The Right Answer to the Wrong Question: Identifying Superior Active Portfolio Management

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Practitioner's Digest

Few topics have generated more engaging discussions between academics and investment professionals than the debate over active versus passive portfolio management. Judgments about the value of active management have often centered on whether the average active manager is capable of producing net-of-fee returns that exceed expectations. It is our contention, however, that this is not the best way to frame the issue. Instead, we argue that a more useful question to ask is whether it is possible for investors to identify in advance those managers who are the most likely to generate superior risk-adjusted returns (i.e., alpha) in the future. We address this issue by using a style-classified sample of mutual funds to focus on ways in which investors can select active managers with the best chance of producing superior subsequent investment returns.

Our analysis contains three main findings. First, we calculate the empirical distributions of both historical and forecasted risk-adjusted performance measures for the fund sample. These alpha statistics indicate that while the median manager does not match return expectations on either a backward- or forward-looking basis, a considerable percentage of the managers do exceed that hurdle. Second, we present evidence revealing several tractable relationships between an observable set of fund characteristics and the fund's subsequent investment performance. Chief among these explanatory factors are a fund's past performance—which is consistent with the notion that superior performance tends to persist over time—and the level of its expense ratio. Finally, we show that by using a selection process that controls for these factors, among others, investors can significantly increase their probability of selecting an active manager whose future risk-adjusted returns will exceed expectations. We also demonstrate the considerable economic advantage enjoyed by an investor who employs this selection process.

This evidence strongly suggests that superior active managers do exist and that investors have a reasonable chance of finding them. Further, it also appears to be true that once they identify and select these superior managers, investors are rewarded for their efforts. This leads to two implications: (i) there is a place in an investor's portfolio for the properly chosen active manager; but that (ii) the investor who selects funds in a random manner will find passive indexing to be a better alternative. While identifying truly skillful portfolio management is hardly an exact science, investors can improve their chances greatly by recognizing that a fund's past risk-adjusted performance is more likely than not to repeat itself in the future.

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ABSTRACT

The debate over the value of active portfolio management has often centered on whether the average active manager is capable of producing returns that exceed expectations. We argue that a more useful way to frame this issue is to focus on identifying those managers who are the most likely to generate superior risk-adjusted returns (i.e., alpha) in the future. Using a style-classified sample of mutual funds, we document several tractable relationships between observable fund characteristics and its future alpha, most notably the tendency for performance to persist over time. While median managers produce positive risk-adjusted performance approximately 45% of the time, we document a selection process that improves an investor's probability of identifying a superior active manager to almost 60%. We conclude that there is a place in the investor's portfolio for the properly chosen active manager.

Few topics have generated more engaging discussions between investment professionals than the debate over active versus passive portfolio management. The case for active management—which can involve either the selection of individual securities or tactical adjustments to the asset classes in an investor's long-term strategic allocation—is typically rooted in the belief that it is possible to produce superior investment performance than could otherwise be obtained by simply matching market-wide trends. Conversely, the case for passive (or index) investing—buying and holding well-diversified collections of securities having the desired risk exposure—rests on the notion that active managers have not proven themselves capable of consistently outperforming the relevant benchmarks over time, particularly when transaction costs and management fees are taken into account.

There is substantial evidence to support both positions. Dating to the work of Sharpe (1966) and Jensen (1968), who find that active equity managers who produced superior performance in one period were equally likely to generate superior or inferior performance in the next, for many years the predominant academic view was that attempting to actively manage an investment portfolio was a value-decreasing proposition. Mirroring this finding has been the rapid development of the market for indexed investment products, such as index mutual funds and exchange-traded funds. More recently, however, academic research has begun to embrace the notion that active managers can add value to their investors. For instance, Brown and Goetzmann (1995) document that both superior and inferior fund performance tend to persist over consecutive one-year investment horizons. Further, several studies (e.g., Chen, Jegadeesh, and Wermers (2000), Baker, Litov, Wachter, and Wurgler (2005)) show that fund managers possess significant stock-picking skills that translate into higher abnormal returns. Beyond this, it appears that investors are quite willing to believe that active management is worthwhile, as evidenced by the rapid expansion of the mutual fund industry during the past two decades.[1]

In this study, we seek to extend this literature by focusing on ways in which investors can select active managers with the best chance of producing superior subsequent investment returns. Our underlying premise in this investigation is that the central issue defining the debate between active and passive management has not always been framed correctly. Specifically, rather than judging the quality of active management solely on the basis of such factors as how the "average" fund performs relative to its benchmark or where a given manager ranks relative to his or her peer group, it is our contention that investors are better served by concentrating their efforts on finding the subset of available managers who are consistently able to deliver superior risk-adjusted returns.

Using an exhaustive sample of equity mutual funds characterized by a variety of investment styles over the 1979-2003 period, we document several key findings. First, we calculate the empirical distributions of past and forecasted risk-adjusted performance measures (i.e., alphas) for the fund sample. These statistics indicate that while the median manager does not match return expectations on either a backward- or forward-looking basis, a considerable percentage of the managers do exceed that hurdle. Second, we present evidence indicating several tractable relationships between an observable set of fund characteristics and the fund's subsequent investment performance. Chief among these explanatory factors are a fund's past performance—which is consistent with the notion that superior performance tends to persist over time—and the level of its expense ratio. Finally, we show that by using a selection process that controls for these factors, among others, investors can significantly increase their probability of selecting an active manager whose future risk-adjusted returns will exceed expectations. We also demonstrate the extent of the economic advantage enjoyed by an investor who employs this selection process. We conclude that these findings provide investors with a more balanced impression of the relative merits of active portfolio management.

1. Asking the Right Question

Proponents of the passive approach to investing often cite two facts in support of the argument that active portfolio management is not a value-adding endeavor. The first is that the average fund manager is not capable of consistently producing a return in excess of that to a benchmark index, such as the Standard & Poor's 500, particularly after accounting for the costs of active management. As typified by the now classic discussion in Ellis (1975), this view holds that since professional asset managers fund managers appear to be unable to repeatedly beat the market, an active approach to money management is a "loser's game," the object of which is not to make good investment decisions but to avoid making bad ones. Ellis concluded that active investment managers should consider the following advice: "Don't do anything because when you try to do something, it is on average a mistake (p. 25)."[2]

A second argument that is often used to build the case against an active approach to portfolio management is that the typical (i.e., median) manager in a given peer group is not capable of producing superior investment returns. Representative of this perspective is Bogle (1998), who examines the risk-adjusted performance of mutual fund managers in the nine Morningstar investment style groups defined by market capitalization (large, mid, small) and relative valuation (value, blend, growth) characteristics. Using five years of return data ending in 1996 for a sample of 741 funds, he documents that in eight of the nine style categories—small-cap growth being the exception—the average active fund manager was not able to outperform the relevant style-specific benchmark on a risk-adjusted (i.e., average excess fund return divided by fund standard deviation) basis. Further, Bogle documents that this passive management advantage in risk-adjusted performance averaged almost 25% across the entire sample, a result he attributed directly to the cost of running an active management strategy. In the face of this inability of the median active manager to produce superior net-of-expense returns, Bogle concludes: "No matter what fund style investors seek, they should emphasize the low-cost funds and eschew the high-cost funds. And, for the best bet of all, they should consider indexing in the category…they seek…in their portfolios (p. 40)."[3]

Both of the preceding points provide investors with useful information as they consider how and where they should commit their investment capital. However, both can also be viewed as "straw man" arguments in the sense that they frame the active versus passive management debate by asking the wrong questions. That is, when judging the quality of active fund managers, the important questions are *not*: (i) does the average fund manager beat a given benchmark?; or (ii) does the median manager in a given peer group produce superior risk-adjusted performance? Ultimately, the problem inherent in each query is that it seeks to establish in very narrow terms that either active or passive management is uniformly "better" than the other. For most investors, making this judgment on the basis of the average fund's performance is too limiting inasmuch as both actively and passively managed funds may play a role in their portfolios depending on their needs and preferences. Rather, it is our belief that investors should ask themselves the following: Is it possible to identify in advance those active managers who offer a reasonable opportunity to produce superior risk-adjusted performance? In other words, are there some active managers that consistently outperform and, if so, can investors select those managers before the fact with some degree of success? Only when the answer to this question is unambiguously "no" can we conclude that passive forms of investing clearly dominate an active approach.

