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Mutual Fund Styles

We propose a new empirical approach to determination of mutual fund styles. This approach is simple to apply, yet it captures nonlinear patterns of returns that result from virtually all active portfolio management styles. We find that the largest equity fund category, "Growth" typically breaks down into several styles that differ in composition and strategy.

Our classification method identifies fund groupings that are useful predictors of cross-sectional *future* performance, as well as past behavior. Not only are they superior to common classifications such as "Growth" or "Income," but they also out-perform classifications based upon risk measures and analogue portfolios.

I. Introduction

Investment objectives and stylistic classifications are widely used in the investment industry to characterize differences between money managers. In the mutual fund industry, for instance, funds are typically grouped according to the type of securities in which they invest. Equity funds range from "Aggressive Growth" managers who hold low dividend, high growth stocks, to "Income" managers who seek high yield equities. Such fund classifications are ubiquitous, but what do they actually tell us? Do they help explain differences in future returns among funds? Do they tell us anything about the strategies of investment managers? Are they useful benchmarks for evaluating relative performance? These fundamental questions about mutual fund classification are the motivation for this research.

In this paper, we find that existing classifications do a poor job at forecasting differences in future performance. We propose a different method for grouping mutual funds which is relatively impervious to strategic gaming of benchmarks. As a result of our classification, we find that equity fund managers broadly fall into some familiar and not-so-familiar patterns of behavior. The familiar patterns include "Small-Cap," "Growth," "Growth and Income," "Income," and "International" styles. The unfamiliar styles resemble "Trend-chasers" "Value" and "Glamour" managers. This new categorization does a superior job at forecasting *future* differences in mutual fund performance, and reveals something about the aggregate behavior of mutual fund managers as well. The results of this analysis are encouraging with respect to the power of simple multinomial statistics to capture differences among portfolio managers. To our knowledge, we provide the first strong empirical justification for the use of simple categorization schemes used widely in the investment industry. While current industry categories may do a poor job at explaining differences in out-of-sample returns, future alternatives, including the one we propose in this study, should do much better. Our procedure is not offered as a superior alternative to current multi-variate, continuous measures such as estimated factor-loadings for risk evaluation and performance measurement. Due to its extreme simplicity, it may not capture all the characteristics that potential investors may find useful in their allocation decisions. It does, however, show how the mutual fund managers separate themselves by strategies. Stylistic classification provides an overview of the key factors that separate managers. As such, it has the potential for identifying aspects of manager behavior.

II. Background

The definition of standard equity mutual fund categories is generally broad enough to allow a wide range of different investment policies. A trade organization, The Investment Company Institute uses a very general description of the largest investment category:

> Growth Funds invest in the common stock of well established companies. Their primary aim is to produce an increase in the value of their investments (capital gains) rather than a flow of dividends.
>
> (Investment Company Institute, 1991, p.12)

This definition makes it obvious that the typical growth fund manager has great latitude in the types of stocks to hold, the timing of purchases and sales, the level of fund diversification, the industry concentration of the portfolio, and a host of other factors that go into determining the returns to client investments. Given this broad latitude, it is not surprising to find widely divergent behavior among funds pursuing the same objective. The financial press has identified several cases in which funds apparently misclassified themselves (see, for instance, Donnelley, 1992). Such misclassification may have implications for regulatory bodies. The S.E.C. has a stated mandate to insure that the composition of a fund does not contradict its objective, if that objective is included as part of its name. Such governmental concerns are not unfounded. For instance, recent papers by Witkowski (1994) and Kim, Shukla and Tomas (1995) find that the movement of many mutual funds is better explained by the performance of a style index other than their own. In this paper, we find some evidence suggesting that such misclassification may be intentional. On average, it works to improve *ex post* relative performance measures.

Because management styles are so widely used as the basis for performance measurement and compensation, there is a great need for stylistic classifications that are objectively and empirically determined, consistent across managers and related to the manager's strategy. The objectivity is important because of the moral hazard inherent in allowing managers to self-report their styles, without objective verification. The consistency is needed for purposes of performance comparison. The desirability of such a classification scheme is clear to all participants in the industry, and industry alternatives to the existing classification procedures have begun to evolve (see Tierney and Winston, 1991 and Christopherson, 1995 for examples). Beyond the need in practice for meaningful styles, there is a fundamental question of whether any classification system, i.e. multi-nomial statistic, is sufficient to characterize differences in fund management. If it is, then the widespread practice of stylistic classification is justified as an approach to understanding differences among managers.

To examine these questions, we develop a "style classification" algorithm that is consistent with asset pricing models. The consistency is useful, because the multi-nomial style statistic represents a "coarsening" of a fully specified stochastic model of portfolio returns, and it is useful to clarify where and how this coarsening takes place. The algorithm we propose groups funds based upon the cross-sectional time-series of past returns as well as upon the response to exogenously specified and endogenously determined stochastic variables. Using mutual fund data from 1976 through 1994, we find that our "styles" typically differ from standard classifications based upon investment objectives.

As many as half of all currently classified "Growth" funds fall into different style categories, according to our procedure. Besides finding evidence of misclassification, we identify some styles that *not* captured by the traditional objectives. These include "Value" managers, "Trend-chasers" and "Glamour Stock" managers. We show that these stylistic classifications are superior to the currently used classification system based principally upon the yield vs. growth characteristics of securities held in the fund. As evidence of this, we find that our derived classifications specified *ex ante* do a better job of predicting cross-sectional variation in fund returns than do traditional mutual fund classifications. In addition, we find that simple classifications capture major differences in manger behavior, when that behavior manifests itself in the temporal pattern of returns. While these classifications provide less information about important measures such as the magnitude of fund loadings on major macro-economic factors, they provide a useful means to identify widespread, common patterns in manager behavior.

The implications of these results are broad. A return-based classification system such as the one we have implemented can reduce the incentive to "game" the styles to improve relative *ex post* rankings. More formal classification procedures for mutual funds may help investors better understand the future behavior of their investments, and may provide *ex post* or *ex ante* performance benchmarks. From the perspective of researchers interested in understanding investment manager behavior, a stylistic classification that allows types of categories such as "value" and "glamour" may actually characterize how managers actually behave. A by-product of the estimation procedure is the creation of a parsimonious set of robust factors that are composed of positive weights on existing mutual funds. These style factors typically outperform pre-specified macro-economic factors in out-of-sample tests on fund returns, and thus may have further implications for asset pricing.

This paper is divided into five sections. Section III gives some background on some statistical and strategic issues in the paper. Section IV describes the data. Section V describes the methodology. Section VI reports the results of the empirical analysis. Section VII concludes.

III. Statistical and Strategic Issues

II.1 Statistical Issues: time varying portfolio weights

There is a long tradition of characterizing mutual funds according to parameters estimated via a linear model of returns. The technology of asset pricing was first applied by Jensen (1968) to grouping mutual funds according to their systematic risk characteristics. Conner and Korajczyk (1986), Lehmann and Modest (1987), Grinblatt and Titman (1988 and 1989) and Elton and Gruber (1992) all apply linear asset pricing methods to differentiate mutual funds on the basis of systematic risk characteristics. Quantitative methods of security aggregation first appeared in the Finance literature in the work of Elton and Gruber

(1969), who developed a classification algorithm that used a linear model of fundamental characteristics that proved useful for grouping securities and forecasting cross-sectional differences. Carleton and McGee (1970) suggest that the related techniques of switching regressions and hierarchical clustering methods may be used to aggregate financial assets.

