact on the overall portfolio, as well as the true historical exposures to a set of benchmarks. In the same way, investors could use RBSA in the investment selection process of mutual funds: the verification of the historical style exposures of mutual funds could lead to inferences about the relation of individual funds to the overall portfolio.

A natural way for mutual fund investors to establish a mutual fund investment objective would be to consult the fund's prospectus. Evidence in, for instance, Brown and Goetzmann (1997) or Kim, Shukla, and Thomas (2000) indicates that fund misclassification with respect to the stated objective occurs. Kim, Shukla and Thomas (2000) test whether funds are misclassified with respect to a set of fund attributes (characteristics, investment style, and risk/return measures) and find that 54% of the funds have attributes which are not in line with their stated objectives.

An alternative manner to ascertain a fund's investment policy would be to rely on the classification provided by a mutual fund data vendor. Typically the division of funds into different investment classes is based upon the fund's prospectus or the self-declared style by the fund manager [diBartolomeo and Witkowski (1997)]. The classification by data vendors may be in conflict with the actual exposures too [see for instance diBartolomeo and Witkowski (1997) or Otten and Bams (2000)].[1] For instance, Otten and Bams (2000) apply RBSA and report that 15% of the funds in their sample of U.K unit trust funds are significantly misclassified (95%-confidence intervals). Without significance testing, 27% of the funds exhibit style deviations. As illustrated, the number of funds (%) withheld as misclassified in the different studies varies greatly, depending on the dimensions for which misclassification is examined, as well as whether or not statistical criteria (significance testing) are taken into consideration to withhold a fund as misclassified. 'Dimensions' refer to the number of fund attributes taken into consideration to assess misclassification. Most studies are confined to return data only. Moreover, the criteria set out to determine misclassification and the set of asset classes chosen play an important role. If our set of asset classes consists only of a general equity index and a bond index, a small cap fund that is predominately exposed to the equity factor is most likely assessed as classified correctly. If we add a small cap index to our set of factors, it is evident that a small cap fund not predominately exposed to the small cap index is labeled misclassified. We discuss this issue in more detail in section 3.

Given the occurrence of mutual fund misclassification return-based and characteristic-based style analysis can be used in order to gain insight in the actual investment policy. The latter relies on actual portfolio holdings and thus analyses the stocks held in mutual fund portfolios [e.g. Daniel, Grinblatt, Titman and Wermers (1997), Chan, Chen and Lakonishok (1999) or Wermers (2000)]. The main drawback of this approach is that information on actual mutual fund holdings is in most cases not readily available.[2] RBSA allows determining the exposure of mutual fund returns to the returns of certain asset classes. The asset classes are typically chosen to be a number of selected passive style indices. Contrary to characteristic-based style analysis the input for RBSA is readily available, which makes it an attractive tool from a practical point of view.[3] However, the methodology is not without caveats that should be kept in mind. Other classification systems are suggested in the literature as well [Bailey and Arnott (1986), Tierney and Winston (1991), Brown and Goetzmann (1997) or Kim, Shukla and Thomas (2000)], and the most important results of these studies are also discussed in section 3.

In its original form (as introduced by Sharpe), RBSA boils down to estimating a constrained regression in order to determine the exposure of the mutual fund returns to different factors (returns on asset classes). Two constraints are imposed. First, the coefficients should add up to one in order to

1 Moreover, different databases may classify identical funds into dissimilar classes. Gallo and Lockwood (1997) compare the classification of funds by two databases CDA Investment Technologies and Morningstar and highlight that "… CDA and Morningstar classify many funds differently."

2 Mutual fund portfolio holdings are generally only available on a quarterly basis. Timely information on holdings may be difficult to obtain [see for instance comments in Lucas and Riepe (1996)]. If the mutual fund managers commit window dressing practices, inferences from reported portfolio holdings may be misleading. Chan, Chen and Lakonishok (1999) compare the two approaches and conclude that the two approaches in general give similar results on the fund's style. In the cases where the two approaches yield different results however, the characteristic based approach is better in predicting future fund performance.

3 A reliable time-series of historical fund returns is required.

interpret the coefficients as portfolio weights. Secondly, since mutual funds are legally prohibited to effect short sales, coefficients are set to be positive. The principal goal of RBSA is to find the best mimicking strategy that is in accordance with the investment style of the mutual fund.

Sharpe presented RBSA as a way to retrieve the effective asset mix of mutual funds. RBSA has been applied to problems related to (i) mutual fund classification, (ii) performance evaluation and object gaming, (iii) construction of diversified portfolios or efficient portfolios of mutual funds with specified factor loadings and (iv) risk assessment. Object gaming is defined as the practice of deliberately deviating from the stated objective to attain higher relative performance.

In this paper we confine the discussion mainly to applications of RBSA to mutual funds. In principle, the general framework of RBSA can be carried over to hedge funds as well. In the early stage of research, the success of applying RBSA was feebly: the underlying factors were not well understood and the dynamic strategies commonly applied by hedge fund managers resulted in non-linear returns not well captured by traditional RBSA. Modifications have greatly improved the applicability of RBSA. Possible solutions are to add specific factors to capture the specific investment opportunities and dynamic trading strategies [e.g. Mitev (1995) or Fung and Hsieh (1996)] or to use special hedge fund indices [Schneeweis and Spurgin (1998) or Lhabitant (2001a,b)]. Given that hedge funds can engage in leverage and short sales practices, the portfolio and short sales restrictions are often omitted. The recent innovations in the hedge fund RBSA-methodology have resulted in a growing number of applications to this industry.

In the remainder of this paper I first present the methodology and limitations of RBSA. Afterwards, I give an overview of the empirical evidence on mutual fund misclassification and the main applications of RBSA. Finally, I conclude.

2. Methodology

2.1. Sharpe's (1992) model

The econometric model proposed by Sharpe belongs to the class of asset factor models. An asset factor model is defined as a special case of a factor model whereby each factor represents the return on an asset class, and the sensitivities of the fund to the factors add up to one. Because of legal short-sell restrictions faced by mutual fund managers the restriction of positive sensitivities is usually imposed as well. The model can therefore be written as:

$$(1) \quad R_t = \alpha + \sum_{i=1}^{K} \beta_i R_{it} + \varepsilon_t \quad \text{with } t=1,\ldots,T \text{ and } \mathrm{E}[\varepsilon_t R_{it}] = \mathrm{E}[\varepsilon_t] = 0 \quad \text{for } i = 1,\ldots,K.$$

subject to:

$$\text{(1.a)} \quad \sum_{i=1}^{K} \beta_i = 1 \quad \text{and} \quad \text{(1.b)} \quad \beta_i \geq 0 \qquad \text{with } i = 1,\ldots,K$$

R_t equals the fund return at time *t*, R_{it} denotes the return on asset class *i* at time *t*, K is the number of asset classes, ε_t is the idiosyncratic noise term, β_i is the factor sensitivity of R_t to the specified factors R_{it}. Because of the first restriction (1.a), which is also called the portfolio restriction, $\sum_{i=1}^{K} \beta_i R_{it}$ can be interpreted as the return on a passive portfolio with the same investment style as the fund. The second restriction (1.b) represents the short-selling restriction in this model. A feature of the model is that it decomposes a fund's return into a component that is attributable to style, given by $\sum_{i=1}^{K} \beta_i R_{it}$, and an idiosyncratic return component, given by $\alpha + \varepsilon_t$.

