Investment Style Misclassification and Mutual Fund Performance

Dennis Bams, Roger Otten, Ehsan Ramezanifar[1]

School of Business and Economics, Maastricht University- the Netherlands

December 2016

Abstract

Mutual fund investors rely on the information provided in a mutual fund's prospectus when selecting funds. In addition to that the SEC mandates funds to stick to their stated investment style. However, previous research has shown that, over shorter horizons, a substantial proportion of funds in fact deviate from their stated investment style. Previous empirical findings regarding the impact of this behavior on fund performance is mixed. In this paper we extend the previous literature by introducing a novel measure to evaluate long-term style deviation. Our measure of fund style misclassification is more granular, incorporates parameter uncertainty in its measurement and allows for statistical inference. Using a sample of 1,866 US equity funds over the 2003-2015 period we document that: 1) about 14% of individual funds are significantly misclassified, 2) in the long run misclassified funds significantly underperform well-classified funds by 0.92% per year based on alpha from the Carhart model, and 3) misclassified funds appear to be younger, smaller in size and charge higher expense ratios. From this we infer that monitoring long term style deviation is critically important for investors. Maintaining a consistent style is a crucial ingredient for achieving good long term risk-adjusted performance.

[1] Corresponding author: Ehsan Ramezanifar, Visiting Researcher, University of California San- Diego, Ph.D. Candidate in Finance, School of Business and Economics, Maastricht University- the Netherlands
E- mails: eramezanifar@ucsd.edu, e.ramezanifar@maastrichtuniversity.nl Phone: +1858 261 8034

1 Introduction

Every mutual fund has its own stated investment style, which is documented in the investment prospectus. Investors rely on the stated investment style as a source of a fund manager's investment strategy. According to a survey by the Investment Company Institute (ICI), 40% of retail investors indeed use the fund prospectus to learn about a fund's investment objective. In addition, on March 31, 2001, the Security and Exchange Commission (SEC) reemphasized that all mutual funds must invest in accordance with their self- claimed investment style.[2] However, previous studies on mutual funds style analysis show that a substantial number of funds deviate from their investment style mandates (see diBartolomeo & Wikowski (1997), Brown & Goetzmann (1997), Kim, Shukla & Tomas (2000), Kim, White & Stone (2005), Cremers and Petajisto (2007), and Mason et al. (2012) among others). A deviation from the stated investment style has a clear message to the investors; they may not get what they expect from their investments.

Moreover, style deviation is also relevant to institutional investors who diversify their portfolios by holding several mutual funds with different investment styles. For example, if a pension fund already holds investments in a value fund and wants to diversify the portfolio by investing in a growth fund, the plan sponsor should be able to assure that the growth fund will not deviate and become a value fund. Logue (1991) reports that institutional plan sponsors in pension funds want managers to maintain their investment style through an entire market cycle. diBartolomeo and Witkowski (1997) show that investment style misclassification has a significant effect on investors' ability to build diversified portfolios of mutual funds. Froot and Teo (2008) document that institutional investors make decisions at

[2] Section 13 (a), item (3), of Investment Company Act of 1940, version January 3, 2012 states that an investment company, unless authorized by a majority of its shareholders, will not deviate from its investment policy. Moreover, SEC mandates all mutual funds to maintain a minimum of 80 percent of the value of the portfolio in securities that are consistent with the fund's stated investment style.

the style level. In addition, Cooper et al (2005) find that a change in a mutual fund's stated investment objective affects mutual fund flows. From this, we infer that the stated investment objective is relevant to fund investors, both individual and institutional, when selecting funds.

Because the characteristics of the underlying stocks, like value- growth and market cap, may change over time, some deviation from the stated investment style on a long-term basis is unavoidable, especially if a fund manager passively holds the same stocks over time. For example, a small-cap stock may grow up and become a large-cap stock. However, too much style deviation may be a strong indication that fund managers have changed the investment strategy and have veered away from a fund's stated objective (*Financial Post*, February 14, 2013).[3] Hence, investors should be aware of the level of style deviation to consider whether the deviation means they're still meeting their long-term investment objectives. Consequently, it is relevant to quantify the extent of style deviation and to classify a mutual fund in terms of investment style deviation. Some studies address this by classifying funds in only two groups, either to be following the correct style (well-classified group) or deviating (misclassified group) (see Kim, Shukla, and Tomas (2000), Brown and Goetzman (1997) and Dibartolomeo and Witkowski (1997) among others).

Other studies define measures to detect style drift in mutual funds (see Idzorek and Bertsch (2004) and Brown, Harlow and Zhang (2015) among others). A style drift measure shows the volatility of fund's style changes over time but does not address how far mutual funds are away from the stated investment objective. For example, imagine a fund manager of a growth mutual fund that consistently pursues a value investment style over a long time period. In this particular case, the style drift measure would be almost zero over time.

[3] Beware of style drift in mutual funds, National Post's Financial Post & FP Investing (Canada), February 14, 2013, David Pett

We believe that the extent of misclassification may differ substantially between funds, and believe it is important to allow for a more granular qualification of misclassification. Yet, the growing literature on style analysis in mutual funds has not focused on providing a single statistic that takes to account the level of style misclassification for different investment style mutual funds. In the following, we propose a measure that allows us to rank all mutual funds on a continuous scale, from highly misclassified, in case a fund deviates strongly from its stated investment objective, to well-classified, in case a fund completely adheres to its stated investment objective. Our novel measure relies on the Return Based Style Analysis (henceforth RBSA) framework of Sharpe (1988, 1992) and is a refinement of the asymptotic confidence interval of the investment style estimates approach of Lobosco and DiBartolomeo (1997) and Kim, White & Stone (2005).

Our approach has two distinctive features. First, we determine the asymptotic multivariate distribution of the investment style estimates, which is a combination of quadratic programming and standard bootstrapping. This allows for a rich set of statistical inference, such as the comparison of the stated investment style with all other investment styles to detect any statistical significant deviation. We find that 14% of US equity mutual funds in our sample are significantly misclassified based on long term style analysis.

Second, we introduce the *Style Concentration Index* (henceforth *SCI*) which is a granular measure of a fund's style misclassification. The SCI varies between zero and one and includes statistical uncertainty as an important ingredient. The SCI represents the distance between the actual investment style and the stated investment style of a mutual fund. The closer this index is to one, the more the fund is far away the stated investment style and known as a misclassified fund. Alternatively, the closer the SCI is to a value of zero, the higher the extent to which the fund is more concentrated on the stated investment style and known as a well-classified fund.

This paper focuses on the Lipper objective codes as a proxy of stated investment style.[4] Using a sample of 1,866 US equity mutual funds with monthly returns over the period 2003-2015, our empirical analysis leads to two main contributions.[5] First, we examine the relation between the level of style deviation and fund performance. Because many mutual funds in some way stray from the stated investment objective, to understand its impact on fund investors it is important to study the performance consequences of this behavior. Previous empirical findings are mixed. While Wermers (2012), Budiono and Martens (2009) and Swinkels and Tjong-A-Tjoe (2007) demonstrate that style deviation is profitable, Brown, Harlow and Zhang (2015) and Chan, Chen, and Lakonishok (2002) find that funds which have more investment style discipline outperform funds with less investment style discipline.

Contrary to previous studies, this paper focuses on the relationship between style deviation and fund performance on long-term basis (10+ years), whereas previous work focused on short-term style deviation (1-3 years). To examine this relationship, we sort all mutual funds into buckets based on their misclassification level. We find that misclassified funds in the long run significantly underperform well-classified funds by 0.92% per year on a style-adjusted return basis and by 1.18% per year on a net return basis, respectively. For example, funds that are in the highest misclassification bucket exhibit an abnormal return of -2.01% per year using the Carhart model, whereas funds that adhere to the stated investment levels exhibit an abnormal return of -1.09% per year. The results are robust using alternative performance measures and alternative style benchmarks.