There are reasons to expect that linear models might poorly characterize mutual fund returns. Single factor and multiple factor linear models are only exactly correct when portfolio weights remain fixed through time and when the systematic risk characteristics of the securities held in the portfolio remain fixed as well. While it is common to assume securities change little, we have no basis for presuming that portfolio weights remain fixed. Indeed, active fund management clearly implies the strategic re-allocation of portfolio weights across assets. While typical examples of such active allocation are market-timing and portfolio insurance strategies, buy-and-hold as well as active security selection can also result in time-varying systematic risk characteristics. Recent studies of mutual fund manager behavior report unambiguous evidence of strategic changes in mutual fund portfolios. Grinblatt, Titman and Wermers (1993) identify herding activity by mutual fund managers. Ferson and Schadt (1993) find managers rebalance in anticipation of changing economic conditions. Brown, Harlow and Starks (1993) find systematic changes in risk, conditional upon past performance. Lakonishok, Schleifer, Thaler and Vishney (1991) find "window dressing" accounts for portfolio rebalancing by pension fund managers.

Active portfolio management affects performance measurement in non-trivial ways. Dybvig and Ross (1985), for instance, show how linear risk models fail to properly rank fund managers when they change their asset weights through time. Conner and Korajczyk (1991)consider how to risk-adjust for non-linear portfolio strategies by mutual fund managers. Grinblatt and Titman (1993) avoid problems posed by non-linearities by explicitly considering active strategies as the basis for a benchmark-free approach to performance measurement.

While such non-linearities present problems for style identification as well, our procedure accommodates non-linear strategies by allowing factor loadings to change on a month-by-month basis. This is crucial in light of the fact that many fund managers actively vary their exposure to the market, and their exposure to industry sectors. To the extent that groups of managers change these exposures together, (i.e. they "herd" into the market, or in and out of sectors) our procedure will group them together into a style. Although it is a relatively simple technique, when we compare the stylistic categories formed in the space of past returns to alternate categorization schemes formed in the space of fixed factor loadings, we find it to be superior in explaining the out-of-sample cross-section of mutual fund returns. Our method, which relies upon a low-dimensional multi-nomial statistic with intuitive interpretation as a style, compares favorably to the use of continuous multi-variate measures such as factor loadings . We find some evidence, in the form of time-varying factor loadings, that this is due to the presence of dynamic management styles in the mutual fund universe.

II.2 Strategic Issues: self-misclassification

Thus far we have been concerned with the ability of the existing stylistic classifications to pick up management behavior when it is dynamic and not well captured by static models of investment. Of great concern is the further issue of selecting a procedure that prevents *ex post* changes in style in order to improve relative historical performance. If we use a self-reported fund objective, announced *ex post*, it may have been chosen to minimize poor relative performance. Anecdotal evidence (cited above) from the financial press suggests that such misrepresentation takes place. We find some empirical evidence to back up the casual observation that funds may switch to improve their relative historical rankings. Using equity mutual fund data over the period 1976 through 1992, described in further detail below, we found 237 cases in which equity mutual funds switched their fund objective. For each of these, we subtracted the average objective return from the fund return in the year before the switch, using first the *old* objective and then the *new* objective. That is, the net gain for fund I is defined as: $(r_{i,t} - r_{j,old}) - (r_{i,t} - r_{j,new})$, where $j_{i,old}$ is the style from which the fund switched in period t+1 and $j_{i,new}$ is the style to which the fund switched, *ex post*. Thus, we define the difference between these as the net gain or loss in *ex post* performance of the previous year. The average net gain in benchmarked returns was .098, or 9.8%, with a t-statistic of 5.47, assuming all switches were independent. While this simple test does not prove that fund managers were switching for strategic purposes during this period, the results are certainly consistent with such an interpretation. Were we to use self-reported styles for benchmarking, without checking to see whether the fund recently reclassified itself, we might be misled regarding the relative performance of the fund. This is also true if we were to base the stylistic classification of the fund upon its current portfolio holdings. "Window-dressing" is a common end-of-period ploy of fund managers to throw out poor performers and/or change the apparent strategy of the fund. Since our procedure uses past returns, not portfolio holdings, it is not fooled by window-dressing. In most cases, even if we knew the fund switched, mutual fund data vendors do not provide an historical record of past fund classifications, so the true benchmarked history is impossible to reconstruct.

IV. Mutual Fund Data

Morningstar, Inc. provided the monthly returns of the mutual funds in the equity category for the period from 1976 though June 1995, together with a classification into fifteen categories: Equity-Income, Growth and Income, Growth, Small-Company, Europe, Foreign, World, Pacific, Financial Sector, Health Sector, Natural Resources Sector, Precious Metals Sector, High Technology Sector, Utilities Sector and Unaligned Sector. These equity categories include funds that invest in bonds as well as stocks. The distinction between equity funds and bond funds is generally one of degree. Even all-equity funds typically hold cash balances. Like most databases of mutual fund returns, the Morningstar database is not free of survivorship bias, and the effect of fund attrition has an unknown effect upon *ex post* classification. In order to address the problem of changes in fund classification, we merged the Morningstar database with the annual Weisenberger database, used by Goetzmann and Brown (1993). This is updated through 1992, the last volume in which Weisenberger provided a comprehensive *Panorama* section to their mutual fund annual, based upon funds that were willing to report their performance results over the previous year. While not entirely free of bias, the database identifies changes in fund styles through time. In addition, we use a third source of mutual fund data that provides rich material for cross-sectional analysis: the Morningstar On-disc database. While only available since 1993, this CD-ROM program provides information on the composition of each fund and summary statistics about the securities in the fund. We cross-indexed this information with the monthly returns and Weisenberger datasets to allow an analysis of our endogenously determined styles by a broad range of characteristics.

V. Methodology

IV.1 Stochastic Specification

The objective of the analysis is to use past returns to determine a natural grouping of funds that has some predictive power in explaining the future cross-sectional dispersion in fund returns. Such groupings are referred to as *styles*. If there are K such styles the *ex post* total return in period t for any fund can be represented as:

$$R_{jt} = \alpha_{Jt} + \beta' I_t + e_{jt} \qquad \textbf{(1)}$$

where fund j belongs to style J. There are several ways of interpreting this equation. In a traditional financial economics framework, this equation refers to a multifactor or a multibeta model. The factor loadings on factors I_t are given by β_t . These loadings are allowed to change through time. AS Sharpe (1992) points out, if we regard the factors I_t as returns on index portfolios, the factor loadings can be thought of as equivalent portfolio weights associated with a dynamic portfolio strategy that might be associated with the style in question. In an interpretation closer to that of financial practitioners β_{Jt} refers to a characteristic of a typical stock in the *Jth* style classification (size, market to book, price earnings multiple, etc.) and I_t is the return to that attribute (c.f. Lakonishok, Shleifer and Vishney, 1993).

