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Identifying and correcting misclassified South African equity unit trusts using style analysis

1. INTRODUCTION

To constitute a style, an investment philosophy should be held in common by some group of investors. Style might be said to be a reflection of a portfolio manager's guiding investment philosophy and may be characterised by the fundamental set of principles that is consistently applied in the investment decision making process[1].

Over time, different styles have evolved to mean different things to different groups of investors and it is unlikely that there will ever be broad consensus on what exact equity characteristics distinguishes one style from another. Style analysis therefore ultimately involves the grouping or classification of assets based on some set of differentiating criteria.

The idea that styles may exist amongst equity portfolios originated when the investment community began actively gathering and analysing data on investment managers. Although style descriptions weren't well defined at that stage, researchers began to notice a clustering of the performance of investment portfolios, the stocks of which had similar characteristics (King, 1966; Farrell, 1975). A clustering of portfolio returns was also found to occur amongst those portfolios whose managers had similar investment philosophies about the key determinants of stock price movements (LeClair, 1974).

The first research into the characteristic and returns-based grouping of stocks and portfolios can be found in the work of King (1966). Farrell (1975) used cluster analysis to study risk and return patterns and, like King (1966), was able to identify natural groupings of stocks and portfolios. Perhaps the most prominent study on style was conducted by Sharpe (1988, 1992) who developed a returns-based technique which relies on analysing covariances in manager return patterns. He proposed that the basis of style analysis was in determining a portfolio's 'effective asset mix' in terms of a predefined set of indices.

To identify and differentiate between investment manager styles, analysts and theorists had relied on subjective judgement (Arnott and Bailey, 1986). By identifying the investment style and objective of a portfolio manager the investor is obtaining information about the manager's area or niche of expertise (Tierney and Winston, 1990; Troutman, 1991). If a style has clear differentiating criteria then sensible benchmarks can be constructed to represent the styles (Cowhey and Rennie, 1990).

In more advanced uses, Barneby, Good and Hermansen (1986) claim that style management may facilitate performance measurement, allow for better risk control and diversification, and allow the investor, pension fund trustee or consultant to share the controls and responsibilities of active management especially in the case of multi-manager portfolios. Christopherson (1995) argues that style analysis can also be a useful tool for selecting meaningful benchmarks for investment managers and, if appropriately selected, specialist style benchmarks are a fairer comparison than generic benchmarks.

2. LITERATURE REVIEW

Multi-factor models used in style analysis assume that the return of an asset is a function of the asset's sensitivity to some set of style factors as determined by the style betas or coefficients in the model. Bauman and Dowen (1986) applied a four factor model consisting of price-to-earnings, level of systematic risk, market capitalisation and a 'neglect' factor. They concluded that a multi-factor model can show modest improvements in explaining the return of US mutual funds over the single factor CAPM. Choosing the appropriate style factors and combinations of factors can be critical to the outcome of the model (Jones, 1990). Although the style factors between various models can differ greatly, the common prerequisite is that all exposures to the factors, also called the factor loadings, need to be determined at the beginning of the period.

Grinold and Kahn (1994) identify three categories into which all factors fall. Firstly there are macro-factors which respond to external influences such as exchange rates, inflation or bond yields. The second type of factors are cross-sectional factors which have no link to the economy but rather compare the

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[1] For a comprehensive definition of style see Christopherson, J. and Williams, C. (1997): Equity Style : What It Is and Why It Matters, In *The Handbook of Equity Style Management*, Ch1, Edited by T. Daniel Coggin, Frank J. Fabozzi and Robert D. Arnott, 2nd Edition, Frank J. Fabozzi Associates.

attributes of individual stocks. These factors are more commonly used in composition-based style analysis

Thirdly there are statistical factors which process large amounts of data in an attempt to capture either factor exposures or identify the factors themselves. These factors, unlike cross-sectional factors, are more commonly used in returns-based style analysis. The difficulty with statistical factors is that they may be difficult to interpret in the context of portfolio management.