2.2. Prerequisites and limitations

In order to get feasible results a number of prerequisites have to be fulfilled. The asset classes should be [Sharpe (1992), Lobosco and diBartolomeo (1997), de Roon, Nijman and ter Horst (2000)]:

- mutually exclusive;
- no linear combinations of other asset classes;
- exhaustive.

To prevent problems due to multicollinearity, it is advisable to examine the correlations between the factors (returns on asset classes). If the factors are highly correlated, they capture the same style characteristics, and one asset class should be dropped from the model. In a related paper, Christopherson (1995) shows that because of susceptibility to noise and specific risk, the sole inspection of correlations to determine the factor exposures of mutual funds is insufficient. More specifically, he draws a random sample of stocks belonging to the Russell 2000 index (small caps) and calculates the correlation between the return of these stocks and the return on four Russell style indices. 16% of the selected stocks are more highly correlated to large capitalization Russell indices than to the Russell 2000 index. Nevertheless, the correlation pattern arises due to noise or specific risk: the equally weighted portfolio of these stocks exhibits the same characteristics (such as P/E, beta, market capitalization, …) as small caps. If a mutual fund's portfolio is made up of these stocks, the factor exposures to the Russell style indices resulting from RSBA would be misleading. Furthermore, asset classes should be linearly independent. If one asset class is a perfect linear combination of other asset classes, style analysis may yield different sets of sensitivities which are exactly equivalent [Lobosco and diBartolomeo (1997)]. Finally, since we want to find the best mimicking portfolio, the asset factor model should be able to span the fund's portfolio asset mix.

The set of factors is an essential element in the conduct of RBSA. Two elements should be kept in mind, namely the selection of the asset classes and the number of asset classes. Even the choice between indices that are generally viewed as representing the same style is of importance, as illustrated in Bueton, Johnson, and Runkle (2000). For instance, the style exposures change substantially depending on whether the Russell 2000 Growth index or the BGI Small Cap Growth index is used in the model. Both indices are generally viewed as representing the same style and are strongly correlated (0.99).[4] The authors suggest applying ordinary style analysis for asset allocation analysis only if the fund's assets are indexed to well-prescribed indices. This recommendation is in line with Bailey and Tierney (1993) and Bailey (1992a,b) who suggest to create specific benchmarks based upon the universe of securities fitting the manager's investment style. Lucas and Riepe (1996) allude to the same topic. They quote the case of a domestic fund investing in domestic companies that derive a majority of their revenues from sales abroad. Clearly, the performance of the companies, and as a consequence, the performance of the fund will be influenced by factors in foreign economies. Suppose that a recession hits the foreign countries but not the domestic economy. RBSA will result in low factor sensitivity to the domestic index (and high factor sensitivities to foreign indices). Preferably, one would like to combine RBSA with fundamental information on the securities in the fund's portfolio.

In most papers the definitions and the number of asset classes are not well motivated. Typically, a set of prespecified indices which are taken to represent certain style characteristics are chosen, and little concern is devoted to the number of factors to be used. This might cause problems due to linear dependency of the indices as is illustrated by Lobosco and diBartolomeo (1997). Sharpe (1992) uses 12 asset classes, where as in most subsequent papers the number of asset classes is smaller (see Appendix 2). In a related paper, Brown and Goetzmann (1997) rely on a statistical measure to determine the number of factors. Based on the likelihood ratio test of Quandt (1960) they find evidence that at least eight separate categories should be employed in their analysis.

A consequence of the imposition of restrictions (1.a) and (1.b) is that the exposures are not unbiased estimates. In effect, a factor sensitivity that would have been negative if model (1) was estimated without restrictions is forced to be 0 in the constrained model [Lobosco and diBartolomeo (1997)]. de Roon, Nijman, and ter Horst (2000) quantify the biases that arise from imposition of the constraints (see Appendix 1). Following de Roon, Nijman, and ter Horst (2000) we make a distinction between three types of style analyses, namely strong, semi-strong and weak style analysis. In strong style analysis both restrictions should be satisfied, in case of semi-strong style analysis only the portfolio constraint is imposed, where in case of weak style analysis no constraints are imposed.

de Roon, Nijman, and ter Horst reason that the imposition of the constraints should be made dependent on the purpose of RBSA. In short, they suggest using strong style analysis for performance evaluation of mutual funds. Given that, in this instance, the aim of style analysis is to find the best mimicking benchmark the imposition of both constraints are necessary. Weak style analysis should be used in the construction of efficient portfolios from mutual funds that have fixed exposures to certain asset classes. A necessary condition in this research conduct is that the correlation between the return on the benchmark assets and the error term is zero. The imposition of the portfolio and/or positivity constraint when the actual style coefficients are no positively weighted portfolios results in correlations which are not necessarily zero. Hence, semi-strong and strong style analysis are not appropriate. Finally, to determine the portfolio holdings of mutual fund managers weak style analysis is the best option, although even the weak style coefficients will not represent the actual weights assigned to the factor classes by the mutual fund manager. Mutual funds may only hold a subset of the assets constituting the index, weight the assets differently than the index or the fund's portfolio beta could be different from 1.

Even if the above criteria are taken into consideration, the original model proposed has its limitations. One important drawback is that in RBSA it is assumed that the sensitivities to the factors remain fixed over the sample period. In reality style changes in time have been documented [see e.g. Otten and Bams (1999), Chan, Chen and Lakonishok (1999), Kim, Shukla and Thomas (2000), or Swinkels and Van Der Sluis (2001)][5]. Chan, Chen and Lakonishok rank funds by style (with respect to size and with respect to book-to-market) at the end of each year and the funds' rankings are rescaled to be bounded between 0 and 1. The correlation between a fund's ranking on size or book-to-market and the future style rank measure at the end of the third subsequent year is calculated subsequently. The style is measured using either RBSA or characteristic-based style analysis. For the overall sample the correlation based on RBSA is about seventy percent, although the average absolute difference in style ranks is substantial (± 15%). The authors also mention that large shifts in style do occur.

To visualize the time-varying property of style coefficients, it is common practice to estimate Sharpe's model over rolling windows [Sharpe (1992), Lucas and Riepe (1996), Buetow, Johnson, and Runkle (2000), and Otten and Bams (1999)]. It is then possible to graph the style exposures through time. This approach might help to get a first impression of the time variation of style coefficients. To arrive at a sounder conclusion about the time-varying character of style exposures, one could additionally investigate if the difference of style exposures at various time points is also statistically significant. Moreover, the approach of style analysis with rolling windows still assumes that the sensitivities are constant over the rolling window. Finally, given that the rolling windows are overlapping and the fact

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4 See also Brown and Mott (1997).

5 For other comments on the impact of style dynamics see also Christopherson (1995) and Trzcinka (1995).

that every observation in RBSA is equally weighted, there is a delay in the recognition of a style change.

