On Mutual Fund Investment Styles

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Most mutual funds adopt investment styles that cluster around a broad market benchmark. Few funds take extreme positions away from the index, but those who do are more likely to favor growth stocks and past winners. The bias toward glamour and the tendency of poorly performing value funds to shift styles may reflect agency and behavioral considerations. After adjusting for style, there is evidence that growth managers on average outperform value managers. Though a fund's factor loadings and its portfolio characteristics generally yield similar conclusions about its style, an approach using portfolio characteristics predicts fund returns better.

Many crucial investment decisions are commonly delegated to professional investment managers. Portfolio managers, however, follow a wide variety of approaches and adopt different criteria for stock selection—identifying underappreciated or cheap securities, seeking growth potential, or following past price trends, to cite a few examples.

The bewildering variety of approaches followed by money managers raises two broad questions. The first concerns the nature of the product that professionally managed funds deliver. In the case of mutual funds, a fund's stated objective (such as growth, income, or balanced) historically served as a limited form of product differentiation. However, these descriptions are generally too vague to be very informative. Because money managers are given much latitude, the agency aspect of their roles prompts a second question. In particular, managers' personal career considerations may lead them to alter their behavior and adopt approaches that are more in favor with investors and financial consultants, with possibly adverse consequences for fund performance. This article provides evidence on these two questions, focusing on the investment approaches followed by equity mutual fund managers.

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The institutional investment community has responded to the proliferation of investment approaches by more closely scrutinizing a manager's investment style. The heightened attention to style is driven by several motives. Accounting for style aids performance evaluation by giving a clearer picture of a manager's stock selection skill. The manager of a portfolio of small stocks may appear to disappoint relative to a broad market index, for example, but performance may be outstanding relative to a small stock benchmark. A second motive is to enhance control of the portfolio's overall risk. For example, a pension plan sponsor might select a few active managers who are expected to yield superior performance. This may be scant comfort, however, if they all follow similar styles and select similar stocks, so that the overall portfolio is highly undiversified relative to a broad benchmark.

The explosion of assets under management by mutual funds in recent years has intensified the focus on style. Equity funds' net assets soared from $240 billion in 1990 to $4 trillion in 1999. In part, the growth has been fueled by the rise in defined contribution or 401(k) pension assets. Administrators of such plans have a fiduciary responsibility to provide a variety of asset classes to participants. Accordingly, many plans provide a menu of funds drawn from different styles. More generally, individual investors are becoming more knowledgeable about allocating their assets across funds with different styles.

This article's analysis of the product offered by mutual funds uses a style classification scheme that draws on academic research on the behavior of stock returns. It is widely used in the pension fund industry and is quickly becoming the norm in the mutual fund industry, forming the basis of approaches adopted by major fund trackers such as Morningstar and Lipper Analytical Services.[1] Specifically, the style categories are based on two dimensions: market capitalization and value-growth orientation. Given the large amount of money that is allocated on the basis of the size-value style classification, it is important to evaluate whether it provides a meaningful description of fund managers' behavior.

Specifically, we begin by providing evidence supporting the usefulness of size and value-growth as style descriptors. Given that this approach helps describe a fund's product type, we document the characteristics of fund portfolios. We also analyze consistency in fund styles over time and the forces that may drive managers to change styles. Although the issue of fund performance is not our main concern, our analysis lets us check whether differences in style are associated with differences in performance. Finally, this article compares different methods of style identification.

Our analysis adds to the existing literature in several respects. On the methodological front, we directly confront the size-value style classification

[1] Hemmerick (1998) reports on software, based on work by William Sharpe, to analyze a fund's style along similar dimensions.

scheme with several alternatives based on expanded style dimensions. Previous research [Brown and Goetzmann (1997), Carhart (1997)] shows that size and value help account for differences in fund performance, but no direct comparisons with more general style factors have been undertaken. Instead of basing a fund's style on the sensitivities of its return to factors, an alternative approach uses the characteristics of the fund's holdings. Grinblatt and Titman (1989) and Daniel et al. (1997) use such an approach to evaluate fund performance. On a related note, Daniel and Titman (1997) find that stock characteristics do better than factor loadings in explaining the cross-sectional behavior of average returns. We confront the return-based and characteristics-based approaches to style classification.

The results on funds' styles highlight the potential importance of nonperformance distortions (because of agency or other reasons). Numerous studies generally indicate that mutual funds as a group do not outperform passive benchmarks.[2] This finding is even more striking when juxtaposed against the voluminous research documenting various return anomalies. For example, a portfolio of "value" stocks (with high ratios of book-to-market value of equity) generated on paper returns that have in the past substantially exceeded the return on the Standard & Poor's (S&P) 500 index. The puzzle then is why so few funds consistently generate superior performance. One explanation borrows from related research on the pension fund industry (which generally has not displayed superior performance either). Although there are important differences in the structures of the pension and mutual fund industries, the conjecture is that mutual fund managers' behavior may be colored by considerations beyond the maximization of portfolio return or diversification.[3] Insofar as these choices degrade performance, the result is the general underperformance of mutual funds.

In turn, funds' preference for one investment style over another (due to behavioral or agency reasons) may affect the structure of asset prices. Barberis and Shleifer (2000) show how funds' pursuit of styles can account for observed patterns in stock returns. For example, if funds favor a style and allocate more resources to that style than is warranted by underlying fundamentals, the prices of stocks belonging to that style category may temporarily deviate from fair values. Although we do not study the performance of the

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[2] See, for example, Jensen (1968), Ippolito (1989), Elton et al. (1993), and Malkiel (1995). Other studies examine whether there is persistence in performance [Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), Brown and Goetzmann (1995), Elton, Gruber, and Blake (1996)].

[3] Some evidence is accumulating about mutual fund managers' incentives and how they shape funds' behavior. Grinblatt, Titman, and Wermers (1995) investigate herding behavior for mutual funds. Brown, Harlow, and Starks (1996), Chavalier and Ellison (1997) find that a mutual fund's past performance affects its future risk-taking behavior. Khorana (1996) documents that prior to a change in management, a fund's portfolio turnover tends to be relatively high, possibly reflecting window-dressing or herding behavior. Karceski's (1998) model suggests that funds tend to favor growth stocks over value stocks.

different style classes, our analysis identifies the relative concentration of funds across styles.[4]

We sharpen our evidence on funds' product types and the presence of nonperformance distortions by checking for consistency in styles. The notion that styles delineate distinct fund products rests on the premise that managers who follow a specific style select from a well-defined domain, such as small stocks or growth stocks. In this respect, checking for consistency helps verify that styles correspond to meaningful dimensions of fund behavior. More practically, drift in a fund's style introduces additional variability in the overall portfolio relative to a benchmark. Style drifts may reflect the manager's attempt to time the style indices. Alternatively a manager may deviate from his declared style in hopes of recovering from past losses or to follow the crowd and adopt whichever style has been successful. Accordingly, we check whether funds are successful in timing styles and if they alter their styles in response to past performance.

Our results are as follows. We confirm that size and book-to-market provide useful descriptors of fund styles. A three-factor model that includes these style dimensions does about as well as more elaborate style-classification methods on an out-of-sample basis. Fund styles tend to cluster around a broad index, such as the S&P 500 index, with few funds taking extreme positions relative to the index. When they choose to stray from the benchmark, however, they are more prone to favor growth stocks and stocks with good past performance. These results from the mutual fund industry, together with related evidence from the pension fund industry, are consistent with explanations related to agency or behavioral factors.

Funds overall are consistent in following their styles, confirming that the dimensions we use are helpful in distinguishing fund product types. Style shifts are most notable for funds with poor past performance, particularly in the case of value funds that have performed poorly. These results on style shifts are also consistent with an agency or behavioral explanation.

In the aggregate, funds do not possess any ability to time the style factors. Following up on a common belief among investment managers, we find some evidence that on a style-adjusted basis, growth fund managers tend to outperform value managers.

Our basic findings are not sensitive to how we identify fund style. Confronting the returns-based and characteristics-based approaches in those cases where they differ, we find that the approach based on portfolio characteristics tends to do a better job in predicting future fund performance.

The rest of the article is organized as follows. Section 1 describes the data and provides evidence supporting the size-value approach to style classification. Section 2 gives some details on the characteristics of mutual fund

[4] Chan, Karceski, and Lakonishok (2000) provide evidence on the recent operating performance of size-value equity asset classes.

portfolios. Section 3 examines funds' exposures to common return factors. As a bridge to prior research, we also provide some results on average fund performance classified by style in Section 4. Section 5 deals with funds' style timing and whether style shifts are related to past performance. A comparison of the two approaches to style analysis is contained in Section 6. A final section concludes.

1. Mutual Fund Investment Styles

1.1 Data

Our analysis is based on two data sets from Morningstar. The sample includes all domestic equity funds existing at the end of 1997. Data on defunct funds are available as well, but they begin only in 1989. Given that our focus is on fund styles and not fund performance, the presence of a survivorship bias in the earlier years of the sample period may be less worrisome. The first data set reports monthly fund returns from January 1976 to December 1997. A second data set reports funds' portfolio holdings beginning in 1983. After merging the two data sets and checking against the Compustat file, there are 3336 funds with information on returns and holdings as of the end of 1997.

Table 1 reports the number of funds at the end of each calendar year over the sample period. The size of the sample grows over time, with particularly high growth during the 1990s. In addition, the table compares the performance of the sample with the return on several market indices. To measure aggregate fund performance, we compute monthly returns on the equally weighted portfolio of funds and then compound to get calendar year returns. Average returns for the fund sample are calculated over the period starting in 1979, when the Russell indexes begin.[5] The verdict on aggregate performance is familiar—net of expenses, the fund sample fails to match the performance of the overall market. The average return on the fund portfolio is 16.32%, which is lower than the return on any of the other market indices. In particular, funds' average underperformance relative to the S&P 500 index is 1.6%. This is not too far from estimates of funds' expense ratios that have been reported in other studies [for example, Carhart (1997), Gruber (1996), Sirri and Tufano (1998)]. Note that the evidence suggests underperformance even before taking into account the survivorship bias that affects this sample before 1989.[6]

[5] The Russell 1000 and Russell 2000 indexes are widely used as benchmarks by investment managers and consultants. The Russell 1000 index is a value-weighted index of the largest 1000 U.S. stocks, and the Russell 2000 index is a value-weighted index of the next 2000 largest U.S. stocks.