[4] Lipper's objective codes are assigned based on the language that the fund uses in its prospectus to describe how it intends to invest. Morningstar is a widely-used source for style analysis but the classification method is not based on the fund's prospectus.

[5] Kim et al. (2005) use 2 U.S. mutual funds from 1979 through 1997. Horst et al. (2004) use 18 U.S. based internationally mutual funds with international MSCI growth and value indices, from 1989 through 1999. Swinkels and Van der Sluis (2006) use 12 international funds and 87 asset allocation funds and finally, Kim et al. (2000) assess U.S. funds in 7 objective groups over the period from 1993 through 1996.

Second, by taking advantage of the Style Concentration Index measure, we investigate the relationship between the level of misclassification on a long- term basis and fund characteristics like size, age, turnover, and expense ratio. Prior studies suggest that several fund characteristics are related to incentives for fund managers to alter the investment style and the associated risk levels. For example, diBartolomeo and Witkowski (1997) show that young mutual funds may be especially prone to misclassification. Frijns et al. (2013) report that funds that switch more aggressively, have on average higher expense ratios and are younger. Huang, Sialm & Zhang (2011) also point out that funds with higher expense ratios experience more severe performance consequences when they alter risk. Unlike most of the previous literature in which show this relationship base on the style drift, this study investigates the relationship base on long- term style deviation. We divide the funds into several buckets using the fund characteristics and sort them by their level of misclassification. We find that higher misclassified funds appear to be younger, smaller in size and more expensive. The results are robust to using sub-periods.

From these results we conclude that long term style misclassification is a serious detrimental phenomenon in mutual funds. We believe that the Style Concentration Index as a single statistic allows investors and regulators to better understand and monitor the level of misclassification in mutual funds.

The remainder of the paper is organized as follows. In section 2, we introduce the methodology related to measuring the misclassification level. In section 3, we describe the data that are used in the empirical application. Section 4 contains empirical results while in section 5 we address the robustness of these results. Finally, section 6 concludes the paper.

2 A Measure of Misclassification Level

2.1 Asymptotic distribution of the style estimates

Typically, in the RBSA approach, the fund return is compared with the return on a number of selected passive style indices. The indices represent distinct investment styles within particular asset classes (e.g. value, growth, small caps). The style of the fund is represented by the loadings on the indices. RBSA explains the return for a given fund *i* with the following model:

$$R_{it} = \sum_{k=1}^{N} \beta_{ik} I_{kt} + u_{it} \qquad t = 1, \ldots, T \tag{1}$$

$$s.\ t: \qquad \sum_{k=1}^{N} \beta_{ik} = 1 \tag{2}$$

$$\beta_{ik} \geq 0 \qquad k = 1, \ldots, N \tag{3}$$

where R_{it} denotes the return of mutual fund *i* at time t, *N* is the number of style classes, β_{ik} is a style estimate that expresses the sensitivity of the fund return to the factor-mimicking portfolio return of index *k*, I_{kt} denotes the return of index k at time t and u_{it} reflects idiosyncratic noise, orthogonal to the style indices, i.e. $E(I_{kt}u_{it}) = 0$.[6] There are two main constraints. First, as equation 2 shows, style estimates are restricted to add-up to one, in order to give them the interpretation of portfolio weights. Second, as equation 3 shows, positivity constraints are imposed on the style estimates to meet the short-selling constraint that fund managers are mostly subject to.[7]

---

[6] A few prerequisites should be met before any reliable results are to be obtained. First, the benchmarks should be mutually exclusive which means they may not include any securities that already form part of any other basic asset classes considered in the model. Second, indices should be exhaustive benchmarks, meaning as many securities as possible should be included in the chosen asset classes. Thirdly, the correlation between returns on the basic asset groups considered in the proposed model should be low.

[7] Horst et al. (2004) investigated the effect of the portfolio and short-selling constraints in style analysis. They argue that although there is no straightforward analytical expression to define the benefit of imposing constraints, if both constraints are the case in reality, this results in more efficient parameter estimates.

Almazan, Brown, Carlson, and Chapman (2004) report that about 70% of mutual funds dare not allowed to pursue any short selling activities and only 2% actually do sell short. The positive weight interpretation of the parameter estimates turns out to be useful for two reasons. First, it provides parameter estimates that are more efficient, and second this standardization towards portfolio weights is an attractive feature in the formulation of a standardized measure for the misclassification level. However, because of the computing difficulties for obtaining estimated style regression with restrictions, many previous studies refuse to consider the constraints in the RBSA method (see for example Annaert and Van Campenhout (2007) and Swinkels and Van der Sluis (2006) among other). Using the quadratic programming, we estimate the style weights by considering two main constraints. In addition, one shortcoming of Sharpe's RBSA is the fact that it only focuses on point estimates for the factor loadings. Lobosco and DiBartolomeo (1997) figure out the lack of a precision measure by proposing a method to approximate confidence interval for style estimates based on a Taylor expansion. However, the method is valid only in the special case in which none of the style estimates are zero or one that prevents us to obtain the asymptotic distribution of the style regression coefficients. In this study, by combination of quadratic programming and a standard bootstrapping algorithm, we build up the asymptotic multivariate distribution of the investment style estimates. The asymptotic distribution plays an important role in testing the significance of style estimates. One statistical test focuses on the ability to identify whether a fund invests in a particular type of security. Another relevant test is to check whether a fund is more invested in one type of style than in another one, also requiring the asymptotic distribution. It allows us for rich statistical inferences, such as the comparison of the stated investment style with four other investment styles to detect any statistical significant deviation. The null hypothesis for this statistical test is as follow:

$$H_0: \beta_{stated\ style} > \beta_j \quad j = 1, \ldots, 4 \tag{4}$$

Where $\beta_{stated\ style}$ represents the stated investment style estimate of a fund and β_j includes four other investment style estimates. Using a p-test, we test the null hypothesis whether the stated investment style is significantly different from all other investment style estimates. In appendix A, we show the procedure to arrive at the asymptotic distribution of the investment style estimates.

2.2 Style Concentration Index

We define our measure of misclassification level, the Style Concentration Index, base on the RBSA approach. Previous studies divide mutual funds into two groups only in which funds are either considered to be completely well-classified or completely misclassified funds. Our measure provides a more granular specification of the style misclassification level. This continuous measure is further fine-tuned by also incorporating the statistical significance level of the measure. Specifficly, we assign each fund a number between zero and one, which represnets the distance between the actual invetmnet style of fund and the stated invetsment style. Low numbers represent low amont of misclassification and high numbers represent large amount of misclassification.

The Style Concentration Index is defined based on two- step procedure method. First, as mentioned in section 2.1, we obtain the asymptotic distribution of a fund's stated invetment style estimate. Second, we choose the 0.05 critial value of the probability distribution of changes in the stated invetemnt style estimate, therefore, one minus this value represnts the Style Concentration Index. For example, let assume a fund that claims in the prospectus to peruse the growth style. We first obtain the asymptotic distribution of the β_{Growth} , which denotes the fund's stated investment style estimate. Second, we define the Style Concentration Index (SCI) of the fund as one minus the value of β_{Growth} at the 5% probability level of its distribution.

$$SCI = 1 - \beta_{0.05}^{Stated\ Style} \quad (5)$$

Where $\beta_{0.05}^{Stated\ Style}$ represents the stated investment style of a mutual fund at the five percentile of its distribution. The asymptotic distribution of style estimates are always between zero and one, allowing the measure to be interpreted as a standardized degree. As the SCI gets close to zero, it shows that the fund is highly likely to be a well-classified fund and obviously, as the SCI gets close to one, it shows that the fund is highly likely to be a misclassified fund.