2. The Benefit of Active Management: Lessons from Prior Research

Whether or not active portfolio management produces superior risk-adjusted returns has received a considerable amount of attention in the academic literature. Generally, this research can be divided into two categories: *performance persistence* studies, which attempt to document the existence of managers whose portfolios generated sustained levels of "outperformance," and *manager attribute* studies, which attempt to establish that (at least some) active managers possess certain skills, talents, or characteristics that can lead to superior investment performance.

As noted before, the early performance persistence literature was not encouraging for professional investors.[4] Indeed, using newly developed statistical methods for calculating expected returns (e.g., reward-to-variability ratio, CAPM), both Sharpe (1966) and Jensen (1968) find little evidence to support the notion that, on average, managers could maintain superior investment performance in successive holding periods. They conclude that the capital markets were highly efficient and that good managers should "…concentrate on evaluating risk and providing diversification, spending little effort (and money) on the search for incorrectly priced securities (Sharpe, p. 138)."

However, Carlson (1970) notes that the benchmark used in estimating expected returns can make a difference; he shows that most of the funds in his sample outperformed the Dow Jones Industrial Average, but failed to match the Standard & Poor's 500 and NYSE Composite indexes. While also documenting the sensitivity of performance results to the benchmark employed, Malkiel (1995) argues that, after accounting for the survivorship bias problem in his fund sample, there was little evidence of persistent risk-adjusted performance during the decade of the 1980s.[5]

With some exceptions, more recent empirical research has cast active fund managers in a more favorable light. Grinblatt and Titman (1989) replicate Jensen's procedure using an extensive set of benchmark portfolios and find evidence of a slight persistence effect. In Grinblatt and Titman (1992), the authors extend their earlier analysis to a larger fund sample and find more persuasive evidence of persistence in successive five-year holding periods. Hendricks, Patel, and Zeckhauser (1993), using a survivorship bias-free sample, show a strong correlation between the funds that generated alphas from one twelve-month period to the next, a result they called the "hot hands" effect. Brown and Goetzmann (1995) investigate this effect in more detail and find a short-term pattern of persistence for both the best and worst (i.e., "icy hands") managers, but not for the average fund. Elton, Gruber, and Blake (1996) also reexamine the "hot hands" result of Hendricks, Patel, and Zeckhauser with a more expansive model for predicting expected returns. Once again, they find support for the notion that past risk-adjusted performance is predictive of future performance, particularly for those funds best able to control their expenses. Finally, Carhart (1997) also offers evidence of performance persistence using the Fama-French three-factor model to estimate alpha, but argues that most of that result could be explained by fund expenses and return momentum in the underlying holdings.[6]

A second branch of the literature attempting to justify the role active portfolio management focuses on various characteristics of the managers themselves. In a sense, these studies can be viewed as efforts to explain *why* fund performance might persist over time. One line of reasoning taken is that active managers possess superior investment prowess in the form of either security selection or market timing skills. For instance, Wermers (2000) examines the composition of a broad collection of funds and documented that these portfolios held stocks that outperformed the market by an average of 1.3% per year, a finding supported by Chen, Jegadeesh, and Wermers (2000) in their examination of fund purchases and sales. More recently, Baker, Litov, Wachter, and Wurgler (2005) and Kosowski, Timmerman, White, and Wermers (2005) also show that some active fund managers possess legitimate stock selection skills. Finally, Bollen and Busse (2001) find a significant number of fund managers who were able to profitably rebalance their portfolios in advance of general market movements.[7]

Related to this research on investment ability are several studies that focus on the specific characteristics that active managers possess. Alford, Jones, and Winkelmann (2003) demonstrate that managers who exhibit more investment discipline produce superior returns. Specifically, they show that active fund managers who do a better job of controlling their tracking errors outperform both passive portfolios and other active managers with less risk-budgeting prowess. Additionally, it appears that better-trained managers are also more likely, on average, to produce better performance. Chevalier and Ellison (1999) show that managers who attended more selective undergraduate colleges (i.e., those requiring higher SAT scores) generated substantially better returns than those managers trained at lower-SAT institutions. They also document that young managers have a slight tendency to outperform older managers on a risk-adjusted basis, but that there is no such advantage for those managers who have received an MBA degree. Shukla and Singh (1994) demonstrate that managers who have earned the Chartered Financial Analyst (CFA) designation also run funds that were riskier, better diversified, and outperformed those managed by non-CFA holders.

The clear conclusion that can be drawn from the preceding discussion is that active portfolio management can, in fact, add value over time. Thus, the relevant question once again becomes whether investors can identify in advance those managers who are the most likely to produce superior performance in the future. Hints of this sort of predictability exist in other studies, such as Grinblatt and Titman (1993) and Kahn and Rudd (1995), although the latter work also points out the need to account explicitly for a fund's investment style. Further, in their study of the linkage between fund risk and manager incentives, Brown, Harlow, and Starks (1996) show that active managers act as if they are participants in a style-specific "tournament," which in the present context suggests that the effort to predict superior performance might be similarly constrained. We explore the intersection of these topics in the next sections.

3. Identifying Superior Managers: An Empirical Analysis

3.1 Measuring Superior Performance

Over time, the incremental benefit (i.e., "value added") to an investor from selecting an active portfolio manager can be measured by the difference between the active portfolio's actual return (net of fees and expenses) and the return the portfolio *should* have produced given the capital commitment and level of risk involved. This return difference is typically called the portfolio's *alpha coefficient* and can be summarized more directly as:

$$\text{Alpha} = (\text{Actual Return}) - (\text{Expected Return}). \tag{1}$$

In practice, expected returns can be measured in three ways: (i) benchmark portfolio returns, (ii) peer group comparison returns, and (iii) return-generating (i.e., risk factor) models.[8] While each of these approaches has advantages and drawbacks, in this study we employ the three-factor return-generating model of Fama and French (1992, 1993) to estimate the expected returns to an actively managed portfolio.[9]

3.2 Data and Methodology

To examine the issues of fund performance persistence and the ability of investors to forecast superior managers in advance, we employed alpha coefficients (a_j) estimated from the following model:

$$ER_{jt} = a_j + b_{jM}ER_{Mt} + b_{jSMB}R_{SMBt} + b_{jHML}R_{HMLt} + e_{jt} \tag{2}$$

where ER_{jt} is the month t excess return to the j-th fund, ER_{Mt} is the month t excess return on the Russell 3000 value-weighted portfolio of NYSE, AMEX, and NASDAQ stocks, R_{SMBt} is the difference in month t returns between small cap and large cap (i.e. "small minus big") portfolios, and R_{HMLt} is the difference in month t returns between portfolios of stocks with high and low book-to-market (i.e., "high minus low") ratios.

Data for our analyses are survivorship-bias free monthly returns from the Center for Research in Security Prices (CRSP) database. We gathered the relevant information for all mutual funds that met the following screening criteria: (i) must be a diversified U.S. domestic equity fund, (ii) cannot be an index fund, (iii) requires at least 36 prior months of returns to be included in the analysis at any particular date, and (iv) assets under management must exceed $1 million.[10] In order to insure that enough funds and benchmarks were available in each investment style category, we limited the time frame of our analysis to the period from January 1979 to December 2003.

