Complementary or Contradictory? Combining Returns Based & Characteristics Based Investment Style Analysis.

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1. Abstract

This study is the first to combine returns based (RBS) and characteristics based (CBS) style analysis into a single style analysis model. We address the issue of whether RBS and CBS style analysis are complementary. Out of sample tests confirmed two things; membership of style groups explain a significant degree of cross sectional performance of mutual funds and secondly the cumulative effect of combining BFI (Best Fit Index) and CBS analysis significantly improves on the CBS and BFI models in isolation. The ex post explanatory power of the combined model is greater than the individual parts. The model provides a useful tool for asset managers to identify their true competitors and wealth managers and advisors to perform due diligence.

JEL G10, G11, G14, G20, G23

Keywords: Style Analysis, Mutual Funds, Portfolio, Benchmarking, Fund Manager Selection

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1. Introduction

In this paper we combine returns based style analysis, using a parsimonious Best Fit Index (BFI) methodology with characteristics based analysis (CBS) to provide a combined BFI-CBS methodology with which to identify the style of a large and heterogeneous sample of US diversified equity mutual funds; we find that our methodology improves on the out of sample forecasting properties of either model on its own..

There has been much debate in the literature about the relative merits of Returns Based Style (RBS) analysis and Characteristics Based Style Analysis (CBS) as in Coggin and Fabozzi (2003), and comparisons of the efficiency of the various models employed in style analysis Brown and Goetzmann (1997) and Chan et al. (2002). The majority of studies seem to come down in favour of CBS analysis where there is any difference in outcome, (see Chan et al. (2002) and references therein). Few of these papers address the issue of whether these methods are contradictory or complementary, preferring to focus on the relative attractiveness of the various methods or any apparent shortcomings. Some, such as Dor and Jagannathan (2003) conclude that RBS may be a useful precursor to CBS analysis whilst Brown and Goetzmann (1997) use portfolio characteristics to check their returns based GSC styles. Surz (2003) suggests how returns based analysis and characteristics based analysis could be used in conjunction with each other; RBS being utilised to identify the 'Style' component and CBS analysis being utilised to identify two components of 'Skill'; sector allocation and stock selection. We also note that organisations such as Morningstar which favour CBS style analysis, as evident from Rekenthaler et al. (2006), provide a large amount of other portfolio data alongside this style analysis, including a best-fit index based on regression analysis and portfolio returns. Both of these approaches have used returns based and portfolio characteristics based information in conjunction with each other but have not combined the information into a single style analysis model. Our empirical results confirm that returns based and characteristics based style analyses are complementary.

When comparing benchmarking methods used in academic research and by investment practitioners Chan et al. (2009) note that benchmarking measures that use size and value-growth orientation accurately reflect investment styles but that more comprehensive measures of portfolio characteristics do a better job of matching equity managers' value-growth orientation than a simple price book rank. They also observe that benchmarks which aim to reflect portfolio characteristics perform better than regression based benchmarks. Our BFI-CBS methodology takes note of these observations; we use the Best Fit Indices to establish the 'investment domains' of our sample managers, along the lines of size and 'style', and then use our multidimensional characteristics based analysis to form style groups within those domains. Our findings show that the combined BFI-CBS methodology performs best out of sample with the CBS alone performing better than RBS alone which is consistent with the views expressed above. Our model provides a useful tool for asset managers to identify their true competitors and wealth managers and advisors to perform due diligence in fund comparisons, selection and diversification.

In Section 2 we review the style analysis literature, in Section 3 we describe the data, in Section 4 describe the methodologies, while in Section 5 we analyse our results in more detail. Section 6 contains out-of-sample robustness checks on our methods; in Section 7 we present a qualitative assessment of our style groups and finally in Section 8 we provide our conclusions.

2. Review of Style Analysis Literature

Investment managers have a range of investment philosophies and operate various investment processes to implement differentiated investment styles. Our aim is to observe that these different investment styles, US equity investment managers are a heterogeneous group, and to consider the different systematic approaches in the literature aimed at identifying these styles for the purpose of forming comparative peer groups or identifying appropriate benchmarks. Appropriate peer groups and benchmarks facilitate portfolio diversification and performance appraisal.

The analysis of investment management style typically falls into three broad categories, although there are many variants: identification of style through portfolio characteristics, identification of style through portfolio returns, and assessment of portfolio performance. Through these avenues it is possible to consider many of the key elements important to identification of investment styles, the risks being undertaken by portfolio managers and whether investors are being adequately compensated for the risks taken. Our analysis is the first to combine returns based style analysis and characteristics based analysis; based initially on portfolio returns and then refined by portfolio characteristics.

2.1 Classification of Stocks and Equity Investment Styles

Much of the early analysis of equity investment style focuses on identifying styles of stock, with Fama French(1992), in their three factor model of equity returns, building on the earlier work of Fama (1972), Sharpe (1967), Lintner (1970), Nicholson (1977), Basu (1977), Banz (1983) and Reinganum (1983), who contributed ground breaking work on the effect of the market factor (beta), valuations (Price to Equity or Price to Book), and size (small cap large cap). In parallel with these discoveries King (1966) and Farrell (1974) produced studies which suggested that common or latent factors explained stock price behaviour; in King's case a market factor, an industry factor and company factor, which was supplemented by Farrell (1974) with a cluster based classification according to growth, cyclical or stable return characteristics. The search for groupings of stocks and investor types has relevance beyond the sphere of theory and analysis; it is of direct relevance for institutional investors who dominate global equity markets and has influenced the policies and actions of these institutions and the consultants and advisors that are a part of this trillion dollar industry. These findings of Farrell (1974) gave pension plan sponsors an opportunity to reduce volatility within and across style groups within the equity asset class. The importance of this analysis however goes beyond diversification and has an important role to play in selection, benchmarking and rewarding investment managers, and a whole industry has grown up to provide these service functions.

Traditionally many academics, consultants and index providers following in the footsteps of Fama and French (1992) based their classification on a size and book value to price, or price to earnings metric as noted by Fabozzi (1998). Growth was often taken to mean high PE (price–to-earnings per share ratio) or high PBR (price–to-book value per share ratio) and effectively defined as the absence of value whereas 'core' was some undefined middle-ground. Much of the debate on investment styles focuses on the relative returns of value and growth stocks with high price to book being used as a proxy for growth stocks and low price to book being taken as a proxy for value stocks. Many studies such de Bondt and Thaler (1987) Lakonishok et al. (1994) conclude that 'value', as defined, outperforms 'growth' with some such as Fama and French (1992) suggesting that the value premium may be due to value stocks being riskier or Lakonishok et al. (1994) suggesting that it is easier to spot mispricing in value stocks. Arshanapalli et al. (1998) establish the superior performance of value over growth stocks without any consideration of any measure of growth at all; they define value as high book-to-market stocks and growth as low book to market stocks. Speidell and Graves (2003) observe that although growth portfolios may result in higher price to book or price earnings ratios that it is misleading to use this 'output' characteristic as an 'input' variable; a high valuation multiple is not an adequate measure of growth. Brush (2007) also states that studies based upon this premise are only comparing 'high book-to-market' stocks with 'low book-to-market' stocks not growth and value. Many observers such as Brown and Goetzmann (1997) and Michaud (1998) feel that this approach does not capture the diversity of investment styles. We note that all of the major index providers and mutual fund data base providers Russell, Standard & Poor's/Citigroup, MSCI and Dow Jones Wilshire plus Morningstar and Lipper have abandoned ranking by a single valuation multiple for their stock style indices and established growth-value orientation based on valuation and growth metrics reflecting their concern that a two-dimensional model, comprising size and a single valuation metric, may fail to capture the diversity and complexity of the range of investment styles operated in the U.S. equity market and thus fail to provide adequate tools for benchmarking or peer group assessment.

2.2 Multidimensional Classification and Growth-Value Orientation

Brown and Goetzmann (1997) and Speidell and Graves (2003) express the opinion that a new framework of classification will better differentiate the various investment styles being pursued in the equity market and concur with Bailey and Tierney (1995) who observe that different styles lead to differentiated portfolios and differentiated performance. We share the belief that classification of equity investment style is a multi-dimensional issue reflecting different combinations of revealed preference for income, growth and asset backing, as a form of product differentiation. Kaplan et al. (2003a) highlight the fact that growth-orientation and value-orientation are distinct concepts something that becomes more apparent when growth is measured directly rather than implied from valuation. They also note the general rule that growth-oriented stocks have weak value orientation and vice versa are sometimes observed to be inaccurate. These growth-valuation nuances are widely accepted both in academic literature and practitioner writing although the exact terminology or definition may differ. Christopherson and Williams (1997), outline a typical categorisation employed by practitioners when they describe Russell's categorisation of U.S. manager styles comprising four broad style categories: Value, Growth, Market-Oriented and Small-Capitalization and a range of sub-styles. Value consists of Low P/E, Contrarian, and Yield, Growth consists of

Consistent Growth and Earnings Momentum, and Market-Oriented contains managers with a Value Bias, Growth Bias, Market-Normal and Growth at a Price (GARP). Brown and Goetzmann (1997) produce a methodology which also generates a wider range of mutual fund styles than traditional industry classification and performs well in terms of predicting out of sample cross-sectional performance. The results of Michaud's (1998) study of the U.S., Japan and the UK also indicates that value may be multidimensional. There are at least three distinct kinds of equity value styles highlighted by his 'value style factors' and he criticises the central assumption of consultants or index providers that only use price to book as a measure of the growth-value dimension. Our combined BFI-CBS produces a systematic method for identifying a broad spectrum of equity investment styles.