[6] Part of the mutual funds' portfolios may also be held as cash, representing a drag on performance (and on volatility as well) relative to equities over most of this period.

Table 1
Description of sample of mutual funds and aggregate performance

			Return on:			
Year-end	Total number of funds	Equally weighted portfolio of funds	CRSP	S&P 500	Russell 1000	Russell 2000
1976	270	26.36	26.52	23.85		
1977	284	2.25	−4.16	−7.18		
1978	294	11.54	7.81	6.57		
1979	300	27.12	23.58	18.44	22.32	43.09
1980	310	32.21	32.74	32.42	31.88	38.60
1981	325	−0.12	−4.27	−4.91	−5.09	2.05
1982	352	26.30	20.18	21.41	20.32	24.95
1983	398	21.02	23.06	22.51	22.12	29.12
1984	452	−0.73	5.10	6.27	4.73	−7.30
1985	519	27.27	31.16	32.16	32.26	31.05
1986	623	14.14	16.89	18.47	17.86	5.68
1987	737	1.95	2.81	5.23	2.93	−8.76
1988	852	14.37	17.50	16.81	17.24	24.91
1989	893	22.47	29.37	31.49	30.41	16.24
1990	962	−5.14	−4.82	−3.17	−4.14	−19.52
1991	1032	33.39	30.57	30.55	33.01	46.03
1992	1177	8.68	8.00	7.67	9.04	18.42
1993	1314	12.76	10.97	9.99	10.17	18.90
1994	1998	−1.75	−0.63	1.31	0.37	−1.83
1995	2440	31.22	35.73	37.43	37.78	28.45
1996	2789	19.95	21.25	23.07	22.42	16.51
1997	3336	24.97	30.46	33.36	32.83	22.37
Mean (1979–1997)		16.32	17.36	17.92	17.81	17.31
Standard deviation (1979–1997)		12.66	13.58	13.22	13.59	18.13

At the end of each calendar year from 1976 to 1997 the number of domestic equity mutual funds with at least one observation on monthly rate of return that year is reported. Monthly rates of return are calculated for the equally weighted portfolio of funds with available data and are compounded over the calendar year to obtain annual rates of return. Also reported are the annual returns for the CRSP value-weighted index (denoted CRSP), the S&P 500, the Russell 1000 index, and the Russell 2000 index. The last two rows report the mean and standard deviation of returns (over the period 1979–97) on the portfolio of funds and the market indexes.

1.2 Size and value as style dimensions

Though many style dimensions might be used, in practice investment managers generally tend to break the domestic equity investment universe down into four classes: large-capitalization or small-capitalization growth stocks and large-capitalization or small-capitalization value stocks.[7] Correspondingly, we focus on two dimensions to identify a manager's style: size (defined by the stock's equity market capitalization), and value-growth (book-to-market value of equity). Perhaps not surprisingly, academic research also finds that size and book-to-market are important for capturing the variation in stock returns [see, for example, Fama and French (1992, 1993) and Chan, Karceski, and Lakonishok (1998)].

Although the style dimensions we use are widely accepted in practice, it is possible that they do not fully correspond to the investment criteria fund managers actually use. To begin, then, we provide evidence that size and book-to-market are meaningful descriptors of fund style. In particular,

[7] For example, most pension plan sponsors use these categories when they screen investment managers. Recently another class, midcapitalization stocks, has emerged.

if fund managers' investment domains coincide with these dimensions, then a fund's return should track its style-specific benchmark (based on size and book-to-market) more closely than a generic benchmark (such as the S&P 500). More generally, we can generate a fund's customized benchmark from different style classification models. The models can then be compared on the basis of how much a fund's realized returns deviate from the returns on the various style-specific benchmarks.

We provide results for the following style classification procedures. The S&P 500 index is a popular yardstick for mutual fund performance, so we take it as our first style benchmark. The other procedures are based on estimated time-series regressions of the form

$$r_{pt} - r_{ft} = \alpha_p + \sum_{j=1}^{K} \beta_{pj} s_{jt} + \epsilon_{pt}. \tag{1}$$

Here r_{pt} is the return in month t for fund p, r_{ft} is the return on a one-month Treasury bill, and s_{jt} are K style indices. The estimated coefficients β_{pj} in Equation (1) represent fund p's average style over the estimation period with respect to each of the indices.

Our models vary with respect to the choice of style indices. Fama and French (1992, 1993) find that three factors—the market and mimicking portfolios for size and book-to-market—can explain the cross-section of average returns and the common variation in returns. Accordingly, we use the Fama-French factors as style indices, so a fund's loadings on the factors provide one way to identify a fund's style. Alternatively we use for the style indices either the first three or four statistical factors extracted from stock returns using the asymptotic principal components method of Connor and Korajczyk (1991).[8] Brown and Goetzmann (1997) perform a cluster analysis on fund returns and identify eight style dimensions. In our application of their style model we use for s_{jt} the returns on five of the Brown and Goetzmann indices (corresponding to the returns on growth and income, growth, income, value, and glamour funds).[9]

Sharpe (1992) provides a different style classification procedure that is widely used in the investment management industry. This procedure regresses a fund's return on the returns to cash and a variety of equity classes. The regression coefficients are constrained to be nonnegative and sum to one, so they can be interpreted as portfolio weights. The model thus yields the fund's effective asset mix. In our implementation of this approach we use four equity classes: the Russell 1000 value index, the Russell 1000 growth index,

[8] The data on the principal components were graciously supplied by Bob Korajczyk.

[9] Because our sample includes only domestic equity funds, we exclude three other style indices representing global timing, international, and metal funds. We thank Stephen Brown and William Goetzmann for supplying the data on their style centers.

the Russell 2000 value index, and the Russell 2000 growth index.[10] Adding the coefficients on the small value and small growth indices, for instance, captures the fund's orientation toward size. Because negative weights are not allowed under this procedure, a fund cannot be more aggressive on the size-value dimensions than the Russell indices. As another difference, note that in the Fama-French model the effect of one style factor on return is largely independent of the level of the other factor. The book-to-market factor each month, for example, is measured as the return averaged across big and small value stocks, minus the return averaged across big and small glamour stocks. In this respect the Fama-French three-factor model does not capture potential differences in the value effect across big and small stocks.[11] On the other hand, the Sharpe model allows for separate effects from each of the underlying equity asset classes and so might provide a more accurate customized style benchmark.

At each year end from 1978 to 1996, we construct for each fund customized benchmarks using different style models. We compare the models in terms of the cross-sectional distribution of funds' tracking error volatilities (the standard deviation of the difference between the fund's return and the return on its style benchmark). To avoid data-snooping, we use one time period (the prior 36 months) to estimate the parameters used in the style benchmark, and a disjoint time period (the subsequent 12 months) to calculate the tracking error volatility. Table 2 reports the decile breakpoints for the distribution of out-of-sample tracking error volatility (in percent per month) from each style model. When measured against the S&P 500, the median tracking error volatility is 1.95% per month (or 6.74% on an annualized basis). The principal components models fare worst in predicting fund returns out of sample. Median tracking error volatilities are the highest for the principal components models (above 2.60% per month, or 9% annualized). Our verdict on the poor performance of the principal components models echoes the findings of Farnsworth et al. (2000), who compare the average pricing errors generated by a variety of asset pricing models in a controlled sample. In comparison median tracking error volatilities from the three-factor, Brown and Goetzmann and Sharpe models tend to bunch together between 1.4% and 1.5% per month (or 4.8% and 5.3% per year).

Another way to judge a model's ability to capture fund styles is to look at the dispersion across funds' tracking error volatilities. When a general benchmark such as the S&P 500 is used, tracking error volatilities range from 1.03% at the tenth decile to 3.78% at the ninth, yielding a large difference of 2.75%. Using a customized benchmark that is more closely aligned

[10] Stocks within the Russell 1000 (or Russell 2000) set are subdivided into a growth category and value category based on book-to-market and earnings growth forecast.

[11] As an illustration of how the Fama-French assumption might not be consistent with the data, in 1999 large value stocks outperformed small value stocks, but small growth stocks did better than large growth stocks.