To place each active manager represented in the sample into the appropriate peer group, we sorted the fund universe using a 3 x 3 classification system similar to that popularized by Morningstar. That is, at the beginning of every sample year, each qualifying fund was placed into one of nine different investment style cells: large-cap value (LV), large-cap blend (LB), large-cap growth (LG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), small-cap value (SV), small-cap blend (SB), and small-cap growth (SG). Unfortunately, Morningstar has only been classifying mutual funds using these categories since 1992, which puts a severe limitation on the potential scope of the analysis. However, it is possible to use characteristic information about the individual portfolios to create an accurate mapping of each fund into its "optimal" style cell; see, for instance Schadler and Eakins (2001) and Ben Dor, Jagannathan, and Meier (2003). We accomplished this task by using relative rankings implied by the Fama-French SMB and HML factors from equation (2), which we estimated each January for all sample funds using the prior three years of returns.[11] The number of active managers mapped into each cell of the style grid—which also defines the size of the relevant peer groups—is shown in Table 1 for every year between 1979 and 2003. Notice that the listed values reflect the tremendous growth in the number of active investment products available to investors over the sample period, particularly starting in the latter half of the 1990s.

[Insert Table 1 About Here]

3.3 Historical Alpha Distributions: In-Sample Results

As an initial assessment of the ability of active managers to produce superior risk-adjusted returns, we calculated a time series of alphas for every fund in our sample using the three-factor return-generating model in equation (2). Specifically, in calculating these fund-specific historical alpha coefficients, we used the following multi-step procedure:

1. For every sample fund, we gathered monthly return data for as much of the period from January 1976 to December 2003 as was available, as well as monthly return data for each of the three risk factors (i.e., ER_M, R_{SMB}, and R_{HML});
2. Beginning in January 1979, on a given month t during the sample period we calculated the parameters (i.e., a_j, b_{jM}, b_{jSML}, b_{jHML}) of (2) for fund j using the prior 36 monthly returns (up to and including the return for month t);

3. The intercept (a_{jt}) estimated on month t approximates the j-th manager's level of value added over the previous three-year period. We label this fund-specific abnormal return as the month t "in-sample" past alpha (PALPHA), reflecting the fact that it was generated at the same time and using the same set of data as the expected returns themselves;[12]

4. For each fund j in the sample, a new PALPHA estimate was obtained for every month from January 1979 (or whenever thereafter a fund had a sufficient return history) through December 2003 by rolling the 36-month parameter estimation interval forward by one month. This creates for each sample fund a sequence of highly overlapping alpha estimates, each one based on only one month of data different than the last. (For instance, any fund with sufficient prior return data to begin the estimation process in January 1979 would have 300 alpha values (i.e., 12 months x 25 years), assuming it lasted to the end of the sample period);

5. To better assess the historical ability of the mutual funds in our sample to add value to their investors, for each fund j we calculated the arithmetic average of this sequence of monthly PALHPA values to create for every fund a *mean* past alpha coefficient. Repeating this average abnormal return calculation for every sample fund then generated an empirical distribution of historical fund performance statistics.

Table 2 lists these fund-specific mean PALPHA values occurring at various percentile breaks in a given distribution. Separate average PALPHA distributions are listed for both the entire fund sample and the style-specific peer groups; each distribution also indicates the percentage of positive alpha values.[13]

[Insert Table 2 About Here]

Several conclusions are consistent with the findings reported in Table 2. First, and foremost, it is quite apparent that the average active manager did not outperform expectations, further confirming Sharpe's (1991) contention in this regard. This result is best inferred from the data in the middle and last columns. In particular, the table indicates that mean monthly PALPHA value for the median manager was -0.17%. Further, all nine of the style groups produced negative average risk-adjusted returns, with values varying from -32 basis points per month (i.e., MB) to -1 basis point (i.e., SG). Additionally, the overall incidence of active funds producing positive alphas was barely one-third. Interestingly, the lone entry in the last row of the table shows that the Standard & Poor's 500 index itself had, on average, a slight positive level of outperformance (i.e., 0.04% per month) over the sample period compared to expectations generated by equation (2).

There are two important implications of the preceding results. First, they underscore the conventional wisdom that the average active manager failed to produce positive risk-adjusted returns, net of fees, over an extended period of time. This finding proves to be true regardless of the portfolio's investment objective, although there is substantial variation in the alpha distributions produced by the various style categories. On the other hand, it is also important to recognize that not all of the active managers in the sample produced returns that fell short of expectations during the sample period. In fact, a second point is that a substantial number of funds *did* produce positive alphas and that the proportion of superior performers varied widely by fund style (e.g., 33.97% for all portfolios, with a high of 48.86% for the small-cap growth style and a low of 24.74% for large-cap blend funds). Indeed, the rewards to the investor able to identify these managers were dramatic; the mean level of abnormal performance at the 95-th percentile in the overall sample was 79 basis points per month. In this regard, given that the mean monthly PALPHA at the 5-th percentile of the same distribution was -155 basis points, it is also worth noting that the data show the substantial benefit to investors who *avoided* the worst-performing managers.

3.4 Forecasted Alpha Distributions: Out-of-Sample Results

While the results just presented are instructive, the PALPHA statistics do not by themselves indicate whether it is possible for investors to identify in advance those active managers capable of producing superior *future* performance. To address this issue, we also created for each fund in the study an out-of-sample alpha forecast, which we call FALPHA. To be able to distinguish between past actual and future predicted abnormal performance, our fund-specific FALPHA values were estimated in the following manner:

1. As before, on a given month t, the past 36 months of fund and factor return data were used to estimate the risk parameters (b_{jm}, b_{jSMB}, b_{jHML}) for each active manager j using equation (2);
2. To estimate the j-th fund's predicted return over an n-month forecast period *subsequent* to month t, the returns for the risk factors (i.e., ER_{Mt+n}, R_{SMBt+n}, and R_{HMLt+n}) over this future period were used in conjunction with the month t estimated parameters to compute the expected excess return for fund j (i.e., ER_{jt+n}) according to (2);

3. The *future* alpha coefficient (FALHPA) for the j-th fund over the period from month t to month t + n was then calculated by differencing the fund's actual excess return over this period and its estimated expected excess return. In the analysis reported below, this out-of-sample forecasted alpha is measured using three different future n-month time horizons: one month, three months, and 12 months.

Thus, the difference between our estimation of an active manager's historical and forecasted value added is that, while both PALPHA and FALPHA use the fund's estimated risk parameters on a given month t, the former estimates abnormal performance simultaneously with the other return-generating model coefficients while the latter forecasts alpha using factor returns that fall outside the parameter estimation period. For every fund in our sample, the initial FALPHA forecast takes place in January 1979 (or whenever thereafter a fund had a sufficient return history) and new forecasts are then established by rolling the estimation interval forward by one period (i.e., month, quarter, or year) to recalculate a fund's risk parameters and subsequent expected excess return. Complete distributions of these out-of-sample alpha forecasts were generated by continuing this rolling prediction process for each active manager through the end of 2003.

The three panels in Table 3 show frequency distributions of the entire set of FALPHA values (i.e., not just fund-specific averages) for the one-month, one-quarter, and one-year forecasts, respectively. Using predictions obtained over the entire 1979-2003 estimation interval, each panel in the display lists the FALPHA value falling at various percentile rankings for: (i) the entire active manager sample, (ii) each of the nine style-specific active manager peer groups, and (iii) the Standard & Poor's 500 index, which may also be viewed as a portfolio whose performance can be evaluated by the three-factor expectations model in equation (2).