Arnott, Kelso, Kiscadden, and Macedo (1989) investigated whether the factors that are commonly used to identify investment styles have some degree of predictability in being able to generate meaningful return forecasts. Arbel, Carvel and Strebel (1983) showed that a style of investing in small capitalisation stocks with low price-to-earnings ratios that have been neglected by institutional investors generated persistently abnormally high returns. Fama and French (1996) found that a simple three factor model based on such ratios was able to explain most, if not all, of the return in a style portfolio. Ferson and Harvey (1991) applied a four factor model and found that analysing the change in style factor sensitivities over time adds greater predictive power.

The composition-based approach to style analysis examines the portfolio from the individual component asset level to determine the style orientation of the portfolio manager. The technique evaluates how the portfolio manager actually combines individual securities. Grinblatt and Titman (1993) examined performance based on portfolio composition and found that portfolio managers who followed an aggressive growth style earned significantly positive risk-adjusted returns. Trzcinka, (1995) argues that if more information is considered in the evaluation process, provided that it is complete and unbiased, it will on average produce a more accurate picture of a portfolio manager's true investment style.

Christopherson (1995) argues that style analysis should be based on portfolio composition for the reason that the security selection process may reveal far more about how the fund will be managed in the future than by some process of examining fund returns. One weakness of the composition-based approach to style analysis is that it typically requires substantial amounts of data hence the resulting models can be costly and time consuming to implement.

Returns-based style analysis by contrast uses statistical relationships between returns of investment portfolios to define the style of the portfolio under examination. This technique therefore assigns style on the basis of return pattern analysis with the fundamental assumption that return patterns imply a certain style. Returns-based style analysis and classification methods are parsimonious with the underlying data. All that is needed is a sufficiently long series of returns whereas characteristic-based style analysis may require costly and complex data.

The results of returns-based techniques are usually summarised and analysed in terms of correlation coefficients or covariance matrices. Returns-based style analysis permits investors, financial advisors and pension fund consultants to quickly and cost-effectively analyse large number of managers. DiBartolomeo and Witkowski (1997) argue that returns-based style analysis may be a superior technique to a composition-based method for two reasons. Firstly, returns are the ultimate goal of the investor. Secondly, the characteristic-based methods discussed above require the researcher to decide, before commencing the investigation, on a set of differentiating characteristics and establish boundaries and measurement techniques for them.

In selecting an appropriate returns-based model the choice is usually between models that constrain the coefficients of the indices to sum to one (Sharpe, 1988; 1992; DiBartolomeo and Witkowski, 1997) and those that operate without constraints. Constrained estimation of model coefficients usually involve some form of quadratic optimization. If the regression coefficients are constrained to sum to one then the coefficients intuitively act as portfolio weights. Unconstrained models can be estimated using techniques that have well-developed statistical properties.

Brown and Goetzmann (1997) argue returns-based style analysis is useful for analysts monitoring funds of portfolio managers who style-rotate, since changes in their performance patterns could be identified against a static set of style indices. On the other hand Trzcinka (1995) argues that returns-based style analysis is less useful for diversification purposes and information dissemination than the composition-based approach since it examines far less information

A weakness of returns-based style analysis is that statistical models can be notoriously unstable (Trzcinka, 1995). Furthermore Schwert (1989) suggests that very long time series, such as 50 years, are needed to demonstrate reliable relationships. Stock return data can also have a very low information content and using such data can lead to unreliable estimates (Christopherson, 1995). Also, whereas composition-based style analysis is able to capture a change in a portfolio manager's style, a returns-based style analysis assumes that portfolio managers do not change their styles over the time period. It is often the case, however, that an active manager intentionally and strategically changes his style (Brown and Goetzmann, 1997; Trzcinka, 1995).