Along the same lines, Brown and Goetzmann (1997) apply an algorithm based upon the switching regression technology that allows the factor loadings to change on a monthly basis in order to accommodate non-linear return patterns. Swinkels and Van Der Sluis (2001) apply a Kalman smoother to model explicitly the time-varying exposures in a weak style analysis context. In this instance the complete data sample is used to estimate the model. The authors mention that applying this technique to semi-strong style analysis is possible by reparameterization of the sensitivities. Introducing the short-selling restriction into the model as well, which is necessary to perform strong style analysis is more difficult due to the introduction of non-linearities in the model. The Kalman smoother is only capable of capturing smooth changes in the timepath of the coefficients. Capturing abrupt changes proves to be a difficult task. Neumann (1999) compares 4 different methods for estimating time-varying coefficients in *univariate* regression models (moving windows least squares (MWLS), recursive discounted least squares (RDLS), flexible least squares (FLS) and state space models with random walk coefficients (RWM)). In case of abrupt level shifts no method performs well, although the best alternatives are MWLS and RDLS. Given gradual coefficient changes, RWM yield the best results while none of the models performs well under all types of coefficient instability. An alternative approach could be to test whether one or more breaks do occur by applying breaktests [e.g. Andrews and Ploberger (1994), Hansen (1997) or Bai and Perron (1998)]. These tests allow seeking for one (Andrews and Ploberger, Hansen) or more breakdates (Bai and Perron) at unknown breakdates. If we are faced with a single a priori unknown breakdate, the χ^2-distribution cannot be used to assess statistical significance of the Quandt statistic (1960). The Quandt-test selects the largest Chow statistic over all possible breakdates. Appropriate critical values were proposed by a number of authors including Andrews (1993) and Andrews and Ploberger (1994), while Hansen (1997) derives the approximate asymptotic p-values. The procedure outlined in Bai and Perron (1998) allows testing for multiple breaks. In essence, it is a sequential break test: if a break is encountered the sample is split in two (at the breakdate), and the test is repeated on the subsamples. The framework of the test procedure is flexible, rendering it possible to test for pure or partial breaks (in case a subset of parameters remains unchanged), and assuming various hypotheses about the structure of the data and the errors across segments.

The estimation of the original model by applying quadratic programming makes it problematic to assess whether the individual sensitivities are statistically accurate estimates of the true factor exposures. Lobosco and diBartolomeo (1997), Kim, Stone and White (2000) and Otten and Bams (2000) have tackled this problem. In the first paper, the confidence intervals for the individual style weights are derived.[6] The confidence intervals are helpful in interpreting the robustness of the results and can be applied to verify the statistical significance of style weight differences in time. Moreover, large confidence intervals may point to a lack of diversity of the factors. The method is not valid in general given that it produces a biased sampling distribution when the true style coefficients are zero or one. Kim, Stone and White (2000) suggest a procedure to obtain statistically valid asymptotic confidence intervals based on Andrews (1999) regardless of the true style coefficients. Moreover, they explore the use of a Bayesian approach to style analysis. The implementation of this latter approach is hampered by the extreme computational cost when the style weights are near the boundaries (0 or 1). In the third paper, Otten and Bams (2000) derive the asymptotic distribution of the style weights by combining Kuhn-Tucker optimization and Monte Carlo simulation. The proposed significance testing makes it not only possible to investigate whether coefficients are significantly different from zero, but also to verify whether the coefficients are significantly different from each other.

An overview with respect to the methodology applied in the empirical studies is given in Appendix 2. More specifically, per study the table indicates (if mentioned in the original paper) the data sample, purpose and form of style analysis, description of the chosen style factors and the mutual fund database source.

3. Empirical Evidence and Applications

3.1 Evidence on Fund Misclassification

A mutual fund can be misclassified with respect to the stated objective in the prospectus, the self-declared style or with respect to the classification put forward by a data vendor. RBSA makes it possible to learn about the actual investment policy by determining the effective asset mix of the mutual fund, thereby circumventing problems related to misclassification. As a result RBSA can be applied to assign funds to classes based on actual investment styles and is as such a handy tool to pierce through the veil of object gaming. The new classification engrafed on RBSA allows us to create homogeneous groups of funds. Two remarks can be formulated with respect to the level of homogeneity. Firstly, do we consider equity funds as a uniform group or do we apply a finer delineation into growth funds, balanced funds, etc? This should ultimately depend upon the research questions one wants to answer. Secondly, these classes based on RBSA are formed on the sole basis of return data. A more in-depth approach would be to group funds with respect to several attributes as is done in Kim, Shukla and Thomas (2000). This is of importance because empirical studies in general do not study the entire mutual fund industry but limit their sample to a subgroup of funds according to investment objective and policy (e.g. equity funds, balanced funds, …). The underlying assumption is that the group of mutual funds under study is homogeneous. The division of the funds into different categories is mostly based upon the classification provided by a data vendor. This classification could

6 This paper uses monthly data to establish the confidence intervals. The use of daily data could result in a substantial reduction of the confidence intervals

be subject to misclassification since data providers rely on the prospectus or on the self-stated investment style of the fund to assign funds to various classes. As a result, the groups of funds examined may be less homogeneous than implicitly assumed. To illustrate this point, consider for example the paper by Blake and Morey (1999) in which they study the influence of Morningstar ratings on mutual fund performance. They limit their sample to growth funds. Studies on mutual fund style [e.g. Brown and Goetzmann (1997), diBartolomeo and Witkowski (1997), and Otten and Bams 2000)] have shown that this category has a pronounced hybrid character. Unless we verify empirically that the funds are indeed growth funds we cannot be sure that we are actually obtaining results with respect to the growth fund category only. Instead we are most likely comparing growth funds with other fund categories with different characteristics. The ranking of the funds in the sample (although all are labeled growth funds) will be flawed because of this heterogeneity.

The empirical evidence on mutual fund misclassification is mixed. diBartolomeo and Witkowski (1997) report that 40% of the equity funds in their sample are misclassified.[7] A fund is considered misclassified if the predominant factor loading is different from the category declared in the prospectus. ter Horst, Nijman and de Roon (1998) report that in their sample of Dutch mutual funds only funds with the investment object 'International Equity' ('International Bonds') are subject to style deviations, in the sense that these funds are highly exposed to Dutch equity (Dutch CBS bond index). These results indicate that a domestic market effect is at hand. ter Horst, Nijman and de Roon declare a fund misclassified if the estimated maximum factor exposure does not coincide with the self-reported investment style.

To assess the robustness of style deviations it is important to look at the statistical significance of style divergences. Otten and Bams (2000) report that 27% of the funds in their sample predominantly load on a different than expected factor, but only 15% of these funds exhibit statistically significant style deviations (95%-confidence intervals). In a previous paper, Otten and Bams (1999) retrieve, at least at first sight, corroborating evidence of fund misclassification. 75% of the growth funds in their sample display value tilts and 50% of the value funds are driven by growth returns. However, the accompanying confidence intervals are broad, so the authors conclude that the style deviations are not statistically significant. By taking into account significance intervals the degree of misclassification is likely to reduce, since style deviations attributable to chance or noise are filtered out. It should be kept in mind that the papers mentioned above rely on strong RBSA.