[Insert Table 3 About Here]

As with the in-sample alpha (i.e., PALPHA) distributions shown earlier, the alpha forecasts summarized in Table 3 once again confirm that the average active fund manager does not beat expectations, even on a forward-looking basis. For the overall sample, which pools funds across the investment style classes, the FALPHA values falling at the 50-th percentile of the monthly, quarterly, and annual distributions are -18, -49, and –219 basis points, respectively. Even more telling is that, with the single exception of the 12-month forecasts for MV, none of the median future alpha values are positive for any of the individual style peer groups or forecast periods. Typical of this pattern are the quarterly FALPHA forecasts in Panel B, which vary from -0.09% (MV) to -1.30% (SV). Further, while not surprising given the findings in Table 2, it is also the case that the S&P 500 benchmark outperforms the median active manager in each style category; in fact, when FALPHA is measured on a quarterly basis, the mid-point of the forecasted alpha distribution for the S&P index is actually positive.[14]

On the other hand, Table 3 also indicates that there are a lot of funds that *are* capable of adding value. Indeed, the main premise of this study is that investors have to ask the right question when judging the quality of active portfolio management and focusing on the performance of the median manager is the wrong approach to take. Instead, since an investor's goal should be to identify in advance those managers most likely to produce superior risk-adjusted performance, the results listed in the last column of each panel should be encouraging. Specifically, when viewed across all of the style groups and the entire sample period, the percentage of predicted alpha values that are positive range from 40.12% for annual FALPHA forecasts to 46.09% for monthly ones. Additionally, this statistic climbs to around 50% for certain fund peer groups (e.g., MV), although it also appears to be consistently lower for others (e.g., SB). Finally, the findings in Table 3 imply something of the benefit from identifying a superior active manager. Looking once again at the quarterly forecasts in Panel B, notice that the forecasted outperformance for the observation at the 75-th percentile (i.e., the bottom of the top quartile) of the overall sample exceeds 200 basis points, which is four times greater than the comparable value for the S&P 500 index.[15]

3.5 Persistent Fund Performance: Regression Analysis

The out-of-sample alpha distributions just considered suggest quite strongly that there are an appreciable number of active managers capable of producing positive future abnormal returns. Therefore, the logical next question is whether it is possible for investors to identify these superior managers before the fact. Our initial attempt to address this subject involved estimating several versions of the following regression equation:

$$\begin{aligned} FALPHA_{jt+n} = c_0 + c_1PALPHA_{jt} + c_2EXPR_{jt} + c_3ASSET_{jt} + c_4TURN_{jt} \\ c_5DIVERS_{jt} + c_6VOL_{jt} + e_{jt} \end{aligned} \tag{3}$$

The primary variables of interest in this specification are $PALPHA_{jt}$, which is the in-sample historical alpha measured for the j-th fund over the three-year period ending in month t, and $FALPHA_{jt+n}$, the out-of-sample alpha for the same fund forecasted one n-month period into the future. The degree of correlation between FALPHA and PALPHA, which is captured by the parameter c_1, provides a direct assessment of the extent to which risk-adjusted performance persists in our sample of active fund managers.

The remaining explanatory factors in equation (3) represent control variables for other influences that have been identified in the literature as having an impact on investment performance. Of particular importance is $EXPR_j$, the expense ratio of the j-th fund, which previous studies have shown to be a prominent effect separate from that of alpha persistence. The other control variables for the j-th fund's future performance include: assets under management ($ASSET_j$), portfolio turnover ($TURN_j$), the level of portfolio diversification ($DIVERS_j$), and the level of return volatility (VOL_j).[16] Values for each of these additional regressors were measured as average effects during the 36-month estimation period ending in month t.

To facilitate both time-series and cross-sectional pooling of observations, data for all variables were standardized within each style-specific peer group on a given date in a manner similar to that used in Brown, Harlow, and Starks (1996). This normalization process also permits a direct comparison of the size and statistical reliability of the various parameter estimates. The initial regressions were estimated using a cross-sectional procedure based on the methodology in Fama and MacBeth (1973). This involved three steps. First, for every fund in the sample on a given month, we estimate the three-factor model in (2) using the prior 36 months of data. Second, we calculate FALPHA for each fund over the subsequent one-, three-, and 12-month periods, once again standardizing the data within the relevant style tournament. These future abnormal returns then become the dependent variables in three separate cross-sectional regressions in which PALPHA and EXPR, along with the other controls, are the regressors. Finally, repeating the first two steps for a series of different months that are rolled forward on a periodic basis generates a time series of parameter estimates that summarize the various predictive relationships for future fund returns.

[Insert Table 4 About Here]

Table 4 lists the average values from the time series of these estimated coefficients for each of the alpha forecast periods. P-values, based on t-statistics computed from the means of those parameters, are also listed. Four different versions of the regression model were estimated for each FALPHA forecast period. Models 1 and 2 focus on the separate ability of PALPHA and EXPR, respectively, to predict the performance of an active manager's future investments. Models 3 and 4 then examine the combined influence that these explanatory factors exert, both without and with the remaining control variables.

In general, the findings in Table 4 suggest the existence of some extremely strong fundamental relationships among the individual variables despite an overall low level of future alpha predictability. It also appears that the regression-wide prediction power, as indicated by the coefficients of determination reported in next-to-last column of each panel, does not change greatly as the alpha forecast period increases from one month in the future to one year. The listed findings are useful for what they indicate to investors about the direction and strength of the various interactions between the observable characteristics of a fund and the risk-adjusted returns it subsequently produces.

In particular, notice that all three versions of the most basic relationship between past and future alpha (i.e., Model 1) produce positive coefficients—0.049 for one-month returns, 0.058 for three-month returns, and 0.058 for twelve-month returns—the first two of which are highly statistically significant. This implies a strong degree of performance persistence in the active fund sample for forecast periods as long as one year in the future. Similarly, the basic regressions between FALPHA and EXPR generate significantly negative parameters (i.e., -0.012, -0.021, -0.046, respectively), which is consistent with those studies cited previously finding that lower-expense funds typically provide higher risk-adjusted returns, all other things being equal. However, both the relative magnitudes of the parameters for Models 1 and 2 and their respective coefficients of determination also indicate that PALPHA is 2-4 times more important as an explanatory variable than EXPR. This relative assessment is confirmed by the regression specification that places the two regressors together; that is, the monthly and quarterly versions of Model 3 show that, when combined, the strength of PALPHA remains stable while that of EXPR is substantially reduced.

The inclusion of the other control variables does not appear to diminish the alpha persistence effect, nor does it appear to further affect the influence that fund expenses exert on future performance. On the other hand, when viewed collectively, these additional explanatory factors do appear to lead to measurable increases in the forecasting ability of the overall regression model. For instance, for all three definitions of the dependent variable, the explanatory power of the models roughly triples when the main independent factors (PALPHA and EXPR) are supplemented by the other control variables (e.g., the mean adjusted R^2 value for the three-month FALPHA regressions in Panel B increases from 0.043 to 0.130). The combined impact that the control variables have on the explanatory power of Model 4 is notable given that three of these four additional factors (ASSET, DIVERS, and VOL) are statistically insignificant at conventional levels when considered separately. Further, the coefficients for two of the controls (ASSET and VOL) change signs for various definitions of FALPHA. Of course, both of these results suggest the possibility that these variables may exhibit some degree of multicollinearity. However, in tests not reported directly in Table 4, the extent of this problem appears to be modest and not considered to be a severe concern.[17]

Another interesting finding present in the full specification of the prediction model involves the parameter for TURN, which is positive and significant for each of the three forecast periods. Taken at face value, this suggests that the more active the manager is (i.e., the more trading activity in the portfolio), the more likely the fund will produce superior future returns. Although it is quite conceivable that funds with superior past performance (PALPHA), low operating expense ratios (EXPR), *and* high portfolio turnover are the most likely to produce superior future returns, it is important to keep in mind that these are joint effects. Indeed, univariate regressions of FALPHA on TURN not reported in Table 4 produce the less-robust parameters (p-values) of 0.015 (0.032), 0.021 (0.083), and 0.033 (0.142), respectively, for the three definitions of the dependent variable. Thus, caution is advisable before concluding unilaterally that funds with higher portfolio turnover are more likely to produce higher future alphas.[18]