Christopherson (1995) suggested that the main problem with returns-based style analysis is that the role of noise in the data is underestimated by the technique. By contrast, Brown and Goetzmann (1997) argue in favour of returns-based style analysis and find that returns-based style factors are more robust out of sample than using factors based on the macro-economy.

Several studies have examined the relationship between the stated objectives of the fund and their resulting risk and return measures. McDonald (1974) examined the overall performance of a sample of US mutual funds relative to their stated objectives and found a positive relationship between stated objectives and measures of risk. He found that the risk-adjusted performance indicated that the more aggressive funds outperform the more conservative funds.

Farrel, Keown and Martin (1982) examined US mutual funds representing five different investment objectives and found differences in the variability of the funds. Shawky (1982) found that fund risk was consistent with fund objectives and that most of the funds that had inferior performance appeared to have improved the diversification of their portfolios. Ang and Chua (1982) examined the consistency of performance of the funds with different objectives and found that the various funds met their stated objectives but did not do so consistently.

Kim, Shukla and Tomas (1995) used discriminate analysis based on actual risk-return measures, investment style and portfolio characteristics and found that half of the 591 funds in their sample were misclassified in terms of their stated objectives. DiBartolomeo and Witkowski (1997) applied an iterative technique developed by Sharpe (1988, 1992) and defined a set of US mutual fund indices in order to verify the existing fund classifications. They found that 40 percent of the mutual funds in their sample were misclassified. Furthermore, nearly a quarter of these misclassified funds were considered seriously misclassified and belonged in higher risk categories.

Brown and Goetzmann (1997), also concerned with the inadequacy of the US mutual fund classification system, used a technique similar to switching regression to identify classification errors and found that half the designated growth funds in their sample fell into other categories. They found evidence to suggest that portfolio managers may have intentionally misclassified themselves in terms of their style and related objectives so as to improve their ex-post performance figures.

According to DiBartolomeo and Witkowski (1997) misclassification of mutual funds in the US occurs for two reasons. Firstly, the classification system may be too vague and ambiguous leaving much room for subjective interpretation. Secondly, there is an increasing level of competition in the industry. Since management company revenues relate partly to fees on assets under management, the focus of the management company may be drawn away from the investment mandate towards generating performance to attract increased inflows.

The prior research on style, particularly in the US market, suggests that style analysis has a function at virtually every stage of the portfolio management process, from defining the investment universe, benchmarking and asset allocation through to performance attribution and return forecasting. Secondly, style analysis is a sensible and meaningful way to identify, group and classify investment portfolios and investment managers. Thirdly, there is overwhelming evidence in support of the proposition that US mutual funds are misclassified and that style analysis is capable of identifying and reclassifying such funds.

In South Africa the classification of unit trust funds by the industry regulator, the Association of Unit Trusts, is just one of the ways that investors and financial advisors are guided in determining which investment is appropriate given their needs. Classification of these investment portfolios should at least give some insight in the investment orientation of the portfolio as well as an indication of the risk profile of the fund. An inaccurate classification system can produce the wrong signals and may lead to a misallocation of funds to investment managers who are perhaps not ideally suited to manage their funds according to their investment objectives. Thus correct and sensible classification of unit trusts will enable investors and data vendors to objectively rate and assess unit trust funds.

Given the weight of evidence from studies in the US market, the question must be asked whether South African unit trusts are similarly misclassified in terms of the current industry classification system[2]. Furthermore can returns-based style analysis identify and correct this misclassification as was found to be the case in several of the US studies ? No study on style analysis of SA unit trusts has to date been published. The empirical work that is presented in this study applies a systematic returns-based style analysis in an attempt to answer these questions and follows the techniques developed by DiBartolomeo and Witkowski (1997).

2 At the time of writing, a new industry classification system had been proposed, but not yet implemented by the Association of Unit Trusts.