2.3 Investment Funds Styles

Many observers of funds' styles including Bailey and Tierney (1995), Kudish (1995), Damodaran (2003) and Slager and Koedijk (2007) believe that investment managers differentiate themselves, their portfolios and the attendant returns through their investment philosophy, investment process and their investment style. What they believe works in terms of investment, how they implement those beliefs and the investment outcomes or biases which are reflected in their portfolios. Damodaran (2003) and Slager and Koedijk (2007) describe an investment philosophy as a coherent way of thinking about financial markets and how they work including the belief in where market anomalies or investment opportunities may be found. [1] The investment philosophies and processes which spawned the wide range of equity investment styles in evidence today were first documented by Graham (1934), Price (1939) and Fisher (1957). Bernstein and Damodaran (1998) illustrate how the investment process reduces a universe of stocks, through research, stock screening, stock selection, portfolio construction and execution, into a portfolio which has a certain style. Kudish (1995) notes that much attention is paid to investment philosophy and process at the manager selection stage in order to ascertain whether manager performance is explainable and repeatable.

Studies of investment fund styles which aim to identify differentiated style groups tend to take two approaches; to use simulated portfolios as in the case of Connor and Korajczyk (1991), Bassett and Chen (2001), Kothari and Warner (2001) and Kritzman and Page (2003) or to use actual portfolios as in the case of Sharpe (1992), Brown and Goetzmann (1997) and Vardharaj and Fabozzi (2007). Vardharaj and Fabozzi (2007) believe that in order to better understand the motivations and outcomes of actions taken by fund managers wherever possible empirical studies should reflect the constraints faced by investment managers. Clarke et al. (2002) note typical portfolio constraints which an active manager may have such as market capitalization restrictions, value-growth neutrality or economic sector neutrality relative to a benchmark, and turnover constraints which may affect a fund's character and performance. This approach, adopted by Vardharaj and Fabozzi (2007), is consistent with the aim of our study which is to produce a robust method of classifying investment styles for the purpose of peer group formation and benchmarking which has theoretical rigour and practical application.

2.4 Characteristics Based Analysis

One important method of analysing investment style is to consider the portfolio holdings of investment funds and the characteristics of those portfolios with a view to identifying common factors which will facilitate the formation of style groups which may provide insights into estimates of expected future performance of such groups. Early analysis of common factors related to investment style by King (1966) and Farrell (1974) suggests that common or latent factors could be used to form a cluster based classification according to growth, cyclical or stable return characteristics. Their approach was restricted to stocks but paved the way for characteristics based analysis of investment funds which took several forms. Daniel et al. (1997) use characteristics based benchmarks in their work on fund performance. Falkenstein (1996), Christopherson and Williams (1997), Radcliffe's (2003) and Prater et al. (2004) examine mutual funds revealed preferences for certain stock characteristics based on portfolio holdings. Speidell and Graves (2003) note that due to the sophisticated methods of analysis undertaken, and access to the same news sources and databases, what differentiates investment managers is the emphasis placed on different measures of valuation, growth and qualitative factors. An extension of the use of portfolio holdings was also provided by Abarbanell et al. (2003) who used characteristics based analysis to identify behavioural traits in institutional investors in the case of corporate spin-offs.

One of the best known commercial providers of portfolio analysis, risk and performance attribution systems, BARRA, was established by Barr Rosenberg based on his research on factor analysis of returns, including Rosenberg and Rudd (1982) where they acknowledge their debt to King (1966). BARRA factors are often used in portfolio research, Leinweber et al. (1998), De Allaume (1995). Other commercial providers, Morningstar (Kaplan et al. 2003b) & Lipper (Lipper 2008) also adopt characteristics based style classification based on portfolio holdings but also provide supplementary information on ‘best fit’ or benchmark indices.

2.5 Returns Based Analysis

Analysis of the returns of investment funds generally focuses on performance analysis and style analysis, including factor analysis. Performance analysis has followed several different strands with Lakonishok et al. (1994) concluding that ‘value’ (low book to market) outperforms ‘growth’ (high book to market) with some such as Fama French (1992) suggesting that the value premium might be due to value stocks being riskier. More recently Chan et al. (2002) and Davis (2001) ask why more funds haven’t attempted or succeeded in capturing the value premium. Another theme in performance of investment funds has developed in the wake of the style based approach to investment performance pioneered by Fama French (1996.) Significant recent developments in performance analysis include

Kosowski et al. (2006), Fama French (2009) and Busse et al. (2010) who consider whether managers possess luck or skill. This issue is outside the scope of this study which focuses on investment style and identification of the appropriate benchmark and peer group, with the attendant benefits for diversification and performance analysis.

The Best Fit Index model that we propose can be considered a variation on Sharpe's (1964) CAPM model which we develop to consider which benchmark or index reflects an investment fund's 'market' or investment universe. Reflecting concerns about appropriate benchmarks from many authors such as Lehman and Modest (1987), Belden and Waring (2001), Keunzi (2003) and Chan et al. (2009), we run a simple regression against a wide range of equity indices to identify which index best represents the investment universe of a particular fund rather than assuming that it is a broad market universe such as the S&P500 or the Russell 1000.[1] We use this Best Fit Index to identify the broad style grouping of a fund in a manner consistent with Argon and Ferson's (2006) concept of an otherwise equivalent benchmark that is an investment alternative that offers the same risk-reward characteristics as the fund under review. Fama French (2010) query the results of their work on luck and skill argue that CAPM doesn't reflect style tilts associated with SMB(small minus big market capitalisation), HML(High book-to-market minus low book-to-market) and MOM(momentum) factors. Our Best Fit Index approach overcomes these concerns. We are cognisant of Cremers and Petajisto's (2009) work on measurement of active management relative to a suitable benchmark index where they use a wide range of indices from Russell, Standard & Poor's and Wilshire similar to our selection, and note the importance of selecting the correct benchmark index for a mutual fund. The selection of the correct benchmark can facilitate more accurate assessment of risk adjusted return and many commercial research

[1] For some funds of course these indices are the most appropriate benchmark and this is illustrated in Table I where the S&P500 and the Russell 1000 BFI funds are found in the 'Large Core' category

organisations such as Morningstar, Lipper and S&P/BARRA[2] publish best fit indices and risk measures alongside their style information.

Much of the debate about returns based style analysis has included some consideration of Sharpe's (1992) Returns Based Style Analysis (RBSA) in various guises. Returns based style analysis (RBSA) is described by Sharpe (1992) as a specialised form of factor analysis where the factors are index returns. Sharpe's model estimates 'average' economic exposure of a fund to selected asset classes based solely on the co-movements of the fund's returns relative to those asset classes; his aim being to approximate the factors influencing a fund's returns with limited and easily obtainable data. A synthetic 'style' is formed based on an optimised portfolio of index returns which may be regarded as a fund's style or 'style benchmark'.

Debate has taken place in the literature about several aspects of RBSA and the interpretation of the results generated by RBSA. Discussion generally revolves around the following issues. The selection of the appropriate benchmarks and exhaustive cover of the investment universe; by Atkinson et al. (2001) and Dor et al. (2003) and others. The 'timeliness' of the methodology is raised as a concern by Christopherson (1995) where styles or managers may change over the 60 month analysis period. Veres (1997) and Dor et al. (2003) highlight manager change. Some such as Swinkels and Van Der Sluis (2006) or Anneart and Van Campenhout (2007) have sought modelling solutions which may overcome this timeliness issue. Ter Horst et al. (2004) find that Sharpe's constraints on positivity are valid in some respects but they argue, supported by Swinkels and Van der Sluis (2006), that the non-negativity constraint may exclude useful information regardless of whether short sales are allowed. The non-negativity constraint is removed by authors such as Dor et al. (2003) or Agarwal and Naik (2000) who use the methodology to analyse hedge funds where short selling is permitted. There have been a number of modifications or refinements to the original RBSA model that aim to improve the statistical or functional properties of the model.