Table 2
Decile breakpoints for out-of-sample tracking error volatility (percent per month) from different style classification models

Style model	1 (low)	2	3	4	5	6	7	8	9 (high)
S&P 500	1.033	1.281	1.488	1.697	1.947	2.227	2.567	3.018	3.775
Fama-French	0.856	1.038	1.193	1.347	1.511	1.690	1.917	2.207	2.724
Three principal components	1.586	1.919	2.164	2.386	2.600	2.817	3.085	3.400	3.977
Four principal components	1.600	1.954	2.205	2.430	2.649	2.883	3.146	3.481	4.065
Brown-Goetzmann	0.825	1.000	1.151	1.311	1.470	1.640	1.853	2.162	2.676
Sharpe	0.793	0.970	1.110	1.254	1.405	1.577	1.784	2.054	2.562

At the end of each year from 1978 to 1996 each fund is assigned a style benchmark (either the S&P 500 or based on one of five estimated style models). For each estimated style model, the model parameters are estimated for each fund using the prior 36 months of data. The fitted values from each model, using the estimated parameters along with realized values of variables in the model over the subsequent 12 months, yield each fund's style benchmark. A fund's out-of-sample tracking error volatility is the standard deviation of the differences between the fund's realized return and its fitted style benchmark over the subseqent year. Decile breakpoints are calculated for the distribution of tracking error volatilities across all available funds each year. The weighted averages of these breakpoints across all years in the sample period are reported, where each year's weight is the number of available funds that year. The style classification models are as follows. For the S&P 500 model, the style benchmark is the return on the S&P 500; the out-of-sample tracking error volatility is the standard deviation over the subsequent 12 months of the difference between the fund's return and the return on the S&P 500. In the Fama-French principal components, Brown-Goetzmann and Sharpe models 36 months of past data are used to estimate the parameters in a regression: $r_{pt} - r_{ft} = \alpha_p + z_t'\beta_p + \epsilon_{pt}$, where r_{pt} is the return on fund p in month t, r_{ft} is the return on a one-month Treasury bill, and z_t' is a row vector of returns on style indices. In the Fama-French model the style indices are the three Fama-French (1993) factors: the value-weighted market portfolio and zero-investment mimicking portfolios for size and book-to-market. In the principal components models the style indices are the first three or four principal components using the Connor and Korajczyk (1991) asymptotic principal components method. In the Brown-Goetzmann model the style indices are the returns on five style centers from a cluster analysis of fund returns; the centers correspond to growth and income, growth, income, value, and glamour funds. In the Sharpe model the style indices are the returns (in excess of the monthly Treasury bill return) on the Russell 1000 value, the Russell 1000 growth, the Russell 2000 value, and Russell 2000 growth indices. The coefficients β_p in the Sharpe model are constrained to be nonnegative, and their sum does not exceed one. Due to data availability, the sample period is 1981–96 for the Sharpe model and 1978–94 for the Brown-Goetzmann model.

with a fund's style should lower the range across funds. On this basis the models based on principal components provide almost no help in identifying fund style. The range between the first and ninth deciles using either three or four principal components (2.39% and 2.47%, respectively) is almost as large as the range using only the S&P 500. On the other hand the three factor and the Brown and Goetzmann models generate lower dispersion across funds, and the ranges from these models are similar (1.87% and 1.85%, respectively). The Sharpe model generates the smallest variation in tracking error volatilities (1.77%).

In short, Table 2 provides confidence that size and book-to-market do a good job in summarizing mutual fund managers' investment styles. This approach does about as well as the Brown and Goetzmann model, which calibrates style dimensions using historical fund returns. The size-value approach is also relatively straightforward to apply and interpret. Furthermore, the three-factor model has a direct connection to the literature on empirical asset pricing, as well as research on performance evaluation and attribution. Fama and French (1996) and Jegadeesh and Titman (1993) provide evidence that past stock price momentum may be another important factor. Accordingly, in subsequent sections we also provide some results that are based on a four-factor model.

1.3 Consistency in fund styles

A second check that our style categories are meaningful ways to portray fund behavior is to see if there is consistency in fund styles based on size and book-to-market. At each calendar year end we use the past three years of returns on a fund to estimate the three-factor model for every available fund. The estimated loadings on either the size or book-to-market factor are ranked and scaled to fall between zero (for the lowest-ranked fund) and one (for the highest-ranked fund). A high rank for a fund indicates that it is relatively more extreme in its orientation toward large stocks or toward value stocks. Style consistency is measured by the correlation between a fund's past style rank, measured at year end, and its future style rank, measured at the end of the third subsequent year. We choose a three-year gap so that the factor loadings can be estimated over nonoverlapping periods. We also calculate the mean absolute difference between the two periods' style ranks. Table 3 provides the results, based on the pooled sample of fund-year observations.

There appears to be some overall consistency in funds' styles over time. For all funds, the correlations between current and future loadings are about 70%. However, the average absolute differences in style ranks are fairly substantial. Based on the entire fund sample, for example, the mean absolute deviation in style ranks for book-to-market is 0.16. Additionally, there are numerous cases of large shifts in style: for example, the 75th percentile of the distribution of absolute deviations in book-to-market style ranks is 0.23.

The remaining rows in each panel of Table 3 correlate past and future styles for large capitalization and small capitalization funds; and for value and

Table 3
Correlations and average absolute differences between past fund style and future fund style

	Future style for	
	Size	Book-to-market
All funds	0.73	0.71
	(0.15)	(0.16)
Large cap funds	0.79	0.71
	(0.15)	(0.14)
Small cap funds	0.88	0.71
	(0.11)	(0.18)
Value funds	0.73	0.77
	(0.16)	(0.16)
Growth funds	0.74	0.83
	(0.16)	(0.14)

At the end of each year from 1984 to 1994 each fund's past style is compared to its future style. A fund's past style is measured from its monthly returns over the most recent prior three-year period, and its future style is measured from monthly returns over the subsequent three-year period. A fund's style with respect to size and with respect to book-to-market is its loadings on size and book-to-market factors, respectively, from a three-factor model regression: $r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \epsilon_{pt}$. r_{pt} is the return in month t for fund p, r_{ft} is the return on a one-month Treasury bill, r_{mt} is the return on the value-weighted portfolio of stocks listed on both the CRSP and COMPUSTAT databases, and SMB_t and HML_t are the returns on zero-investment factor-mimicking portfolios for size and book-to-market, respectively. Style measures (past or future) for all funds are ranked each year and rescaled from zero (the lowest-ranked fund) to one (the highest-ranked fund). The table reports the simple correlation between past and future style ranks pooled over funds and over years. Also reported in parentheses is the average absolute difference between the past and future style ranks. Statistics are reported for all funds, large capitalization funds (funds in the top 30% when sorted each year by style rank on size), small capitalization funds (funds in the bottom 30% when sorted by size style rank), value funds (funds falling in the top 30% when sorted each year by style rank on book-to-market), and growth funds (funds ranked in the bottom 30% when sorted by style rank on book-to-market).

growth funds. There is more consistency within each of these style classes than for the sample as a whole, suggesting that the dimensions we use are informative about funds' investment approaches. For example, the correlation between past and future styles with respect to size is 0.88 for small cap funds, compared to 0.73 for the overall sample.

2. Mutual Fund Portfolio Characteristics

Taking at face value the evidence on return anomalies, an outside observer might expect to find that mutual funds should aggressively pursue certain investment strategies that have been documented to produce superior returns in the past. An alternative hypothesis is that managers face high personal career risks for adopting these styles. Instead, they choose portfolios that do not deviate markedly from market benchmarks [Lakonishok, Shleifer, and Vishny (1997) refer to such behavior as "bunching at the center"].

Related evidence on such behavior comes from the pension fund industry. In the case of defined-benefit pension plans, for instance, Lakonishok, Shleifer, and Vishny (1992) point out that many parties influence the process of investing pension assets, including corporate managers, treasurers, external consultants, and money managers. Given the multiplicity of such interests, an agency problem arises. One result is that external investment managers are evaluated not only in terms of investment performance but also along dimensions such as prudence, which in practice is influenced by what other managers are doing. Accordingly, a manager's holdings, in addition to the return on the portfolio, are scrutinized. For example, Lakonishok, Shleifer, and Vishny (1994) speculate that money managers' concerns about their careers lead them to tilt toward investing in growth stocks.[12]

Based on the evidence for pension fund managers, one conjecture is that similar nonperformance considerations affect mutual fund managers' choice of investment styles. Mechanically extrapolating the argument about nonperformance distortions within the pension fund industry to mutual funds would not be appropriate, however. Unlike a pension fund, there are typically fewer intermediaries between investors and mutual fund managers. On this account mutual fund managers should be able to concentrate more on maximizing return for a given level of risk. However, other influences may also come into play. Managers' personal career concerns, together with the relatively short horizons over which they are evaluated, may induce them to play it safe and not deviate substantially from popular benchmarks (such as the S&P 500). Furthermore, several mutual fund companies also manage segregated

[12] The agency problem in pension fund management shows up in other forms as well. For example, Lakonishok et al. (1991) find evidence that managers tend to rebalance their portfolios at year end away from poorly performing (and hence potentially embarrassing) stocks toward larger, more successful firms (which are easier to justify to plan sponsors). Similarly, the pressures of relative performance benchmarking may create an incentive for institutions to herd (buy or sell the same stocks at the same time), as studied by Lakonishok, Shleifer, and Vishny (1992).

accounts for pension plans. There may be room for nonperformance distortions because some investors are slow to move away from poorly performing funds because of search costs [see, for example, Sirri and Tufano (1998)], or cognitive biases [Goetzmann and Peles (1997)]. The importance of such distortions in the mutual fund industry is thus an empirical issue.