3. DATA AND METHODOLOGY

The data set consisted of a time series of monthly returns for all 51 South African equity unit trust funds in existence for the 48 months from January 1995 to December 1998[3]. The unit trust returns used were repurchase-to-repurchase with all income and dividends reinvested. The classification system was consistent with that currently in use at the time by Standard & Poors MicroPal, MoneyMate and the financial press. The categories are:

- General Equity Funds
- Index Funds
- Industrial Funds
- Managed Prudential Funds
- Mining and Resources Funds
- Specific Equity Funds.

DiBartolomeo and Witkowski (1997), in their study of US mutual fund misclassifications, were fortunate in being able to gather a large sample of return data from 748 equity mutual funds over a 60 month period. The data set on South African unit trusts is thus considerably smaller in size and shorter in history than in the US because the industry is far younger.

A return series for each of the unit trust categories listed above was calculated and termed the 'category style index'. The monthly return for each category style index is simply the mean of the return of all funds in the category.

A returns-based style analysis was used to determine whether equity unit trust funds were misclassified in terms of their category. The approach employed followed a constrained multiple linear regression as discussed in DiBartolomeo and Witkowski (1997). The approach is outlined briefly below.

A linear combination of the category style indices is used to mimic the performance of each unit trust fund. For every unit trust fund, a coefficient is estimated for each category style index representing the weight of that index in the portfolio. Mathematically, the procedure used is to describe the return history of a particular unit trust as a multi-factor linear model of the form:

$$R_{it} = \sum_{j=1}^{6} a_j X_{jt} + e_t$$

where:

R_{it} = return on fund i in period t.
a_j = coefficient on index j.
X_{jt} = return on index j in period t.
e_t = error term in period t.

[3] Seven funds had only a 47 month performance history and were assigned a return equal to the average of other funds in their category for the month of January 1995.

Essentially, for each unit trust fund, a minimum-variance portfolio was created, reflecting the weightings in the category style indices which best replicate the return pattern of the fund during the time period.

However, one problem that arises is that coefficients estimated using traditional regression approaches may take on either positive or negative values. Investment practitioners often find it intuitively unappealing that an index exerts a negative influence on the return of the portfolio. In addition to the lack of intuitive appeal, traditional regression may also exhibit multi-collinearity. If the independent variables are highly correlated then the reliability of the estimated coefficients in meaningfully describing the underlying relationship may be very much in doubt.

To overcome this Sharpe (1992) and DiBartolomeo and Witkowski (1997) constrain the coefficients of the regression to sum to one. This also is more intuitively appealing as the resultant coefficients can then be thought of a representing asset weights within a portfolio.

Mathematically:

$$\sum_{j=1}^{6} a_j = 1$$

And,

$$0 < a_j < 1$$

Placing bounds on the weights reduces the likelihood that high correlations between the independent variables will cause the coefficients to 'blow up' to unrealistic values. As in a traditional regression, the weights are calculated so as to minimise the sum of the squared differences between the actual dependant variable and the combination of independent variables. Because of the constraints on the weights, the problem of actually calculating the weights is solved using the technique of quadratic programming[4]. The constrained coefficients, or style weights, in this study were estimated using the Goldfarb-Idnani Dual Method (1983). Empirical studies using returns-based style analysis show that the resultant R^2 of a model derived by constrained regression is only marginally different to the R^2 derived by traditional regression (Sharpe, 1992).

Although the purpose of this study is not to critically evaluate the DiBartolomeo and Witkowski (1997) technique, it is worthwhile noting that one shortcoming

[4] For a detailed discussion on gradient method quadratic programming see Sharpe (1984): Practical Aspects of Portfolio Optimisation *In Improving the Investment Decision Process : Quantitative Assistance for the Practitioner and for the Firm*, Edited by H. Russel Fogler and Darwin M. Brayston, Homewoood, IL, Dow-Jones-Irwin.

of the technique is that there is no formal way to calculate the statistical significance of the constrained coefficients. Only in a later study were DiBartolomeo and Lobosco (1997) able to derive an approximation for the confidence interval.