[2] The BARRA risk model has widespread industry use and a long track record.

Lobosco and Di Bartolomeo (1997), Kim et al. (2005) and Anneart and Van Campenhout (2007) although some of the refinements have difficulties dealing with zero exposure to one or more of the style weights or dealing with a large sample single diversified asset class such as US equity mutual fund managers . Our consideration of Sharpe's (1992) RBSA leads us to conclude that it still has a role to play in style analysis, particularly in areas where it is difficult to obtain timely and transparent data such as hedge funds but, given some of the concerns highlighted by the authors above and the abundance of sophisticated equity style indices, it may limit its appeal for single asset portfolios such as equity investment funds.

2.6 Returns Based Style Analysis or Characteristics Based Style Analysis?

Dor and Jagannathan (2003) favour returns based style analysis as a means of evaluation of asset allocation and performance measurement; allowing investors to evaluate the nature of active style and selection decisions taken by an investment manager. They conclude that RBS may be useful, especially as a precursor to CBS, but it is critical to specify the correct benchmarks to avoid misinterpreting the degree of 'active' management and the historical nature of the method could lead to a delay in picking up 'style changes'. They also note the risk of indicating false style signals as correlations in the style indices may give the appearance of style changes which have not actually occurred and are merely anomalies caused by index construction and correlation. Radcliffe (2003) in his review of Returns Based Style analysis (RBS) and Characteristics Based Styling (CBS) concludes that neither RBS nor CBS dominates in terms of explaining future returns and that it is important to use all style information to gain insights into a portfolio's 'true style characteristics'. Surz (2003) illustrates how the RBS and CBS methodologies can be utilised to differentiate between skill and style, with RBS being utilised to identify the 'Style' component and holdings based analysis (CBS) being utilised to identify the two components of 'Skill': sector allocation and stock selection.

Kahn (1996), Buetow and Ratner (2000) and Rekenthaler et al. (2006) conclude that characteristics based analysis is a more reliable method of style analysis. Chan et al. (2002)

in a comprehensive review of mutual fund styles reaches the conclusion that where the results differ CBS does a better job of predicting future fund performance than RBS. Finally, Chan et al. (2006) when comparing benchmarking methods used in academic research and by investment practitioners note that benchmarking measures using size and value-growth orientation accurately reflect investment styles but that more comprehensive measures of portfolio characteristics do a better job of matching equity managers' value-growth orientation than a simple price book rank. They also observe that benchmarks which aim to reflect portfolio characteristics perform better than regression based benchmarks. Thus whilst on balance characteristics based analysis may produce more accurate assessment of style it is useful to use both characteristics and returns based analysis together wherever possible in order to get a more comprehensive assessment of investment style. In our study we address the question of whether returns based and characteristics based style analysis are complementary and illustrate that an integrated model that first incorporates returns-based analysis and then sub-divides the style groups according to characteristics-based analysis has greater explanatory power that either model on its own.

3. Data

The data used in this study comprises portfolio characteristics and total returns data for a large sample of US Diversified Equity Mutual Funds supplied by Morningstar and total return data for US Equity Indices supplied by Russell Indexes and Standard & Poor's Indexes. The fund database was formed by removing all duplicate classes of funds and any identifiable index funds. Multiple share classes of mutual funds have increased significantly over the past decade or so and the issue needs to be addressed in empirical studies. [3] The portfolio characteristics funds were then matched with the fund returns data to provide a sample of funds between 538 and 704 funds for individual periods.[4] Morningstar quarterly portfolio characteristics data is used for the period 2000-2005 although all results presented are

[3] According to the Investment Company Institute Fact Book there were 4,586 equity mutual funds in 2005 and 11,824 Equity Mutual Fund Share Classes.
[4] Details on the cleaning and matching process are available on request.

based on December data for each year. Portfolio characteristics are weighted in proportion to individual funds' equity holdings and are as follows; Market Capitalisation (U.S. $b), Price Earnings, Price to Book, Price to Revenue and Price to Cash Flow (X), Dividend Yield (%), Five Year Earnings Growth Forecast, Earnings Growth, Book Value Growth, Revenue Growth and Cash Flow Growth (% pa 5 years historic data). We also calculate a PEG ratio based on the Price Earnings Ratio and the Five Year Earnings Growth Forecast. Such a large and detailed database only became available when Morningstar revised their Stylebox methodology in 2002. Monthly total returns data for US Diversified Equity Mutual Funds was collected for the period 1998-2006 to facilitate the requirements of the models. S&P Sector weightings information was also obtained for the sample of funds for the Period 2000-2005 which we did not employ in any of our models but used as a qualitative check of our final results.

Monthly total return data was supplied for the following indices by Russell and Standard & Poor's for the period 1996-2005: Large-Cap Growth; Russell Top 200 Growth, Russell 1000 Growth, S&P500 Growth, S&P500 Pure Growth. Large-Cap Core: Russell Top 200, Russell 1000, S&P500. Large-Cap Value; Russell Top 200 Value, Russell 1000 Value, S&P500 Value, S&P500 Pure Value. Mid-Cap Growth; Russell Midcap Growth, S&P400 Growth, S&P400 Pure Growth. Mid-Cap Core: Russell Midcap, S&P400. Mid-Cap Value; Russell Midcap Value, S&P400 Value, S&P400 Pure Value. Small-Cap Growth; Russell 2000 Growth, S&P600 Growth, S&P600 Pure Growth. Small-Cap Core; Russell 2000, S&P600. Small-Cap Value; Russell 2000 Value, S&P600 Value, S&P600 Pure Value.

4. Methodology: Combining BFI and CBS Style Analysis

In this study we employ several different methodologies to establish style groups based on portfolio characteristics and portfolio returns. We combine two of the methodologies, outlined in 4.1 and 4.2, to establish a two stage model 'BFI-CBS' which is introduced in this paper to address the question whether returns based and characteristics based style methodologies are complementary. The validity of our style group formation is tested using procedures formulated by Brown and Goetzmann (1997) in terms of explanation of the cross section of returns in the out of sample period which is described in 4.3.

4.1 Stage 1: Best Fit Index (BFI) Methodology

We consider whether a single ‘Best Fit Index’ can adequately represent individual funds’ various investment styles. This method has intuitive appeal because we know that funds are often explicitly benchmarked against a stock market index. In order to establish whether the Russell and Standard & Poor’s indices can explain a large proportion of the monthly returns of our sample of mutual funds we ran individual regression analysis for each fund in our sample against twenty seven Russell and Standard & Poor’s U.S. equity indices encompassing the full range of style and value-growth permutations. We recorded the results for each regression and selected the index with the highest r^2 or best-fit index for each fund to create our Best Fit Index (BFI) sample. The methodology is outlined below.

For each mutual fund for we run a series of Ordinary Least Squares regressions for a 36 month period against twelve Russell Indices and fifteen Standard & Poor’s indices’ monthly returns to establish which individual index of the 27 indexes provided the best explanation or best fit of each individual fund’s returns.

$$r_{it} = \alpha_i + \beta R_{It} + \epsilon_{it} \qquad \text{Equation 1}$$

Where:

r_{it}= return on fund i for month t

α_i = alpha

R_{It}= return on index I for month t; I is calculated individually for each of the 27 Russell or S&P indices

ϵ_{it}= error term

Thus for each fund in the sample, e.g. 1,930 funds for the period Jan 2003 to Dec 2005, the index with the highest r^2 is selected from twenty seven sets of regression results and we record the index name and it's r^2. Each fund is then assigned to a style group comprising all funds whose performance is best explained by a particular index. The number of style groups is then consolidated into the typical 9 segment style box as used by Morningstar and others, based on index correlations.[5] The result is nine style groups ranging from large-cap growth to small-cap value. This process is repeated for each year end from 1998-2005. Thus we have eight sets of results based on 36 months returns. This provides us with seven sets of Best Fit Index (BFI) Style groups which can be used for out of sample testing as the final year's returns are used for testing the prior period.

This concludes the first stage of our two-stage combined returns based and characteristics based analysis. The results of this stage are used in two ways; first as an input to the combined BFI-CBS model and secondly as a comparative model to judge the contribution of the combined model relative to a single stage BFI model.

4.2 Stage 2: Characteristics Based Style Analysis (CBS) Methodology

We use the results of our first stage (BFI) as the starting point on our 2nd stage Characteristics Based Style Analysis (CBS). The CBS analysis is run separately for each style group i.e. large cap value through to small cap growth, to provide a more differentiated breakdown of each style group; a finer classification.

[5] Appendix I shows index correlations over the period 1996-2005. A wide range of style indices became available from 1996 onwards.