Figure 1 shows an example of three different mutual funds that have three different Style Concentration Indexes.

(Figure 1: Example of different Style Concentration Indexes)

3 Data

Our study sets out to investigate long term style deviation where most previous studies have investigated short term deviation. For this reason we only consider mutual funds which have constant stated investment style over the sample period based on the Lipper objective codes. An explicit change of the stated investment objective requires approval from the shareholders and it also may force some existing investors to close their accounts.[8] Kim, Shukla, and Tomas (2000) find that more than 92% of mutual funds did not change their stated objective over their sample period.

In addition to investigating long term style deviation we utilize a much larger database both in terms of number of funds (1,866) and sample period covered (2003-2015). We retrieve mutual fund data from the Center for Research in Security Prices (CRSP). The CRSP mutual

[8] Section 13 (a), item (3), of investment Company Act of 1940, version January 3, 2012, states that "deviation from its policy in respect of concentration of investments in any particular industry or group of industries as recited in its registration statement, deviation from any investment policy which is changeable only if authorized by shareholder vote."

fund database includes information on monthly total returns, total net assets (TNA), expense ratio, fund age, turnover ratio, and other mutual fund characteristics.[9] Total returns are provided by CRSP and are after fees, expenses and brokerage commissions, but before front-end or back-end loads. Dead funds are included in order to mitigate potential survivorship bias. Following previous studies such as Berk and Binsbergen (2013), Mason et al. (2012), Nanda, Wang, and Zheng (2009), Kacperczyk et al. (2008), Chen et al. (2004) and Elton, Gruber and Blake (2001), we consider six selection criteria to arrive at our dataset.

First, to facilitate comparison with the previous literature, we restrict our analysis to domestic U.S. equity mutual funds, so we drop all balanced, bond, international and sector funds.

Second, because some mutual funds which have different share classes may enter into the database multiple times at the same period, we aggregate all share classes into a single fund to eliminate such redundant observations.

Third, we drop all fund observations where the size of the fund in the previous quarter does not exceed $1.5 million.

Fourth, we check the mutual funds' asset composition and remove all funds from the database which have negative weights to exclude short-selling considerations.

Fifth, since we focus only on actively managed mutual funds and and remove all index funds from our sample. We also exclude all funds which have a zero turnover ratio in one year to make sure that our sample includes actively managed funds, only.

Sixth, we include only funds that exist for at least 30 months during the estimation period.

[9] Monthly total returns values are calculated as a change in NAV including reinvested dividends from one period to the next. NAVs are net of all management expenses and 12b-1 fees. Front and back-end load fees are excluded.

The number of distinct U.S. mutual funds that meet our selection criteria over the sample period from July 2003 through December 2015 is 1,866 funds. These funds are classified into four main investment style classes, based on the Lipper Prospectus Objective codes, which are provided by CRSP as well.[10] We focus only on mutual funds that have an invariant stated investment objective during the sample period.

Initially, we form six equally-weighted portfolios, which will be analysed in more depth. We construct an equally-weighted portfolio containing all individual funds, an equally-weighted portfolio of funds that did not survive the whole sample period (referred to as dead funds), and equally-weighted portfolios of mutual funds with the following particular investment objectives: growth, income, growth/income and small cap.

As we only consider U.S. equity funds, the relevant style benchmarks are all U.S. indices which are all monthly total returns. We include the U.S. value index (S&P500 Value index), the U.S. growth index (S&P500 Growth index), the U.S. small cap index (S&P600 index) and two fixed income classes, cash (30-day Treasury bill rate) and bonds (30-years bonds). We retrieve the data on equity indices from FactSet Research System Inc., and obtain fixed income data from CRSP. This leads to a 5-factor RBSA model, to infer a fund's investment style. Table 1 provides summary statistics on the different equally weighted portfolios (panel A) and benchmarks (panel B). In particular panel A shows that a substantial part of the sample, i.e. more than 36% of all funds in our sample, did not survive during the entire sample period. These funds also register a significantly lower return which would introduce survivorship bias if not included in our analysis. Therefore dead funds are included.

(Table 1: Summary statistics mutual funds, 2003-2014)

[10] http://www.crsp.com/products/documentation/lipper-objective-and-classification-codes

A potential concern in the RBSA analysis is the impact of multicollinearity between different benchmarks. As Horst et al. (2004) discuss, the difference between actual portfolio holdings in mutual funds and estimated exposures to style indices, is more likely related to multicollinearity problems, caused by the correlations between the different indices. Hence, to figure out the impact of multicollinearity among benchmarks, we determine Variance Inflation Factors (VIF). The VIF associated with style index *i* is given by

$$VIF_i = \frac{1}{1-R_i^2} \tag{5}$$

Where R_i^2 is the coefficient of variation of the linear regression of style index *i* on the other style indices. Table 1, panel C shows that all VIFs are less than 10, which is the relevant threshold that is applied as a common rule of thumb in multicollineary analysis. Hence, despite the high correlations between the style indices, we do not expect any issues arising from multicollinearity problems. As a robustness check, we will employ Russell indices in section 5 in order to investigate the sensitivity of our results to the choice of benchmarks.

Table 2 reports summary statistics on fund's Total Net Assets (TNA), 52 week low Net Asset Value (NAV), 52 week high Net Asset Value (NAV), age, expense ratio and turnover ratio.

(Table 2: Summary statistics of mutual fund characteristics, 2003-2015)

4 Results

In this section, we first determine mutual funds as either significant well-classified or significant misclassified. Next by using SCI, we rank all mutual funds from highest misclassified funds to the lowest misclassified funds. This ranking allows us to investigate a potential relationship between the style deviation level and fund performance and fund characteristics.

4.1 Investment Style Misclassification

In table 3, we report the parameter estimates of the RBSA model for the four style-related equally-weighted portfolios of funds. Panel A shows the estimated style weights including all funds within the particular style category.

(Table 3: Results RBSA model)

We find that for both panels the income fund is mainly exposed to the value benchmark, the growth fund to the growth benchmark, growth/income fund to the growth and value benchmarks and finally the small cap fund is up to 87% exposed to the smaller companies benchmark. These results, based on point estimates only, suggest that mutual funds indeed invest in line with their stated investment style. In panel B, 95% confidence intervals are provided per style category. The confidence intervals show that the point estimates are relatively precise reflections of the portfolio weights.

Table 3 does not produce evidence of serious style deviations by mutual fund managers. It may be the case that the construction of equally-weighted portfolios averages out misclassification effects that are present in individual funds. DiBartolomeo & Witkowski (1997), Indro et al (1998) and Kim, Shukla & Tomas (2000) find that more than 50% of U.S. mutual funds differ from their benchmarks, and over 30% of the funds are significantly misclassified. We fine-tune our analysis by investigating the misclassification phenomenon at the individual mutual fund level.

(Table 4: Mutual fund misclassifications based on individual fund returns)

In Table 4, for each mutual fund, we compare the distribution of stated investment style estimate with the other investment style estimates distribution. In our particular setting that leads to 4 different comparisons per style. For example if the stated investment objective of mutual fund is value, there are 4 comparisons includes value with growth, value with small cap, value with Cash and value with Bond. When the expected value of the stated style estimate is lower than one or more other expected value of style estimates, we consider it to be misclassified. Base on the asymptotic confidence interval of the style estimates, we identify a fund as significantly misclassified if its stated style estimate is significantly lower than one or more other style weights. Subsequently, if the stated style estimate is greater than all other style weights, we put the fund into the well-classified funds group.