A fund was initially considered misclassified if the predominant weight, as indicated by the coefficients generated by the constrained linear regression, represented a category style index other than the category under which it was originally classified. As in the DiBartolomeo and Witkowski (1997) study, if the predominant weight was a weight less than 75 percent in the original category style index then an additional test was performed. The additional test regressed the fund individually on each category style index to determine the univariate R^2. If the highest observed R^2 resulted from the same category style index that had the predominant weighting in the previous constrained regression then the unit trust fund was finally considered misclassified.

This additional test was motivated by the possibility of a "barbell" style weight vector. This may happen where a fund has an equal weighting in two or more different categories and a low weighting in its own initial category. A criticism of the DiBartolomeo and Witkowski (1997) technique is that no reasons are given for the seemingly arbitrary 75 percent cut-off. Furthermore, no investigation was done into the extent to which the reclassification exercise is still meaningful at levels other than 75 percent.

After identifying a misclassified fund, the fund was returned to its appropriate category, or reclassified, as suggested by the index which received the highest weighting when creating the mimicking portfolio. Assuming the possibility that some unit trust funds in the sample were *a priori* misclassified then the category style indices are not necessarily accurate or genuine representations of the category styles since, the category style indices are the simple averages of the fund returns within each category. This means that the misclassified funds distort the returns of each category style index. To counteract this problem the category style indices were recalculated after each reclassification and the process of creating minimum-variance portfolios for each unit trust fund was repeated. The process is repeated until convergence occurs and funds are in their appropriate categories.

A unit trust fund was considered incorrectly classified in terms of its category if the iterative returns-based style analysis, after convergence, resulted in the fund being moving to a category that was different from its initial category.

4. RESULTS

After the first constrained regression it appeared that more than half of the General Equity unit trusts were misclassified. The coefficients of the regressions indicated that, of the 24 General Equity funds in the sample, 13 funds had a predominant weighting in a category style index other than that of General Equity funds. Table 1 shows the 13 General Equity funds which appeared to be misclassified.

Table 1: Constrained regression coefficients of apparently misclassified unit trust funds after the first iteration

	Category Style Index					
	General Equity	Index Fund	Industrial	Managed Prudent	Mining Resource	Specific Equity
ABSA General	0,467	0,000	0,533*	0,000	0,000	0,000
Fedsure General Equity	0,254	0,000	0,000	0,342	0,015	0,389*
Guardbank Growth	0,000	0,741*	0,000	0,235	0,024	0,000
Guardbank Prosperity	0,000	0,584*	0,168	0,249	0,000	0,000
Marriott Equity	0,000	0,480*	0,050	0,322	0,000	0,147
NIB Syfrets Prime Select	0,000	0,000	0,119	0,218	0,030	0,633*
NIB Syfrets Selected Opp's	0,000	0,000	0,907*	0,000	0,000	0,093
Old Mutual Growth	0,230	0,000	0,770*	0,000	0,000	0,000
Old Mutual Investors	0,276	0,338	0,386*	0,000	0,000	0,000
Old Mutual Top Co	0,236	0,171	0,593*	0,000	0,000	0,000
Sage Financial Services	0,000	0,000	0,581*	0,000	0,000	0,419
Sage Fund	0,000	0,532*	0,000	0,364	0,000	0,103
Standard Bank Growth	0,213	0,430*	0,281	0,000	0,000	0,076
Standard Bank Mutual	0,000	0,464	0,000	0,529*	0,000	0,007

* Denotes those funds which received a predominant weight in an category style index that is different to their current industry classification.

As discussed above, if the predominant weighting was less than 75 percent in a category other than its own then a second test was performed to confirm whether the fund was indeed misclassified. The R^2 of a univariate regression of the apparently misclassified funds' returns on each of the style category indices individually was calculated. Of the General Equity unit trusts apparently misclassified after the first constrained linear regression in Table 1, it was found that, after applying the second test, only six of these funds were in fact misclassified as shown in Table 2.