Our portfolio characteristics follow an approach employed by Abarbanell et al. (2003) in their work on institutional investors and corporate spin-offs. This combination of factor analysis and cluster analysis allows us to identify the differentiated products or styles being offered by the mutual fund universe. We use principal factor analysis with the factor loadings providing the inputs for our k-means cluster analysis and this is similar to the approach utilized by Abarbanell et al. (2003), Brown and Goetzmann (1997), Michaud (1998) and Brush (2007). Our variables, which are asset-weighted portfolio statistics, include static or valuation multiple variables, dynamic or growth variables, and a long-term PEG (Price-Earnings to Growth) ratio which combines both. We use twelve variables which we feel reflect different combinations of investors' preferences for income, growth and asset backing.

Factor analysis is a good method for dealing with correlated variables especially when correlations fall into broad categories which also have an intuitive explanation as noted by Bushee (1998). In our sample of portfolio characteristics correlations are high between the various valuation characteristics and also between the various growth characteristics.

The factor equation, (equation 2), could be considered as follows, with an equation of this type applying to each variable and with total variance, including unique variance summing to one:

$$TV = F_1 + F_2 + F_n + (S + E) = 1 \qquad \text{Equation 2}$$

Where:

TV is total variance which is equal to one.

$F_1 + F_2 + F_n$ are the proportions of common factor variance.

$\epsilon = (S + E)$ is unique variance.

Unique variance or uniqueness can be broken down further into specific variance and error variance

$$\epsilon = S + E$$

Where:

S is the proportion of specific variance.

E is the proportion of error variance.

We validated the use of factor analysis using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy which confirmed that the portfolio variables used in our study were suitable for factor analysis. The number of factors to retain is determined by the scree test, the level of eigenvalues and the level of variance explained which all suggest that three factors are retained. In our study the two dominant factors are a valuation factor and a growth factor. A third less significant factor emerged after the 'TMT Bubble' distortion abated which could be thought of as an emerging company factor; this was also retained. We believe that it is vital to incorporate measures of growth as well as measures of valuation and size into any analysis of equity investment style.

Within our style groups we are trying to establish groups of mutual funds which share a group of portfolio characteristics which are more similar to the other members of their style group or cluster than to members of other style groups or clusters. We are looking for clusters, based on our common factors for growth and valuation, which may be viewed as distinct equity investment styles. We adopt the k-means cluster analysis the method used by Abarbanell et al. (2003) to further refine our style groups using factor loadings to form clusters of most similar funds; k-means cluster analysis is an optimization method which forms a pre-determined number of groups or clusters based on a selected number of characteristics. The k-means methodology is an exclusive clustering algorithm i.e. data are grouped in an exclusive way, so that if an observation, in our case a mutual fund, belongs to a definite cluster (or style) then it cannot be included in another cluster, which is desirable for our purposes. The algorithm assigns each observation to the cluster whose centroid is nearest. The centre or centroid of a cluster is the arithmetic mean for each dimension of all the points in the cluster, based on the most commonly used Euclidean measure of similarity.

This iterative process continues until all objects remain in the same cluster as in the previous iteration. It should be noted that unlike sorting based classification systems the number of funds in a group or the percentage of funds in a group is not pre-determined, as is the typical case in style analysis when one third of funds is allocated to growth, one third core and one third value, the number of funds in each cluster (style group) is determined solely by its portfolio characteristics.

Thus our two stage methodology has generated 27 style groups or 9 primary style classes each with 3 sub-groups which we test for their out of sample explanatory properties. Our CBS methodology outlined above is also implemented for the raw sample of funds which have not been assigned to style groups by the BFI model and 9 style clusters are formed; like the BFI sample the resulting style groups are used for comparison with the combined BFI-CBS method.

4.3 Out of Sample Testing

The aim of any classification system such as style analysis is to identify styles which behave similarly within a class and behave differently between classes. It is with these aims in mind that we construct our out of sample testing procedures. Our expectations of an investment style are that portfolio characteristics and portfolio biases will be similar within styles and these similarities will lead to similar performance over time under varying economic or market conditions.

If we consider the proposition, that funds within a style group should behave similarly, we can test this by asking the simple question, does membership of a style group have any explanatory power for subsequent performance? Using the methodology employed by Brown & Goetzmann (1997) an out-of sample test is formulated for the styles produced which we use to test our combined BFI-CBS analysis, our returns based Best Fit Index analysis and our portfolio characteristics based analysis. The basic method runs a regression of dummy variables which represent styles formed in the previous period against fund returns in the following twelve month period. Dummy variables are given a categorical value of 1 if a fund belonged to a style group and 0 if they did not belong to that group. Membership of a style class is mutually exclusive and exhaustive.

Out of sample regression equation:

$$r_{jt} = \alpha + \sum_{i=1}^{8} \beta_i \delta_{it} + \epsilon_{jt} \qquad \text{Equation 3}$$

Where:

r_{jt}=fund returns at time t

δ_i =dummy variables 1 to 9 representing membership of each style group with dummy 1 dropped.

β_i = sensitivity coefficient for each fund to each style group

ϵ_{jt}= error term

The model represented by equation 3 represents the CBS version with nine dummy variables. The BFI and combined BFI-CBS models have twenty seven dummy variables.

For the returns based BFI analysis we form style groups on the basis of thirty six months observed data and then tested for twelve months out of sample. In the case of our characteristics based style analysis we form our style clusters every December for the period 2000-2005 and use the monthly returns and annual returns for the subsequent 12 months to establish whether membership of a style group explains performance. In the case of the combined BFI-CBS model we formed the style groups on the basis of thirty six months returns data plus the portfolio characteristics data for each December for the period 2000-2005. This test satisfies our criteria of establishing whether funds within a style group behave similarly.

5. Analysis of Results

The results in terms of style groups identified by the two stage filtering process are in line with expectations based on prior discussion and consistent with the findings of studies noted in the literature; ranging from groups characterised by growth-orientation, with higher growth rates and higher PE's, through to value-oriented groups with lower PE's and lower growth rates. The first stage of the filtering process matches funds broadly speaking with domains or investment universes which are broadly characterised e.g. by the Russell 1000 Growth Index, the Russell 1000 Index and the Russell 1000 Value Index. The second stage forms factors from twelve portfolio characteristics; the formation of clusters takes place on the basis of the factors and not directly on the underlying portfolio characteristics. Table I illustrates the dispersion of funds across the various style or sub-style groups.

Investors may decide that small market segments such as Mid-Cap, Small-Cap or Small-Cap are sufficiently detailed to perform peer group and benchmarking comparisons but may decide that larger segments such as Large-Cap Core would benefit from further differentiation and may wish to increase the number of clusters. If we look at the results of one year more closely, 2004 in Table II, we can see that the sub-groups are clearly differentiated on the basis of portfolio characteristics.

Table I: Overview of BFI-CBS Style Groups 2000-2005

BFI-CBS	2000	2001	2002	2003	2004	2005
Large-Growth 1	25	40	14	54	12	22
Large-Growth 2	29	10	12	28	51	54
Large-Growth 3	25	12	47	2	12	28
Large-Core 1	37	36	22	56	52	57
Large-Core 2	11	66	71	16	81	34
Large-Core 3	54	21	43	80	17	16
Large-Value 1	26	41	27	49	66	30
Large-Value 2	39	18	38	38	50	79
Large-Value 3	32	34	54	35	12	3
Mid-Growth 1	40	4	39	55	24	20
Mid-Growth 2	20	44	28	16	28	43
Mid-Growth 3	3	39	39	30	45	13
Mid-Core 1	3	7	19	24	25	21
Mid-Core 2	30	20	20	14	14	25
Mid-Core 3	2	13	6	14	13	9
Mid-Value 1	22	30	17	14	10	6
Mid-Value 2	21	12	43	12	5	26
Mid-Value 3	12	7	7	9	13	12
Small-Growth 1	1	3	27	3	33	35
Small-Growth 2	31	26	14	33	22	28
Small-Growth 3	20	32	37	23	36	18
Small-Core 1	10	5	5	9	8	7
Small-Core 2	6	9	7	13	24	22
Small-Core 3	6	8	10	15	10	13
Small-Value 1	12	12	17	17	8	14
Small-Value 2	7	7	18	15	23	16
Small-Value 3	14	24	6	16	10	16
Total Sample	538	580	687	690	704	667

(Source: Morningstar, Russell & Standard & Poor's data 1996-2005)

Column 1 illustrates the breakdown of style groups at their primary level e.g. Large Cap Growth and at their secondary, BFI-CBS level, e.g. Large Cap Growth 1-3

Where BFS = Best Fit Index Style Group and CD1-CD27 are BFI-CBS Style Groups.