3.6 Persistent Fund Performance: Additional Tests

As an extension of the cross-sectional regression tests in the last section, we estimated a series of pooled time-series regression equations in Table 4 using a logit model in which FALPHA is transformed into a binary variable. That is, rather than reflecting the actual level of the manager's future risk-adjusted performance, the dependent variable in (3) now takes the value of one if the forecasted alpha in a given period is positive and zero otherwise. These logit regressions are designed to reduce the potential influence of extreme alpha outliers in the sample. Table 5 summarizes these calculations. Once again, the reported findings are qualitatively comparable to those shown previously. In particular, the performance persistence effect continues to be the dominant relationship defining an investor's ability to discover a manager who will generate positive risk-adjusted future returns. Regardless of the form of the regression or the alpha forecast period, the coefficient on PALPHA is positive and highly statistically significant, which in turn drives the significance of each of the applicable overall model specifications. Low fund expenses also remain associated with positive future alphas. Of the remaining control variables, TURN once again appears to the most reliable—with the previous caveats noted—in that it maintains a consistent sign and level of statistical significance.[19]

[Insert Table 5 About Here]

4. The Probability and Economic Consequences of Superior Active Management

4.1 The Probability of Finding a Superior Active Manager

The preceding analysis provides clear evidence that investment performance persistence is a statistically significant and identifiable phenomenon that depends on a multitude of observable factors. In this section, we refine the investigation by asking a related question: How do these myriad relationships between past and future performance affect an investor's chance of identifying in advance a superior active manager? To address this issue, we use the logit regression models described above to assess the *probability* that an active fund manager generates a positive future alpha. Table 6 presents the findings for a two-way classification of the data involving the relative levels of a fund's past alpha and expense ratio statistics. Specifically, each cell in the table reports the proportion of managers from a given cohort—which is defined by the number of standard deviations the past values of the particular characteristic fall from those of the median fund—that generate a positive alpha during the following three-month period. As before, the cohorts are estimated over 1979-2003 and rebalanced on a quarterly basis. Further, the other explanatory variables from the logit regression model (e.g., fund risk, diversification, turnover, and assets) are set equal to their mean values.

[Insert Table 6 About Here]

To help interpret the display, notice that the median past manager (i.e., PALPHA = 0, EXPR = 0) has a less-than-equal chance of generating a positive alpha over the following three-month period (i.e., a reported outperformance proportion of 0.4434).

This is not surprising given our earlier findings that the average manager does not produce returns that beat expectations. However, this probability improves when the investor focuses on those managers with a track record of low expenses and superior performance. For instance, holding past performance constant at the median level (i.e, the PALPHA = 0 cohort), selecting a low-expense fund enhances the investor's probability of achieving superior future risk-adjusted returns. While the benefit of choosing low-expense funds is well established (e.g., Elton, Gruber, and Blake (1996), Bogle (1998)), the middle row of Table 6 provides direct evidence of how this variable impacts the chance of identifying a superior manager. In particular, the last entry in this row indicates that there is 3.29 percentage point difference in the probability of selecting a manager who can produce a positive alpha just by avoiding high-expense funds and picking low-expense ones instead.

Conversely, even when a fund's expense ratio is "normal" (i.e., a cohort with EXPR = 0), an investor can significantly increase the probability of selecting a superior future manager by concentrating on the set of superior past managers. The middle column of the display documents that moving from the worst past performers to the best increases the outperformance proportion from 0.3982 to 0.4895, a difference of 9.13 percentage points. This probability differential appears to be fairly constant even when the investor also controls for the fund's expense ratio in the selection process; the last row of values in Table 6 shows that picking the best past managers rather than the worst improves the probability of realizing a positive future alpha by about nine percentage points regardless of fund expenses. Finally, it is also interesting that these past performance and expense ratio effects are not symmetric. That is, notice that the best past alpha, high expense cohort produces a chance of future outperformance that is closer to breakeven (i.e., a proportion of 0.4729 in the (+2, +2) cell)), but selecting a low-expense manager from the group with the worst track record is likely to lead to future substantial underperformance (i.e., a proportion of 0.4143 for the (-2, -2) cohort).

[Insert Table 7 About Here]

It is also useful to consider the impact on these outperformance probabilities when the initial levels of the other explanatory variables are set away from their average values. Table 7 reproduces the analysis in Table 6 assuming that an investor also selects managers having the "best" characteristics for these controls, defined as values that fall two standard deviations away from the respective medians. Given the previous regression results, this leads to performing the PALPHA/EXPR sort on those funds with the lowest return volatility, highest turnover, and largest asset base. The biggest difference in the reported findings is the marked increase in outperformance proportions for each cohort. For instance, the (0, 0) cell—which indicates median levels of past performance and fund expenses—now produces managers who have a 53.47% chance of generating positive future alphas. Further, when managers are chosen from among the low expense, high past alpha cohort, the probability of future outperformance rises to almost 60% (i.e., 0.5965). Also notable in this regard is that the *worst* combination of past alpha and fund expense now produces managers that have almost a 50% chance of generating a positive alpha. Finally, a comparison of the respective last row and last column of Tables 6 and 7 shows that there is little difference in the proportion differential between the highest and lowest values of the PALPHA and EXPR cohorts; thus, the primary impact of changing initial values of the other control variables is to alter the overall level of identifying a superior manager without changing the relative contributions of the past performance and fund expense effects.

The findings in Tables 6 and 7 support the conclusion that it is possible for investors to dramatically increase the probability of identifying an active manager capable of adding value by considering information that is available in advance. In particular, both a fund's past performance and its expense ratio are especially important controls to take into account when selecting a manager. Focusing on the best manager cohort defined by these two variables increases the investor's odds of choosing a superior manager from considerably less than one-in-two to better than breakeven; the odds increase further to three-in-five when additional controls for fund turnover, risk, and assets under management are employed in the selection process.[20]

4.2 The Economic Benefit of Identifying Superior Managers

Does improving the probability of selecting a superior active fund manager lead directly to an increase in returns to the investor? To examine this issue, we simulated a number of investment strategies that were designed to emphasize the difference between portfolios formed on the basis of the various selection variables. Starting with the entire mutual fund universe, we first calculated alphas for each fund with a full set of return data during a given 36-month estimation period starting in 1979. The fund sample was then split into one of ten portfolios according to past alpha values. These decile portfolios, which were arranged from lowest PALPHA (i.e, Portfolio 1) to highest PALPHA (i.e., Portfolio 10), were then rebalanced on a quarterly basis with each reestimation of the model in equation (2) through the end of 2003. For every fund in each decile portfolio, we then calculated the alpha over the subsequent three-month period. Within each decile group, a weighted average of these future alphas was computed (using relative fund assets as weights) and this quarterly average was annualized. Figure 1 illustrates the results of this procedure.

[Insert Figure 1 About Here]

The graph clearly shows the value of selecting active fund managers who have a history of superior performance. In particular, notice that both of the top two PALPHA fund portfolios were able to generate, on average, yearly alphas of about 1.50% (i.e., +147 and +158 basis points for Portfolios 9 and 10, respectively). On the other hand, the display also makes transparent the value to the investor of avoiding managers with the worst track records; each of the bottom three decile portfolios generate average annual alphas worse than -1.00% and the average alpha for Portfolio 1 is -2.18%. These findings underscore the “hot hands” and “icy hands” conclusions of the performance persistence literature (e.g., Hendricks, Patel, and Zeckhauser (1993), Brown and Goetzmann (1995)), while also providing additional guidance as to where in the overall distribution of fund performance this breakpoint occurs. Finally, it should be mentioned that choosing an active manager from among the top one or two past performance deciles is not a severe restriction on the investment process; as shown in Table 1, 10% of the investable universe available in 2003 consisted of more than 560 funds.