An issue that is mainly overlooked is the influence of survivorship bias upon fund misclassification. Results in Otten and Bams (2000) indicate that survivorship bias might be an issue. 22% of the dead U.K. funds were significantly misclassified compared to 15% of misclassified funds in the total

of the style weights.

sample. Data samples that are not free of survivorship bias could therefore be underestimating the rate of misclassification. Obviously, the subject should be studied more thoroughly to arrive at meaningful conclusions.

Evidence that mutual funds within the same investment category do not make up a homogeneous group is backed by studies analyzing more than one dimension of mutual funds. RBSA concentrates on return data and thus can be viewed as a one-dimensional classification system. Attempts have been undertaken to classify mutual funds on the grounds of more than one characteristic. LeClair (1975), using multiple discriminant analysis, reports that 70% of the funds are categorized into the class coinciding with their stated objective.[8] The classification was, however, very poor with respect to balanced funds for which only 15% were placed in their original category. On a more recent note, Kim, Shukla and Thomas (2000) study the relationship between fund objective and fund characteristics (7), investment style variables (8) and risk/return variables[9] (5). Based on principal factor analysis they find that the most important factors are (listed in order of importance): standard deviation of returns, income ratio, beta, R^2, price to earnings ratio, price to book ratio, % stocks, debt as percent of total capitalization, market capitalization and average return. Funds are assigned to the attributes-based objective groups by applying discriminant analysis. They find that, on average, the attributes-based objectives of only 46% funds are the same as their stated objectives. As a consequence, they reject the null hypothesis that funds are homogeneous within a stated objective group and distinct from funds in other stated objective groups.

What drives fund misclassification? A first observation is that the number of funds withheld as misclassified is dependent, as mentioned above, upon the research design: definition of misclassification, statistical significance level (if any), and fund group homogeneity (cf. remarks with respect to the level of homogeneity) put forward. A second observation is that deviations between the actual investment policy and the stated objective are far more prominent than explicit changes in stated fund objective. Brown and Goetzmann (1997) mention that 237 of the 2283 equity funds in their sample (± 10%) switched their stated objective over the period 1976-94. Kim, Shukla and Thomas (2000) report that over their three year data sample about 8% of the funds changed their stated objective which is far beneath the attributes-based misclassification of 54% reported in the same study. The reluctance towards explicit changes in stated objective may be related to the fact that an explicit modification of the stated objective could be subject to the approval of existing shareholders. The shift in objective is a time-consuming process that could result in divestments of existing

[7] Although not explicitly tested the classification in Gallo and Lockwood (1997) based on weak form RBSA is distinct from the classification based on Morningstar or CDA Investment Technologies.

[8] Five variables are considered: mean return, variability of return, fund size, average portfolio turnover and variability of portfolio turnover. The multiple discriminant analysis indicates that standard deviation of return, fund size and average portfolio turnover rate are the most important discriminating variables.

[9] Early work by Martin, Keown and Farrell (1982) reports that the means for three extra-market measures (i.e. extra-market variance component, square of correlation coefficient between portfolio and market returns, and the ratio of extra-market variance component to total variance are not equal over investigated investment objectives.

investors. [Kim, Shukla and Thomas (2000)]. This kind of hypothesis has not been tested empirically. A possible testable hypothesis would be to conduct an event study to verify if, after controlling for other factors influencing fund flows, statistically more disinvestments take place around the objective change date. A simpler reason may be embedded in the ambiguity of the classification system at hand [diBartolomeo and Witkowski (1997), Kim, Shukla and Thomas (2000)]. The distinction between related classes is sometimes vague, leaving room for interpretation and unintended or deliberate misclassification.

Another reason behind mutual fund misclassification (to which more research attention has been devoted) is that mutual funds try to game their objective in order to attain superior performance vis-à-vis their peers. This motivation is related to performance evaluation. The basic idea behind relative performance evaluation is that mutual fund managers in general have restrictions on the asset classes in which they can invest. Hence, comparing mutual fund performance without taking into account this restriction would be an example of comparing apples with oranges. Indeed, if we want to assess the stock selection skills of fund managers it would be unfair to compare roughly the performance of value funds and growth funds over a period in which the performance of value stocks dominated the performance of growth stocks. Clearly, on average the growth funds will have inferior relative performance because of their limitation to invest predominantly in growth stocks. Therefore, assessing the performance of funds by comparing their performance to that of their peers with the same stated investment objective seems the correct decision. However, this method will yield biased results if there is a discrepancy between the fund's actual investment policy and the stated objective. Self-evidently, if we reconsider the example above, the best shot of becoming the growth fund with the highest performance relative to its peers (other funds with 'growth stocks' as investment objective), is to be a value fund disguised as a growth fund. We refer to the practice of deliberately deviating from the stated objective to attain higher relative performance as *object gaming*. The fact that relative fund performance and rankings are important in attracting new inflows would hand an incentive to mutual funds to game their objective class. Several studies have documented that top-performing funds get the bulk of investors' inflows [see for instance Sirri and Tufano (1992) and Gruber (1996)]. Moreover, it has been shown that ranking systems affect the investment decisions of mutual fund investors [see for instance Blake and Morey (1999) and references therein].

Thirdly, there is a possible relation between fund misclassification and agency problems. The preference of mutual fund managers for certain stocks may be related to career concerns. For instance, anecdotal evidence in Chan, Chen and Lakonishok (1999) documents that most mutual funds that deviate from a widely followed benchmark as the S&P500 have a preference towards glamour stocks and past winners.[10] Amongst other motives, this preference for glamour stocks above value stocks may

[10] Davis (2001) examines the exposures of U.S. equity funds (over the period 1962-98) to the Fama-French three factor model and concludes that mutual funds are reluctant to take value stocks into portfolio.

be driven by career concerns taking into account the short horizons over which managers are evaluated. In general, it will take some time before value investment strategies become profitable, while fund managers may reap the profits from glamour stock investments more rapidly given price momentum. Hence, the growth tilt may cause value funds to deviate from their stated objective. Furthermore, Chan, Chen and Lakonishok (1999) document that poorly performing funds are more prone to alter their style with respect to book-to-market. These deviations could be interrelated with the short evaluation horizon of mutual fund managers as well. Besides, diBartolomeo and Witkowski (1997) indicate that new funds are often managed by managers of existing funds until the fund has reached a size which justifies the appointment of a separate manager. Funds assigned to the same manager are likely more vulnerable to be managed in a similar fashion, notwithstanding different stated objectives. This may induce style deviations.

Finally, it is possible to look for fund attributes that influence the probability of misclassification. diBartolomeo and Witkowski (1997) conduct a probit analysis and report that the likelihood of misclassification is negatively influenced by the size of the fund complex and positively correlated with the assets under management. This result is not surprising in the light of the higher level of standardized governance policy in rule by big fund complexes. The number of assets under management, in combination with limited liquidity in specific market segments, can render it difficult for large funds to follow strictly the performance of the asset class to which it is compared.