BFI model: $r_1 = \alpha + \beta R_1 + \epsilon_1$

Where; r_1= return on fund 1, α = constant, βR_1= return on index 1 and ϵ_1= net effect of all other unobservable factors

The results of OLS regressions of individual funds against each of the 12 Russell Indices and 15 Standard & Poor's indices' fund for the 36 month in-sample period are collected and the Best Fit index (BFI) is selected. Factors are generated by principal factor analysis with oblique promax rotation using 12 portfolio characteristics. Market Capitalisation, Price Earnings, Price to Book, Price to Revenue, Price to Cash Flow , Dividend Yield , Five Year Earnings Growth Forecast, Earnings Growth, Book Value Growth, Revenue Growth , Cash Flow Growth and Prospective Price Earnings Growth Ratio. Factor 1 can be thought of as a valuation factor, Factor 2 as a growth factor and Factor 3 loads very heavily on the PEG ratio which was favoured by Small-Cap GARP managers. The results are then allocated to 3 style groups for each BFS Style using k-means cluster analysis which optimizes the similarities of factor scores within clusters. This results in 27 differentiated BFI-CBS styles.

Table II clearly illustrates that US equity fund managers are not a homogenous group with a wide range of outcomes for the mean values of style groups for the attenuated version of portfolio characteristics which we illustrate. From these figures we can clearly observe that different fund styles reveal different combinations of preferences for valuation, growth, and income and market capitalisation.

Table II: Portfolio Characteristics of BFI-CBS Style Groups 2004

BFI-CBS Style Groups Dec-04		Market Capitalization	Price Earnings Ratio	Dividend Yield	Forecast Growth	Historic Growth	PEG
Large-Growth	1	20.2	18.2	1.0	13.1	8.7	1.4
Large-Growth	2	37.8	22.2	0.8	13.8	14.1	1.6
Large-Growth	3	34.1	27.5	0.5	16.0	22.7	1.7
Mid-Growth	1	17.9	23.1	0.6	14.4	19.4	1.6
Mid-Growth	2	12.3	26.9	0.3	15.6	15.5	1.7
Mid-Growth	3	8.9	21.1	0.5	14.6	14.2	1.4
Small-Growth	1	2.9	27.6	0.2	18.2	16.1	1.5
Small-Growth	2	2.3	23.3	0.4	14.8	9.9	1.6
Small-Growth	3	2.2	21.5	0.3	16.8	17.4	1.3
Large-Core	1	43.4	20.5	1.0	13.2	13.9	1.6
Large-Core	2	38.4	17.7	1.4	11.3	10.9	1.6
Large-Core	3	17.3	16.2	0.9	13.8	13.5	1.2
Mid-Core	1	8.2	18.6	1.0	11.3	9.1	1.7
Mid-Core	2	6.7	21.5	0.5	14.8	16.2	1.5
Mid-Core	3	7.3	16.2	1.0	12.8	17.7	1.3
Small-Core	1	9.4	21.9	0.6	14.9	18.5	1.5
Small-Core	2	1.6	18.7	0.7	14.4	12.0	1.3
Small-Core	3	1.2	21.8	0.6	12.4	2.9	1.8
Large-Value	1	36.2	16.3	1.7	10.8	12.3	1.5
Large-Value	2	32.1	16.6	2.1	9.6	7.4	1.7
Large-Value	3	24.1	14.8	1.3	12.2	14.4	1.2
Mid-Value	1	9.3	16.2	1.5	10.5	9.9	1.5
Mid-Value	2	4.9	14.7	1.0	12.1	17.0	1.2
Mid-Value	3	9.5	18.1	1.2	11.7	11.8	1.6
Small-Value	1	1.3	13.9	0.7	12.9	16.6	1.1
Small-Value	2	1.0	19.1	0.8	12.8	5.6	1.5
Small-Value	3	1.1	16.0	1.0	11.7	12.2	1.4

(Source: Morningstar)

Mean values for Market Capitalisation US$ billion, Price Earnings (X), Dividend Yield (%), Five Year Earnings Growth Forecast (% pa.), Five Year Historical Earnings Growth (% pa.), and PEG ratio (PE/5y earnings growth forecast). Number of funds in each style group is in parenthesis. Total sample for 2004 is 704 funds.

The first stage of the filtering process is OLS regression against a wide range of indices and selection of the highest r^2; hence there is no judgemental element involved. This can however sometimes leads to anomalies when funds may have similar $r^{2's}$ for different indices or where funds seem to be pursuing a style which differs from the expected style. When considering the mean market capitalisation of a small number of style anomalies seemed to be apparent when considering the market cap relative to other style groups under the same growth-value orientation category. We find some anomalies in a group which accounts for less than 2% of the sample in the formation period. We explored these anomalies and found that they were being caused by the same groups of funds in most instances; a handful of very small cap funds tracking the S&P 500 bringing the average market capitalisation down for a group of core funds or a small number of very small growth funds tracking the S&P500 Pure Growth Index which had a similar effect on a growth category Large-Cap Growth Group 1. In terms of a peer group review or for fund selection it is likely that such funds would be excluded or treated independently from the main classification groups.

After investigating this handful of anomalies we are confident that this two stage filtering process clearly identifies a diverse range of funds reflecting the range of styles in the market, as illustrated in Table II. We therefore first need to consider whether these style groups perform in a similar manner out of sample and secondly whether the combination of returns based and a characteristics based style adds to the explanatory power for the cross section of fund returns.

6. Out of Sample Testing

Having established a broad spectrum of investment styles on the basis of our BFI-CBS methodology we test whether membership of a style group plays a significant role in explaining ex post performance of mutual funds for the year subsequent to formation, using a methodology based on the approach of Brown and Goetzmann (1997) to see if funds within style groups behave similarly out-of-sample. The test employs a cross- sectional regression of fund returns for the 12 month period following the establishment of style groups. Membership of style groups, which is exclusive and exhaustive, is represented by dummy variables. We illustrate the results in Table III.

We note that the r^2 for the annual returns for 2005 is considerably below other years although the monthly returns figure is in line with other years. The statistical significance is also considerably lower for 2005 but after considering the raw data and monthly return results we have to conclude that it is an aberration which does not have a meaningful impact on the results overall[6]; the mean r^2 is reduced from 0.49 to 0.44 by the inclusion but this result is a strong result, with a high level of statistical significance verified by the high levels of F statistics which rejects the null hypothesis that membership of style groups does not explain a significant proportion of out of sample returns of mutual funds belonging to designated style groups.

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[6] We note that Brown & Goetzmann (1997) had a similar problem.

Table III: Out of Sample Results for Combined BFI-CBS 2001-2006

	Combined BFI-CBS adj. r^2 annual return	ANOVA F	Combined BFI-CBS adj. r^2 monthly return
2001	0.64	37.23	0.47
2002	0.51	23.37	0.39
2003	0.37	15.89	0.32
2004	0.44	21.71	0.39
2005	0.12	4.52	0.31
2006	0.53	29.36	0.38
Mean	0.44		0.38
Median	0.48		0.38

Cross-sectional regression of annual out of sample returns of mutual fund against dummy variables signifying membership of a BFI-CBS style group. Membership of style groups is exhaustive and exclusive. Combined BFI-CBS initially filters funds to nine BFI styles categories using the BFI methodology. Within each of the nine categories the CBS methodology is utilized to generate three sub-categories resulting in twenty seven differentiated styles. Style groups are formed in the basis of 36 months in sample and tested for the subsequent 12 months out of sample.

$$r_{jt} = \alpha + \sum_{i=1}^{26} \beta_i \delta_i + \epsilon_{jt}$$

Where: r_{jt}=fund returns at time t , δ_i =dummy variables 1 to 27 representing membership of style group, β_i = sensitivity coefficient for each fund to each style group, ϵ_{jt}= net effect of all other unobservable factors

As the comparative results in Table IV show, the BFI-CBS model which combines returns based and characteristics based style analysis performs better out of sample than the component models in isolation. The BFI-CBS records a mean r^2 of 0.44; the CBS mean r^2 of 0.38 and the BFI model mean r^2 of 0.33 for the comparable period. These findings are consistent with Chan et al. (2002) who conclude that where there is any difference in the outcome for RBS and CBS analysis that CBS tend to perform better. These results also compare favourably with the results of Brown and Goetzmann (1997), mean r^2 of 0.30 for the period 1978-1994. The work of Brown and Goetzmann (1997) was a major motivation for this study which develops the idea of utilising portfolio characteristics in conjunction with returns based analysis.