Regardless of how we interpret the equation, the style classifications will explain the cross-sectional dispersion of fund returns. Writing the equation as :

$$R_{jt} = \mu_{Jt} + \varepsilon_{jt} \tag{2}$$

where μ_{Jt} is the expected return for style J conditional upon the factor realization I_t. If the idiosyncratic return component ε_{jt} has zero mean *ex ante* and is uncorrelated across securities, the classification into styles will suffice to explain the cross-sectional dispersion of fund returns to the extent that μ_{Jt} differs across styles.

The task of assigning funds to style categories can be thought of as a problem in endogenously defining regimes (see for instance Quandt 1959 and 1960). In this way, it bears a "family" resemblance to switching regression, although, unlike the switching regression, an exact solution to the stylistic classification problem is only obtained through exhaustive combinatorics. The approach we use finds a local optimum via the minimization of a "within-group" sum of squares criterion, over a specific time period, t=1...T. The inputs to the procedure is a T by N matrix of monthly returns for a set of N mutual funds. We group the N funds together into K styles by minimizing the within-style mean returns for each period t=1..T. Thus, we are jointly estimating the time-series of mean returns for the styles J=1..K (μ_{Jt}) for t=1..T, and the membership to each style. The benefit of the resulting classification is that groups could result from either fixed portfolio strategies, such as similar asset compositions, or from dynamic portfolio strategies, such as portfolio insurance rebalancing.

The classification procedure assumes that we know the number of styles. Conditional upon restrictions upon the exact number of groups, Equation (2) is perfectly well-specified and can be used to estimate the style groupings. Equation (1) gives further insight into the nature of time-varying portfolio strategies, however, the parameters in this equation are not identified without further restrictions[1]. In order to implement our style classification [SC] algorithm, we pre-specify a number of styles.

A modification of the basic algorithm is a *generalized* least squares procedure, which allows time-varying and fund-specific residual return variance. By scaling observations by the inverse of the estimated standard deviation, we decrease the influence of extreme observations in the classification process. Amihud, Christiansen and Mendelson (1992), for instance, find this skrinkage improves forecasts of security returns. The details of the GSC procedure are provided in the Appendix.

It is important to note that the SC and GSC procedures makes minimal demands on the available data. We can estimate Equation (2) *without needing to know* factor loadings or style attributes represented by the vector β_{Jt} Which may well change from period to period. We only need to know *ex post* returns on individual funds. There is a direct analogy between our estimation technique and cluster analysis procedures. The criterion being minimized in Equation (2) via the SC algorithm is the same criterion applied in the *k-means* clustering approach (see, for example, Hartigan, 1975). Cluster analysis usually attempts to minimize the squared differences within groups of k characteristics. In this context, the characteristics might include risk exposure and the features of the average stock in the fund portfolio. In our classification procedure, the k characteristics are month-by-month returns and the group means are the conditional expectations appearing in Equations (1) and (2). These characteristics are explicitly time-variant and capture not only risk but also dynamic portfolio strategies that are specific to particular fund styles.

Because we relax the requirement of constant portfolio weights through time, we would not expect to identify perfect analogues to the categories derived using a fixed linear time-series model, or even a very rich set of cross-sectional characteristics, including stock portfolio composition, observed at one point in time. None-the-less, after estimating categories based upon our classification algorithm, we report cross-tabulations with Morningstar mutual fund data fields, and also use the Sharpe (1992) procedure for estimating approximate fixed-positive-weight portfolio analogues using a standard set of wide-spanning asset class returns provided by Ibbotson Associates. These two procedures give some intuition about the resulting mutual fund clusters. Our comparisons yield evidence of different management strategies, which relate to known classifications such as "Growth" and "Value" management.

IV.2 How Many Styles?

Because the procedure relies upon prespecifying the number of styles, it is natural to ask what is the right number. To address this question, we use a likelihood ratio test suggested by Quandt (1960) for each successive decrease in the number of pre-specified styles from nine. The test statistic for K styles (as opposed to K+1) styles is

$$LR = Tm\left(\ln \frac{ssq_K}{Tm} - \ln \frac{ssq_{K+1}}{Tm} \right)$$

where T is the number of time periods, m the number of funds and ssq_K and ssq_{K+1} are the appropriate heteroskedasticity adjusted sum of squared errors. This should be approximately distributed as χ^2 with 2T degrees of freedom.

Applying this measure to successive levels of fund aggregation, we find evidence for using at least eight separate categories. There is some ambiguity about the appropriate degrees of freedom, as well as the appropriateness the χ^2 distribution in this case (see Quandt [1960]). None-the-less, the observed test statistics are very large. For k=8 through k=3 styles, the test statistic values are: 4682.9, 4092.1, 32217.3,6555.5, 7106.2 and 10197.7. In each case, the p-values are arbitrarily close to zero, indicating that an increase in the number of styles is useful in explaining returns. This result is similar to that reported for χ^2 tests for the number of factors, where typically too many factors are identified (see, for example, Brown [1989]). An important caveat is that the χ^2 test is sensitive to departures from Normality.[2] Using fewer than five groups, the distribution of the group returns suggests that the χ^2 test is well-specified. For these low number of groups, the algorithm clearly forces disparate funds together, increasing and increase the model error. When the number of groups is increased beyond five, it is difficult to judge the relative magnitude of incremental improvement, however the sign of the test is positive for all values below nine, suggesting more groups are needed.

IV.3 Comparing Procedures

A key question of interest is "How does the GSC classification perform relative to standard industry definitions of management styles or classification by investment objective?" As Trzcinka (1995) points out, there are no generally accepted standards for comparing stylistic classifications. Styles are put to such a range of uses, from developing benchmarks for risk and return, to establishing specifications used in investment management contracts. Despite this ambiguity, we borrow a natural measure from the asset pricing literature. We examine how well industry objectives vs. Stylistic categories explain out-of-sample cross-sectional differences in returns.

Specifically, we compare the empirically determined styles with the style classifications provided by Weisenberger over the period 1976 though 1992, and Morningstar over the period 1993 through 1994. The reason we use Weisenberger for the early period rather than Morningstar, is that mutual fund styles change through time. The Weisenberger style codes were obtained at the end of each year in the sample period, and thus they have no *ex post* bias. Funds are classified using the GSC algorithm applied to data up to and including the Weisenberger publication date, with the number of styles chosen to match the number of industry objectives extant in the last month of the estimation window. Fund returns are then computed over the following year. Results are qualitatively similar using a one month test period and using rolling month-by-month returns for 24, 36, 48 and 60 months to classify funds. However, the performance of the industry based styles categories is notably inferior to the other methods. This is not surprising, since the other methods used data subsequent to the publication date of the industry styles to classify funds. For this reason, we report results using a one year test period.

In the next step of the procedure, we cross-sectionally regress fund returns on a matrix of dummy variables that indicate whether each fund belongs to a particular style. If the style classification contains information about future differences in returns, we would expect these regressions to explain a significant amount of cross-sectional variance. This same procedure is performed for the industry classifications. A comparison of adjusted R^2 indicates which has the superior predictive ability. This procedure resembles classical time-series cross-section tests of pricing models, except that the cross-sectional regressors are not loadings, but a matrix of dummy variables.

As an alternative to the classification based upon returns, we report a variety of other reasonable classification schemes. First, we classify funds based upon latent variable factor loadings derived from principal components analysis applied to the time-series matrix of fund returns in the estimation period. We apply the classification algorithm to the fund loadings on these factors. This is analogous to the principal component reduction used by Elton and Gruber (1969) who used loadings as the inputs to a classification algorithm. We estimate the loadings following the procedures described in Conner and Korajczyk (1986) and Lehmann and Modest (1987).