2.1 Methodology

Table 4 paints a portrait of fund styles along the dimensions of size (panel A), book-to-market (panel B), and past returns (panels C and D). As a basis of comparison we use the S&P 500. Though other benchmarks have begun

Table 4
Portfolio characteristics for mutual funds

Panel A: Distribution (in percent) of fund net assets, by firm size

		Firm size category									
Sample	Portfolio average	1 (small)	2	3	4	5	6	7	8	9	10 (large)
S&P 500	0.98	0.66	1.53	2.40	3.26	4.49	5.76	7.56	10.62	16.70	47.01
Funds	0.94	10.71	6.59	6.80	10.60	9.53	12.46	13.90	24.81	4.27	0.32
% of funds		26.12	9.73	8.10	8.62	9.85	11.03	11.93	10.91	3.17	0.54

Panel B: Distribution (in percent) of fund net assets, by book-to-market

		Book-to-market category									
Sample	Portfolio average	1 (growth)	2	3	4	5	6	7	8	9	10 (value)
S&P 500	0.38	17.71	14.52	11.54	10.24	10.75	10.50	8.06	6.35	6.10	4.22
Funds	0.35	3.19	11.65	14.39	25.63	27.31	11.33	4.64	1.41	0.44	0.02
% of funds		4.48	13.38	18.72	22.38	19.32	11.89	6.65	2.07	1.06	0.05

Panel C: Distribution (in percent) of fund net assets, by past three-year return

		Past return category									
Sample	Portfolio average	1 (loser)	2	3	4	5	6	7	8	9	10 (winner)
S&P 500	0.63	4.09	6.63	7.75	8.33	9.90	11.17	12.85	13.91	13.39	11.96
Funds	0.63	0.00	0.03	0.55	2.75	15.37	28.30	28.78	14.61	9.05	0.56
% of funds		0.02	0.34	1.60	4.80	13.58	25.63	28.42	18.52	6.52	0.57

Panel D: Distribution (in percent) of fund net assets, by past one-year return

		Past return category									
Sample	Portfolio average	1 (loser)	2	3	4	5	6	7	8	9	10 (winner)
S&P 500	0.60	4.32	6.50	7.57	8.71	12.59	12.50	11.43	12.62	11.70	12.05
Funds	0.62	0.00	0.04	0.33	2.19	12.39	35.40	26.04	14.68	6.60	2.33
% of funds		0.03	0.28	0.88	4.06	14.91	29.00	24.37	15.78	7.48	3.22

The sample period is January 1984 to December 1997. At every calendar year end for each fund, weighted average characteristics (expressed as percentile rankings) are calculated across all stocks held in the fund's portfolio. The calculations are based on the fund's most recently reported holdings as of the year end. The characteristics are size (equity market capitalization), book-to-market value of equity, past three-year stock return beginning four years and ending one year ago, and the most recent past one-year stock return. Based on its portfolio characteristic a fund is assigned to one of 10 groups determined by the decile breakpoints of all domestic stocks in the S&P Composite Index. Total market value is calculated across all stocks in the index belonging to the decile and expressed relative to the total value of stocks in the index. Total fund net assets is also calculated across all funds assigned to the decile and expressed relative to the total net assets of all funds. The percentage of fund observations in each decile is also calculated. To compute the overall average characteristic of the index and the aggregate fund portfolio, all domestic equity stocks are ranked by the relevant characteristic and assigned a score from zero (lowest) to one (highest). The portfolio average for the index is the capitalization-weighted average of these ranks across all stocks in the index; the average for the fund portfolio is the weighted average across stocks in the aggregated portfolio of all funds, with weights given by the value of all funds' holdings of the stock. All the reported statistics are weighted averages over all year ends, where the weights are the number of funds reporting holdings in that year.

to be widely accepted by investors, the S&P 500 index has been the most popularly used reference portfolio through much of our sample period. To give a robust perspective, we follow two approaches in measuring fund style. First we look at the characteristics of fund portfolios, and in the subsequent section we look at funds' loadings on the Fama-French factors.

The details underlying the calculations in Table 4 are as follows. At the end of each calendar year all available domestic stocks are ranked by the relevant characteristic (for example, size) and given a percentile ranking from zero (for the lowest-ranked firm) to one (for the highest-ranked firm).[13] Given the holdings of a portfolio, we can calculate the weighted average of the percentile rankings over all stocks in the portfolio. A stock's weight is the percent of the portfolio's value invested in the stock.

This procedure can be applied to any portfolio. We first compare two portfolios: the fund sample in the aggregate, where we pool the equity holdings of all funds into a "superfund," and the S&P 500 index.[14] This comparison tells us whether funds as a whole are more or less aggressive with respect to size or book-to-market relative to the index.

We also want to make comparisons across funds, so in our second exercise we take the unit of analysis to be an individual fund. For each fund portfolio we compute its weighted average characteristic as described. To see whether the fund has a more or less aggressive style, we compare it to a benchmark distribution given by the stocks in the S&P 500 index. That is, we use the size (or book-to-market) ranks of the stocks in the S&P 500 to determine decile breakpoints at each year end. Comparing each fund's weighted average characteristic to these breakpoints lets us place each fund into a decile. We look at the percentage of funds in each decile as one measure of where funds are concentrated. In addition we look at the distribution of funds by market value of their equity holdings. Specifically, for the benchmark the combined capitalization of all S&P 500 stocks in each decile is calculated and expressed relative to the total capitalization of the index. The ratio represents the relative magnitude of the asset pool available in the benchmark for investors who wish to select from a particular category of size or book-to-market. Similarly, for all funds falling in a particular decile we calculate the total value of their equity holdings and express this as a fraction of total fund net assets. This fraction tells us the concentration (in terms of dollars invested) of funds in a decile. Finally, the distributions for the index and for funds are averaged across time.[15] As an illustration, decile 10 for the S&P 500 in Panel A of Table 4 contains the largest 10% (or 50 stocks) in the index, and these issues on average account for 47.01% of the value of the index.

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[13] Our use of percentile rankings makes it more meaningful to compute averages over time when the entire distribution of characteristics (such as market value) has undergone considerable shifts.

[14] We use the most recently reported holdings as of the year end for each of the underlying mutual funds.

[15] When we average the distributions of funds, we weight each annual observation by the number of funds in the sample that year.

2.2 Size

The mutual fund sample in the aggregate tends to hold smaller firms than those in the S&P 500 index (panel A). The weighted-average size characteristic for the index is 0.98, and the weighted-average size for the fund sample (the superfund) is 0.94. The difference is perhaps not surprising, because the funds cannot all be concentrated in the same set of large S&P stocks and because there are many firms who are much smaller than those in the index.[16]

There are many funds concentrating in smaller stocks compared to the S&P 500. About 26% of the funds, for example, have a weighted-average size rank that places them in the bottom decile. However, these small capitalization funds do not amount to a large percentage of total fund holdings (for example, the funds in the bottom decile represent only 11% of total fund holdings). Arguably, the market for the smaller stocks may be less informationally efficient. In this category, then, fund managers may be operating under the belief that they can distinguish themselves by exploiting opportunities in small cap stocks.

2.3 Book-to-market

The superfund, which has a weighted average book-to-market rank of 0.35 (panel B), is more oriented toward growth stocks than the S&P 500, which has a rank of 0.38 on book-to-market.[17] Nonetheless, funds tend to be heavily clustered around the index. The S&P 500's weighted average book-to-market rank puts it in the fourth decile. If we look at this and the adjacent two deciles, we find that 60% of the funds, representing 67% of fund holdings, have average book-to-market ranks falling in the third to fifth deciles.

Conversely, very few funds have average book-to-market ratios that are relatively extreme. Given the extensive evidence on book-to-market effects on returns, for instance, it might be expected that there would be more concentration of funds in stocks with high book-to-market ratios. There is little evidence of this, however. For example, the top three deciles in Panel B represent about 17% of the capitalization of the S&P 500. However, only 3.2% of the funds have average book-to-market ranks that put them in these deciles. Moreover, these funds are relatively small, accounting for only 1.9% of holdings. At the other tail of the distribution, the bottom decile makes up roughly the same percentage (about 18%) of the capitalization of the index as the top three deciles. Here, however, funds appear to have a larger appetite for growth stocks with relatively low book-to-market ratios. The book-to-market ratios of about 4.5% of the funds fall in the lowest decile, representing about

[16] If anything, the comparison with respect to size understates the difference in dollar magnitudes because we use percentile rankings. For instance, at year end 1997 the weighted average size for the S&P 500 is about $47 billion, whereas the weighted average size for the mutual fund sample is roughly half as large ($26 billion).

[17] In the calculations all stocks with negative book values are excluded.

3.2% of total holdings. Put another way, the holdings of the funds that are relatively more growth-oriented are almost twice the holdings of the value-oriented funds, even though the underlying investable pools in the index have virtually the same amounts.

2.4 Past stock return

A close cousin of the investment strategy based on book-to-market is a strategy based on long-horizon past returns [see, for example, DeBondt and Thaler (1985), Chopra, Lakonishok, and Ritter (1992)]. Hence, another characteristic that funds may be taking into account when selecting their portfolios is a stock's past rate of return. Panel C of Table 4 reports the distribution of funds classified by past three-year returns. Specifically the characteristic under consideration is the weighted average (across all of a fund's holdings) of the return beginning four years and ending one year ago.

In panel C the superfund and the S&P 500 index have the same weighted average rank on past three-year return (0.63). The index is periodically revised, however, and stocks that have done well are more likely to be introduced. Accordingly, the fact that the two portfolios share the same rank is more impressive than it may seem at first, given that there are delays in turning over fund portfolios.

When we compare funds' willingness to take relatively extreme bets, the results for past losers (with low past returns) parallel those for deep-value stocks. The bottom four deciles contain roughly 27% of the value of the index. However, funds falling into these deciles account for only 3% of fund holdings. In short, there are few takers for strategies based on either deep-value or long-term reversals.

Strategies that focus on deep-value stocks and past losers both tend to select stocks that are out of favor with the market. In other words, a fund manager would be hard-pressed to provide a persuasive conventional rationale to investors to justify these holdings. The evidence in Table 4 is consistent with the conjecture that fund managers shun strategies based on such apparently unattractive stocks, possibly due to personal career risks. Furthermore, studies in psychology suggest that individuals tend to extrapolate past patterns too far into the future. Hence, fund managers may be assuming that the poor past performance of deep-value stocks and past losers will persist and avoid such securities.

From this perspective, stocks that have performed well in the past should be easier to justify and hence relatively more attractive to fund managers. Panel C confirms a sharp disparity between funds' appetites for long-term past losers and past winners. The top two deciles are comparable to the bottom four deciles in terms of percentages of the value of the index (the top two deciles represent about 25%). This end of the distribution is more popular with funds. Funds placed in these two deciles hold about 10% of total fund equity investments.

Intriguingly, there is one set of past winners where the evidence on profitability and the availability of an attractive story happily coincide. Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) find price continuations over intermediate horizons. Panel D provides results based on the weighted average of the past year's return on a fund's holdings. In the aggregate funds are more tilted toward past winners than the index. The weighted average rank for the superfund is 0.62 compared to 0.60 for the index. Further, quite a few funds position themselves in the upper deciles of the distribution. About 11% of funds fall in the top two deciles, and they make up roughly 9% of total fund holdings. Grinblatt, Titman, and Wermers (1995) find that funds tend to follow momentum strategies. Our suggestion here is that the attractiveness of this strategy dovetails neatly with behavioral or agency considerations as well.