Table IV: Comparison of Out of Sample Results for Combined BFI-CBS Model, Characteristics Based Model and Best Fit Index Model for 2001-2006

	CBS adj.r^2	BFI adj.r^2	Combined BFI-CBS adj.r^2
2001	0.59	0.53	0.64
2002	0.37	0.41	0.51
2003	0.39	0.30	0.37
2004	0.34	0.35	0.44
2005	0.10	0.07	0.12
2006	0.49	n.a.	0.53
Mean	0.38	0.33	0.44
Median	0.38	0.35	0.48

Comparative results of out of sample cross-sectional regressions of annual returns of mutual fund against group membership for CBS, BFI and combined BFI-CBS style groups. Where CBS is Characteristics Based Style analysis BFI is Best Fit Index analysis and BFI-CBS is the combined returns based and characteristics based analysis. Membership of style groups under each model is exhaustive and exclusive.

Style groups are formed in the basis of 36 months in sample and tested for the subsequent 12 months out of sample.

$$r_{jt} = \alpha + \sum_{i=1}^{n} \beta_i \delta_i + \epsilon_{jt}$$

Where: r_{jt}=fund returns at time t , δ_i =dummy variables representing membership of style groups where n=8 for and n=26 for BFI and BFI-CBS, β_i = sensitivity coefficient for each fund to each style group, ϵ_{jt}= net effect of all other unobservable factors

Our findings confirm two things; membership of style groups formed on the basis of our combined BFI-CBS model explains a significant degree of cross sectional performance of mutual funds in the twelve months subsequent to being allocated to a style group, and secondly the cumulative effect of combining Best Fit Index and Characteristics Based Style analysis significantly improves on the CBS model and BFI models when run in isolation.

7. Qualitative Assessment of Style Groups: Do Our Results Make Practical Sense for Investors?

In order to evaluate the quantitative output of the BFI-CBS model, which is the culmination of our work on characteristics based and returns based style analysis, we need to undertake some qualitative analysis to confirm that our results make sense from the point of view of an investor or plan sponsor. It should be noted that we did not include any of our sector weighting information in our style analysis we held the information back in order to provide an independent qualitative assessment of the results generated by our models. In Table V we illustrate the S&P sector weightings of our BFI-CBS Large-Cap fund styles. These styles form a graduated spectrum ranging from growth-oriented to value-oriented styles. Sector weightings as a percentage of the total portfolio are illustrated, with sectors strongly identified with a growth style and a value style highlighted. The sectors illustrated as being more likely to be found in portfolios pursuing a growth or a value oriented style have been noted throughout this study in the context of investment philosophies, benchmarks and the comments of other authors, consultants and the index providers.

Table V: Standard & Poor's Sector Weightings by Style Group BFI-CBS Large Cap Groups Dec 2005

31/12/2005 Mean		***Growth***								***Value***
Sector Weight		LG1	LG2	LG3	LC1	LC2	LC3	LV1	LV2	LV3
Software	***Growth***	**6.9**	**6.3**	**3.7**	**4.6**	**3.7**	**3.2**	**1.1**	**2.2**	**0.4**
Hardware	***Growth***	**16.7**	**15.0**	**8.2**	**11.1**	**9.1**	**7.5**	**3.4**	**5.3**	**5.7**
Media	***Growth***	**5.1**	**3.4**	**9.6**	**3.1**	**3.6**	**4.8**	**4.8**	**4.0**	**1.7**
Healthcare	***Growth***	**20.4**	**20.2**	**13.3**	**14.4**	**14.5**	**13.3**	**11.1**	**8.6**	**4.8**
Telecomm		1.7	1.0	2.2	1.9	1.2	2.7	6.0	4.0	1.8
Consumer Services		15.0	12.4	12.9	8.7	9.9	7.3	5.0	5.9	12.2
Business Services		9.3	7.8	9.2	4.9	8.6	5.3	3.3	3.9	11.4
Consumer Goods		4.7	8.8	10.2	9.6	5.9	9.1	12.4	7.3	5.3
Industrial Materials		5.7	9.2	10.6	13.4	16.2	12.8	15.7	14.2	19.9
Financial Services	***Value***	**10.6**	**10.3**	**14.9**	**16.3**	**15.8**	**23.2**	**21.7**	**28.3**	**10.3**
Energy	***Value***	**3.9**	**5.5**	**4.6**	**10.3**	**10.3**	**8.6**	**9.4**	**13.1**	**26.5**
Utilities	***Value***	**0.0**	**0.1**	**0.7**	**1.6**	**1.0**	**2.4**	**5.9**	**3.4**	**0.0**
Price Earnings		26.0	20.3	18.5	17.6	17.0	15.6	15.3	14.6	13.5
Number of Funds		22	54	28	34	16	57	30	79	3

(Source: Morningstar Fund's Standard & Poor Sector Weightings)

Sector weightings as a percentage of the total portfolio are illustrated above, with sectors strongly identified with a growth style and a value style highlighted. BFI-CBS style clusters form a graduated spectrum of styles ranging from growth-oriented to value-oriented.

The style groups we form have economic exposure that is consistent with the sector exposure published by Christopherson and Williamson (1997), Brown and Goetzmann (1997) and others. Thus we find our large-cap growth funds (LG1-LG3) have relatively more exposure to 'Growth' sectors such as software, IT hardware, media and healthcare. This is entirely consistent with the relatively higher PE multiples and forecast eps growth rates for these groups seen in Table II. Our large-cap value funds (LV1-LV3) have relatively more exposure to 'Value' sectors such as financials, utilities and energy. Our 'Market-Oriented' or 'Core' funds have less extreme positions on these sectors although we also note that LC1 has more of a 'growth orientation' with a higher PE and more exposure to the Hardware sector whilst LC3 has more of a 'value orientation' with more exposure to Financials.

8. Conclusions

When we combine our Best Fit Index methodology and our Characteristics Based Style methodology into a two stage BFI-CBS process for assessing the style of Equity Diversified mutual funds our results confirm that both the roles of benchmarking and peer group formation are performed in a manner which is superior to either method on its own. The BFI-CBS methodology provides a means of classification of equity investment styles that has academic rigour and is suitable for practical application; with intuitive appeal and empirical support. The ability to identify the benchmark which most closely matches a fund's investment universe also has useful properties when assessing risk adjusted returns or active risk.

The BFI-CBS approach builds on the concept of market segmentation and the constraints which are placed on portfolio managers, as noted by Bernstein (1999), Vardharaj and Fabozzi (2007) and others. Many studies such as Chan et al. (2002) and Rekenthaler et al.

(2006) conclude that Characteristics Based Style analysis is a more reliable method of style analysis than Sharpe-style Returns Based Style analysis where the results from these approaches differ. We illustrate in Table IV that our combined BFI-CBS method produces out of sample results which are superior to CBS, or BFI methodologies in terms of explaining the cross-section of fund returns.

Our out of sample tests confirm two things; membership of style groups formed on the basis of our combined BFI-CBS model explain a significant degree of cross sectional performance of mutual funds in the twelve months subsequent to being allocated to a style group, and secondly the cumulative effect of combining Best Fit Index and Characteristics Based Style analysis significantly improves on the CBS model and BFI models when reported on their own. This implies that the ex post explanatory power of the combined model is greater than the individual parts. Our empirical results confirm that returns based and characteristics based style analyses are complementary.

Having found that our empirical results were robust we turned to qualitative analysis of our results, in the manner of Brown and Goetzmann (1997), where we cross-referenced our style groupings with the funds sector weightings and found this to be consistent with recognized style-biases of a range of investment styles. The results illustrated are consistent with investment practice and academic consideration of style and economic exposure and present similar characteristics to the qualitative data presented by Christopherson and Williamson (1995) and Brown and Goetzmann (1997). Large-cap growth funds have relatively more exposure to 'Growth' sectors such as software, IT hardware, media and healthcare; consistent with their relatively higher PE multiples and forecast eps growth rates. Large-cap value funds have relatively more exposure to 'Value' sectors such as financials, utilities and energy. Many studies do not publish comparable qualitative data such as sector weightings or industry exposure which can be used to cross check style classifications but we excluded our sector weighting information from our characteristics based analysis in order to provide an independent qualitative assessment of the results generated by our models.[7]

We therefore conclude that our BFI-CBS methodology provides a highly effective method for forming peer groups and identifying the relevant benchmarks for performance evaluation and diversification purposes. Whilst we feel this methodology performs a useful filtering task and narrows down the universe of potential managers to smaller style groups we believe that it should not take the place of detailed 'due diligence' of an investment manager's investment philosophy, investment process and investment performance. We believe it takes one a long way down the road to manager selection but like other authors cited in this study we would urge those selecting investment managers to use all available information.

[7] We also confirmed the validity of our results by investigating examples of individual mutual funds which authors such as Dor et al (2003) had cited as being misclassified. Contrary to their findings for the 'Goldman Sachs Growth & Income' fund which they described as a 'Value-Growth Blend' our analysis confirmed that it was, as its prospectus described and Morningstar classified it, a Large-Cap Value fund. Our BFI analysis confirmed that it most closely tracked the Russell 1000 Value Index and our combined BFI-CBS placed it in the middle of our large-cap value style group, 'LV2' in Table I.