Second, we pre-specify factors, and use the space of pre-specified factor loadings to apply the SC algorithm. This approach has extensive precedent in the empirical literature. Chen, Roll and Ross (1986) and Berry, McElroy and Burmeister (1988) for example, pre-specify macroeconomic risk factors for analysis of stock portfolios and industry characteristics. In application to mutual funds, Lehmann and Modest (1987), Grinblatt and Titman (1989), Elton, Gruber, Das and Hvakla (1993) and Hendricks, Patel and Zeckhauser (1991) all pre-specify "control" portfolios according to factors such as size and dividend yield. Other examples are legion. For the purposes of this analysis, we use 8 indices: gold, the EAFE - US global equity index, The EAFA European Equity Index, the EAFA Pacific equity index, U.S. treasury-bills, commercial paper, long-term government bonds, long-term corporate bonds, high-yield bonds, the S&P 500, small stocks and IPO's, all obtained from

Ibbotson Associates. This approach has several advantages. First, the profile of each category has some intuitive interpretation -- one group may be tilted towards bonds, while another is tilted towards stocks, for instance. Second, it suffers less from the difficulty of heteroskedasticity across funds that introduces systematic error into the endogenously determined principal components. Third the coefficients when properly scaled, have the natural interpretation as portfolios. The drawbacks are, of course, that the procedure does not allow for temporal variation in the portfolio weights. Finally, we cluster in the space of "Sharpe coefficients" (See Sharpe, 1992) estimated on the same capital market indices as above. These are estimated via a constrained optimization procedure, under the assumption that the weights remain fixed over the estimation period, that they are non-negative, and that they sum to one. They thus have an interpretation as a portfolio of passive, investable indices.

As a benchmark to the performance of these various classification alternatives, we also report cross-sectional regression results for the factor loadings themselves. In other words, as independent variables in the cross-section regression, we use the coefficients estimated for each fund obtained by regression of the individual fund return series on (1) the set of SC styles, (2) the first k principal components, where k corresponds to the number of extant industry objectives, (3) the capital market indices described above, and (4) the Sharpe coefficients. This allows us to quantify how much is lost by reducing the continuous coefficients down to a simple classification scheme.

VI. Empirical Results

V.1 Summary of GSC Categories

In Table 1, we report the cross-tabulation of the GSC categories with the Morningstar categories. Since Morningstar categories are identified only at one point in time, i.e. the end of the sample period, we would not expect a perfect correspondence. The key feature of Table 1 is that the "Growth" category, which is the single largest designation for Morningstar, is spread widely across several different GSC categories, especially 1,3,4 and 5. While it is common to approximately control for risk in mutual fund studies by focusing only on Growth funds (see Hendricks, Patel and Zeckhauser, 1993, Brown and Goetzmann, 1993 and Ibbotson and Goetzmann, 1994, for instance) Table 1 indicates that many different portfolio strategies can fall under that broad rubric. Indeed the GSC algorithm groups a significant percentage of Growth funds with Growth and Income funds, suggesting that these labels may not provide particularly useful distinctions for investors. Also note that the small company category splits into two distinct groups -- apparently average capitalization of the stocks in the portfolio is not a sufficient statistics for performance. For the sector funds, the Morningstar classifications and GSC classifications generally agree. Health, Metals, Utilities and Unalligned (possibly real estate) are unambiguous.

Technology sector and Natural Resource sector (which includes forest products as well as oil and gas) are split. It is clear from Table 1 that GSC group 8 is the precious metals fund category: it includes no funds other than metal sector funds. It also appears that category 1 is composed mostly of Growth and Income funds, Category 2 is composed mostly of Growth funds and most utility sector funds fall into Category 3, suggesting it is an Equity-Income category.

Table 2 provides further insight into the characteristics of the GSC categories. For each category, we estimate the mean and standard deviation of portfolio weights, assuming a twenty-four-month (non-overlapping) return interval. Following Sharpe(1992), we constrain the coefficients to be positive, so that they may be scaled as weights in short-sale constrained analogue portfolios. Groups 1 and 2 have large average exposure to the S&P 500, groups 4 and 6 have a large exposure to the small stock index, groups 5 and 7 have large exposures to non-US indices. Group 8 has a large exposure to gold.

Table 3 provides further evidence on the dynamics of manager strategies. We decrease the non-overlapping estimation interval to six months in order to pick up variations in exposure to key indices. In addition, we estimate the correlation of the style return to the previous period's index return. Thus, positive correlations indicate "trend-chasing" while negative coefficients indicate a "contrarian" approach. Groups 1 and 3 both have negative portfolio weight correlations to lagged S&P 500 return values. Groups 5,6 and 7 all have positive portfolio weight correlations to lagged S&P 500 return values. Group 7, an international style, is most heavily weighted towards the EAFE index and is little invested in the U.S. market. Group 7 managers tends to buy the EAFE stocks when returns were low last period. Group 5, the other international style has much greater weight on the S&P 500, and appears to be a "trend chaser" with respect to the U.S. market.

Table 4 reports cross-tabulations of Morningstar On-Disc categories with GSC and Morningstar groups. It reveals useful information about fund strategies. For instance, it indicates Average PE ratios, Average Price to Book ratios and average *ex post* five year earnings growth. These measures have been found to explain differences in security returns. They also appear to explain differences in manager style. While these data represent a snapshot of the funds as of the last date in our database, we believe they provide an important validation for the style classification procedure.

There are two styles that are composed of Morningstar "Small-Cap" funds. Number 4 managers invest in stocks with low price to book ratios and low price to earnings ratios. These are "value" managers. Number 6 managers invest in companies with high price-to-book and high ex post earnings growth. These are "glamour" stock managers who purchase companies which have grown rapidly in the past. Number 4 managers buy stocks with low betas, number 6 managers buy stocks with high betas. Number 4 managers buy financial, cyclicals and services, Number 6 managers buy health care stocks and high technology issues. In the terminology of Lakonishok, Vishny and Schleifer (1994) these are "Glamour" managers. In view of the behavioral model proposed by these authors, it is not surprising to find that these managers are also "trend chasers" as evident from the results of the previous table, and engage in almost twice the amount of trading of their counterparts in group number 4, the "value" managers.

Taken together, Tables 1,2 ,3 and suggest a stylistic categorization that is somewhat different from the typical industry groupings. The following summarizes our GSC styles.

Category 1: **"Growth and Income"** Comprised primarily of Morningstar "Growth" and "Growth and Income" funds, Category 1 funds have the highest positive weights of any category on the S&P 500. They invest in relatively high-cap. companies.

Category 2: **"Growth"** comprised primarily of Morningstar "Growth" funds, Category 3 funds have a major exposure to the S&P 500, and to a lesser extent, small stocks. Their exposure to debt asset classes is minor.

Category 3: **"Income"** Comprised primarily of Morningstar "Equity Income","Growth and Income" and "Utility Sector" categories, Category 2 funds have the highest cash balances and the highest exposure to debt asset classes.

Category 4: **"Value"** Comprised mostly of "Small-Cap" funds, this category seeks stocks with low price to book and low price earnings ratios. This is consistent with value management.