Table 2: Univariate R^2 of misclassified unit trust funds after the first iteration

	Category Style Index					
	General Equity	Index Fund	Industrial	Managed Prudent	Mining Resource	Specific Equity
Guardbank Growth	0,887	0,948*	0,816	0,872	0,433	0,816
NIB Syfrets Prime Select	0,912	0,811	0,892	0,882	0,251	0,915*
NIB Syfrets Selected	0,896	0,754	0,915*	0,862	0,142	0,868
Old Mutual Growth	0,957	0,834	0,962*	0,942	0,217	0,882
Sage Fund	0,929	0,940*	0,874	0,897	0,343	0,869
Standard Bank Mutual	0,909	0,914*	0,882	0,900	0,328	0,851

* Denotes those funds where the univariate R^2 is greater for a category style index that is different to their current industry classification such that they will be reclassified.

After the first iteration involving the constrained linear regression and reclassification of the equity unit trusts, it was found that the six funds in Table 2 were indeed all misclassified. This represents one quarter of the General Equity unit trusts that were in existence over the period January 1995 to December 1998. These six funds were more appropriately placed in other categories as shown in Table 3.

Table 3: Reclassified unit trust funds after the first iteration

	Existing Classification	Suggested Classification
Guardbank Growth	General Equity	Index Fund
NIB Syfrets Prime Select	General Equity	Specific Equity
NIB Syfrets Selected Opp's	General Equity	Industrial
Old Mutual Growth	General Equity	Industrial
Sage Fund	General Equity	Index Fund
Standard Bank Mutual	General Equity	Index Fund

After moving the six unit trust portfolios in Table 3, the category style indices were recalculated to incorporate these new portfolios and the constrained linear regression, or optimisation, was repeated for once again for each unit trust fund. Since the above process is iterative and ultimately converges to a point where all funds are correctly classified, it was expected that the second iteration would identify fewer misclassified funds than the first iteration.

Table 4: Constrained regression coefficients of apparently misclassified unit trust funds after the second iteration

	Category Style Index					
	General Equity	Index Fund	Industrial	Managed Prudent	Mining Resource	Specific Equity
ABSA General*	0,398	0,000	0,602*	0,000	0,000	0,000
Fedsure General Equity*	0,155	0,000	0,056	0,298	0,024	0,468*
Guardbank Prosperity*	0,177	0,738*	0,080	0,005	0,000	0,000
Marriott Equity*	0,000	0,611*	0,070	0,149	0,000	0,171
Standard Bank Growth*	0,304	0,464*	0,201	0,000	0,000	0,032

* Denotes those funds which received a predominant weight in an category style index that is different to their current industry classification.

The six unit trust portfolios that initially appeared to be misclassified after the second iteration are shown in Table 4. None of these funds were amongst those that appeared to be misclassified after the first iteration. The reason is that they would have already been moved, after the univariate test, to their appropriate categories as shown in Table 3. Also, since the category style indices were recalculated after the first iteration, the funds in Table 4 now appear misclassified in terms of the revised category style indices. The funds in Table 4 were each subjected to a second test to determine their univariate R^2 in relation to these revised categories.

Table 5: Univariate R^2 of misclassified unit trust funds after the second iteration

	Category Style Index					
	General Equity	Index Fund	Industrial	Managed Prudent	Mining Resource	Specific Equity
Fedsure General Equity	0,946	0,858	0,921	0,943	0,273	0,947*
Guardbank Prosperity	0,944	0,971*	0,888	0,941	0,371	0,888
Marriott Equity	0,952	0,957*	0,907	0,929	0,340	0,907

* Denotes those funds where the univariate R^2 is greater for a category style index that is different to their current industry classification such that they will be reclassified.