If mutual fund misclassification does occur, what are the implications? diBartolomeo and Witkowski (1997) try to quantify the economic impact of misclassification by measuring the annual unexpected wealth created be misclassified funds in their sample, given their classification. Hence, they calculate the difference in returns between the misclassified funds and the 'pure' index, multiplied by the amount of assets involved. The pure index consists of the funds per category after reclassification. The economic impact was 1 billion dollars if simple differences were used and nearly 4 billion dollars when absolute differences were used. It appears that mutual fund investors on average gained from mutual fund misclassification in terms of wealth. Though, the positive impact was achieved by taking on additional risk, which questions the profitability of misclassification in different market conditions. The misclassification may indeed result in unwarranted risk exposures. Kim, Shukla and Thomas (2000) report that 23% of misclassified funds have lower risk than their stated objectives, while 31% have a higher risk profile. Of those funds with a higher risk profile, 29% successfully gain their objective and attain better relative performances, while the relative performance ranking of 55% remains unchanged and 13% are negatively influenced. With respect to object gaming, Otten and Bams (2000) conclude that misclassification does not enhance relative performance. On average, significantly misclassified funds underperform properly classified funds by 1.00% p.a.[11] The

[11] A fund is considered misclassified if it does not load predominantly on the benchmark that is in line with its investment category. All other funds are considered correctly classified.

underperformance is even higher for significantly misclassified dead funds who have an inferior performance of 2.09% p.a. vis-à-vis the correctly classified peers.

3.2. Applying RBSA to Relative Performance Evaluation

RBSA can be applied in performance evaluation studies. It is common in performance studies to compare the return of a fund to the return of a set of benchmarks. To be sure that the set of benchmarks is in accordance with the actual investment policy of the fund RBSA can be used. RBSA yields the best mimicking portfolio corresponding to a fund's actual investment policy. This mimicking portfolio represents a passive strategy to which the fund's subsequent performance can be evaluated. The return of the fund is then decomposed in a part attributable to style and a part that can be assigned to active selection skills. Sharpe (1992) indicates that a benchmark portfolio should be a viable alternative that is not easily beaten and is low in cost and identifiable a priori. He proceeds by stating that RBSA provides a method resulting in benchmarks meeting these properties.

The performance evaluation application of RBSA shows a lot of resemblance with the commonly used Fama and French's (1993) 3-factor or Carhart's (1995) 4-factor performance evaluation models. The angle of incidence is different. The 3- or 4-factor models are directed at evaluating mutual fund excess performance consistent with an asset pricing model with 3 or 4 risk factors. The Fama-French model is an extension of a standard single index model in view to documented anomalies on size and book-to-market. To accommodate the one-year momentum anomaly documented by Jegadeesh and Titman (1993) Carhart adds a factor MOM to the Fama and French model.

Fama-French model:

(2) $$r_{it} = \alpha_{iT} + b_{iT} VWM_t + s_{iT} SMB_t + h_{iT} HML_t + \varepsilon_{it} \qquad \text{with } t=1,2,\ldots,T$$

Carhart model:

(3) $$r_{it} = \alpha_{iT} + b_{iT} VWM_t + s_{iT} SMB_t + h_{iT} HML_t + p_{iT} MOM_t + \varepsilon_{it} \qquad \text{with } t=1,2,\ldots,T$$

r_{it} = return on a portfolio in excess of one-month T-bill return;

VWM = excess return on a value-weighted aggregate market proxy;

SMB, HML and MOM are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns.

Instead, the strong form RBSA yields the best mimicking portfolio in line with the investment policy of a fund taking into account investment restrictions. The principal goal of RBSA is not performance evaluation. Nonetheless, the mimicking portfolio can be used as a passive benchmark to which the performance of the fund can be compared in the subsequent period. Given that the factors in (2) run parallel with the styles considered in various mutual fund studies (i.e. small/large capitalization and growth/value) the factor model is nevertheless sometimes used to infer a fund's style (e.g. Chan, Chen and Lakonishok (1997). They report that growth funds display better style-adjusted performance than value funds. On average, the difference in alpha is 1.2% p.a. Note that in this instance no restrictions are imposed, incoherent with the recommendation of de Roon, Nijman, and ter Horst (2000) to apply strong form RBSA for performance evaluation purposes.

In performance evaluation, the average return of a mutual fund is evaluated against the proper benchmarks taking into account investment style. de Roon, Nijman and ter Horst (2000) investigate whether actively managed funds yield better performance than the mimicking portfolio composed of passively managed funds. They test whether a set of eighteen US-based international funds outperforms a combination of two passive funds (Vanguard 5000 index and Vanguard International Growth). The underperformance of the active managed funds ranges from 0.48% to 6.48% p.a.

Corroborating evidence that, on average, mutual funds do not systematically beat the market is retrieved in other papers like Sharpe (1992), de Roon, Nijman and ter Horst (1998)[12]. On the contrary, Otten and Bams (1999) report significant outperformance for the equally weighted group of small cap funds in France and United Kingdom and the equally weighted portfolio of specialist funds in Italy. The annualized style-adjusted alpha's are 2.43, 1.82 and 4.18. For all other funds in their sample, except French index funds that have significant inferior performance, the style-adjusted alphas are not statistically different from zero.

3.3. Applying RBSA to Portfolio Diversification and Formation of Efficient Portfolios of Mutual Funds with Specific Factor Exposures

Finally, misclassification renders it difficult for mutual fund investors to obtain their chosen level of effective asset mix and diversification. Due to disparity between the investment objective and the actual asset allocation of the selected funds, mutual fund investors may have undesired high exposures to certain asset classes. This argument also applies to plan sponsor or banks that want to monitor their overall portfolio of funds. Unnoticed style deviations of funds in portfolio may result in undiversified and sub-optimal portfolios. Application of RBSA can provide a solution to form efficient portfolios of mutual funds with specific factor loadings.

Sharpe (1992) already noted that the investor's effective asset mix could be determined by taking the value-weighted average of the exposures of the funds in portfolio. The weights are the relative sums invested in the funds.

de Roon, Nijman and ter Horst (2000) illustrate the correct use and biases of the different forms of style analysis in order to form efficient portfolios with fixed exposures to certain asset classes by assuming that an investor chooses his mean-variance efficient portfolio from the set of 18 mutual funds in their sample.[13]

Baierl and Chen (2000) present an optimization method for choosing mutual funds (or managers) to attain a certain asset allocation. The problem posed is to find an allocation over funds that mimic most closely the target asset allocation. The chosen funds should be mean-variance efficient in terms of active return and should additionally satisfy the minimum investment requirements imposed by funds. Firstly, eight fund classes are created by cluster analysis. The funds with the highest information ratio, the lowest tracking error and the highest alpha per class are used in the optimization procedure. Secondly, in order to obtain the input for the optimization procedure, RBSA is run to obtain style weights and active returns. Finally the optimization method produces the set of funds satisfying all criteria. The method examplified and yields sensible results.

diBartolomeo and Witkowski (1997) demonstrate that the formation of diversified portfolios based on their revised reclassification is superior to the formation of diversified portfolios among the original classifications.