Category 5: **"Global Timing"** Invest principally in non-US equities, however they pursue a dynamic strategy of increasing exposure to the U.S. market when it rises, and the variability of this U.S. exposure suggests a timing strategy.

Category 6: **"Glamour"** is comprised primarily of Morningstar "Growth" and "Small Company" funds. Category 4 funds have a major exposure to the small stock. The equities in the typical portfolio have relatively high price-to-book and P/E ratios, and high *ex post* five year earnings growth. These are also domestic "trend-chasers," displaying positive correlation to preceding S&P index returns.

Category 7: **"International"** Global equity managers who are not strongly exposed to the U.S. market through time, but do appear to vary their exposure to European and Pacific markets considerably.

Category 8: **"Metal Funds"** Comprised entirely of funds from the "Precious Metals and Commodities" Morningstar category.

V.2 Predictability of Categories

How useful is this new stylistic categorization? Table 5 reports the results of out-of-sample cross-sectional regressions for each of the categorization methods as well as for the industry objective classifications. We omit sector funds from the analysis, since there is relatively little ambiguity about their classification. Instead of using the entire history of fund returns to form styles, we use a rolling period of 24 months for estimation purposes. This will result in less "stable" styles, but it relaxes the assumption that funds belong to the same style over the entire period, and only uses ex post information.[3] Columns 1,2 and 3 in each panel show the adjusted R^2 that results from the application of the iterative relocation algorithm to different spaces: the space of returns, the space of "Sharpe coefficients," and the space of principal component loadings. Column 4 reports the results based upon the industry objective classification. Notice that, although adjusted R^2's differ for various estimation intervals, grouping in the space of returns and grouping in the space of factor loadings typically explains significant amounts of performance. Grouping funds according to the Sharpe coefficients performs about as well as using the industry codes. This may be due to the fact that, for any fund, a significant number of coefficients are zero, due to the non-negativity constraint. For each estimation period, the GSC algorithm applied to returns marginally outperforms the algorithm applied to loadings on principal components. This may be due to the fact that the model of classification in equation (1) is well specified when loadings change through time, but principal components relies upon stationary loadings. The GSC categories explain about a third of cross-sectional variation of returns, *ex ante*. The Weisenberger categories explained on average 16 % of the variation in fund returns, while classifying funds according to Sharpe coefficients explained only about 8 % on average.

The last four columns in each panel of Table 5 report the percentage of cross-sectional variation explained by the estimated factor loadings themselves. We would expect these to have greater explanatory power, since they are continuous, rather than dummy variables. This is particularly important for outlying funds which have extreme exposures to some factor. While the GSC algorithm will either group this outlier by itself, or lump it in with distant neighbors, the factor loadings themselves may capture the magnitude of its deviation in cross-section. In addition to using the Sharpe coefficients and principal component factor loadings as regressors, we also create indices based upon the SC centers in the space or returns, and also estimate unconstrained loadings on passive indices. This last column allows us to examine how much explanatory power the Sharpe procedure gives up in return for its positivity constraint. The Sharpe positivity constraint is useful, because it allos the coefficients to be interpreted as a vector of portfolio weights on investable indices. Our stylistic categories do not have this property. Consequently, our GSC procedure is not intended as a competing procedure to the Sharpe "Style analysis." In this paper, we show that the two tools that can be used together to identify common strategies among managers. The GSC procedure identifies aggregate behavior, and the Sharpe procedure helps interpret it as strategy.

The second panel of the Table shows that the loadings themselves all perform better than the classification indicators. Typically, they explain on average about 6% more cross-sectional variance out-of-sample. This suggests that, in absolute terms, factor loadings, however they are constructed, are a superior method of risk-adjustment. On the other hand, the GSC procedure does not do badly on a relative scale. Stylistic grouping is not an alternative method for risk-adjusting manager returns. However, given benchmarking by style is a common practice, our analysis indicates that there is not a great deal of information lost by using simple stylistic classifications that are appropriately chosen.

It is interesting to note that the loadings on the GSC centers typically outperform the constrained loadings on pre-specified financial indices and a little better than the loadings on principal factors. They do almost as well as the unconstrained loadings on the pre-specified factors. It is tempting to conjecture that the "Glamour" vs. "Value" division in the styles is responsible for the success of the simple multi-nomial statistic, since this division may capture one of fundamental factors found to be superior in out-of-sample tests on U.S. equities by Fama and French (1992) and Lakonishok, Vishny and Schleifer (1994).

V.3 Interpretation

It is not surprising that the categories based upon returns beat the standard industry classifications. Categories like "Growth" and "Growth and Income" represent an invitation to fund management gamesmanship. Once a fund is classified into a particular category, there is little incentive to pursue an investment strategy that will insure that future fund performance will we close to the category average in the future. Sirri and Tufano (1992) and Goetzmann and Peles (1992) report evidence that mutual fund investors flock to superior performers in each fund category. Given this information, fund managers are not rewarded by maintaining strategies consistent with their industry classification. As a result, we find that the GSC categories, formed via returns and loadings "agree to disagree" with the standard industry classifications. It is evident that the industry classifications have relatively little power to explain differential fund performance.

It is also not surprising that classification based upon returns typically equals or beats classification based upon principal factor loadings for longer holding periods. The principal component loadings represent a linear projection of the monthly returns upon a reduced space. Both the reduction of dimensionality and the linearity of the projection represent constraints that "coarsen" the information about fund returns. The advantage of the classification based upon scaled principal components is the natural interpretation of the groups in term of systematic risk classes. The disadvantage is that funds are subject to misclassification due to non-linear strategies.

It is likewise not surprising to find that loadings on principal components outperformed loadings on prespecified asset series'. The principal components were selected so as to maximally spread returns in the preceding period. While Chen, Roll and Ross (1986) show that pre-specified factors likewise spread returns, co-linearities among factors appear to increase the standard error of the factor loadings, and thus make fund classification via the SC procedure more difficult. The major advantage to estimating positive-constrained coefficients on pre-specified factors is that it provides some insight into the composition and behavior of the categories.

Our results provide mixed signals regarding the approach to characterizing funds according to their profile of loadings on pre-specified indices. Even when the loadings are not constrained to be positive, we find no evident advantage in term of explanatory value. When loadings are used to identify styles, they perform as poorly as the standard industry classifications. Thus, their incremental advantage obtains in circumstances when the loadings themselves, rather than a derived stylistic classification, can be used. Their disadvantage is that loadings on correlated indices will be estimated with inaccuracy, due to colinearities.

VI. Conclusion

We have shown that a simple procedure based upon the switching regression technology applied to monthly returns dominates other style classifications based upon standard investment objectives and does better than classification based upon observed factor loadings. Given the potential "category gaming" by fund managers, it is useful to have a classification method that uses publicly available and independently verifiable time-series information about returns.

Why are we interested in styles at all? Our stylistic classification algorithm identifies a few major types of fund strategies. While these may not exhaust the range of different fund managers, they provide an overview of what strategies differentiate managers. Our results validate the use of traditional, self-reported categories such as equity-income, growth and income, and growth. We find, however that funds apparently do not always correctly categorize themselves. We find two somewhat surprising divergences from standard industrial categories. First, we find evidence of "Value" vs. "Glamour" managers, rather than a monolithic small-cap group. Second, we find evidence that style involves dynamic strategies, rather than simply fixed portfolio weights.