2.5 Interpretation

To sum up, funds' styles generally do not deviate notably from a widely followed benchmark, such as the S&P 500. Although there are many small capitalization funds, the bulk of fund assets is invested in the largest stocks. Though funds generally tend not to take extreme bets (relative to the S&P 500 benchmark) in terms of either book-to-market ratios or past return, they have a tendency to favor glamour stocks and past winners. Put another way, funds seemed to be averse to strategies involving deep value stocks or long-term past losers. Viewed in this light, it may not be a complete surprise that historically few mutual funds consistently outperformed market benchmarks.

Similar findings have been made about the investment styles of pension fund managers [Lakonishok, Shleifer, and Vishny (1997)]. In the pension fund industry, multiple intermediary parties are involved in investment decision making. Accordingly, there is more scope for money managers to follow their own self-interests, with adverse consequences for portfolio performance. The key finding in this section is that although intermediaries play a smaller role in the mutual fund industry, the evidence for nonperformance distortions persists.

Several reasons may explain why both pension fund and mutual fund managers have some preference for glamour stocks and past winners.[18] Because glamour stocks generally have a record of good past returns, a tilt toward glamour may appear to be safe from the standpoint of personal career risk. Extrapolative biases may also lead managers to favor stocks with strong past performance. To the extent that funds tend to herd, possibly as a result of the focus on relative performance, selecting stocks that have done well in the

[18] It should be noted that some mutual fund managers also provide money management services to pension plans. To avoid complaints from clients, a manager generally seeks to avoid large dispersion across the performance of the different accounts. In many cases this might mean that the same stocks are selected for different clients' portfolios. As a result the nonperformance considerations apparent in the pension plan accounts may spill over to the mutual fund accounts.

past would also represent a prudent choice. Fund managers' decisions may be swayed by analyst recommendations. Research reports from brokerage firms are widely disseminated, and there is some evidence that analysts are more likely to favor glamour stocks and past winners [Stickel (1997)]. Additionally, the fact that analysts recommend such stocks may provide a convenient rationalization for a manager to tilt toward these stocks. Another possibility is the perception that value strategies take a long time to become profitable, whereas glamour stocks and past winners at least have price momentum working in their favor over the intermediate term. Finally, there may be an element of hubris in fund managers' disposition toward glamour stocks. Insofar as a relatively larger component of the valuations of growth stocks is tied to intangible future prospects, there may be more room for superior analysis to detect and take advantage of such opportunities.

Another explanation for funds' tendency to bunch at the center is that fund managers follow strategies that cannot be easily summarized by a single characteristic, such as book-to-market or past stock return. Instead they may focus on many other security characteristics so that the end result is a portfolio that does not deviate too much from a diversified benchmark index. It is also possible that managers realize that superior long-term performance is unachievable in an efficient market, and hence many are closet indexers. Finally, in the earlier part of the sample period, fund managers may not have been aware of the existence of strategies based on deep value or overreaction, and they may have been slow in adjusting their approaches.

3. Mutual Fund Factor Exposures

Table 5 provides another perspective on the distribution of fund styles from the standpoint of the three-factor model

$$r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \epsilon_{pt} \qquad (2)$$

based on monthly returns. Here r_{mt} is the return on the value-weighted portfolio of stocks that appear on both the CRSP and Compustat databases, and SMB_t and HML_t are the returns on zero-investment factor-mimicking portfolios for size and book-to-market.[19] In our context, the estimates of β_{2p} and β_{3p} serve as measures of fund p's orientation toward firm size and book-to-market. A positive (negative) β_{2p} coefficient would mean the fund is oriented toward small (large) stocks. Similarly, a positive (negative) coefficient β_{3p} indicates that the fund has a tilt toward value (growth) stocks.

Panel A of the table gives the distribution of funds' factor loadings. At each calendar year end, we estimate the three-factor model for all funds with

[19] We thank Gene Fama for supplying the data on returns for the market and the factor-mimicking portfolios.

Table 5
Distribution of estimated factor loadings for mutual funds

Panel A: Distribution of factor loadings for mutual funds

Loading on:	1 (low)	2	3	4	5	6	7	8	9	10 (high)
Market	0.510	0.714	0.798	0.860	0.909	0.949	0.987	1.031	1.092	1.240
Size	−0.263	−0.140	−0.062	0.008	0.081	0.173	0.293	0.440	0.624	0.935
Book-to-market	−0.706	−0.412	−0.267	−0.155	−0.065	0.004	0.071	0.143	0.232	0.406

Panel B: Distribution of factor loadings for benchmark indexes

Loading on:	R1G	R1V	R2G	R2V	S&P 500
Market	0.985	1.031	1.095	0.966	1.001
Size	−0.164	−0.103	0.989	0.837	−0.215
Book-to-market	−0.405	0.374	−0.316	0.336	−0.014

At the end of each year from 1978 to 1997 the following model is estimated for every fund with a complete history of monthly returns over the prior three years: $r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \epsilon_{pt}$. r_{pt} is the return in month t for fund p, r_{ft} is the return on a one-month Treasury bill, r_{mt} is the return on the value-weighted portfolio of stocks listed on both the CRSP and COMPUSTAT databases, and SMB_t and HML_t are the returns on zero-investment factor-mimicking portfolios for size and book-to-market, respectively. Funds are assigned to decile portfolios based on the estimated coefficients from the model and the equally weighted average coefficient across funds within a decile is calculated. The numbers reported in panel A are the weighted averages across years, where the weights are the number of fund observations available in that year. The factor model regression is also applied each year to several market benchmarks; averages over the sample period of the loadings for the benchmarks are reported in panel B. The benchmark portfolios are the Russell 1000 Growth Index (R1G), the Russell 1000 Value Index (R1V), the Russell 2000 Growth Index (R2G), the Russell 2000 Value Index (R2V), and the S&P 500.

a complete history of returns over the prior three years. Based on the estimated coefficients, funds are then assigned to deciles. Within each decile we calculate the equally weighted average of the coefficient estimates; the reported values are the weighted averages over all years of the coefficients (each year's weight is the relative number of funds in the sample that year).

As a basis of comparison, panel B of the table reports estimates of the three-factor model applied to popular market style indices including the Russell 1000 Growth Index (denoted R1G), the Russell 1000 Value Index (R1V), the Russell 2000 Growth and Value Indexes (R2G and R2V, respectively), and the S&P 500 index. The Russell indices are the most commonly used style-based benchmarks for performance evaluation.[20]

The results for funds' style for size based on sensitivities generally agree with our earlier findings based on funds' holdings. In terms of the number of funds, a large fraction of fund portfolios loads more heavily on small stocks than does the S&P 500 index. The S&P 500 index has an average sensitivity to the size factor of −0.215. On average 94% of funds have sensitivities above this value. This finding is one reason why a typical fund finds it difficult to keep up with the S&P 500 when large stocks substantially outperform small stocks (as they did in 1998).

Funds' portfolio exposures are generally not heavily tilted toward either value or growth. To evaluate the extent of departures away from the market benchmarks, note that the bottom two deciles of funds have average *HML*

[20] Although historical returns are available for all these composites, data on the historical composition of the indices (required for calculating portfolio characteristics) is less readily available for the Russell indexes. Accordingly, the comparisons based on portfolio characteristics in the previous section use only the S&P 500 index. We defer a discussion of the relative merits of each approach to style identification to a later section.

loadings less than the sensitivity of the R1G (−0.405). At the other tail, the sensitivity of the Russell 1000 value benchmark is 0.374, and only the top decile of funds has an average *HML* sensitivity larger than this. As in panel B of Table 4, then, funds tend to cluster around the benchmark, and, insofar as they take extreme positions, they tilt toward growth rather than value.[21]

To sharpen the last point, note that the Russell value and growth indexes do not represent portfolios that are especially slanted toward extreme value or growth. Effectively half of the market capitalization of the Russell 1000 index is assigned to the value index and half to the growth index. In this sense, a fund does not have to take a very extreme position toward value or growth to appear more aggressive than the corresponding Russell indexes.

4. Fund Style and Fund Performance

The relation between a fund's style and its performance appears to have received little attention in prior research. One commonly voiced belief, at least among practitioners in the pension fund industry, is that growth-oriented managers are more likely to outperform their style benchmarks than are value-oriented managers.[22] This section explores whether there is any difference across styles with respect to performance.

Table 6 provides estimates of alphas and loadings for portfolios of equity funds that are sorted by size and book-to-market characteristics. Specifically, at the end of each year from 1984 to 1996 all funds are sorted by their value-weighted average size rank characteristic and assigned to one of three portfolios. The first group comprises funds ranked in the top 20% by their size characteristic; the second group includes funds ranked in the middle 60%; the third group includes funds ranked in the bottom 20% by size. Within each size classification we use the same procedure to sort funds by their value-weighted average book-to-market rank characteristic to one of three portfolios. The categories are chosen so that we can break out funds that take relatively extreme positions with respect to size and book-to-market. For each of the resulting nine portfolios, equally weighted returns are calculated over the subsequent 12 months, and the process is repeated. At the end of the sample period a three-factor model or a four-factor model including a momentum factor is applied to the complete history of returns on each portfolio.[23]

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[21] We also replicated our results using Sharpe's (1992) method of style identification. The general findings from this approach and from the three-factor model are similar.

[22] See, for example, Coggin and Trzcinka (1997), who look at pension funds. Davis (2001) also finds differences in favor of growth-oriented mutual funds based on alphas from the three-factor model.