Gallo and Lockwood (1997) compare the portfolio performance of 500 portfolios of different classification systems. The external classifications systems considered are based on CDA Investment Technologies (CDA) and Morningstar (MSTAR)[14]. A preliminary analysis leads to the conclusion that portfolios formed on the basis of the four-style Morningstar classification yield better performance than portfolios on grounds of the CDA-classification. Further, they conduct weak-form style analysis using 4 asset classes over the period 1978-85. Funds are then assigned to the respective classes based on their predominant loading (LOAD). To compare the performance of the classification systems, the performance of two portfolios representing naive investment strategies is examined as well. With NAIVE1 one fund is selected randomly from the total sample, with NAIVE4 four funds are randomly selected from the total sample. The performance over the 1986-93 period of 500 portfolios per classification method are then compared by looking at the differences in mean reward-to-variability ratios (MRVAR). The mean is calculated by taking the average over the 500 portfolios per classification method. The MRVAR based on the LOAD classification is equal to 0.923 and dominates the MRVAR of the other methods. The LOAD-MRVAR is statistically different from the other methods. The NAIVE4 and MSTAR-MRVAR are not statistically different (the NAIVE4 MRVAR is even higher than the MSTAR-MRVAR). In other words, style diversification based on the 4-way style classification based on Morningstar is not meaningful.

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12 With the exception of funds with the investment style 'Netherlands Equity' that display outperformance in the RBSA.

13 This application was also suggested in Lucas and Riepe (1996).

14 The aggressive growth and small-company classes are merged. The other two classes are equity income, growth and income and growth. The CDA-classes are growth and income, growth and aggressive growth.

Related papers by Brown and Goetzmann (1997) and Christopherson (1995) have also looked at the predictability of fund returns conditional on the used classification system. Christopherson studies the information content embedded in the conditional forecast errors[15] based on effective asset mix and simple assignment to single style indices and concludes that little value is added by relying on the effective asset mix. Brown and Goetzmann concentrate on the question whether the existing classification by Weisenberger and Morningstar or their proposed empirically determined style classification system is better in explaining the dispersion in future fund returns. They conclude in favor of their alternative system that is related to the switching regression technique. The classification put forward is able to explain on average around six percent more cross-sectional variation out-of-sample, making it (only just) the better classification system.

3.4 Risk Assessement

In RBSA we compare the return of a mutual fund with the return of one or more style benchmarks. But what about the risk profile of the mutual fund? In traditional RBSA, the assumption would be that the style benchmark risk is identical to the manager's risk. This assumption should not necessarily hold. If risk is measured by variance, for well-diversified portfolios, beta can be approximated by dividing the fund’s risk by the risk of the market index portfolio. In analogy to this relationship, Sortino, Miller and Messina (1997) propose a ratio of the manager's risk to the style benchmark risk. The risk can be measured by standard deviation or downside risk.

An additional drawback is that accounting for risk in a RBSA-framework is hampered by the short periods over which the style analysis is often conducted. Therefore, the authors propose to work with bootstrapped returns. [see Effron and Tibshirani (1993) for details]. The procedure is applied to 81 individual mutual funds. The main conclusion to bear in mind is that the risk associated with the fund and style benchmarks may indeed differ.

In a related paper on the hedge fund industry Lhabitant (2001a) links RBSA to the Value-at-Risk methodology to estimate the risk level of a mutual fund.16 Once the style exposure of a hedge fund to a set of hedge fund indices is calculated, the value at risk (the maximum loss during a specified period of time at a given level of probability) can be estimated by computing the systematic and specific value at risk. Lhabitant describes the procedure as follows: the systematic risk is calculated by *forcing* the price of each individual risk factor in the most disadvantageous direction and estimate the overall impact on the fund, taking into account risk factor correlation. The specific risk is defined as the difference between total risk and systematic risk. The calculation of the value at specific risk can then

[15] Defined as the fund's realised return and the conditional forecasted return (CFT). The CFT equals the product of the effective-mix solution at time t and the realised style index return over the subsequent return in case of the style (effective-mix) solution. The CFT is the return of the class to which the fund is assigned in case the simple assignment to a single style index is considered.

[16] Lhabitant only imposes the short sales restriction in his analysis.

calculated numerically or parametrically in the usual fashion. The total value-at-risk figure is obtained by taking the square root of the sum of the squared value at market risk and the squared value of the value at specific risk. If we zoom in on the resulting VaR-figures, the monthly average VaR reported is 10.97% (figures used ar expressed as a percentage of the net asset value and calculated for a one-month holding period and at 99% confidence interval), but there is great variation across investment styles and across time (especially around the LTCM crisis). The exception rate is with 1.06 percent considerably higher than the expected one-percent level. If august 1998 (Russian crisis, LTCM default) is omitted, the overall exception rate drops to 0.43%. On average the magnitude of the observed exceptions, expressed in absolute terms, is 4.85% over the VaR.

4. Conclusion

What is the investment objective and policy of a mutual fund? Misclassification with respect to the stated objective in the fund's prospectus and to the classification put forward by data vendors renders it difficult to answer this question. Sharpe (1992) introduced a method to determine the fund's effective asset mix, which has been applied to problems related to fund classification, performance evaluation and object gaming, the construction of diversified portfolios or portfolios of mutual funds with prespecified factor loadings and risk assessment. Given that only return data is needed to implement the model it has become an investment tool widely put to use by academics and practitioners. Nevertheless, the method is not without caveats (which are often passed over) and a number of prerequisites, limitations and improvements to the original model should be taken into consideration. These arguments could be grouped into three categories: (i) set-up of RBSA, (ii) proper conduct of RBSA, and (iii) extentions of the original model.

(i) Since the imposition of constraints leads to biases, the type of RBSA used (weak, semi-strong or strong form) should be made dependable on the purpose of the analysis. de Roon, Nijman and ter Horst (2000) suggest applying strong form RBSA to performance evaluation. Further, for the construction of efficient portfolios from mutual funds with fixed exposures to certain asset classes and to assess the portfolio holdings of mutual fund managers, weak style analysis is recommendable.

(ii) With respect to the proper implementation of RBSA, the choice of the asset classes is a crucial factor. Ideally, RBSA would be applied only if the fund's assets are indexed to well-prescribed indices, in which instance the selection of the asset classes is self-evident. In all other cases, the choice of the factors in the conduct of RBSA is a critical element. One should turn to factors that are mutually exclusive, linearly independent and exhaustive. If prespecified indices are used, it is desirable to list the properties of the indices. If possible, one could engage in sensitivity testing to get a hold on the effect of replacing the chosen asset classes by similar indices representing the same style. In all instances, the factor selection should not be taken for granted, neither by the researcher nor by the reader. Further, the impact of survivorship bias should be better understood.

(iii) A number of improvements to the original model and some issues for further research can be formulated. Significance testing should be conducted with RBSA. Besides, the use of daily data could enhance the precision of the confidence intervals. Further modifications are likely to be related with the time-varying nature of the factor exposures. Not only smooth changes, but also erratic movements may occur and should be taken into account. A promising avenue for further research would be to find out the style behavior patterns that can be extracted from conditional style analysis, and extend the applications of style analysis in risk management. Finally, it would be interesting to investigate mutual fund style behavior over the life cycle of funds.