8. References:

Abarbanell, J. S., B. J. Bushee, et al. (2003). "Institutional Investor Preferences and Price Pressure: The Case of Corporate Spin-Offs" Journal of Business 76(2): 233-261.

Agarwal, V. and N. Y. Naik (2000). "Generalised Style Analysis of Hedge Funds." Journal of Asset Management 1(1): 93-109.

Anneart, J. and G.Van Campenhout (2007) “Time Variation in Mutual Fund Style Exposures” Review of Finance 11: 631-661.

Argon, George O., and Wayne E. Ferson (2006). “Portfolio Performance Evaluation.” Foundations and Trends in Finance 2:2: 83-190.

Arshanapalli, B., T. D. Coggin, et al. (1998). "Multifactor Asset Pricing Analysis of International Value Investment Strategies." Journal of Portfolio Management (Summer): 10-23.

Bailey, J. V. and D. E. Tierney (1995). Ch21: “Controlling Misfit Through the Use of Dynamic Completeness Funds.” In R. A. Klein and J. Lederman eds. Equity Style Management: Evaluating and Selecting Investment Styles. Chicago-London, Irwin Professional Publishing. 433-478.

Banz, R. W. (1983). "The Relationship Between Return and Market Value of Common Stocks." Journal of Financial Economics (9): 3-18.

BARRA (1992). New S&P/BARRA "Style" Indexes. BARRA News Letter

Bassett, G. W. and H.-L. Chen (2001). "Portfolio Style: Return-Based Attribution Using Quantile Regression." Empirical Economics. 293-305.

Basu, S. (1977). "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis." Journal of Finance 32(3): 663-682.

Belden, S. and M. B. Waring (2001) “Compared to What? A Debate on Picking Benchmarks.” Journal of Investing. Winter 2001: 66-72

Bernstein, P. L. and A. Damodaran eds.(1998). Investment Management. New York, John Wiley & Sons.

Bernstein, R. (1999). Style Investing: Unique Insight into Equity Management. New York, Wiley.

De Bondt, W. F.M. and R. H. Thaler (1985) " Does the Stock Market Overreact?" Journal of Finance 40: 793-805.

De Bondt, Werner F.M. and R. H. Thaler (1987) "Further Evidence on Investor Overreaction and Stock Market Seasonality" Journal of Finance 42: 557-581.

Brown, S. J. and W. N. Goetzmann (1997). "Mutual Fund Styles.” Journal of Financial Economics 43(3): 373-399.

Brush, J. S.. “Value and Growth, Theory and Practice: A Fallacy That Value Beats Growth.” Journal of Portfolio Management Spring (2007). 22-32.

Bushee, B. J. (1998). "The Influence of Institutional Investors on Myopic R&D Investment Behaviour" The Accounting Review 73(3): 305-333.

Busse, J.A., A. Goyal et al. (2010) “Performance Persistence in Institutional Investment Management” Journal of Finance 65(2):765-790

Cattell, R. B. (1952). Factor Analysis. New York, Harper.

Chan, L., K., H.-L. Chen, et al. (2002). "On Mutual Fund Investment Styles." Review of Financial Studies 15(5): 1407-1437.

Chan, L., K., S. Dimmock, G, and J. Lakonishok,(2009) “Benchmarking Money Manager Performance: Issues and Evidence.” Review of Financial Studies 22(11):4553-4599

Child, D. (2006). The Essentials of Factor Analysis. London-New York, Continuum.

Christopherson, J. A. (1995). “Equity Style Classifications: Adventures in Return Pattern Analysis” Journal of Portfolio Management (Spring). 32-43.

Christopherson, J. A. and C. N. Williams (1997). Ch 1: “Equity Style: What It Is and Why It Matters.” In T. D. Coggin, F. J. Fabozzi and R. D. Arnott eds. Handbook of Equity Style Management. *2nd ed* John Wiley: 1-19.

Clarke, R., H. de Silva, et al. (2002). "Portfolio Constraints and the Fundamental Law of Active Management." Financial Analysts Journal (Sept/Oct): 48-66.

Coggin, T. D. and F. J. Fabozzi eds (2003) 3rd ed., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc.

Connor, G. and R. A. Korajczyk. (1986) “Performance Measurement With The Arbitrage Pricing Theory: A New Framework For Analysis.” Journal of Financial Economics 15(3) : 373-394.

Cremers K. J. M, and A. Petajisto (2009) ‘How Active is Your Fund manager? A New measure The Predicts Performance’ Review of Financial Studies 3329-3365

Damodaran, A. (2003). Investment Philosophies: Successful Strategies and the Investors Who Made Them Work. Hoboken, NJ, Wiley.

Daniel, K., M. Grinblatt et al. (1997) “ Measuring Mutual Fund Performance with Characteristic-Based benchmarks” Journal of Finance (52) 3: 1035-1058

Davis, J. L. (2001). "Mutual Fund Performance and Manager Style." Financial Analysts Journal (Jan/Feb): 19-27.

De Allaume, W. J. D. (1995). Ch3: “The Sponsor's Perspective.” In R. A. Klein and J. Lederman ed. Equity Style Management: Evaluating and Selecting Investment Styles. Chicago-London, Irwin Professional Publishing. 49-66.

Dor, A. B., R. Jagannathan, et al. (2003). "Understanding Mutual Fund and Hedge Fund Styles Using Return-Based Style Analysis." Journal of Investment Management 1(1): 94-134.

Dor, A. B. and R. Jagannathan (2003b). Ch1. “Style Analysis: Asset Allocation and Performance Evaluation.” In: T. D. Coggin and F. J. Fabozzi eds., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc.

Everitt, B. S., S. Landau, et al. (2001). Cluster Analysis. London, Arnold.

Fabozzi, F. J. (1998). Ch4: “Overview of Equity Style Management.” In F. J. Fabozzi ed. Active Equity Portfolio Management. New Hope, Pa, Frank J Fabozzi Associates: 57-70.

Falkenstein, E. G. (1996). "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings." Journal of Finance 51(1): 111-135.

Fama, E. F. (1972). "Components of Investment Performance." Journal of Finance 27(3): 551-567.

Fama, E. F. and K. R. French (1992). "The Cross-Section of Expected Stock Returns." Journal of Finance 47(2): 427-465.

Fama, E. F. and K. R. French (1993). “Common Risk Factors in the Returns on Stocks and Bonds.” Journal of Financial Economics (33): 3-56

Fama, E. F and K.R French, (1996) “Multifactor explanation of asset pricing anomalies.” Journal of Finance 51 (1), 55–84.

Fama, Eugene F., and Kenneth R. French (2010). “Luck Versus Skill in the Cross-Section of Alpha Estimates." Journal of Finance 65:5, 1915–1947.

Farrell, J. L. (1974). "Analyzing Covariation of Returns to Determine Homogenous Stock Groupings." Journal of Business 47: 186-207.

ter Horst, J. R., T. E. Nijman, et al. (2004). "Evaluating Style Analysis." Journal of Empirical Finance 11: 29-53.

Jensen, M.C. (1968) “The Performance of Mutual Funds in the Period 1945-1964” Journal of Finance (23): 389-416

Kaplan, P. D. (2003a). “Holdings-Based and Returns-Based Style Models.” Morningstar Research Report. Chicago, Morningstar.

Kaplan, P. D., J. A. Knowles, et al. (2003b). Ch 5: “More Depth and Breadth than the Style Box: The Morningstar Lens.” In: T. D. Coggin and F. J. Fabozzi eds., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc.131-158

Kim T-H, White H, and Stone D (2005) ‘Asymptotic and Bayesian Confidence Intervals for Sharpe-Style Weights’ Journal of Financial Econometrics 3(3):15-343

King, B. F. (1966). "Market and Industry Factors in Stock Price Behavior." The Journal of Business 39(1): 139-190.

Kosowski, R., A. Timmermann et al. (2006) “Can Mutual Fund ‘Stars’ Really Pick Stocks? New Evidence from a Bootstrap Analysis”. Journal of Finance (61) 6: 2551-2595

Kothari, S. P. and J. B. Warner (2001). "Evaluating Mutual Fund Performance." Journal of Finance 56(5): 1985-2010.

Kritzman, M. and S. Page (2003) “The Hierarchy of Investment Choice” Journal of Portfolio Management 29 (4): 11-23.

Kudish, D. J. (1995). Ch19: “Reversing Manager-Selection Failure: Using Style Allocation to Improve Fund Returns.” In R. A. Klein and J. Lederman eds. Equity Style Management: Evaluating and Selecting Investment Styles. Chicago-London, Irwin Professional Publishing. 399-420.