The focus of this paper is the development of a classification algorithm which is consistent with commonly used asset pricing models. Stylistic classification is unlikely to replace the use of continuous, multi-variate models for risk-adjustment, nor should it. The absolute magnitude of systematic risk exposures will always be important to portfolio decisions. Our analysis in this paper suggests, however, that there are a few intentional, recognizable strategies within the population of investment managers. As the finance profession continues to investigate the behavioral basis for investment decisions, it will be useful to further identify and study these common patterns. The GSC algorithm is a potentially useful tool to do so. Its advantage over heuristic classification is that researchers may use it to decompose "styles" into more familiar measures such as time-varying factor loadings and risk premia.

Appendix: GSC methodology

The GSC can be thought of as an extension of a standard iterative relocation algorithm such as kmeans. It is motivated by the insight that, if $r_{it} = \mu_{It} + e_{it}$ and $var(e_{it}) = \sigma_i \sigma_t z_{it}$ where z_{it} is i.i.d Normal for both I and t with mean 0 and variance 1, then $var(e_{i.}) = \sigma_i^2 E(\sigma_t)^2$ and $var(e_{.t}) = \sigma_t^2 E(\sigma_i)^2$ where we interpret σ_τ and σ_ι as independent and identically distributed drawings from a population of time series and cross sectional standard deviations respectively independent of z_{it}. This is not inconsistent with a variety of GARCH or other processes for returns. As a result, $var(e_{it})$ is proportional to $var(e_{i.}) \times var(e_{.t})$. Therefore, it is a simple matter to infer the variance of each time and fund residual as proportional to the marginal time and fund variances in excess of the estimate of μ_{It}. Since the efficient (GLS) estimate of μ_{It} depends on σ_i, we need a second pass (GLS) for efficient estimation of both μ_{It} and $var(e_{it})$.

Computationally, this is how we proceed. For a given definition of the clusters, calculate $\hat{\mu}_{It} = \dfrac{\sum_{i\in I} R_{it}}{count(i \in I)}$. Once this is done, compute $\hat{e}_{it} = R_{it} - \hat{\mu}_{It}$ For all I, then calculate $var(\hat{e}_{i.})$, and for all t calculate $var(\hat{e}_{.t})$. Numerically, these numbers tend to be small, so we normalize them by the average marginal variances.

We now do a GLS correction for the mean, computing $\hat{\mu}^*_{It} = \sum_{i\in I} \dfrac{R_{it}}{var(\hat{e}_{i.})} / \sum_{i\in I} \dfrac{1}{var(\hat{e}_{i.})}$. We use this updated GLS estimate of the mean to update var measures. We also use this formula to update centroid means whenever funds are switched from one cluster to the next, although, for computational simplicity we do not update var measures at each switch). Denote the clusters formed at the jth switch as I(j). Then the criterion function at the jth switch is proportional to $SS_{j} = \sum_{t=1}^{T} \sum_{I\in I_j} \sum_{i\in I} \dfrac{(R_{it} - \hat{\mu}^*_{It})^2}{var(\hat{e}^*_{i.})\, var(\hat{e}^*_{.t})}$ using the result that $var(e_{it})$ is proportional to $var(e_{i.}) * var(e_{it})$.

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Table 1

Cross-Tabulation of Equity Funds by Morningstar and GSC Categories

Summary of Results Using GSC Algorithm : January 1976 - December 1994

GSC GROUP	1	2	3	4	5	6	7	8	Total
Equity-In	23	3	74	5	0	0	0	0	105
Europe	0	0	2	1	17	0	17	0	37
Foreign	0	0	2	2	137	1	136	0	278
Growth	196	296	54	117	1	77	0	0	741
Growth-In	247	34	89	21	0	0	0	0	391
Pacific	0	0	0	0	42	0	28	0	70
Small Com	0	16	7	132	0	115	1	0	271
Sp. Finan	1	0	5	7	2	0	0	0	15
Sp. Healt	2	7	0	0	0	7	0	0	16
Sp. Metal	0	0	0	0	1	0	0	35	36
Sp. Nat.	7	0	8	1	9	0	6	1	32
Sp. Tech	0	7	0	3	1	19	0	0	30
Sp. Unali	2	5	4	24	1	0	0	0	36
Sp. Util	1	2	75	1	3	1	0	0	83
World	3	3	12	4	85	7	27	1	142
Total	**482**	**373**	**332**	**318**	**299**	**227**	**215**	**37**	**2283**

The table reports the cross-tabulation of mutual fund GSC categories with Morningstar style categories, The Morningstar categories are those attributed to the funds as of 1994 by the company itself, and thus do not take into account style shifts through the sample period."Equity-Inc." is equity-income,"Europe" is the European equity category, "Foreign" is the non-US equity category, "Growth" is the growth fund category, "Growth-In" is growth and income, "Pacific" is the pacific equity fund category, "Small Co" is the small cap. stock fund, "Sp. Finan" is financial services funds, "Sp. Healt" is the health sector, "Sp. Metal" is the precious metals sector, "Sp. Nat." is the natural resource sector, "Sp.Tech" is the technology sector, "Sp. Unali" is the sector funds that are Unalligned. It includes miscellaneous sector funds, e.g. REIT funds are included in this category. "Sp. Util" is the utility sector. "World" is the global sector. The GSC procedure is a maximum likelihood method described in the text. It allows portfolio weights to vary on a quarterly basis, with eight factors were pre-specified. A likelihood ratio test suggested by Quandt and Ramsey (1978) was performed, which showed that the cross-section of mutual fund returns were driven by at least eight separate factors, for which loadings may vary.

Table 2

Mean and Standard Deviation of 24 Month (nonoverlapping) Sharpe Implied Portfolio Weights (December 1978 - December 1994)

	IPO	SMALL	S&P	JUNK	LT CORP	LT GVT	CPAPER	T BILLS	GOLD	EAFE	EUROPE	PACIFIC
Group 1												
Mean	0.00088	0.14190	0.75792	0.0072	0.0132	0.0172	0.0060	0.0273	0.0134	0.0000	0.0092	0.0062
Std.Dev	0.00121	0.04295	0.05583	0.0112	0.0156	0.0258	0.0130	0.0304	0.0115	0.0000	0.0145	0.0131
Group 2												
Mean	0.00192	0.29909	0.67357	0.0000	0.0000	0.0051	0.0000	0.0000	0.0127	0.0000	0.0066	0.0018
Std.Dev	0.00274	0.07125	0.09463	0.0000	0.0000	0.0154	0.0000	0.0000	0.0324	0.0000	0.0131	0.0055
Group 3												
Mean	0.00172	0.12419	0.48548	0.0480	0.0795	0.0282	0.0843	0.0977	0.0211	0.0176	0.0090	0.0039
Std.Dev	0.00220	0.06922	0.05546	0.0552	0.0975	0.0245	0.0977	0.0832	0.0209	0.0283	0.0100	0.0103
Group 4												
Mean	0.00388	0.57963	0.36383	0.0000	0.0083	0.0056	0.0000	0.0000	0.0190	0.0000	0.0210	0.0004
Std.Dev	0.00392	0.08008	0.06691	0.0000	0.0135	0.0168	0.0000	0.0000	0.0237	0.0000	0.0305	0.0007
Group 5												
Mean	0.00130	0.22508	0.18613	0.0068	0.0070	0.0178	0.0511	0.0149	0.0292	0.1509	0.2796	0.0307
Std.Dev	0.00143	0.09681	0.24990	0.0180	0.0211	0.0342	0.0871	0.0385	0.0427	0.1132	0.2172	0.0467
Group 6												
Mean	0.00462	0.61241	0.35686	0.0000	0.0000	0.0000	0.0000	0.0000	0.0177	0.0000	0.0105	0.0000
Std.Dev	0.00593	0.13444	0.17015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0510	0.0000	0.0315	0.0000
Group 7												
Mean	0.00058	0.06468	0.03004	0.0140	0.0212	0.0000	0.0240	0.0149	0.0154	0.2758	0.2187	0.3209
Std.Dev	0.00130	0.06293	0.06069	0.0278	0.0387	0.0000	0.0605	0.0385	0.0243	0.3090	0.1875	0.3010
Group 8												
Mean	0.02292	0.10274	0.00332	0.0000	0.0000	0.0000	0.0000	0.0000	0.7557	0.0364	0.0466	0.0425