[23] The momentum factor is measured as the difference between the return on the top and bottom quintile portfolio of stocks ranked by past one-year return. Equally weighted portfolios are formed at the end of each calendar year from all domestic common stocks listed on the New York and American Stock Exchanges.

Table 6
Mutual fund performance (percent per month) and loadings from three-factor and four-factor models, classified by investment style

		Rank on book-to-market		
Rank on size	Loading on:	1 (value)	2	3 (growth)
Panel A: Fund performance under three-factor model				
1 (Large cap)	Constant	0.000	−0.049	0.007
	Market	0.756*	0.851*	0.897*
	Size	−0.150*	−0.155*	−0.169*
	Book-to-market	0.118*	−0.027	−0.306*
2 (Mid cap)	Constant	−0.028	0.007	0.107
	Market	0.828*	0.894*	0.947*
	Size	0.047*	0.080*	0.245*
	Book-to-market	0.176*	−0.084*	−0.525*
3 (Small cap)	Constant	0.045	−0.005	0.347*
	Market	0.871*	1.012*	1.063*
	Size	0.618*	0.659*	0.799*
	Book-to-market	0.219*	−0.233*	−0.667*
Panel B: Fund performance under four-factor model				
1 (Large cap)	Constant	0.018	−0.051	−0.005
	Market	0.754*	0.851*	0.898*
	Size	−0.171*	−0.154*	−0.156
	Book-to-market	0.107*	−0.026	−0.298*
	Past return	−0.031	0.002	0.020
2 (Mid cap)	Constant	−0.024	−0.005	0.076
	Market	0.827*	0.895*	0.949*
	Size	0.042	0.094*	0.279*
	Book-to-market	0.173*	−0.076*	−0.506*
	Past return	−0.008	0.020*	0.051*
3 (Small cap)	Constant	0.061	−0.023	0.296*
	Market	0.870*	1.013*	1.067*
	Size	0.600*	0.679*	0.855*
	Book-to-market	0.210*	−0.222*	−0.636*
	Past return	−0.026	0.030	0.084*

At the end of each year from 1984 to 1996 all funds are sorted by the value-weighted average size rank from their portfolio holdings and assigned to one of three portfolios. The first portfolio comprises funds ranked in the top 20% by size ranks; the second portfolio includes funds ranked in the middle 60% by size ranks; the third portfolio includes funds ranked in the bottom 20% by size ranks. Within each size classification all funds are also sorted by the value-weighted average book-to-market ranks from their portfolio holdings and assigned to one of three portfolios. The first portfolio includes funds ranked in the top 20% by book-to-market ranks; the second portfolio includes funds ranked in the middle 60%; the third portfolio contains funds ranked in the bottom 20% by book-to-market ranks. For each of the resulting nine portfolios, equally weighted returns are calculated over the subsequent 12 months. This table reports estimated factor loadings from a three-factor time series regression (panel A) or a four-factor time-series regression (panel B) applied to the complete history of returns of each portfolio. A * indicates that the estimated coefficient is at least two standard errors away from zero. Returns are expressed as percent per month. In panel A, the model is $r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \epsilon_{pt}$, using monthly returns over the sample period. Here r_{pt} is the return in month t for portfolio p, r_{ft} is the return on a one-month Treasury bill, r_{mt} is the return on the value-weighted portfolio of stocks carried on both the CRSP and COMPUSTAT databases, and SMB_t and HML_t are the returns on zero-investment factor-mimicking portfolios for size and book-to-market. In panel B, the model is $r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}UMD_t + \epsilon_{pt}$, where UMD_t is the return on a zero-investment factor-mimicking portfolio for price momentum (return over the prior year).

Panel A provides some indication that growth managers do better than value managers on a style-adjusted basis. The difference between the alphas of the growth and value managers, for example, is positive in each of the three size categories, averaging 0.143% per month (or 1.7% per year). The differential is driven by the small cap funds, where it amounts to 0.302% per month. One explanation for the performance gap between the two groups is that growth funds buy stocks with good past performance and hence benefit

from momentum effects. On the other hand momentum effects work against value funds, who are generally invested in past losers.

Panel B confirms that growth and value funds' sensitivities to the momentum factor differ in the hypothesized direction. Adjusting for the momentum factor using a four-factor model benchmark reduces the annualized average difference in the alpha to 1.2% in panel B. Intriguingly, therefore, growth managers appear to generate stronger performance than value managers. Growth stocks may predominantly represent companies with few tangible assets and where expectations about the future are more important (such as science and technology stocks). In such cases growth fund managers perhaps add value through specialized knowledge, particularly for smaller stocks, which are less widely followed.

5. Shifts in Fund Style

Table 3 suggests that although funds are generally consistent in following a style, there can be notable shifts in a fund's style (as reflected in the average absolute differences between a fund's style rank over two periods). Drifts in style may arise because managers vary their style exposures in anticipation of high returns to a particular style, or because they gravitate to whichever style happens to be in favor. Additionally, shifts in fund style may reflect managers' career concerns arising from agency considerations. Funds that are performing poorly face the prospect of losing clients; hence, managers may come under pressure to try a different approach. For this reason, we also see whether a fund's past performance is associated with shifts in style.

5.1 Style timing

Henriksson and Merton (1981) suggest the following model, which allows for timing ability on each of the different factors:

$$\begin{aligned} r_{pt} - r_{ft} = {} & \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p} SMB_t + \beta_{3p} HML_t \\ & + \beta_{4p} \max(0, r_{mt} - r_{ft}) + \beta_{5p} \max(0, SMB_t) \\ & + \beta_{6p} \max(0, HML_t) + \epsilon_{pt}. \end{aligned} \tag{3}$$

Equation (3) assumes that funds select one of two values for their exposure to a style, depending on whether the style factor is expected to perform favorably or not. In the case of the market factor, for example, funds' market exposure is either β_{1p} during down-market months when the return on the market falls below the Treasury bill return, or $\beta_{1p} + \beta_{4p}$ in up-market months when the return on the market exceeds the Treasury bill return. Part 1 of Table 7 provides estimates of Equation (3) for the equally weighted portfolio of mutual funds.

As in previous studies of market-timing by funds [Henriksson (1984), Connor and Korajczyk (1991), Ferson and Schadt (1996)], we find no evidence

Table 7
Style timing ability of mutual funds

Panel A: Factor loadings for all months

	Variable						
Constant	$r_m - r_f$	*SMB*	*HML*	$[r_m - r_f]_+$	$[SMB]_+$	$[HML]_+$	Adjusted R^2
0.060	0.840	0.182	−0.065	−0.011	0.011	0.004	0.974
(0.61)	(38.16)	(4.69)	(−1.30)	(−0.27)	(0.17)	(0.05)	

Panel B: Factor loadings for months sorted by *HML*

	Variable				
Months sorted by *HML*	Constant	$r_m - r_f$	*SMB*	*HML*	Adjusted R^2
1 (low)	−0.551	0.808	0.185	−0.296	0.972
	(−2.54)	(29.94)	(4.99)	(−3.47)	
2	0.027	0.856	0.099	0.060	0.947
	(0.15)	(24.79)	(1.90)	(0.26)	
3	0.378	0.843	0.241	−0.311	0.966
	(1.62)	(30.80)	(6.28)	(−1.23)	
4 (high)	0.076	0.833	0.197	−0.069	0.978
	(0.28)	(36.38)	(5.23)	(−0.88)	

Equally weighted returns are calculated across all mutual funds with available data in each month from 1983 to 1997. In panel A, the following time-series regression is estimated for the equally weighted fund portfolio using all months: $r_{pt} - r_{ft} = \alpha_p + \beta_{1p}[r_{mt} - r_{ft}] + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}[r_{mt} - r_{ft}]_+ + \beta_{5p}[SMB_t]_+ + \beta_{6p}[HML_t]_+ + \epsilon_{pt}$, where r_{pt} is the return in month t for fund p, r_{ft} is the return on a one-month Treasury bill, r_{mt} is the return on the value-weighted portfolio of stocks listed on both the CRSP and COMPUSTAT databases, and SMB_t and HML_t are the returns on zero-investment factor-mimicking portfolios for size and book-to-market, respectively. For variable x, the timing variable $[x_t]_+$ is defined to be $\max(0, x_t)$. In panel B of the table, monthly returns on the fund portfolio are sorted into four groups, based on the contemporaneous return on *HML*, the Fama-French book-to-market factor portfolio. Group 1 (group 4) comprises the 25% of months with the lowest (highest) returns on *HML*. A three-factor model, as in panel A but with the timing variables omitted, is fitted to fund returns using each of the four sets of returns. The average return on *HML* across months in group 1 (the 25% of months with the lowest return on *HML*) is −2.69%; in group 2 is −0.60%; in group 3 is 0.84%; in group 4 is 3.29%. t-statistics are reported in parentheses. Returns are measured as percent per month.

that the equally weighted fund portfolio is able to time the market factor. The estimated timing coefficient is actually negative (−0.011), although it is not reliably different from zero. Similarly, the timing coefficients for the size and book-to-market factors are both close to zero.

There is much interest in timing the value-growth factor, so in Part 2 of Table 7 we provide another test for funds' ability to time *HML*. If there is such ability, funds should raise their exposure to *HML* in months when the return to *HML* is high. Accordingly, in Part 2 of Table 7 we sort all months in the sample period into quartiles based on the return on *HML*. The observations in group 1, for instance, make up the 25% of months with the lowest values for *HML*, or when glamour stocks do best relative to value stocks. The three-factor model is then fitted to each set of monthly returns.[24]

We check for style timing by seeing if the fund portfolio's loading on *HML* increases across the four sets of monthly observations. With only one exception the coefficient on *HML* is negative, so the fund portfolio tends to covary with glamour stocks (in line with the results from Table 4). There does

[24] Splitting the sample period into subsets reduces the number of observations used to fit each regression. Furthermore, sorting months by *HML* tends to diminish the variability in *HML* within each subset. As a result, the loadings on the value factor in the subperiod regressions are generally measured imprecisely.

not appear to be any systematic pattern in the loading on *HML* across the four regressions.[25]

5.2 Style shifts and past performance

Although most funds may be consistent in following a particular style, there may be specific instances in which funds are more prone to switch styles. In particular, a fund manager with poor past performance may be more likely to cave in to pressures to drop a style that has apparently been unsuccessful and try something different. To test this conjecture, we sort funds into portfolios on the basis of a two-way within-group classification. The first sort is by a fund's past performance (the compound return on the fund over the past two years), and the second sort is by the fund's portfolio characteristic (either size or book-to-market). We then compare each group's current style with its future style measured in the subsequent year.