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Appendix 1 : Types of Style Analysis and Biases

Assume:

K factor portfolios with return vector R_t;

N mutual funds with return vector r_t;

a_i is the i^{th} element of a;

b_i is the i^{th} row of B;

I_K vector of ones with dimension K;

ω_{GMV} is the global minimum variance portfolio of the factor portfolios;

R^{GMV} is the return to the global minimum variance portfolio;

GMV is the global minimum variance portfolio.

Linear factor model:

(1) $r_t = a + BR_t + \varepsilon_t$ with $\mathrm{E}\left[\varepsilon_t R_{i,t}\right] = \mathrm{E}\left[\varepsilon_t\right] = 0$ for $i = 1,\ldots,K$.

Weak form of RBSA:

To illustrate the bias problem suppose that a_i en b_i are the solutions to the following minimization problem:

(2) $\min_{\alpha,\beta} \mathrm{E}\left[\left(r_{i,t} - \alpha - \beta' R_t\right)^2\right]$

Semi-strong form of RBSA:

Suppose that $\tilde{a}_i$ and $\tilde{b}_i$ are the solutions to the following minimization problem:

(3) $\min_{\alpha,\beta} \mathrm{E}\left[\left(r_{i,t} - \alpha - \beta' R_t\right)^2\right]$ *s.t.* $\beta' \mathrm{I}_K = 1$ (portfolio constraint)

$\tilde{a}_i$ and $\tilde{b}_i$ can be expressed as:

(4) $\tilde{a}_i = a_i + \left(b_i' \mathrm{I}_K - 1\right) \mathrm{E}\left[R_t^{GMV}\right]$

(5) $\tilde{b}_i = b_i + (1 - c_i)\omega_{GMV} = c_i \left(\dfrac{b_i}{b_i' I_K}\right) + (1 - c_i)\omega_{GMV}$ with $c_i = b_i' \mathrm{I}_K$

Hence $\tilde{b}_i = b_i$ if $c_i = 1$.

If the portfolio restriction is not valid, $\tilde{a}_i$ and $\tilde{b}_i$ will be biased estimates of the actual factor loadings and intercept. The degree of bias is proportional to the GMV-portfolio.

Strong form of RBSA:

Suppose $\hat{a}_i$ and $\hat{b}_i$ are the solutions to the following minimization problem:

(6) $\min_{\alpha,\beta} \mathrm{E}\left[\left(r_{i,t} - \alpha - \beta' R_t\right)^2\right] \qquad s.t. \quad \beta' \mathrm{I}_K = 1 \; and \; \beta \geq 0$

We have the following relations:

If the asset classes are ordered as follows $R_t^{'} = \left(R_{1t}^{'}, R_{2t}^{'}\right)$, in a way that the short-selling restriction is not binding for R_{1t} and binding for R_{2t}, then $\hat{b}_{1i}$ are equal to the portfolio constrained coefficients in a regression of r $_{i,t}$ on R_{1t} only.

Hence:

(7) $\hat{a}_i = a_i^{(1)} + \left(b_i^{(1)'} \mathrm{I}_1 - 1\right) \mathrm{E}\left[R_{1t}^{GMV}\right]$;

(8) $\hat{b}_{1i} = b_i^{(1)} + \left(1 - c_i^{(1)}\right) \omega_{GMV}^{(1)} = c_i^{(1)} \left(\frac{b_i^{(1)}}{b_i^{(1)'} \mathrm{I}_1} \right) + \left(1 - c_i^{(1)}\right) \omega_{GMV}^{(1)}$ with

(9) $c_i^{(1)} = b_i^{(1)'} \mathrm{I}_1$;

(10) $r_{i,t} = a_i^{(1)} + b_i^{(1)'} R_{1t} + \varepsilon_{i,t}^{(1)}$;

(11) $b_i^{(1)} = b_{1i} + \Sigma_{11}^{-1} \Sigma_{12} b_{2i}$.

Compared to the weak style coefficients two biases occur. Firstly, the portfolio constraint results in a bias that is proportional to the GMV-portfolio. Secondly, the short-selling restriction results in a bias due to the fact that the estimated coefficients are based on the subset R_{1t} only, instead of the entire set of R_t. The degree of bias is related to (11).

Appendix 2: Methodological Issues in Empirical of Return Based Style Analysis

Authors	Time Period & Mutual Fund Sample	Purpose & Type of RBSA	Description of Asset Classes	Mutual Fund Data Source and Type of Funds
Sharpe (1992)	1985-89 395 funds or 636 funds	• Performance evaluation • Strong form	• *12 asset classes*: Salomon Brothers 3-month Treasury Bill index Lehman Brothers Long-Term Government Bond index Lehman Brothers Long-Term Government Bond index Lehman Brothers Mortgage-Backed Securities index Sharpe/BARRA Value Stock index Sharpe/BARRA Growth Stock index Sharpe/BARRA Medium Capitalisation Stock index Sharpe /BARRA Small Capitalisation Stock index Salomon Brothers Non-U.S. Government Bond index FTA Euro-Pacific Ex Japan index FTA Japan Index	• *Jaye C. Jarrett & Company Inc.* Utility Stock Funds Growth Equity Funds Growth and Income Equity Funds Small Stock Funds Balanced Funds High-Quality Bond Funds Convertible Bond Funds
Christopherson (1995)	1986-91 107 funds[1]	• Predictability of fund Returns	• *5 classes*:[1] Russell Market-Oriented index Russell Small Cap index Russell Value index Russell Growth index 20-year Treasury bond returns	
Lucas and Riepe (1996)	Various funds used as examples[2] 30/6/87-31/12/95 are fund's inception date	• Fund classification • Performance evaluation • Efficient portfolios	• *9 asset classes*: 3-month Treasury Bills 5-year zero coupon bond 20-year zero coupon bond S&P500/ BARRA Growth index S&P500 BARRA Value index Wells Fargo Nikko small-Cap Growth index Wells Fargo Nikko Small-Cap Value index MSCI EAFE[3] Salomon Brothers Non-U.S. Govt. 1+	• *Morningstar*

Sortino and Messina (1997)	1990-1996 81 mutual funds	• Risk assessment & Performance evaluation	*asset classes*:[3] BARRA small-cap, medium and large cap indices (7) 30-day T-bills Ibbotson and Sinquefield long-term corporate bond index MSCI Europe EX U.K. index MSCI Pacific Basin ExJapan	• *Jaye C. Jarrett & Company Inc.* Large cap funds Medium cap funds small cap funds
DiBartolomeo and Witkowski (1997)	11/1990-10/95 748 U.S. equity funds	• Fund classification • (Performance evaluation) • Strong form	• *6 asset classes*: Each asset class is made up by the return on an equally-weighted portfolio of all funds in the particular category.	• *Micropal*[4] Aggressive growth Growth Growth-income Income International Small capitalization
Gallo and Lockwood (1997)	1978-93 fund assignment to categories:(*) 1978-85 performance tests: 1986-93 195 equity funds	• Fund classification(*) • Weak form	• *4 asset classes*: Wilshire large-cap growth index Wilshire large-cap value index Wilshire small-cap growth index Wilshire small-cap value index	• *Morningstar* 5 styles: Equity income, growth and income, growth, aggressive growth, and small-company or 4 styles: small-company and aggressive growth are merged • *CDA Investment Technology* Growth and income, growth and aggressive growth
Lobosco and diBartolomeo (1997)	12/dec/1998-31/12/94 Reich&Tang Equity Fund	• Demonstration of technique to establish confidence intervals • Strong form	• *4 asset classes*: 3-month Treasury bills Lehman Aggregate Index Russell 3000 index MSCI EAFE index [5]	
ter Horst, Nijman and de Roon (1998)	1/1990-7/1997 241 Dutch equity, fixed income (and other types) of funds	• (fund classification) • Performance evaluation • Strong form	• *6 classes*: MSCI World equities index MSCI Europe equities index CBS Netherlands equities index	• *Micropal*