Since the iterative process is convergent the result is that only three funds, shown in Table 5, were reclassified after confirmation by the second test in the second iteration. This is half the number of funds that were reclassified after the first iteration. Once again, all the funds that are misclassified are general equity funds. The new categories of the funds that were reclassified after the second iteration are in Table 6.

Table 6: Reclassified unit trust funds after the second iteration

	Existing Classification	Suggested Classification
Fedsure General Equity	General Equity	Specific Equity
Guardbank Prosperity	General Equity	Index Fund
Marriott Equity	General Equity	Index Fund

The funds in Table 6 were moved to their new categories as suggested by the second test and the style category indices were once again recalculated to incorporate the new funds in each category. The process of constrained regression was then repeated for a third time.

The results of this third iteration are shown in Table 7. Initially two unit trusts appeared misclassified since their predominant weight, as identified by the coefficients of the constrained regression, was in a category other than their original category.

Table 7: Constrained regression coefficients of apparently misclassified unit trust funds after the third iteration

	Category Style Index					
	General Equity	Index Fund	Industrial	Managed Prudent	Mining Resource	Specific Equity
Old Mutual Top Company*	0,332	0,219	0,450*	0,000	0,000	0,000
Standard Bank Growth*	0,340	0,495*	0,145	0,000	0,000	0,019

* Denotes those funds which received a predominant weight in an category style index that is different to their current industry classification.

As before, the second test of a univariate regression was carried out to confirm the apparent misclassification. It failed to confirm that the two funds in Table 7 were misclassified. The second

iteration seemed to have moved the last of the misclassified funds into their appropriate categories. Of the 24 unit trust funds originally classified as general equity, 9 of these funds had left the general equity fund category by the time the iterative process converged. In total 38% of the general equity unit funds in the sample were shown to be misclassified. DiBartolomeo and Witkowski (1997), in a similar study on US mutual funds, found that 40% of the total 748 mutual funds in their sample ended up in a category other than the one declared in their investment prospectus. Table 8 shows the number of funds in the initial and final categories and the movements.

Table 8: Initial and final number of unit trusts per category

Category	Initial Number of Funds	+/- Change	Final Number of Funds
General Equity	24	- 9	15
Index Funds	2	+5	7
Industrial	4	+2	6
Managed Prudential	8	-	8
Mining & Resources	9	-	9
Specific Equity	4	+2	6
Total	51	0	51

The average mean-squared error for the reclassified funds relative to their initial and final category style indices are shown in Table 9. As expected, the average mean-squared error is notably reduced when a fund is moved from the category in which it was originally classified to its new one. DiBartolomeo and Witkowski (1997) also found this to be the case for US mutual funds which were reclassified. There were not enough reclassified funds in this study to determine to what extend the differences in the mean-squared error were longitudinally statistically significant.

Table 9: Average mean squared error of the residual for misclassified unit trust funds

From Initial Class	To Final Class	Mean Square	Mean Square	Percent
General Equity	Index Funds	2,656	1,075	-147,00
General Equity	Industrial	5,978	4,194	-9,09
General Equity	Specific Equity	2,464	1,555	-5,85
Total Funds	9	Average percentage change		-9,88

How the category style indices themselves changed in terms of their risk and return profile as a result of the misclassified funds being moved to their appropriate categories investigated next. Table 10 shows the change in average monthly return and the change in risk measured by standard deviation. The risk of the general equity fund category increased after the nine funds had been moved to more appropriate categories. This could be explained by the fact that five of the funds which moved were actually index funds.

Table 10: Standard deviation and average monthly return for initial and final category style indices

	Initial Category Style		Final Category Style	
	Standard Deviation	Average Return	Standard Deviation	Average Return
General Equity	6,449	0,707	6,716	0,721
Index Funds	6,449	0,127	5,993	0,321
Industrial	6,894	0,851	7,019	0,856
Managed Prudential	5,364	1,008	5,364	1,008
Mining & Resources	6,997	0,001	6,997	0,001
Specific Equity	5,939	1,057	5,862	1,108

The average monthly return for the final general equity fund category was however almost the same as under the initial classification scheme. The difference between the risk of the index fund category and the risk of the general equity fund category is more pronounced under the final classification than it was under the initial classification. While the average monthly return increased substantially in the index fund category, the risk was lowered. Industrial funds showed an increase in risk under the new classification but little change in the average monthly return.