In the classification by past fund return, there are four groups: group 1 (winners) comprises the 20% of funds with the highest past return; group 2 comprises funds ranked in the eighth to sixth deciles by past fund return; group 3 comprises funds ranked in the fifth to third deciles; group 4 (losers) includes the 20% of funds with the lowest past return. The second sort by portfolio characteristic assigns a fund to one of three groups. Group 1 includes funds ranked in the top 30% on the relevant characteristic (either size or book-to-market); group 2 includes the intermediate 40% of the ranked funds; group 3 includes the funds ranked in the bottom 30% by the characteristic. For each of the resulting 12 portfolios, the simple average of the size or book-to-market characteristic across all component funds is calculated at the portfolio formation year end to give the portfolio's current style and at the end of the subsequent year to give its future style. Each fund's characteristic is based on its most recently reported holdings prior to the year-end. The average across all portfolio formation years (weighted by the number of fund observations in each year) is reported in Table 8, as well as the average across all funds in each portfolio of the absolute difference between past and future characteristics.

There are notable shifts with respect to book-to-market in panel B. The average absolute difference is 0.077 across all past winners and 0.1 across all past losers. Funds with poor returns are thus altering their styles, particularly with respect to book-to-market. From an investor's standpoint, the table suggests that a fund manager who has performed poorly is more prone to style drift, thereby upsetting the structure of the investor's overall portfolio.[26]

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[25] We obtain similar results on the absence of style timing ability from Treynor-Mazuy quadratic regression models. Additional results (not reported, for the sake of brevity) suggest that funds are unable to time the size factor.

[26] Lynch and Musto (2000) also find evidence that funds with poor past performance are more likely to switch styles.

Table 8
Shifts in mutual fund style, classified by prior fund performance

Rank on:		Past 2-year return	Past size rank	Future size rank	Mean absolute difference	Past book-to-market rank	Future book-to-market rank	Mean absolute difference
Past return	Size							
Panel A: Fund style with respect to size								
1 (winner)	1 (large cap)	34.38	0.730	0.708	0.065	0.581	0.596	0.073
	2 (mid cap)	35.94	0.411	0.412	0.065	0.553	0.572	0.081
	3 (small cap)	36.88	0.133	0.153	0.041	0.534	0.549	0.074
2	1	23.19	0.860	0.838	0.050	0.568	0.566	0.072
	2	23.21	0.567	0.566	0.074	0.553	0.558	0.095
	3	23.20	0.216	0.228	0.051	0.502	0.516	0.102
3	1	16.04	0.858	0.832	0.060	0.501	0.493	0.086
	2	15.92	0.566	0.581	0.089	0.522	0.508	0.091
	3	15.63	0.226	0.237	0.050	0.445	0.449	0.111
4 (loser)	1 (large cap)	6.99	0.755	0.734	0.091	0.415	0.386	0.103
	2 (mid cap)	5.36	0.369	0.384	0.078	0.379	0.362	0.102
	3 (small cap)	2.65	0.116	0.132	0.035	0.397	0.399	0.095
Panel B: Fund style with respect to book-to-market								
1 (winner)	1 (value)	35.16	0.400	0.397	0.050	0.830	0.821	0.060
	2 (medium)	34.80	0.469	0.468	0.057	0.548	0.556	0.079
	3 (growth)	37.52	0.405	0.407	0.066	0.277	0.331	0.092
2	1	23.14	0.566	0.567	0.053	0.820	0.781	0.075
	2	23.11	0.579	0.576	0.059	0.551	0.548	0.093
	3	23.38	0.504	0.495	0.068	0.245	0.306	0.101
3	1	15.69	0.565	0.572	0.071	0.765	0.705	0.094
	2	16.09	0.597	0.591	0.067	0.488	0.481	0.094
	3	15.76	0.490	0.494	0.067	0.215	0.265	0.098
4 (loser)	1 (value)	4.74	0.423	0.433	0.078	0.648	0.572	0.120
	2 (medium)	5.03	0.449	0.455	0.074	0.381	0.386	0.105
	3 (growth)	5.50	0.364	0.360	0.055	0.146	0.171	0.074

At the end of each year from 1984 to 1994 every fund with available data is assigned to 1 of 12 portfolios on the basis of a two-way within-group classification. Each portfolio's past style with respect to size or book-to-market is then compared with its future style. In panel A, a fund is assigned to a portfolio on the basis of its past two-year compound return and its value-weighted average firm size characteristic. In panel B, the classification is by past two-year compound return and the fund's value-weighted average book-to-market characteristic. In the classification by past return, there are four groups: Group 1 (winners) comprises the 20% of funds with the highest past return; group 2 comprises funds ranked in the eighth to sixth deciles by past fund return; group 3 comprises funds ranked in the fifth to third deciles of past return; group 4 (losers) includes the 20% of funds with the lowest past return. Within each of these four groups, funds are sorted by their value-weighted average characteristic (size or book-to-market) and assigned to one of three groups. Group 1 includes funds ranked in the top 30% on the relevant characteristic; group 2 includes the intermediate 40% of the ranked funds; group 3 includes the funds ranked in the bottom 30% by the characteristic. For each of the resulting 12 portfolios, the simple average of the size or book-to-market characteristic ranks across all member funds is calculated at the portfolio formation year end to give the portfolio's past style and at the end of the subsequent year to give its future style. Each fund's characteristic rank is based on its most recently reported holdings prior to the year end. The weighted average across all portfolio formation years is reported in the table, where the weights are the number of fund observations in each year. Also reported is the weighted average over years of the mean absolute differences between the past and future characteristic ranks across all funds within a portfolio.

The style shifts for poorly performing funds are driven by the behavior of value funds. The average absolute difference for style ranks with respect to book-to-market is 0.12 for value funds with poor past performance, compared to 0.06 for value funds with good past performance. Value strategies generally entail investing in stocks that are out of favor. When performance has been poor, the manager of a value fund may have even less stomach for holding "ugly" stocks that, unlike more glamorous issues, do not come with appealing stories to justify their holding.

6. Comparing Approaches to Style Measurement

The previous sections drew on two approaches to style analysis based on either portfolio characteristics or factor loadings. Each approach has its merits and drawbacks.

Because a fund's holdings provide a snapshot of its investments at a given date, the characteristics of its portfolio should yield an up-to-date indicator of its investment style. However, long time-series data on fund holdings are more difficult to obtain. When available, the holdings data are sampled relatively infrequently. Operationally, the need to match these data with information, such as the book value of equity or earnings, from COMPUSTAT introduces additional complexity.

The merit of the loadings-based approach is that it is grounded on the behavior of realized fund returns, which are more readily accessible. On the other hand, a long record of past returns is needed for the factor loadings to be estimated reliably. In this respect the return earned on the fund several years ago may say little about its current style.

In additional, unreported work we examine the correlations between style ranks based on either portfolio characteristics or return loadings. The two approaches generally give similar readings of a fund's investment style. For instance, the correlation between the characteristics-based style rank and loadings-based rank is 83% for size and 76% for book-to-market. On the other hand the correlations between current and future styles are generally higher under the characteristics-based approach. The correlations between current and future styles are about 70% when loadings are used (see Table 3) and about 80% when characteristics are used. Furthermore, the average absolute differences between current and future style ranks are generally smaller when portfolio characteristics are used. These findings suggest that fund styles may be measured more precisely using portfolio characteristics.

In specific cases, however, the two approaches can give very different readings. These instances are interesting because they provide a natural arena to stress-test the two approaches and evaluate their performance. Accordingly, we examine instances where the two approaches are most at odds with one another (for example, a fund is deeply value-oriented based on loadings but deeply growth-oriented based on portfolio characteristics). The evidence in the previous sections suggests that funds display less persistence with respect to book-to-market, so we focus on this style dimension.