The results based on individual funds in table 4 suggest that especially growth (29%) and income (26%) funds are significantly misclassified while small cap (1.5%) and growth/income (5%) funds mostly seem to adhere to their stated investment style. Taking into account the information in the asymptotic distribution function, leads to slighter lower overall levels of misclassification, 14% compared to 17% based on point estimates alone. Interestingly for growth and income funds only respectively 61% and 47% of funds are significantly well classified. From this, we infer that style deviation is indeed a serious issue, especially for growth and income oriented funds.

4.2 Style Concentration Index and Fund Performance

After establishing the level of misclassification we now turn to the influence of different level of misclassification on fund performance. As mentioned in introduction, there are conflicting of the empirical findings with respect to the effect of style deviation on fund performance. As mentioned in introduction, some studies report that deviation from investment style for mutual funds over time can generate significant outperformance while some other studies show that there is an inverse relationship between fund performance and misclassification behavior.

Recently, Brown, Harlow and Zhang (2015) study the effect of style volatility on future fund performance on a short- term basis (3,6 and 12-month) and infer that for fund managers having less style volatility is one way that they can show their superior skill to potential investors. They argue that managers with stable investment styles are easier for investors to be accurately evaluated.

To examine the effect of different misclassification level on fund performance, specifically on a long-term basis, we employ a decile analysis. In table 5 we rank order funds with respect to their Style Concentration Index into several deciles and following Khorana (2001), Del Guercio and Tkac (2002), Lynch and Musto (2003), Nanda, Wang, and Zheng (2004), Keswani and Stolin (2008), Gil-Bazo and Ruiz-Verdu (2009), and Sensoy (2009), we compute the average return, style- adjusted return and risk- adjusted return of the funds in each decile.

The top decile, refers to the decile 1, contains the highest misclassified mutual funds, where the average value of their SCI is 0.95. The bottom decile, referred to as decile 10, contains the highest well-classified mutual funds, where the average value of their SCI is 0.09.

(Table 5: Relationship between Style Concentration Index and Fund Performance)

Our results indicate that the level of misclassification has a significantly negative influence on fund performance. The most misclassified funds (decile 1) underperform the highest well classified funds (decile 10) significantly by 1.18% (return), 1.07% (style adjusted return), 0.71% (CAPM alpha), 0.84% (FF alpha) and 0.92% (Carhart alpha) per year. From this we infer that long term deviation from the stated investment style has a significantly negative influence on fund performance. This calls for close style monitoring by investors, specifically for those investors who have buy and hold strategy.

4.3 Style Concentration Index and Fund Characteristics

In this section, we discuss how style deviation is related to fund characteristics. In line with our previous analysis, we use a decile analysis to rank order funds with respect to their Style Concentration Index into several deciles and compute the average fund characteristics in each decile.

(Table 6: Relationship between Style Concentration Index and Fund Characteristics)

We report the results of the relationship between the Style Concentration Index and fund characterstics in Table 6. The results show expense ratios exhibit a significant positive relationship with the Style Concentration Index, which indicates that funds in misclassified categories are substantially more likely to have a higher expense ratio than others. Moreover, columns 5 and 6 show that funds which deviate from their stated investment style are likely to be smaller and younger than funds with more stability in their stated investment style.[11]

The results are confirmed by a regression of the Style Concentration Index on the several fund characteristics.

$$SCI_i = b_1.Turnover_i + b_2.Expense_i + b_3.\log(Size_i) + b_4.Log(Age_i) + \varepsilon_i \qquad (6)$$

where SCI_i is the Style Concentration Index of mutual fund i, $Turnover_i$ is the average turnover of the fund, $Expense_i$ is the annual expense ratio, $\log(Size_i)$ is the logarithm of TNA and Log (Age_i) is the logarithm of the age of the fund.

(Table 7: Relation between Style Concentration Index (SCI) and Fund Characteristics in different styles)

[11] The means in Table 5 are computed following Fama and MacBeth (1973) methodology, where we first in each month run a cross-sectional regression. In a second step, we compute the means of the cross-sectional coefficients over the whole time period. We compute alphas using the Fama and French (1993) methodology.

Table 7 reports the results of the regression analysis. We find that the expense ratio, log (TNA), and log (Age) are significantly related to the Style Concentration Index. A significant positive relationship exists between the Style Concentration Index and the expense ratio, suggesting that funds which deviate more and hence charge higher expense ratios are more likely to be misclassified.

Gil-Bazo and Ruiz-Verdu (2009) also argue that there is a negative relation between fees and performance in which high-expense funds do not perform better than low-expense funds, even before subtracting expenses. They interpret this evidence as an agency problem in which high-expense funds target less performance-sensitive investors, also referred to as naive investors that are not responsive to expenses. Hence, these funds are able to charge them higher fees. Thus, high-expense funds may have bigger incentives to deviate from their stated investment objective to reach better performance and attract more fund flows.

5 Robustness tests

In this section we test whether our previous results are sensitive to benchmark choice or the sample period. Index selection is one of the most important issues in RBSA. Hence, we pay close attention to the benchmark choice in setting up an RBSA model especially when the correlation coefficients between benchmarks are high. As Sensoy (2009) discussed, over 90% of U.S. equity mutual funds use the S&P or Russell benchmark index. According to Table 1, the correlations between benchmarks are high and this may cause problems. To assess the impact of this choice on our results we replace both the S&P500 value and growth benchmark by the Russell 1000 value and Russell 1000 growth and we consider Russell 2000 as small cap benchmark. The aforementioned indices are available from the FactSet Research

System Inc.[12] The results in Table 8 lead us to believe that our results remain unchanged when using alternative benchmarks.

(Table 8: Results Robustness Test RBSA model – Alternative style benchmarks)

As a second robustness check we divide our sample period into two equal sub-periods. The first sub-period runs from July 2003 – September 2009 and the second sub-period from October 2009 – December 2015. The results for both sub-periods are fairly identical and confirm our prior results.

(Table 8: Results Robustness Test RBSA model – sub-sample analysis 2003- 2009)

(Table 9: Results Robustness Test RBSA model – sub-sample analysis 2009- 2015)

As a final robustness test we investigated the relationship between the Style Concentration Index and fund performance, as in table 5, and the relationship between the Style Concentration Index and fund characteristics, as in table 6. Tables 11 and 12 provide the results when applying Russell indices. The results are comparable to the findings in tables 5 and 6, respectively

(Table 10: Relationship between Style Concentration Index and Fund Performance by using the Russell indices)

(Table 11: Relationship between Style Concentration Index and Fund Characteristics by using the Russell indices)

6 Conclusion

Mutual fund investors rely on the information provided in a mutual fund's prospectus when selecting funds. In addition to that the SEC strictly mandates funds to stick to their stated investment style. However, previous research has shown that deviation from the stated investment style is real phenomena among mutual funds. Previous empirical findings regarding the impact of this behavior on fund performance is mixed. In this paper we extend

[12] We also employ the S&P500 pure value and S&P500 pure growth, and they do not have any impact on our previous results

the previous literature by introducing a novel measure to evaluate long-term style deviation. The measure shows the distance between the actual investment style and the stated investment style, while at the same time incorporating parameter uncertainty.