To extend this analysis, we next looked at the performance of portfolios formed using different combinations of the past alpha and fund expense cohorts. Specifically, “Hi” and “Lo” values of PALPHA and EXPR were used to sort funds into portfolios according to the respective upper and lower quartile ranges for those variables. For each set of defining characteristics, a portfolio was formed as an asset-weighted combination of all qualifying funds and this portfolio was rebalanced on a periodic (i.e., monthly or quarterly) basis. Both total and risk-adjusted (i.e., alpha) returns were then calculated over the subsequent investment period. The nominal portfolio returns were computed in two ways: the cumulative value of a one dollar investment made at the beginning of the 1979-2003 sample horizon and the geometric mean annual return the particular portfolio produced during this 25-year period. Additionally, to get a better sense of the incremental value added associated with these hypothetical portfolios, the geometric average and standard deviation of the sequence of alphas they produced were also calculated. Table 8 reports the findings for these investments, which also include portfolios formed by the entire fund sample and the Standard & Poor's 500 index.

[Insert Table 8 About Here]

To facilitate the comparison, notice that for the quarterly rebalancing strategies in Panel A, the cumulative values of one dollar invested in the total fund sample and the S&P index are \$20.212 and \$22.418, respectively, which correspond to average annual returns of 12.915% and 13.389%. By contrast, while forming portfolios controlling for expense ratio alone appears to make little difference (i.e., 12.984% vs. 12.494% for low and high EXPR portfolios, respectively), a more substantial average annual benefit of 162 basis points could have been achieved by selecting portfolios of high past performance funds (i.e., 13.674%) rather than those in the lowest past performance quartile (i.e., 12.053%). Further, the funds comprising this high PALPHA portfolio also outperformed the passive S&P benchmark, on average, by 30 basis points per year.

These total return comparisons are instructive, but it is possible that they misstate the true impact of the manager selection procedure because they do not explicitly control for systematic investment risk. On the other hand, the alphas estimated for the myriad portfolios are performance measures that have been risk-adjusted. For example, the performance of the total fund sample and S&P index just described in total return form translate into quarterly average alphas of 18.1 and 8.8, respectively.[21] The respective alpha volatility statistics, which provide additional information on the predictability of the underlying abnormal return sequences, are 2.153% and 1.700% for the overall fund and benchmark portfolios, indicating that the latter has a tighter distribution of periodic alphas than the former.

In considering the impact of these risk-adjusted numbers, it is important to keep in mind that the underlying portfolios were formed on an asset-weighted basis, meaning the bigger funds in the sample contributed more to the performance statistics. Since one way funds grow in size is through superior past performance, it is possible that the overall fund sample results are being driven by the high past alpha and low expense cohorts. However, notice that portfolios based simply on the lowest and highest expense ratio quartiles do not generate appreciably different levels of abnormal performance; the average three-month alpha values in Panel A of Table 8 are 0.037% for the low expense portfolio and 0.018% for the high expense strategy, leading to an alpha differential of only two basis points. This can be contrasted with the benefit to the investor from investing in a high past alpha versus a low past alpha strategy; here the difference in alpha is almost 300 basis points (i.e., 1.691% versus -1.221%). Also, notice that the alpha sequences associated with the "best" portfolios formed on either EXPR or PALPHA are less volatile than their "worst" counterparts, a difference that is especially large for the expense ratio portfolios (i.e., 2.142% to 4.025%). When the portfolio formation process involves both selection variables, these advantages increase further still. Specifically, the "best" combination portfolio (i.e., highest PALPHA, lowest EXPR) produces an average alpha that is 3.09% higher than that of the "worst" combination portfolio (i.e, lowest PALPHA, highest EXPR) and does so with less volatility in the distribution of quarterly outperformance values.[22]

Collectively, the data in both Figure 1 and Table 8 show that investors can add substantial incremental value to their equity portfolios by: (i) allocating investment capital to active fund managers, and (ii) selecting those managers who have the highest probability of delivering superior performance in future. Invariably, this means considering managers with the best past performance and lowest-expense operations. A possibly surprising consequence of these findings is the extent to which the former effect dominates the latter at a practical level. That is, while controlling expenses remains a valuable characteristic for a fund manager to have, it is far more important that he or she possess tangible security selection or market timing skills. Absent a more direct way to ascertain these talents, the investor can nevertheless benefit from the fact that a manager with superior past risk-adjusted performance is significantly more likely to generate superior future performance and that a portfolio formed on this fact is, on average, more profitable than one that is not.

5. Concluding Remarks

Should investors hire active portfolio managers or should they adopt a more passive approach to investing? The answer to that question depends on many factors, not the least of which is how the central issue is framed. Consistent with the previous literature, in this study we have shown that over the period from 1979 to 2003 the typical mutual fund produced returns that failed to meet expectations. Further, we also showed that the fund manager at the median in terms of past risk-adjusted performance and expense ratio had less than a 50% chance of generating superior returns in the future. Results such as these are widely used (e.g., Bogle (1998), Davis (2001)) to suggest that investors are better served by indexing their investments.

Before settling on that conclusion, however, it is worth considering whether this is even the right way to pose the active versus passive question. Indeed, we have argued that focusing on the behavior of the average fund manager is the wrong way to address the issue of whether active portfolio management is a value adding activity. Far more relevant is the attempt to establish whether there are some active managers who are genuinely skillful and, if so, whether they can be identified in advance with a reasonable degree of reliability. In this regard, similar to Brown and Goetzmann (1995), we presented evidence of significant persistence between past and forecasted alphas for periods as long as one year into the future. Additionally, this performance persistence effect was shown to be separate from (and of greater magnitude than) the influence exerted on investment performance by fund expenses. More importantly, though, we also documented that by including these observable fund traits—along with others such as portfolio turnover and assets under management—in the selection process it is possible to increase the probability of choosing a manager with superior future performance to as much as 60%. The risk-adjusted economic benefit of this approach to selecting the best potential managers while avoiding the worst was shown to average about 300 basis points per annum.

This evidence strongly suggests that superior active managers do exist and that investors have a reasonable chance of finding them. Further, it also appears to be true that once they identify and select these superior managers, investors are rewarded for their efforts. That being the case, it seems logical to wonder why all mutual fund investors (or consultants to those investors) do not try to identify and invest in these managers. There are undoubtedly a multitude of reasons for this, but they are likely to be related to two core issues. First, the volume of the required data and the complexity of the analytics involved might make it difficult (i.e., not cost effective) for many investors to attempt to discern the best managers on their own. Further, the methodology underlying our selection process is not representative of the techniques typically employed by intermediaries who service the investment market. In fact, Morey (2005) demonstrates that more easily observable measures of fund quality (i.e., a five-star Morningstar rating) may not be a reliable indicator of superior future performance. Second, and perhaps more importantly, it is possible that investors do not have a clear understanding of what constitutes true outperformance, opting instead to merely chase funds with the highest total returns in the immediate past (see Capon, Fitzsimmons, and Prince (1996)). However, many funds that attract incremental flows due to higher past returns may simply be taking more risk; Grinold and Kahn (2000) and Waring and Siegel (2003) caution that investors must be able to distinguish a fund's actual alpha from its beta (i.e., systematic risk) to identify superior managers.