At each year end in the sample period we break out those funds that display the largest positive or negative differences between their style ranks under the two approaches. Panel A of Table 9 examines funds that are classified as value under the characteristics-based approach but that are classified as growth under the loadings-based approach (so they receive high ranks on their portfolios' book-to-market ratios, but low ranks on their loadings on *HML*). Similarly panel B looks at misclassifications where the characteristics-based approach indicates a growth fund, whereas the loadings-based approach

Table 9
Return prediction errors (percent per month) from style classification models based on characteristics and based on loadings

		Characteristics-based approach			Loadings-based approach		
Months sorted by *HML*	Funds' actual return	Predicted return	Error	Absolute error	Predicted return	Error	Absolute error
Panel A: Funds classified as value-oriented based on characteristics but growth-oriented based on loadings							
1 (lowest)	6.571	6.213	0.358	1.394	7.564	−0.993	1.693
2	3.806	4.025	−0.219	1.396	4.720	−0.914	1.711
Average	5.189	5.119	0.070	1.395	6.142	−0.954	1.702
3	−4.157	−4.001	−0.156	1.614	−5.132	0.975	1.857
4 (highest)	−0.600	0.214	−0.814	1.345	−1.656	1.056	1.674
Average	−2.379	−1.894	−0.485	1.480	−3.394	1.016	1.766
Panel B: Funds classified as growth-oriented based on characteristics but value-oriented based on loadings							
1 (lowest)	6.624	7.219	−0.596	1.430	5.483	1.140	2.139
2	4.752	5.384	−0.633	1.304	4.013	0.739	1.140
Average	5.688	6.302	−0.615	1.367	4.748	0.940	1.640
3	−4.453	−4.878	0.425	1.359	−3.822	−0.631	1.731
4 (highest)	−3.534	−2.791	−0.743	1.620	−2.036	−1.498	2.421
Average	−3.994	−3.835	−0.159	1.490	−2.929	−1.065	2.076

At the end of each year from 1984 to 1995 two approaches are used to measure styles and to predict returns of mutual funds. Each fund's style with respect to book-to-market is measured using either the characteristics of its portfolio holdings (the characteristics approach) or its past returns (the loadings approach). Based on the differences between the style measures under the two approaches, two sets of funds are selected: the 10% of funds with the largest discrepancies in their style classifications such that they are classified as value-oriented based on characteristics but growth-oriented based on loadings (panel A), and the 10% of funds with the largest discrepancies such that they are classified as growth-oriented based on characteristics but value-oriented based on loadings (panel B). To be eligible for this analysis a fund must have at most 5% of its net assets held as cash. The two procedures for measuring fund style are as follows. The characteristics-based approach is based on the fund portfolio's weighted average size or book-to-market (where the weights are the proportion of fund net assets held in the stock). The portfolio characteristics are calculated at each calendar year end based on the most recent prior data on its holdings. The loadings-based approach is based on the estimated coefficients for the size and book-to-market factors from a three-factor model regression using the past three years of monthly fund returns. Under either procedure, the measures (portfolio characteristics or estimated loadings) for all funds are ranked at the evaluation year and rescaled from zero (the lowest-ranked fund) to one (the highest-ranked fund). Given a fund's style classification, future fund returns are predicted under each approach. Under the holdings-based approach, each stock in a fund's portfolio is matched with a portfolio of stocks having the same quintile rank on size and on book-to-market. The fund's predicted return is the value-weighted return on the matching portfolio given the component stocks' realized future returns. Under the returns-based approach, a fund's predicted return is based on the estimated loadings over the prior three-year period and the mimicking portfolios' realized future returns. Results of the predictions (averaged over all test years) are presented for the two months with the lowest return and for the two months with the highest return (out of the 24 months following the test year end) on *HML*, the mimicking portfolio for the book-to-market factor. Summary statistics are presented for the actual return on the funds (in percent per month) and, for each prediction model, the predicted return, error (actual minus predicted return) and absolute error. Returns and errors are measured as percent per month.

indicates a value fund. The characteristics-based approach uses funds' most recently reported portfolio holdings prior to the year end, and the loadings-based approach uses estimates from a three-factor model over the prior three-year period.

We then see which approach does a better job in predicting the subsequent returns on these two sets of funds. To magnify potential contrasts we examine forecasting performance in those months for which there is a large differential between the returns on value and growth stocks. Specifically, out of the following two years we pick out the two months with the highest realized returns and the two months with the lowest realized returns on *HML* (so we are looking at roughly the 10% most extreme observations in each tail of

the distribution).[27] The approach that gives the lower average forecast error would be the one that does a better job in describing mutual fund styles. Returns are predicted in our experiment as follows. In the characteristics-based approach, we match each stock in a fund's portfolio with an equally weighted portfolio of stocks falling in the same quintile of size and book-to-market. The predicted return for the stock is the future return realized on the matching portfolio.[28] In the loadings-based approach, the predicted return uses the fund's three-factor model loadings estimated over the prior three years and the realized future returns on the mimicking portfolios. Note that under either approach the relevant parameters (either characteristics or loadings) are measured over a period that is disjoint from the prediction period.

In Panel A the characteristics-based approach yields mean errors that are closer to zero. The realized average return is 5.19% in those subsequent two months where growth stocks do best relative to value stocks.[29] The fitted return under the characteristics-based approach is 5.12% with an average error of 0.07%. On the other hand the loadings-based approach yields a fitted return of 6.14% and the error averages −0.95%. Conversely, in those subsequent two months where value stocks do best relative to growth stocks, the funds' actual returns average −2.38%. Average errors are closer to zero under the characteristics-based approach (−0.49%) than under the loadings-based approach (1.02%).[30] The average absolute errors in panel A also tend to be lower under the characteristics-based approach (for example, 1.40% versus 1.70% in the two months with the lowest average *HML*).[31]

Panel B of the table also yields a favorable verdict for the characteristics-based approach.[32] Over the two months with the lowest values of *HML*, the average prediction error under the characteristics-based approach is −0.62%, which is closer to zero than the 0.94% error under the loadings-based

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[27] Because we focus on months with extreme returns, the behavior of the cash portion of funds' portfolios becomes important. Accordingly, we limit our sample of funds to those which are holding less than 5% of their portfolios in cash. Additionally, to mitigate the impact of the idiosyncratic component of fund returns, we only consider funds with at least 25 stocks in their portfolios.

[28] Stocks eligible for the matching portfolios comprise all domestic equities listed on the NYSE, AMEX, and Nasdaq markets. These are ranked independently by size and book-to-market each calendar year end and assigned to quintiles, where the quintile breakpoints use only NYSE issues.

[29] The average style rank on book-to-market for the sample of funds in panel A is 0.68 based on holding characteristics and 0.30 based on loadings.

[30] As other studies [see, for example, Chan, Karceski, and Lakonishok (1998)] have found, months with the largest outperformance of value stocks relative to glamour stocks are generally down-market months. As a result the fund returns for the two months with the highest values of *HML* are generally negative. As a further illustration of this point, the average return on the Russell 1000 Growth Index is −2.31% for these months, whereas the average return on the Russell 1000 Value Index is −0.24%.

[31] The noise component in monthly returns is large. Although this averages out across months when we work with mean errors, this will not be the case when we work with the absolute errors. This helps explain why the differences across the two approaches are smaller when we compare the average absolute errors.

[32] On average, the funds in this panel have an average style rank of 0.29 on book-to-market based on fund holdings, and an average style rank of 0.68 based on loadings.

approach. In the two months with the highest values of *HML*, the corresponding mean errors are −0.16% and −1.07%. In short, when the two approaches give conflicting readings on a fund's style, the approach based on characteristics more closely matches funds' subsequent actual performance.

7. Conclusion

Our analysis of mutual fund investment styles provides new evidence on two issues: What is the product offered by equity mutual funds, and are fund managers' style choices colored by nonperformance considerations? We use style dimensions that draw on prior empirical research on the sources of return covariation and that are standard practice in the investment management industry. In addition, we employ two procedures for style identification: One is based on the characteristics of fund portfolio holdings; the other is based on estimated loadings from factor models.

Size and book-to-market are useful descriptors of fund styles. In particular, a style model based on these factors (in addition to the market factor) does about as well as more complicated, high-dimensional models. There is generally consistency in funds' styles, further validating the use of size and book-to-market. Importantly, such consistency existed in the early part of the sample period before investment style analysis became popular, suggesting that size and book-to-market correspond to how fund managers structure their portfolios.

Most mutual funds adopt styles that bunch around an overall market index, with few funds taking extreme positions away from the index. When funds deviate from the index, they are more likely to favor growth over value and high past return over low past return. For example, only 10% of funds on average have larger exposures to the book-to-market factor than the Russell 1000 Value Index, even though the latter index does not represent an overly aggressive bet on value stocks. Roughly twice as many funds, on the other hand, are more aggressive on the growth dimension than the Russell 1000 Growth Index.

Evidently a fund manager who chooses to be bold finds it safer to err on the side of growth. Intriguingly, similar findings—bunching at the center and a tendency to favor glamour stocks—have been found for pension fund manager styles [see Lakonishok, Shleifer, and Vishny (1997)]. We conjecture that the glamour bias may be due at least in part to agency as well as behavioral considerations. Growth stocks generally have a favorable history of past returns and hence may appear to be safer choices as far as managers' personal career risks are concerned. The preference for growth stocks may also reflect a behavioral trait, such as fund managers' extrapolative bias. Herding pressures, arising for example from the practice of relative performance evaluation, would also motivate managers to select stocks that have done well in the past. Hubris may lead managers to think that they have superior abilities

to detect intangible growth opportunities, thereby predisposing them toward growth stocks.

Our findings have important implications for evaluating fund performance and also for controlling the risk of the investor's overall portfolio. In particular, our results on the distribution of fund styles suggest that the overall tilt toward glamour investing may be one reason why historically so few funds consistently beat a broad passive benchmark.

Comparing the style-adjusted performance of value and growth funds, there is some evidence that growth managers on average do better than value managers. After adjusting for the Fama-French factors and a momentum factor, growth managers outperform value managers by about 1.2% per year on average. This result is driven by small capitalization funds, where the difference in alphas is 2.82% per year under a four-factor model.

In the aggregate funds do not appear to be able to time movements in the style factors. Accordingly, from the standpoint of an investor's overall portfolio, drifts in style introduce variability that deserves monitoring. Style shifts are most apparent in the case of funds with poor past performance. This finding is consistent with agency or behavioral considerations in fund management. The manager of a poorly performing fund may face stronger pressures to try something different, or to follow the crowd and adopt whichever style has been more successful. Because value funds tend to hold stocks that are out of favor, managers of value funds with low past returns may be particularly susceptible to such pressures. There is some evidence that value funds that have done poorly are more prone to adjust their styles and become more growth-oriented. Managers of growth funds with poor past performance, on the other hand, tend to stick with their style.

The two approaches to style identification (portfolio characteristics and factor sensitivities) generally give similar readings of a fund's style. However when they give different indications of fund style, the approach based on characteristics on average gives more accurate predictions of future fund returns. Although the approach based on factor sensitivities is directly based on the behavior of fund returns, it requires a relatively long time-series (and hence may not provide a sufficiently timely measure) and is subject to measurement error.

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