Using a sample of 1,866 US equity funds over the 2003-2015 period and by taking advantage of the new measure we document that: 1) Investors who pick funds based on the stated investment style can be surprised by what they end up with because about 14% of individual funds are significantly misclassified. 2) misclassified funds significantly underperform well classified funds by 0.92% and 1.18% per year based on Carhart Alpha and total net return respectively and 3) misclassified funds appear to be younger, smaller in size and charge higher expense ratios. From this we infer that monitoring long term style deviation is critically important for investors. Maintaining a consistent style is a crucial ingredient for achieving long term risk-adjusted performance. We believe that the Style Concentration Index offers a meaningful benefit to investors trying to investigate the style deviation level of mutual funds.

Appendix A

Sharpe's model as described in section 2 is compactly rewritten in matrix algebra terms as follows:

$$Y = X\beta + u \tag{1A}$$

$$j'\beta = 1 \tag{2A}$$

$$\beta_k \geq 0 \qquad k = 2, \ldots, N+1 \tag{3A}$$

Where Y is a $(T \times 1)$ vector of fund returns, X denotes a $T \times (N+1)$ matrix where the elements in the first column are all one, and the other columns consist of N style index returns, u is a $T \times 1$ vector of error terms. The $(N+1) \times 1$vector β has as first element the intercept α and the other elements are the style index sensitivities denoted by β_k ($k = 1, \ldots, N$). We are interested in the parameter estimates together with the associated asymptotic distribution for the vector**.** Because of the inequality constraints, we employ the estimation algorithm introduced by Kuhn-Tucker. We show that in the case of a linear regression model this Kuhn-Tucker estimator, denoted as b_{KT}, can be written in terms of a so-called Lagrange estimator, b_L A Lagrange estimator finds optimal parameter estimates subject to equality constraints. Next, the Lagrange estimator can be expressed in terms of the ordinary least squares (OLS) unconstrained estimator, b_U .

The principle behind the Kuhn-Tucker algorithm lies in the treatment of the inequality constraints on the factor sensitivities. When a particular constraint is non-binding then its estimator for the associated factor loading is equal to the OLS estimator. When the particular constraint is binding then its estimator is equal to the Lagrange estimator. Beforehand it is not known which constraints will be binding and which will be non-binding. Therefore, we consider the estimators for all possible combinations of binding and non-binding restrictions.

The combination that leads to the lowest residual sum of squares and that meets all constraints then leads to the optimal parameter estimates. We show that the Kuhn-Tucker solution is expressed in terms of the unconstrained least squares estimator as follows:

$$b_{KT} = \min_{S \in \Omega} \left\{ \left(Y - Xb_S \right)' \left(Y - Xb_S \right) \mid j' b_S = 1; Sb_S = 0 \right\} \tag{4A}$$

Where

$$b_S = \left[I_{N+1} - VS'(SVS')^{-1} S \right] P + \left[I_{N+1} - VS'(SVS')^{-1} S \right] \left[I_{N+1} - P \right] b_U \tag{5A}$$

$$P = \left(X'X \right)^{-1} j \left[j' \left(X'X \right)^{-1} j \right]^{-1} \tag{6A}$$

$$V = \left(I_{N+1} - Pj' \right) \left(X'X \right)^{-1} \tag{7A}$$

and I_{N+1} is the $(N+1) \times (N+1)$ identity matrix. Let S be the matrix that represents the binding inequality constraints, i.e. the associated equality constraint reads

$$S\beta = 0 \tag{8A}$$

For example, the following $2 \times (N+1)$ matrix represents the sub-problem where the second and the third parameter are binding:

$$S = \begin{pmatrix} 0 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 0 & \cdots & 0 \end{pmatrix} \tag{9A}$$

The set of all possible matrices S representing combinations of binding and non-binding constraints is given by Ω. The expressions above show that the Kuhn-Tucker solution is identical to the Lagrange estimator (b_S) for one of the possible sub-problems ($S \in \Omega$), i.e. combination of binding and non-binding constraints. In equation (7A) we show that this estimator is related to the unconstrained estimator and some deterministic matrices. The unconstrained least squares estimator reads

$$b_U = (X'X)^{-1}X'Y \tag{10A}$$

And the associated variance covariance matrix is given by

$$V(b_u) = \hat{\sigma}^2 (X'X)^{-1} \tag{11A}$$

Where $\hat{\sigma}^2$ is the variance of the residuals. The asymptotic distribution of the Kuhn-Tucker estimate follows by employing the standard bootstrapping technique. To arrive at this distribution we proceed as follows:

1. Draw a sample for the error term, denoted with $u^{(i)} \sim N(0, \hat{\sigma}^2 I_T)$
2. Construct a vector of dependent variables $y^{(i)} = Xb_{KT} + u^{(i)}$
3. Estimate the model $y^{(i)} = X\beta + u^{(i)}$ subject to the constraints in (7) and (8)
4. This leads to an estimate $b_{KT}^{(i)}$
5. Repeat steps (1)-(4) 10,000 times. This gives a set $b_{KT}^{(i)} \quad i = 1, \ldots, 10{,}000$

These 10.000 values represent the asymptotic distribution of the Kuhn-Tucker estimator.

Finally, we obtain the asymptotic confidence interval by using the percentiles of the bootstrapped distribution. When bootstrapped samples are completed, we sort the results and then the 5th and 95th largest values show the confidence interval.

References

Annaert, Jan, and Geert Van Campenhout. "Time variation in mutual fund style exposures." *Review of Finance* 11, no. 4 (2007): 633-661.

Almazan, Andres, Keith C. Brown, Murray Carlson, and David A. Chapman. "Why constrain your mutual fund manager? " *Journal of Financial Economics*73, no. 2 (2004): 289-321.

Berk, Jonathan B., and Johan Walden. "Limited capital market participation and human capital risk." *Review of Asset Pricing Studies* 3, no. 1 (2013): 1-37.

Brown, Keith C., and W. V. Harlow. "Investment Style Volatility and Mutual Fund Performance." University of Texas at Austin working paper (2015).

Brown, Stephen J., and William N. Goetzmann. "Mutual fund styles." *Journal of financial Economics* 43, no. 3 (1997): 373-399.

Budiono, Diana, and Martin Martens. "Mutual fund style timing skills and alpha." Available at SSRN 1341740 (2009).

Carhart, Mark M. "On persistence in mutual fund performance." *The Journal of finance* 52, no. 1 (1997): 57-82.

Chan, Louis KC, Hsiu-Lang Chen, and Josef Lakonishok. "On mutual fund investment styles." *Review of financial studies* 15, no. 5 (2002): 1407-1437.

Chen, J., Hong, H., Huang, M., & Kubik, J. D. 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. *American Economic Review*, 94(5), 1276-1302.

Cooper, Michael J., Huseyin Gulen, and P. Raghavendra Rau. "Changing names with style: Mutual fund name changes and their effects on fund flows." *The Journal of Finance* 60, no. 6 (2005): 2825-2858.

Cremers, KJ Martijn, and Antti Petajisto. "How active is your fund manager? A new measure that predicts performance." *Review of Financial Studies* 22, no. 9 (2009): 3329-3365.

Del Guercio, Diane, and Paula A. Tkac. "The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds." *Journal of Financial and Quantitative Analysis* 37, no. 04 (2002): 523-557.

DiBartolomeo, Dan, and Erik Witkowski. "Mutual fund misclassification: Evidence based on style analysis." *Financial Analysts Journal* 53, no. 5 (1997): 32-43.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake. "A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases." *The Journal of Finance* 56, no. 6 (2001): 2415-2430.

Fama, E. F., and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1), 3-56.