Kuenzi D.E. (2003) “Strategy Benchmarks from the Investment Manager’s Perspective”. Journal of Portfolio Management Winter 2003: 46-56.

Lakonishok, J., A .Shleifer,.and R. Vishny (1994) “Contrarian investment, extrapolation, and risk.” Journal of Finance
49, 1541–1578.

Lehmann, B.N., and D. M. Modest (1987) “Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons” Journal of Finance (42)2: 233-265.

Lintner, J. (1970). "The Market Price of Risk, Size of Market and Investor's Risk Aversion." The Review of Economics and Statistics 52(1): 87-99.

Lipper (2008). “Worldwide Holdings-Based Fund Classification Methodology”. Version 1.8. http://www.lipperweb.com/services/global_class.asp

Michaud, R. O. (1998). "Is Value Multidimensional? Implications for Style Management and Global Stock Selection." Journal of Investing 7(1): 61-65.

Nicholson, S. F. (1977). "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios." Journal of Finance 32: 663-682.

Petajisto A. ‘Active Share and Mutual Fund Performance’ (2010) http: ssrn.com/abstract=1685942

Prather, L., W. Bertina, et al. (2004). "Mutual Fund Characteristics, Managerial Attributes, and Fund Performance." Review of Financial Economics 13: 305–326.

Radcliffe, R. C. (2003). Ch 3. “Models of Equity Style Information. “In: T. D. Coggin and F. J. Fabozzi eds., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc. 75-108

Reinganum, M. R. (1983). "Misspecification of Capital Asset Pricing." Journal of Financial Econometrics 3: 19-46.

Rekenthaler, J., M. Gambera, and J. Charlson (2006) “Estimating Portfolio Style in U.S. Equity Funds: A Comparative Study of Portfolio-Based Fundamental Style Analysis and Returns-Based Style Analysis” Journal of Investing 15 (3) pp. 25-33

Rosenberg, B. and A. Rudd (1982). "Factor-Related and Specific Returns of Common Stocks: Serial Correlation and Market Inefficiency." Journal of Finance 37(2): 543-554.

Sharpe, W. F. (1964). "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." Journal of Finance 19(3): 425-442.

Sharpe, W. F. (1992). "Asset Allocation: Management Style and Performance Measurement." Journal of Portfolio Management Winter: 7-19.

Slager, A. and Koedijk, K. (2007) "Investment Beliefs: Every Asset Manager Should Have Them". Journal of Portfolio Management (Spring) 77-83

Speidell, L. S. and J. Graves (2003). Ch 7: "Are Growth and Value Dead?: A New Framework for Equity Investment Styles." In: T. D. Coggin and F. J. Fabozzi eds., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc. 171-193.

Surz, R. J. (2003). Ch 6. "Using Portfolio Holdings to Improve the Search for Skill." In: T. D. Coggin and F. J. Fabozzi eds., Handbook of Equity Style Management. Hoboken, John Wiley & Sons Inc.159-170

Swinkels, L. and P.J. Van Der Sluis (2006) "Return- Based Style Analysis with Time-Varying Exposures". The European Journal of Finance 12(6): 529-552

ter Horst, J. R., T. E. Nijman, et al. (2004). "Evaluating style analysis." Journal of Empirical Finance 11(1): 29-53.

Vardharaj, R. and F. J. Fabozzi (2007). "Sector, Style, Region: Explaining Stock Allocation Performance." Financial Analysts Journal 63(3): 59

Waring, M. B. and L. B. Siegel (2003). "The Dimensions of Active Management." Journal of Portfolio Management Spring: 35-51.

8.1 Appendix I Russell and Standard & Poor’s Index Correlations Jan-1996 to Dec-2005

	Russell Top 200	Russell Top 200 Growth	Russell Top 200 Value	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell 2000	Russell 2000 Growth	Russell 2000 Value	S&P400	S&P400 Growth	S&P400 Pure Growth	S&P400 Pure Value	S&P400 Value	S&P500	S&P500 Growth	S&P500 Pure Growth	S&P500 Pure Value	S&P500 Value	S&P600	S&P600 Growth	S&P600 Pure Growth	S&P600 Pure Value	S&P600 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value
Russell Top 200	1.00																										
Russell Top 200 Growth	0.96	1.00																									
Russell Top 200 Value	0.90	0.74	1.00																								
Russell 1000	0.99	0.95	0.89	1.00																							
Russell 1000 Growth	0.95	0.99	0.72	0.95	1.00																						
Russell 1000 Value	0.88	0.72	0.99	0.89	0.71	1.00																					
Russell 2000	0.67	0.66	0.56	0.75	0.74	0.61	1.00																				
Russell 2000 Growth	0.68	0.71	0.49	0.75	0.79	0.53	0.97	1.00																			
Russell 2000 Value	0.62	0.52	0.65	0.70	0.58	0.73	0.90	0.79	1.00																		
S&P400	0.83	0.77	0.78	0.89	0.82	0.83	0.88	0.84	0.85	1.00																	
S&P400 Growth	0.82	0.80	0.70	0.88	0.86	0.74	0.89	0.89	0.78	0.97	1.00																
S&P400 Pure Growth	0.82	0.79	0.71	0.87	0.85	0.74	0.89	0.88	0.80	0.95	0.97	1.00															
S&P400 Pure Value	0.61	0.47	0.73	0.67	0.50	0.80	0.68	0.55	0.87	0.81	0.68	0.70	1.00														
S&P400 Value	0.78	0.67	0.83	0.84	0.71	0.88	0.79	0.71	0.88	0.95	0.86	0.84	0.92	1.00													
S&P500	1.00	0.95	0.90	1.00	0.94	0.90	0.72	0.71	0.67	0.86	0.84	0.84	0.66	0.82	1.00												
S&P500 Growth	0.97	0.99	0.78	0.96	0.99	0.76	0.69	0.73	0.56	0.80	0.82	0.83	0.50	0.70	0.97	1.00											
S&P500 Pure Growth	0.87	0.90	0.67	0.90	0.93	0.67	0.84	0.88	0.67	0.84	0.89	0.90	0.50	0.70	0.88	0.92	1.00										
S&P500 Pure Value	0.65	0.49	0.81	0.70	0.50	0.86	0.61	0.48	0.82	0.74	0.61	0.63	0.90	0.85	0.70	0.53	0.51	1.00									
S&P500 Value	0.91	0.78	0.98	0.93	0.78	0.99	0.66	0.59	0.75	0.85	0.77	0.77	0.80	0.89	0.93	0.81	0.72	0.86	1.00								
S&P600	0.67	0.64	0.59	0.76	0.72	0.65	0.97	0.93	0.92	0.90	0.89	0.89	0.73	0.83	0.72	0.67	0.81	0.67	0.70	1.00							
S&P600 Growth	0.68	0.67	0.56	0.76	0.75	0.61	0.97	0.95	0.86	0.89	0.91	0.90	0.66	0.79	0.72	0.70	0.84	0.60	0.66	0.99	1.00						
S&P600 Pure Growth	0.64	0.63	0.53	0.71	0.70	0.58	0.95	0.93	0.86	0.85	0.87	0.88	0.66	0.75	0.68	0.66	0.82	0.59	0.62	0.97	0.98	1.00					
S&P600 Pure Value	0.54	0.45	0.60	0.61	0.49	0.67	0.79	0.67	0.92	0.75	0.67	0.70	0.84	0.80	0.60	0.49	0.57	0.80	0.69	0.83	0.76	0.79	1.00				
S&P600 Value	0.65	0.60	0.62	0.73	0.66	0.69	0.94	0.87	0.96	0.88	0.84	0.84	0.80	0.86	0.70	0.63	0.74	0.74	0.72	0.98	0.94	0.92	0.90	1.00			
Russell Midcap	0.86	0.80	0.79	0.92	0.86	0.84	0.91	0.88	0.86	0.97	0.95	0.94	0.78	0.92	0.89	0.84	0.88	0.75	0.87	0.91	0.90	0.86	0.75	0.89	1.00		
Russell Midcap Growth	0.79	0.84	0.58	0.85	0.90	0.60	0.89	0.94	0.69	0.88	0.93	0.90	0.52	0.73	0.81	0.85	0.94	0.46	0.66	0.86	0.90	0.85	0.56	0.79	0.91	1.00	
Russell Midcap Value	0.77	0.61	0.89	0.82	0.63	0.94	0.69	0.58	0.85	0.87	0.75	0.76	0.92	0.95	0.81	0.66	0.62	0.93	0.93	0.74	0.69	0.65	0.78	0.79	0.87	0.60	1.00

Source: Russell and Standard & Poor’s. Russell and Standard & Poor’s Total Return Index Correlations based on Monthly Returns.