Std.Dev	0.02483	0.14125	0.00997	0.0000	0.0000	0.0000	0.0000	0.0000	0.1952	0.1091	0.0713	0.0880

The table reports summary statistics about the time-series of Sharpe coefficients, i.e. implied portfolio weights calculated using the procedure in Sharpe (1992) for each GSC style over the period 1976 through 1994. Coefficients are constrained to be constant over non-overlapping 24 month periods.

Table 3

Mean Standard Deviation and Trading Correlations of 6 Month (non-overlapping) Sharpe Implied Portfolio Weights (December 1978 - December 1994)

	S&P	T BILLS	EAFE-US
Group 1			
Mean	0.88868	0.07536	0.03596
Std.Dev	0.06872	0.06268	0.04653
Corr.	-0.36285	-0.11794	0.08072
Group 2			
Mean	0.92767	0.02873	0.04361
Std.Dev	0.14101	0.07967	0.07964
Corr	0.00976	0.02262	-0.04144
Group 3			
Mean	0.65325	0.27648	0.07027
Std.Dev	0.12637	0.12772	0.07421
Corr	-0.33967	-0.05222	0.07570
Group 4			
Mean	0.80581	0.09788	0.09632
Std.Dev	0.21447	0.16608	0.15136
Corr.	-0.04370	-0.08677	-0.08074
Group 5			
Mean	0.53262	0.13748	0.32990
Std.Dev	0.29663	0.18198	0.19950
Corr.	0.33378	0.05611	-0.04871
Group 6			
Mean	0.90455	0.02557	0.06988
Std.Dev	0.20093	0.09784	0.13963
Corr.	0.18407	0.04409	0.02801
Group 7			
Mean	0.10346	0.14319	0.75335
Std.Dev	0.12823	0.15949	0.18585
Corr.	0.25193	0.10338	-0.26766
Group 8			
Mean	0.17685	0.41080	0.41235
Std.Dev	0.30928	0.41667	0.40264
Corr.	0.25022	-0.00200	-0.06077

This table reports the summary statistics about the time-series of Sharpe coefficients, i.e. implied portfolio weights calculated using the procedure in Sharpe (1992) for each GSC style over the period 1976 through 1994. Coefficients are constrained to be constant over rolling 6 month periods. EAFE-US is the EAFE index of global equity returns not including the US market. Correlation is between change in portfolio position and previous period index return. Change in portfolio position is measured as (-1,0,+1) relative to the previous semi-annual portfolio bought and held into the current period.

Table 4

Cross-Tabulation of Morningstar Performance Fields With Morningstar Classifications and GSC Categories

Average Net Asset Value by Morningstar and GSC categories

	1	2	3	4	5	6	7	8	Total
Equity-Inc	233.15	15.87	582.96	24.54	NA	NA	NA	NA	463.54
Europe	NA	NA	10.55	3	230.75	NA	116.69	NA	160.28
Foreign	NA	NA	151.7	365.95	308.48	1.4	232.43	NA	269.15
Growth	240.36	345.51	174.74	616.2	9.8	356.39	NA	NA	348.6
Growth-Inc	620.84	240.25	529.04	204.59	NA	NA	NA	NA	546.19
Pacific	NA	NA	NA	NA	195.03	NA	187.86	NA	192.08
Small Compan	NA	176.73	41.9	180.11	NA	192.34	41.8	NA	180.98
Sp. Financ	222.2	NA	151.58	208.13	3.1	NA	NA	NA	162.88
Sp. Health	457.3	341.56	NA	NA	NA	231.34	NA	NA	307.81
Sp. Metals	NA	NA	NA	NA	44	NA	NA	132.44	129.98
Sp. Nat. Res	232.43	NA	108.74	183.9	43.67	NA	19.52	20.2	100.35
Sp. Tech	NA	197.71	NA	314.47	176.4	183.1	NA	NA	199.42
Sp. Unaligne	113.1	27.24	185	52.89	81.6	NA	NA	NA	68.15
Sp. Util	369.6	5.3	299.4	37.6	857.03	17.3	NA	NA	306.85
World	1715.8	76.17	554.78	1206.1	290.49	61.77	127.72	2	319.95
Total	445.51	314.96	396.76	344.68	275.51	242.49	197.17	125.88	332.23

Average Value of Fund Characteristics by GSC categories (weighted by fund NAV)

	1	2	3	4	5	6	7	8	Total
Alpha	0.82	-0.52	1.75	2.25	2.4	0.51	3.41	11.88	1.32
Beta	0.92	1.00	0.77	0.94	0.78	1.11	0.58	0.30	0.89
Rsquared	82.91	67.26	67.14	60.76	26.93	41.63	13.33	1.10	62.73
Turnover	36.47	92.92	65.26	122.49	48.64	103.23	47.24	29.60	76.46
P/E Ratio	18.07	19.92	18.79	20.2	25.41	24.00	24.21	29.64	20.52
Price/Book Ratio	3.47	3.64	2.40	3.21	3.22	4.29	2.37	2.54	3.31
5 Year Earnings Growth	4.90	15.31	5.28	9.92	1.45	23.59	1.91	0.36	5.68
Return on assets	7.36	8.63	4.77	8.2	7.37	10.83	6.31	11.38	7.59
Debt to Capital	30.19	27.30	34.00	29.52	28.90	24.81	26.43	19.76	28.37
Median Market Cap.	9144.4	5194.5	4170.1	1415.5	5868.1	820.8	2850.9	1255.1	5613.6
Energy(%)	10.72	5.27	NA	NA	NA	NA	NA	NA	8.51
Financials(%)	18.61	13.88	19.95	15.50	21.31	6.97	17.69	2.66	16.84
Industrial Cyclicals(%)	17.53	NA	NA	NA	NA	NA	NA	NA	17.53
Consumer Durables(%)	6.83	7.76	5.33	8.63	10.69	6.77	12.01	0.20	7.63
Consumer Staples (%)	7.11	5.62	5.42	3.27	5.57	1.98	5.55	0.03	5.36
Services(%)	9.89	13.55	7.94	13.77	11.9	12.09	10.19	1.28	11.02
Retail(%)	4.81	6.07	3.53	6.01	4.23	7.29	5.96	0.09	5.11
Health(%)	8.53	11.36	6.34	6.95	4.06	15.33	4.39	0.02	8.09
Technology(%)	9.28	20.82	3.97	22.75	5.94	36.22	6.59	0.06	13.48