Fama, Eugene F., and James D. MacBeth. "Risk, return, and equilibrium: Empirical tests." *The Journal of Political Economy* (1973): 607-636.

Frijns, Bart, Aaron B. Gilbert, and Remco CJ Zwinkels. "On the Style-based Feedback Trading of Mutual Fund Managers." Available at SSRN 2114094(2013).

Froot, Kenneth, and Melvyn Teo. "Style investing and institutional investors."*Journal of Financial and Quantitative Analysis* 43, no. 04 (2008): 883-906.

GIL-BAZO, J. A. V. I. E. R., and P. A. B. L. O. RUIZ-VERDÚ. "The relation between price and performance in the mutual fund industry." *The Journal of Finance* 64, no. 5 (2009): 2153-2183.

Huang, Jennifer, Clemens Sialm, and Hanjiang Zhang. "Risk shifting and mutual fund performance." *Review of Financial Studies* 24, no. 8 (2011): 2575-2616.

Idzorek, Thomas M., and Fred Bertsch. "The style drift score." *The Journal of Portfolio Management* 31, no. 1 (2004): 76-83.

Indro, Daniel C., Christine X. Jiang, Michael Y. Hu, and Wayne Y. Lee. "Mutual fund performance: A question of style." *The Journal of Investing* 7, no. 2 (1998): 46-53.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng. "Unobserved actions of mutual funds." *Review of Financial Studies* 21, no. 6 (2008): 2379-2416.

Keswani, Aneel, and David Stolin. "Which money is smart? Mutual fund buys and sells of individual and institutional investors." *The Journal of Finance* 63, no. 1 (2008): 85-118.

Khorana, Ajay. "Performance changes following top management turnover: Evidence from open-end mutual funds." *Journal of Financial and Quantitative Analysis* 36, no. 03 (2001): 371-393.

Kim, Moon, Ravi Shukla, and Michael Tomas. "Mutual fund objective misclassification." *Journal of Economics and Business* 52, no. 4 (2000): 309-323.

Kim, Tae-Hwan, Halbert White, and Douglas Stone. "Asymptotic and Bayesian confidence intervals for Sharpe-style weights." *Journal of Financial Econometrics* 3, no. 3 (2005): 315-343.

Lobosco, Angelo, and Dan DiBartolomeo. "Approximating the confidence intervals for Sharpe style weights." *Financial Analysts Journal* 53, no. 4 (1997): 80-85.

Logue, D.E. 1991. Managing Corporate Pension Plans. Washington, DC: Harper Business.

Lynch, Anthony W., and David K. Musto. "How investors interpret past fund returns." *The Journal of Finance* 58, no. 5 (2003): 2033-2058.

Mason, Andrew, Frank McGroarty, and Steve Thomas. "Style analysis for diversified US equity funds." *Journal of Asset Management* 13, no. 3 (2012): 170-185.

Nanda, Vikram K., Z. Jay Wang, and Lu Zheng. "The ABCs of mutual funds: On the introduction of multiple share classes." *Journal of Financial Intermediation* 18, no. 3 (2009): 329-361.

Nanda, Vikram, Z. Jay Wang, and Lu Zheng. "Family values and the star phenomenon: Strategies of mutual fund families." *Review of Financial Studies* (2004).

Sensoy, B.A., 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. *Journal of Financial Economics*, 92(1), pp.25-39.

Sharpe, William F. "Determining a fund’s effective asset mix." *Investment management review* 2, no. 6 (1988): 59-69.

_________, 1992, Asset Allocation: Management Style and Performance Measurement, *Journal of Portfolio Management* 46, 7-19

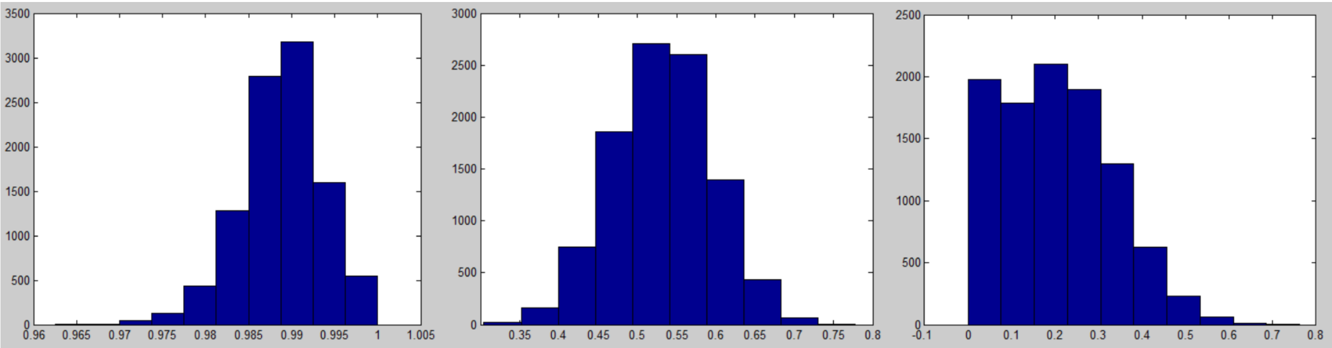
Swinkels, Laurens, and Liam Tjong-A-Tjoe. "Can mutual funds time investment styles?." *Journal of Asset Management* 8, no. 2 (2007): 123-132.

Swinkels, Laurens, and Pieter J. Van Der Sluis. "Return-based style analysis with time-varying exposures." *The European Journal of Finance* 12, no. 6-7 (2006): 529-552.

Ter Horst, Jenke R., Theo E. Nijman, and Frans A. de Roon. "Evaluating style analysis." *Journal of Empirical Finance* 11, no. 1 (2004): 29-53.

Wermers, Russ. "Matter of style: The causes and consequences of style drift in institutional portfolios." Available at SSRN 2024259 (2012).

Figure 1- Example of different Style Concentration Indexes



This figure represents an example of three mutual funds with three different investment styles. The Bar graphs show the asymptotic distribution of the stated investment style for each fund which varies between zero and one. From left to the right, the first Bar graph is an example of the stated style distribution with negative skewness and it shows the high well- classified fund whose five percentile distribution is 0.98, therefore, the *SCI* is 0.02. The second Bar graph shows a symmetric distribution of stated style which the *SCI* is 0.58. The last Bar graph is an example of fund with positive skewness and it represents the high misclassified fund whose *SCI* is 0.99.

Table 1
Summary statistics, 2003- 2015

Panel A: Mutual fund returns

Investment Objective	Mean Return	Standard Deviation	Number of funds
Growth	8.02	16.27	848
Income	7.80	13.94	191
Small caps	9.72	19.22	350
Growth/Income	7.39	15.00	477
All funds	8.15	16.26	1866
Dead funds	6.03	16.91	681

Panel B: Benchmark returns

			Cross correlations				
Benchmark	Mean Return	Standard deviation	Value	Growth	Small cap	Cash	Bond
S&P 500 Value	6.06	15.07	1.00	0.90	0.90	-0.02	-0.32
S&P 500 Growth	7.76	13.47		1.00	0.86	-0.07	-0.31
S&P 600 Small cap	10.58	18.12			1.00	-0.05	-0.34
30 Day treasury Bill	1.25	0.50				1.00	0.00
30 Years Bonds	6.90	14.86					1.00

Panel C: Variance inflation factors in the proposed benchmarks

	S&P 500 Value	S&P 500 Growth	S&P 600 Small cap	30 Day Treasury Bill	30 Years Bonds
R^2	0.88	0.85	0.81	0.02	0.12
VIF	4.43	3.60	2.91	1.00	1.01

Notes these tables provide summary statistics on the U.S. mutual funds (Panel A) and benchmarks (Panel B) that are used in the empirical analysis. Panel A reports annualized total returns with corresponding standard deviations for six equally weighted portfolios of funds. Panel B reports returns and standard deviations on the style benchmarks. Cross correlations between the benchmarks are given in Panel B columns 4 through 8. Panel C reports the Variance Inflation Factors (VIFs) for the style benchmarks and R^2 is the determinant coefficient for the linear regression of a style index i in relation to the other four style indices.