			Salomon Brothers G7 bond index CBS general bond index 3-month Dutch currency deposit	
Chan, Chen, and Lakonishok (1999)	3336 domestic U.S. equity funds	• Fund performance • Fama-French or Carhart factor model	• *3 or 4 asset classes*: excess market return over risk free asset (1-month Treasury bill) Return on zero-investment factor–mimicking portfolio for size Return on zero-investment factor–mimicking portfolio for book-to-market Momentum factor[6]	• *Morningstar*
Otten and Bams (1999)	1991-98 506 domestic equity funds 5 European countries (France, Germany, Italy, Netherlands and United Kingdom)	• Fund classification • Fund performance • Strong form	• *5 asset classes*:[7] Value index Growth index Local small cap index 1-month T-bill rate JPM Government bond index	• Fund Return data are taken from *S&P Micropal*[8] According the authors only the French data is subject to survivorship bias
Buetow, Johnson, and Runkle (2000)	1/1985-9/98 some individual funds: (results are illustrated based on Fidelity Select Technology Fund and Vanguard Index 500, Vanguard Index Growth and Vanguard Index Value funds, and Morningstar fund aggregates	• Fund classification	• *4 up to 13 asset classes*:[9] BGI Small Cap Growth index BGI Small Cap Value index MSCI EAFE ex-Japan index MSCI Japan index Salomon Brothers World Government Bond +1 year index Russell 2000 index S&P MidCap400 index S&P/BARRA Growth index S&P/BARRA Value index Lehman Brothers Mortgage-Backed Securities index Lehman Brothers Corporate Bond index Lehman Brothers IT Government index Lehman Brothers LT Government index Salomon Brothers Treasury Bill Index	• *Morningstar* Small Company Growth Growth and Income Balanced Convertible bond Corporate bond quality Aggressive growth Pacific stock Asset allocation Diversified emerging market stocks Equity-income Europe stock Foreign stock Multi-asset global Speciality miscellaneous

				Speciality financial Speciality health Speciality natural resources Speciality technology Speciality technology Speciality utility Speciality communication World Stock Corporate bond – general Government bond – adjustable-rate mortgage Government bond – general Government bond – mortgage Government bond - treasury
de Roon, Nijman and ter Horst (2000)	1/1982-4/99 or 1/1991-4/99(**) 18 U.S. international funds	• Fund classification(**) • Efficient portfolios • Weak[10] • Semi-strong • Strong	• *2 asset classes*: Vanguard USA Vanguard World or • *3 asset classes* (regional indices): MSCI North America MSCI Europe MSCI Pacific or • Growth and value indices of each country underlying the regional index	• *Morningstar*
Baierl and Chen (2000)	1994-98 2769 mutual funds	• Efficient portfolios	• *5 asset classes*: 1-month T-bill Lehman Brothers Government & Corporate bond index S&P500 index Russell2000 index MSCI EAFE index	• *CDA Wiesenberger*
Kim, Stone and White (2000)	1/1979-8/1997 Fidelity Magellan Fund 9/1991-3/1998 Minicap Fund	• Demonstration of techniques to estimate confidence intervals	• *5 asset classes:* Russell 2000 Growth Russell 2000 Value Russell 1000 Growth Russell 1000 Value	

			30 day T-Bill	
Otten and Bams (2000)	1991-99 304 U.K. domestic equity funds	• Fund classification • Performance evaluation • Strong form	• *5 asset classes*: MSCI Value index MSCI UK Growth index FT small cap UK index 1-month inter-bank rate JPM UK Government Bond Index	• *FT Unit Trust Yearbook*: growth/income income growth small capitalisation Survivorship bias investigated
Swinkels and Van Der Sluis (2001)	5/1979-4/1999 3 global funds	• Fund classification • Weak form and Kalman smoother	• *3 regional asset classes*: MSCI Europe index MSCI USA index MSCI Pacific index	• *Morningstar*: Funds labelled 'World investors'
Lhabitant (2001a)	1994-2000 2934 hedge funds and CTA's	• Risk assessement • Short sales restriction imposed	• *Nine asset classes:* CSFB Tremont Convertible Arbitrage index CSFB Tremont Short Bias index CSFB Tremont Event Driven index CSFB Tremont Global Macro index CSFB Tremont Long Short Equity index CSFB Tremont Emerging Markets index CSFB Tremont Fixed Income Arbitrage index CSFB Tremont Market Neutral index CSFB Tremont Managed Futures index	• *Managed Account Reports* • *Hedge fund Research* • *TASS+* • *Evaluation Associates Capital* Only funds that disclosure voluntary Defunct funds are included for time of Existence

[1] Quarterly data is used in the main part of the empirical research, where monthly data and a different sample is used in other parts of the paper.

[2] Global Fund, Mather fund, Fidelity Asset Manager, American Mutual Fund, Berger 101 Fund, Fidelity Magellan, Janus Venture Fund, DFA U.S. 9-10 Small Company Portfolio, Lexington Corporate Leaders, Twentieth Century Ultra Investors.

[3] There is some confusion on the number of style indices in the analysis. We report the list of benchmarks indicated in the paper under the section ‘Empirical Results’.

[4] For the probit-analysis data from Morningstar was used as well.

[5] EAFA stands for Europe, Australia, Far East.

[6] Measured as the difference between the return on the top and bottom quintile portfolio of stocks ranked by past one-year return. Equally weighted portfolios are then formed at the end of each calendar year from all domestic stocks listed on the New York and American stock exchanges.

[7] The MSCI country index is broken into the Value index and Growth index. The securities of each country are ranked in ascending order with respect to book-to-market. The Afterwards the market capitalizations are summed (starting from the top) until 50% if the market capitalization of the country is reached. Stocks above this treshhold point are assigned to the Value index. The remaining stocks are taken to be growth stocks and are made part of the Growth index. The respective small cap indices are Datastream small cap Italy (Netherlands) for Italy (Netherlands), the FTSE small cap index for United Kingdom, and MIDCAC and MDAX for France and Germany respectively. The last two are midcap indices instead of small cap indices but the authors argue that they are better representations of the actual fund behavior.

[8] Information on fund characteristics are taken from S&P Micropal (France, Italy), Hoppensteds fondsführer 1998 (Germany), ABN-AMRO Beleggingsinstellingen (Netherlands), and Unit Trust Yearbook 1998 (United Kingdom).

[9] Russell 2000 Value and Growth indices are not used together with the BGI Small Cap Value and Growth indices.

[10] The applications of the different forms are as suggested in section 2. Sometimes the other forms are used as a demonstration of the materialization of biases.