5. CONCLUSIONS

The constrained regression technique used in the iterative returns-based style analysis showed that of the 51 unit trusts in the sample, 9 were misclassified in so far as their return patterns more closely resembled the return patterns of categories other than their own. The DiBartolomeo and Witkowski (1997) study had convergence of the iterative process after five cycles but due to the smaller sample size, the iterative process in this study converged after the third cycle at which time all funds had been moved to their more appropriate categories.

All the misclassified funds were from the general equity fund category, which accounted for 38% of all general equity funds in the sample. Five of the misclassified general equity funds moved to the index fund category, two moved to the industrial fund category and two funds moved to the specific equity fund category. After correcting for the misclassified funds, the average monthly return of all the revised fund categories had increased. The standard deviation of monthly return of the revised fund categories increased in the general equity and specific equity fund categories but decreased in the index and industrial fund categories. Consistent with the DiBartolomeo and Witkowski (1997) study, the average mean-squared error of the residual fund returns for reclassified funds dropped by an average of 10% once all funds had been moved to their new categories.

The results indicate that the observed misclassifications were not due to random noise in the market since incorrectly classified funds were moved to categories which were both more and less aggressive than their original category. Incorrectly classified funds alter the risk-return characteristics of their categories and may send inaccurate signals to industry participants trying to make informed decisions based on these characteristics. The mean-squared error of the residual return of reclassified funds strengthens the case in support of their misclassification. Returning the misclassified funds to their appropriate categories can create pure category fund style indices for reporting, benchmarking and analysis purposes.

6. IMPLICATIONS FOR INVESTORS

Unit trust data vendors such as MicroPal, MoneyMate and Hugo Lambrechts' University of Pretoria Unit Trust Review regularly calculate and publish figures calculated on the basis of the current fund classifications system. The empirical results of this study show the categorical misclassification of equity unit trusts under the current scheme and hence, by implication, any calculations based on the current classification of unit trusts such as category average return and volatility are questionable. Investors, portfolio managers and financial advisors frequently look to such publications and information for guidance in their investment decisions. Without conducting a sensible test to verify the existing fund classifications the reliability and accuracy of the data is compromised.

An investor attempting to assemble a selection of unit trusts that is diversified across the various unit trust categories may ultimately end up holding a misclassified fund in an incorrect category. In this instance investors may compound their risk by duplicating their exposure instead of diversifying across the categories. Without the benefit of style analysis investors may be inhibited from properly diversifying across various styles and categories.

Portfolio managers involved in managing unit trust funds are frequently evaluated and rewarded on the basis of performance relative to their peer group. A peer group or fund category containing funds that are misclassified will have distorted performance and volatility figures. Competing investment managers within a category may be induced to assume additional risk to achieve top quartile performance. In this case the average manager is the benchmark and misclassified funds, not corrected for through a verification technique such as style analysis, may result in unrealistic benchmarks.

Portfolio managers who manage unit trust fund-of-funds and wrap funds where the investable universe consists entirely of other unit trusts may be faced with similar problems to that of individual investors and financial advisors. While multi-managers such as these may be considerably more sophisticated than investors or financial advisors, misclassified unit trusts in their investable manager universe may be potentially hazardous.

An attempt by a multi-manager to invest in a misclassified specific equity unit trust in pursuit of a particular market theme may be unsuccessful if the

fund is actually, for instance, a closet index or general equity fund. The absence of style analysis, such as the one in this study, may inhibit the construction of meaningful style orientated manager universes and increase the likelihood that unsuitable funds will find their way into the investable manager universe.

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