Table 2

Summary statistics of mutual fund characteristics, 2003- 2015

Variable	Mean	Std. Dev.
Total Net Assets (TNA) (in Millions)	1062	247.65
52 week low Net Asset Value (NAV) (in Millions)	16.20	13.21
52 week high Net Asset Value (NAV) (in Millions)	19.98	17.52
Age (in Years)	5.18	2.50
Expense Ratio (in Percent)	1.23	1.20
Turnover Ratio	0.76	0.62
Total Number of Funds	1,866	
Total Number of Observations	188,155	

This table provides summary statistics of characteristics of the mutual funds in our sample between July 2003 and December 2015. The Turnover Ratio is defined as the minimum (of aggregated sales or aggregated purchases of securities of a fund divided by the average 12-month Total Net Asset value of the fund. Expense ratio is the ratio of total investment that shareholders pay for the fund’s operating expenses, which include 12b-1 fees.

Table 3
Results RBSA model

Panel A: Estimated style weights

Objective	Value	Growth	Small cap	Cash	Bond	R^2
Growth	0.14***	0.63***	0.22***	0.00	0.00	0.97
Income	0.54***	0.33***	0.04***	0.04***	0.03***	0.98
Small cap	0.01***	0.11***	0.87***	0.00***	0.00	0.96
Growth/Income	0.39***	0.45***	0.10***	0.05***	0.00	0.97

Panel B: 95% Confidence intervals for style weights

Objective	Value	Growth	Small cap	Cash	Bond
Growth	[0.09 – 0.20]	[0.57 – 0.68]	[0.19 – 0.26]	[0.00 – 0.02]	[0.00 – 0.01]
Income	[0.49 – 0.58]	[0.29 – 0.37]	[0.02 – 0.07]	[0.02 – 0.07]	[0.02 – 0.04]
Small cap	[0.00 – 0.07]	[0.06 – 0.16]	[0.83 – 0.91]	[0.00 – 0.02]	[0.00 – 0.01]
Growth/Income	[0.35 – 0.44]	[0.41 – 0.49]	[0.07 – 0.13]	[0.03 – 0.07]	[0.00 – 0.02]

Notes This table presents the parameter estimates of the RBSA model for four equally weighted portfolios of funds. Each row deals with one particular investment objective, where the elements in columns 3 to 7 report the estimated style weights. Panel B reports the 95% confidence intervals for all estimated style weights for the portfolios. Because of the constraints on the parameters these have been constructed by a combination of the Kuhn-Tucker optimization and the standard bootstrapping algorithm. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 4
Mutual fund misclassifications

Mutual fund misclassifications based on individual funds

Objective	% Misclassifications	% Significant Misclassifications	%Significant Well-classification
Growth	29%	23%	61%
Income	26%	26%	47%
Small Cap	1.5%	0.8%	98%
Growth/Income	5%	3.8%	90%
All mutual funds	17%	14%	75%

Notes this table provides evidence of fund misclassification using individual fund returns. We assume that a growth/income fund should predominantly be exposed to the growth or value benchmark, income finds to the value benchmark, growth funds to the growth benchmark and finally small cap funds to the small cap benchmark. If a fund exhibits a higher weight on any other benchmark, we consider it to be misclassified. Column 2 reports the percentage of misclassified funds per investment objective, solely based on the point estimates for style weights. In column 3 and 4, we take account of the significance of the estimated style weights and report the percentage of significantly misclassified funds and significant well-classified funds per investment objective respectively.

Table 5
Relationship between Style Concentration Index and Fund Performance

	SCI	Annual return	Annual style-adjusted return	Alpha-CAPM	Alpha-3F	Alpha-Carhart
Decile 1 (Highest misclassified funds)	0.95	7.69	-2.93	-2.00	-1.95	-2.01
Decile 2	0.75	7.72	-3.40	-1.40	-1.41	-1.44
Decile 3	0.63	6.90	-2.84	-1.18	-1.23	-1.20
Decile 4	0.53	7.09	-3.04	-0.98	-1.13	-1.16
Decile 5	0.45	7.70	-2.83	-0.97	-1.18	-1.26
Decile 6	0.37	7.70	-2.68	-1.16	-1.25	-1.28
Decile 7	0.30	8.41	-2.69	-1.10	-1.30	-1.41
Decile 8	0.24	7.85	-2.84	-1.20	-1.46	-1.57
Decile 9	0.18	8.74	-2.89	-1.02	-1.30	-1.35
Decile 10 (Highest well-classified funds)	0.09	8.87	-1.86	-1.29	-1.11	-1.09
(10)- (1)		1.18**	1.07***	0.71*	0.84**	0.92***
		(2.53)	(3.11)	(1.88)	(2.38)	(2.72)

Note this table presents the relationship between the Style Concentration Index (SCI) and several fund characteristics. We sorted funds into decile and calculated fund characteristics within the portfolios. (10)- (1) represents the test of equal means between the top and bottom decile; we report t- stat in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 6

Relationship between Style Concentration Index and Fund Characteristics

	SCI	Turnover ratio	% Expense ratio	Log (TNA)	Log (Age)
Decile 1 (Highest misclassified funds)	0.95	0.83	1.46	2.71	5.13
Decile 2	0.75	0.67	1.33	2.97	5.15
Decile 3	0.63	0.78	1.26	2.83	5.17
Decile 4	0.53	0.54	1.21	2.85	5.18
Decile 5	0.45	0.85	1.26	2.95	5.19
Decile 6	0.37	0.68	1.19	3.24	5.18
Decile 7	0.30	0.77	1.19	3.22	5.23
Decile 8	0.24	0.72	1.19	2.95	5.22
Decile 9	0.18	0.70	1.19	3.02	5.22
Decile 10	0.09	0.78	1.02	3.22	5.24
(Highest well-classified funds)					
(10)- (1)		-0.05	-0.44***	0.51**	0.11***
		(-0.38)	(-7.36)	(2.49)	(5.48)

Note this table presents the relationship between the Style Concentration Index (SCI) and several fund performance measures.. We sorted funds into decile and calculated fund performance within the portfolios. (10)- (1) represents the test of equal means between the top and bottom decile; we report t- stat in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 7

Relation between Style Concentration Index (SCI) and Fund Characteristics

	Turnover ratio	Expense Ratio	Log (TNA)	Log (Age)
All mutual funds	-0.02**	12.44***	-0.01**	-0.12***
	(-2.04)	(8.41)	(-1.96)	(-7.18)
Dead mutual funds	0.02**	10.28***	-0.04***	-0.11***
	(2.03)	(4.83)	(-2.78)	(-8.12)

Table 7 reports the regression results for Equation (6). SCI is the Style Concentration Index coefficient, Log($Size_f$) is the logarithm of TNA, $Expense_f$ is the annualised expense ratio and Log (Age_f) is the logarithm of the age of mutual fund. We report t-statistics within parentheses. We indicate significance at the 10%, 5% and 1% level, by *, ** and ***, respectively.