Cash(%)	6.38	12.08	9.86	7.75	13.02	9.00	5.71	5.35	8.92
Equity(%)	89.57	84.31	75.08	90.16	83.38	90.10	91.79	91.96	85.83
Bonds(%)	2.73	1.95	9.64	1.35	1.74	0.30	1.31	0.12	3.23
Preferred(%)	0.12	0.40	0.79	0.09	0.91	0.27	0.22	0.25	0.38
Other(%)	1.06	1.11	4.59	0.61	0.90	0.33	0.59	2.32	1.53
Foreign(%)	8.23	9.99	14.54	9.16	88.30	7.87	96.3	81.74	23.68
Sales Charge	2.85	2.88	2.89	2.91	3.50	2.21	1.59	2.45	2.82
Front End Load	2.48	2.55	2.09	2.75	2.89	1.78	1.09	2.16	2.37
Expense Ratio	0.77	1.10	1.04	1.06	1.41	1.28	1.21	1.19	1.04

Panel 1 reports the cross-tabulation of fund net asset values as of December, 1994 for the GSC style categories (columns) and the Morningstar fund objective classifications (rows) as of that date. Abreviations for objective classifications are the same as in Table 1. NA indicates that summary data on net asset values was unavailable for that category. Panel 2 reports the average value of a number fund characteristics calculated by Morningstar Inc. as of December, 1994 for each of the GSC style categories, as well as for the entire sample. "Alpha," "Beta" and "Rsquared" are regression statistics estimated from a single-factor market model using the S&P 500 as the regressor over the history of the fund.

Table 5: Cross-Sectional Return Variance Explained by Ex-Ante Classification Methods and Factor Loadings

	Regressing Returns on Classifications: Adjusted R^2				Regressing Returns on Factor Loadings: Adjusted R^2			
Test period	Return based classifications (GSC procedure)	Classifications based on Sharpe coefficients	Classifications based on principal components	Classifications based on style categories	Constrained pre-specified factors (Sharpe procedure)	Principal factor loadings	GSC centers	Unconstrained pre-specified factor loadings
1978	0.372	0.194	0.287	0.227	0.368	0.44	0.421	0.45
1979	0.359	0.050	0.331	0.234	0.459	0.526	0.533	0.522
1980	0.306	0.135	0.323	0.199	0.423	0.485	0.499	0.498
1981	0.381	0.151	0.388	0.205	0.484	0.518	0.521	0.521
1982	0.390	0.152	0.395	0.188	0.488	0.489	0.470	0.511
1983	0.299	0.057	0.241	0.124	0.308	0.287	0.295	0.304
1984	0.257	0.051	0.221	0.128	0.302	0.297	0.290	0.305
1985	0.177	0.033	0.108	0.038	0.262	0.222	0.224	0.239
1986	0.080	0.013	0.043	0.035	0.148	0.103	0.104	0.127
1987	0.177	0.033	0.131	0.093	0.179	0.174	0.174	0.172
1988	0.400	0.070	0.436	0.194	0.501	0.506	0.504	0.503
1989	0.374	0.066	0.362	0.192	0.421	0.425	0.428	0.426
1990	0.423	0.129	0.376	0.208	0.483	0.476	0.477	0.473
1991	0.351	0.085	0.368	0.193	0.402	0.406	0.411	0.427
1992	0.358	0.064	0.352	0.191	0.398	0.411	0.424	0.459
1993	0.174	0.032	0.166	0.122	0.167	0.177	0.184	0.188
1994	0.196	0.031	0.16	0.107	0.184	0.205	0.207	0.218
mean	0.298	0.079	0.276	0.158	0.352	0.362	0.363	0.373
median	0.351	0.064	0.323	0.191	0.398	0.411	0.421	0.427
std. deviation	0.102	0.053	0.118	0.062	0.124	0.142	0.141	0.139

This table uses a 24 month estimation period prior to and including the Weisenberger publication date to estimate coefficients and form classifications. The number of classifications in each period is specified by the number of industry objective codes provided by Weisenberger(1978-93) and Morningstar (1994). The out of sample test period corresponds to the twelve months between Weisenberger publications. The cross section of test period returns on funds are regressed against (K - 1) dummy variables, where $\delta_{ki} = 1$ for fund I in category k, zero otherwise. The first column gives adjusted R^2 for the categories given by the GSC procedure described in the text, the second and third columns correspond to categories based on constrained Sharpe coefficients and principal factors procedures (using the SC procedure), while the fourth column uses the Weisenberger style categories (1978-93) and Morningstar categories (1994). These are compared to the adjusted R^2 obtained by using the Sharpe coefficients(Column 5), factor loadings (Column 6), loadings on the SC style centers (Column 7), and the unconstrained loadings on capital market returns used to estimate the Sharpe coefficients (Column 8). The data are total returns to US equity mutual funds, excluding sector funds, but including international funds, over the period 1976 through 1994.

Notes

1. A restriction sufficient for identification purposes is to assume that the portfolio strategy is constant over a number of months greater than the number of factors. This might seem unduly restrictive. However, for the purposes of characterizing the time-varying strategies of each style it suffices that we assume a quarterly holding period with two factors given by the return on cash and on equity investments. Other quarterly factors are captured in the α_{Jt} terms. Then monthly data will suffice to estimate equation (1). This approach can be contrasted with Sharpe's (1992) use of a rolling regression technology. The monthly updated portfolio shares should be interpreted as the average style-based portfolio shares for the previous 24 months.

2. In the 8 styles case, there are significant differences in skewness and kurtosis by style category (for a Normal distribution, skewness is zero and kurtosis is 3):

Group	Skewness	Kurtosis
1	0.0172	2.65
2	0.0540	3.45
3	0.1033	3.95
4	0.1481	3.97
5	-0.0670	5.37
6	0.2183	5.32
7	0.1697	5.52
8	0.1015	14.45
Entire Sample	0.0782	4.11

The last four groups show significant departures from Normality, thus, the χ^2 distribution may be inappropriate for evaluating the unusualness of the test statistic. In other words, gains to increasing the number of styes above 5 groups may be overstated.

3. As a measure of style stability, each year we count the number of changes in pair-wise associations between each fund (for all funds that existed over the entire period). The average percentage of fund associations that change each year was 17.6%. In other words 18% of the funds change their "relationship" -- either becoming members of the same style, or becoming members of different styles. To determine whether this rate of change is different than might be expected randomly, we bootstrapped the expected annual percentage change under the null of no cross-sectional structure. This null was constructed by forming a cross-section time series matrix via random draws without replacement from the actual time-series cross-section matrix. The typical rate of change under the null is 27.3%. We find that 12 of 16 of the sample years had percentage changes below the 5% quantile of the bootstrapped distribution, allowing us to reject the null of

hypothesis of no significant style effect that year. For further details of bootstrapping association frequencies see Abraham, Goetzmann and Wachter, 1994 and Goetzmann and Wachter, 1995.