In the final analysis, there may well be no definitive resolution to the active versus passive management debate. As we noted earlier, depending on his or her investment objectives and constraints, a particular investor might reasonably expect to benefit from holding both actively and passively managed funds. However, the preceding analysis makes two conclusions abundantly clear: (i) there is a place in an investor's portfolio for the properly chosen active manager; but that (ii) the investor who selects funds in a random manner will find indexing to be a better alternative. While identifying truly skillful portfolio management is hardly an exact science, investors can improve their chances greatly by recognizing that a fund's past risk-adjusted performance is more likely than not to repeat itself in the future.

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Keywords: Active portfolio management; alpha; manager selection; performance persistence

Notes

[1] For instance, the Investment Company Institute reports that at the end of 2003 there were 4,601 distinct equity mutual funds compared to only 1,099 in 1990. By contrast, in 2003 there were 317 equity index funds.

[2] This is analogous to Sharpe's (1991) assertion that "…after costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar (p. 7)."

[3] Davis (2001) also examines the issue of whether the average manager in style-based peer groups can outperform expectations and reports findings that "...are not good news for investors who purchase actively managed mutual funds (p. 25)."

[4] The following discussion summarizes the highlights of the performance persistence literature; Kazemi, Schneeweis, and Pancholi (2003) provide a more complete treatment of this topic.

[5] For more on the survivorship bias problem in mutual fund performance studies, see Brown, Goetzmann, Ibottson, and Ross (1992).

[6] Another interesting extension of the performance persistence literature involves the estimation of a manager's alpha conditional on the prevailing macroeconomic environment. Representative of this approach are studies by Ferson and Schadt (1996) and Christopherson, Ferson, and Glassman (1998).

[7] Baks, Metrick, and Wachter (2001) frame the active management question in a very different way. Adopting a Bayesian perspective, they pose the following question: How skeptical would an investor's prior belief about a manager's skill level have to be in order to avoid allocating assets to an active fund? Although they do not offer a definitive resolution, the authors nevertheless show that some extremely negative prior beliefs would still lead to active fund investments.

[8] For good discussions of the issues associated with estimating expected returns in the context of portfolio performance measurement, see Lehman and Modest (1987) and Grinblatt and Titman (1994).

[9] We also replicated the findings discussed below using other risk factor models (e.g., Elton, Gruber, and Blake (1996)) as well as the two alternative definitions of expected returns (i.e., benchmark and peer group returns). These findings, which confirm all of the results reported below, are not reproduced in the study but are available upon request.

[10] The purpose of this final screen is to reduce the influence on equally weighted performance statistics resulting from fund share classes with little or no assets.

[11] The factor return data required for this classification procedure was obtained from Ken French and Eugene Fama via the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[12] By way of comparison, in the next section we will calculate "out-of-sample" alpha forecasts (which we will label FALPHA) by using the parameters estimates from (2) from a *prior* 36-month period along with risk factor returns from a *subsequent* period to estimate future expected excess returns and hence *future* alphas.

[13] The statistics in Table 1 indicate that the fund sample grew to 5,614 by the end of 2003, which would appear to be a theoretical maximum for the number of overall funds reported here. However, many of these funds changed style categories during the sample period and, so as not to contaminate the various classifications, for every fund we averaged the monthly alpha coefficients based on its classification at the time. Thus, any fund might potentially have its observations distributed across multiple style groups. While this alpha averaging method insures that no single observation is counted more than once, it does give the illusion of an inflated sample size by potentially counting different "parts" of any given fund as separate entities.

[14] That the S&P 500 index, which is often used as a proxy for the market portfolio in some expected return calculations, could produce *any* alpha may seem at first like a contradiction. However, recall that FALPHA is being measured relative to the three-factor model in equation (2), which uses a broader definition of the market to measure its first risk factor. Thus, even though the S&P 500 is not an "active" portfolio in a traditional sense, but it may still generate relative outperformance when expectations are formed using an alternative market definition.

[15] It also appears from Table 3 that the reported FALPHA distributions are reasonably symmetric, taking the negative median values into account. As noted earlier, the practical implication of this fact is that investors can also benefit from avoiding the selection of inferior managers just as much as they can by choosing superior ones.

[16] Specifically, the variable DIVERS is measured as a fund's coefficient of determination relative to the return-generating model in (2) and VOL is the standard deviation of fund returns. Bogle (1994) has argued that the coefficient of determination (which he calls ExMark) proxies for a number of things, including the extent to which a fund might be a "closet indexer." A fund's return volatility accounts for some of the fund's unsystematic risk influences that aren't otherwise captured in PALPHA.

[17] For instance, the pairwise coefficients representing the correlation matrix between the control variables are: -0.081 (ASSET, TURN); 0.100 (ASSET, DIVERS); -0.032 (ASSET, VOL); -0.076 (TURN, DIVERS); 0.130 (TURN, VOL); and -0.145 (DIVERS, VOL). While all of these coefficients are statistically significant—owing largely to the size of the overall sample—they are uniformly low and suggest that multicollinearity is not endemic in the full model. This conclusion is further confirmed by Variance Inflation Factor (VIF) for Model 4, which varies

between 1.05 and 1.80 for the three panels in Table 8; multicollinearity is typically not regarded as a problem in any regression model until this value exceeds 2.50.

[18] We also tested for the interactive effect that TURN might have with PALPHA and EXPR. Specifically, we estimated an extended version of Model 4 with two additional regressors: (TURN x PALPHA) and (TURN x EXPR). This expansion provided limited additional benefits in explanatory power (e.g., the mean adjusted R^2 for three-month FALPHA increased from 0.130 to 0.139). Further, while the coefficients for both interactive terms were positive, only the first was statistically significant.

[19] Although not reported here, we also tested the relationship between a fund's past and future alpha performance in other ways. Most notably, we produced a complete sequence of time series regressions using equation (3) that pools the entire data sample without averaging on an annual basis. These findings, which are available upon request, are qualitatively comparable to those shown in Tables 4 and 5.

[20] Although it once again represents the "wrong" question, it may nevertheless be interesting to consider how looking at these selection variables improves an investor's probability of choosing an active manager capable of outperforming other active managers. We recalculated the proportions in Tables 6 and 7 with outperformance being defined by generating an alpha that was greater than that of the median manager, rather than one that was positive. Not surprisingly, when the levels of all of the control variables were set equal to their median values, the outperformance proportion was 0.5010. This probability increased to 59.76% when managers were selected from the high past performance, low expense cohort, and raised further to 66.29% when the "best" levels of fund volatility, turnover, and assets were factored into the manager identification process.

[21] It may once again be surprising to see that an investment in the S&P 500 index generates any abnormal return at all. However, recall that risk-adjusted performance is being measured relative to the three-factor model of equation (2) and that the evidence in Table 3 showed that the S&P benchmark has a definite alpha distribution compared to this return-generating model.

[22] The results for the monthly portfolio rebalancing strategies in Panel B of Table 8 support the same general conclusions just discussed for the quarterly rebalanced portfolios, albeit with somewhat lower levels of alpha in the various categories. Accordingly, they will not be described in detail.

Table 1. Style Category Mapping for the Mutual Fund Sample

This table reports the number of mutual funds included in each investment style category by year for the sample period spanning January 1979 to December 2003. Funds style classifications were mapped at the beginning of each year according to the Fama-French return-generating model in equation (2) and the numbers listed represent those funds with at least 36 months of return history prior to the given date. The following classifications are used: large-cap value (LV), large-cap blend (LB), large-cap growth (LG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), small-cap value (SV), small-cap blend (SB), small-cap growth (SG).