Table 8

Results Robustness Test RBSA model – Alternative style benchmarks- Russell indices

Panel A: Estimated style weights for Alive Portfolio

Objective	Value	Growth	Small cap	Cash	Bond	R^2
Growth	0.19***	0.66***	0.14***	0.00	0.00	0.97
Income	0.65***	0.26***	0.06***	0.06***	0.02***	0.98
Small cap	0.00***	0.15***	0.84***	0.00***	0.00	0.96
Growth/Income	0.46***	0.42***	0.05***	0.06***	0.00	0.97

Panel B: 95% Confidence intervals for style weights

Objective	Value	Growth	Small cap	Cash	Bond
Growth	[0.15 – 0.23]	[0.62 – 0.70]	[0.12 – 0.17]	[0.00 – 0.01]	[0.00 – 0.01]
Income	[0.62 – 0.69]	[0.22 – 0.29]	[0.00 – 0.03]	[0.04 – 0.08]	[0.01 – 0.03]
Small cap	[0.00 – 0.04]	[0.11 – 0.18]	[0.81 – 0.87]	[0.00 – 0.01]	[0.00 – 0.01]
Growth/Income	[0.42 – 0.49]	[0.39 – 0.46]	[0.02 – 0.07]	[0.04 – 0..07]	[0.00 – 0.01]

Notes This table presents the parameter estimates of the RBSA model for six equally weighted portfolios of funds. In panel A estimated style weights are given. Each row deals with one particular investment objective, where the elements in columns 3 to 7 report the estimated style weights. Panel B reports the 95% confidence intervals for all estimated style weights.
We indicate significance at the 10%, 5% and 1% level, by *, ** and ***, respectively.

Table 9

Results Robustness Test RBSA model - sub-sample analysis 2003- 2009

Panel A: Estimated style weights for Alive Portfolio

Objective	Value	Growth	Small cap	Cash	Bond	R^2
Growth	0.19***	0.67***	0.14***	0.00	0.00	0.98
Income	0.54***	0.30***	0.06***	0.07***	0.03***	0.96
Small cap	0.01***	0.16***	0.83***	0.00***	0.00	0.96
Growth/Income	0.46***	0.44***	0.05***	0.04***	0.01	0.97

Panel B: 95% Confidence intervals for style weights

Objective	Value	Growth	Small cap	Cash	Bond
Growth	[0.13 – 0.24]	[0.61 – 0.72]	[0.10 – 0.18]	[0.00 – 0.02]	[0.00 – 0.02]
Income	[0.48 – 0.59]	[0.24 – 0.36]	[0.02 – 0.10]	[0.03 – 0.11]	[0.00 – 0.05]
Small cap	[0.00 – 0.05]	[0.10 – 0.21]	[0.78 – 0.87]	[0.00 – 0.03]	[0.00 – 0.02]
Growth/Income	[0.42 – 0.50]	[0.39 – 0.48]	[0.02 – 0.09]	[0.02 – 0.07]	[0.00 – 0.02]

Notes This table presents the parameter estimates of the RBSA model for six equally weighted portfolios of funds. In panel A estimated style weights are given. Each row deals with one particular investment objective, where the elements in columns 3 to 7 report the estimated style weights. Panel B reports the 95% confidence intervals for all estimated style weights.

We indicate significance at the 10%, 5% and 1% level, by *, ** and ***, respectively.

Table 10

Results Robustness Test RBSA model - sub-sample analysis 2009- 2015

Panel A: Estimated style weights for Alive Portfolio

Objective	Value	Growth	Small cap	Cash	Bond	R^2
Growth	0.19***	0.64***	0.16***	0.01	0.00	0.97
Income	0.57***	0.33***	0.04***	0.02***	0.04***	0.96
Small cap	0.02***	0.10***	0.87****	0.01***	0.01	0.98
Growth/Income	0.45***	0.41***	0.05***	0.08***	0.00	0.97

Panel B: 95% Confidence intervals for style weights

Objective	Value	Growth	Small cap	Cash	Bond
Growth	[0.14 – 0.25]	[0.59 – 0.69]	[0.13 – 0.19]	[0.00 – 0.02]	[0.00 – 0.01]
Income	[0.51 – 0.63]	[0.27 – 0.39]	[0.00 – 0.07]	[0.00 – 0.06]	[0.01 – 0.05]
Small cap	[0.00 – 0.07]	[0.05 – 0.15]	[0.83 – 0.90]	[0.00 – 0.03]	[0.00 – 0.02]
Growth/Income	[0.39 – 0.51]	[0.36 – 0.46]	[0.02 – 0.08]	[0.06 – 0.10]	[0.00 – 0.02]

Notes This table presents the parameter estimates of the RBSA model for six equally weighted portfolios of funds. In panel A estimated style weights are given. Each row deals with one particular investment objective, where the elements in columns 3 to 7 report the estimated style weights. Panel B reports the 95% confidence intervals for all estimated style weights.

We indicate significance at the 10%, 5% and 1% level, by *, ** and ***, respectively.

Table 10

Relationship between Style Concentration Index and Fund Performance by using the Russell indices

	SCI	Annual return	Annual style-adjusted return	Alpha-CAPM	Alpha-3F	Alpha-Carhart
Decile 1 (Highest misclassified funds)	0.94	7.44	-3.46	-2.05	-2.18	-2.26
Decile 2	0.74	7.49	-3.50	-1.28	-1.38	-1.41
Decile 3	0.60	6.83	-3.16	-1.19	-1.24	-1.23
Decile 4	0.51	7.41	-2.47	-1.02	-1.05	-1.09
Decile 5	0.41	8.01	-2.27	-0.98	-1.06	-1.14
Decile 6	0.33	7.91	-2.88	-1.49	-1.34	-1.41
Decile 7	0.26	7.65	-2.83	-1.09	-1.44	-1.45
Decile 8	0.21	8.32	-2.76	-1.15	-1.34	-1.33
Decile 9	0.15	8.68	-2.80	-1.18	-1.22	-1.23
Decile 10 (Highest well-classified funds)	0.08	8.92	-1.99	-1.00	-1.04	-1.05
(10)- (1)		1.47***	1.46***	1.04***	1.14***	1.21***
		(2.98)	(4.45)	(2.89)	(3.20)	(3.47)

Note this table presents the relationship between the Style Concentration Index (SCI) and several fund performance basis. We sorted funds into decile and calculated fund performance within the portfolios. (10)- (1) represents the test of equal means between the top and bottom decile; we report t- stat in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 11

Relationship between Style Concentration Index and Fund Characteristics by using the Russell indices

	SCI	Turnover ratio	% Expense ratio	Log (TNA)	Log (Age)
Decile 1 (Highest misclassified funds)	0.94	0.85	1.43	2.66	5.14
Decile 2	0.74	0.70	1.35	2.94	5.14
Decile 3	0.60	0.68	1.21	2.85	5.16
Decile 4	0.51	0.74	1.23	2.81	5.14
Decile 5	0.41	0.67	1.26	2.80	5.21
Decile 6	0.33	0.76	1.25	3.20	5.21
Decile 7	0.26	0.74	1.20	3.00	5.20
Decile 8	0.21	0.61	1.16	3.14	5.21
Decile 9	0.15	0.88	1.20	2.68	5.24
Decile 10 (Highest well-classified funds)	0.08	0.71	0.99	3.27	5.20
(10)- (1)		-0.13	-0.44***	0.61***	0.12***
		(-1.14)	(-7.32)	(3.56)	(5.59)

Note this table presents the relationship between the Style Concentration Index (SCI) and several fund characteristics. We sorted funds into decile and calculated fund characteristics within the portfolios. (10)- (1) represents the test of equal means between the top and bottom decile; we report t- stat in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.