	Mutual Fund Style Category:									
Year	LV	LB	LG	MV	MB	MG	SV	SB	SG	Total
1979	9	23	70	0	3	21	0	3	27	156
1980	7	26	59	2	7	36	2	3	30	172
1981	5	20	32	1	6	39	0	3	25	131
1982	13	23	38	1	5	43	0	1	34	158
1983	14	27	60	1	7	31	0	2	42	184
1984	8	26	55	1	1	37	0	4	35	167
1985	7	23	74	3	1	37	7	1	30	183
1986	5	18	95	3	5	41	12	0	18	197
1987	6	22	80	3	2	51	14	5	16	199
1988	9	29	89	3	8	50	10	7	31	236
1989	12	30	92	2	3	54	0	11	43	247
1990	19	42	92	1	3	46	1	3	53	260
1991	25	63	97	3	3	44	0	2	48	285
1992	32	163	176	7	10	77	3	11	90	569
1993	38	202	166	8	5	92	2	19	103	635
1994	49	269	198	4	16	148	3	24	162	873
1995	57	210	224	20	67	234	24	97	264	1197
1996	86	405	421	20	45	279	47	83	262	1648
1997	160	535	478	52	111	357	83	106	324	2206
1998	355	636	601	160	130	256	133	172	356	2799
1999	469	456	827	157	107	641	261	119	412	3449
2000	771	604	992	316	82	587	215	142	459	4168
2001	812	680	1181	302	129	699	155	110	457	4525
2002	907	962	840	345	193	835	99	194	647	5022
2003	836	1250	1078	226	375	764	242	263	580	5614

Table 2. The Distribution of Past Alphas: 1979-2003

This table shows the values for the fund-specific average of in-sample historical alphas (PALPHA) occurring at various percentile breaks in a given distribution. Separate distributions are listed for mean fund PALPHA values calculated relative to returns from the three-factor model in equation (2). With each method, expected returns were calculated each month from January 1979 to December 2003 using the prior 36 months of return data and the sequence of associated PALPHA values were then averaged for every fund. Separate mean PALPHA distributions are listed for both the entire fund sample and the style-specific peer groups; also indicated is the percentage of positive alpha values.

		Monthly Mean PALPHA Value at Percentile (%):					
Fund Style	**# of Obs.**	**5^{th}**	**25^{th}**	**Median**	**75^{th}**	**95^{th}**	**% Pos. Alphas**
Overall	**19,765**	**-1.55**	**-0.55**	**-0.17**	**0.12**	**0.79**	**33.97**
LV	**2,405**	**-2.07**	**-0.56**	**-0.21**	**0.07**	**0.68**	**30.23**
LB	**3,400**	**-1.43**	**-0.54**	**-0.22**	**-0.01**	**0.38**	**24.74**
LG	**3,388**	**-1.06**	**-0.33**	**-0.06**	**0.17**	**0.81**	**42.65**
MV	**1,423**	**-2.55**	**-0.68**	**-0.23**	**0.11**	**0.69**	**32.75**
MB	**1,712**	**-1.86**	**-0.78**	**-0.32**	**0.08**	**0.65**	**29.21**
MG	**3,212**	**-1.47**	**-0.62**	**-0.20**	**0.20**	**1.03**	**35.40**
SV	**933**	**-2.02**	**-0.65**	**-0.26**	**0.00**	**0.56**	**25.30**
SB	**1,239**	**-1.42**	**-0.60**	**-0.20**	**0.11**	**0.76**	**31.80**
SG	**2,053**	**-1.36**	**-0.45**	**-0.01**	**0.39**	**1.22**	**48.86**
S&P 500 Index Fund				**0.04**			

Table 3. The Distribution of Forecasted Alphas: 1979-2003

This table shows the values of the out-of-sample forecasted alphas (FALPHA) occurring at various percentile breaks in a given distribution. Separate distributions are listed for FALPHA predictions made using forecast periods of one month (Panel A), three months (Panel B), and 12 months (Panel C). In each panel, separate FALPHA distributions are listed for: (i) the entire fund sample, (ii) style-specific peer groups, and (iii) the S&P 500 index; each distribution also indicates the percentage of positive alpha forecasts. Forecasted alphas are measured on a rolling periodic basis over the 1979-2003 investment horizon

Panel A. Monthly Alpha Forecasts

		Monthly FALPHA Value at Percentile (%):					
Fund Style	**# of Obs.**	**5th**	**25th**	**Median**	**75th**	**95th**	**% Pos. Alphas**
Overall	**398,056**	**-4.79**	**-1.56**	**-0.18**	**1.19**	**4.55**	**46.09**
LV	**53,428**	**-4.13**	**-1.54**	**-0.26**	**1.16**	**4.19**	**44.39**
LB	**72,860**	**-3.61**	**-1.15**	**-0.17**	**0.80**	**3.15**	**44.99**
LG	**93,802**	**-4.34**	**-1.28**	**-0.10**	**1.05**	**4.04**	**47.43**
MV	**18,638**	**-5.84**	**-1.85**	**-0.08**	**1.76**	**5.71**	**48.80**
MB	**13,005**	**-4.92**	**-1.72**	**-0.12**	**1.55**	**4.77**	**47.81**
MG	**58,948**	**-5.30**	**-1.90**	**-0.19**	**1.52**	**5.28**	**46.78**
SV	**15,323**	**-6.91**	**-2.36**	**-0.53**	**1.27**	**6.05**	**41.60**
SB	**13,653**	**-5.71**	**-1.97**	**-0.35**	**1.15**	**4.64**	**43.30**
SG	**49,399**	**-5.87**	**-2.02**	**-0.20**	**1.65**	**5.76**	**46.86**
S&P 500 Index Fund	**297**	**-0.75**	**-0.21**	**-0.01**	**0.27**	**0.64**	**47.81**

Panel B. Quarterly Alpha Forecasts

		Quarterly FALPHA Value at Percentile (%):					
Fund Style	**# of Obs.**	**5th**	**25th**	**Median**	**75th**	**95th**	**% Pos. Alphas**
Overall	**126,613**	**-8.85**	**-3.12**	**-0.49**	**2.06**	**8.55**	**44.50**
LV	**17,195**	**-7.53**	**-2.98**	**-0.66**	**1.82**	**6.80**	**42.28**
LB	**23,566**	**-7.07**	**-2.43**	**-0.48**	**1.28**	**6.10**	**42.37**
LG	**30,642**	**-7.95**	**-2.66**	**-0.25**	**1.89**	**7.99**	**46.59**
MV	**6,214**	**-10.82**	**-3.13**	**-0.09**	**2.93**	**9.41**	**49.10**
MB	**4,251**	**-8.21**	**-3.23**	**-0.24**	**2.88**	**9.06**	**47.49**
MG	**19,172**	**-9.71**	**-3.79**	**-0.56**	**2.67**	**10.32**	**45.34**
SV	**4,963**	**-12.37**	**-4.39**	**-1.30**	**1.99**	**10.81**	**38.32**
SB	**4,475**	**-9.95**	**-3.96**	**-1.12**	**1.89**	**8.47**	**40.20**
SG	**16,135**	**-11.07**	**-4.03**	**-0.59**	**3.10**	**10.89**	**45.53**
S&P 500 Index Fund	**295**	**-1.41**	**-0.37**	**0.08**	**0.51**	**1.22**	**54.58**

Table 3. The Distribution of Forecasted Alphas: 1979-2003 (cont.)

Panel C. Annual Alpha Forecasts

		Annual FALPHA Value at Percentile (%):					
Fund Style	**# of Obs.**	**5th**	**25th**	**Median**	**75th**	**95th**	**% Pos. Alphas**
Overall	**28,270**	**-22.20**	**-8.44**	**-2.19**	**4.08**	**23.17**	**40.12**
LV	**3,713**	**-16.75**	**-7.38**	**-2.30**	**2.69**	**15.49**	**37.49**
LB	**5,224**	**-18.58**	**-6.93**	**-2.32**	**1.92**	**15.84**	**35.89**
LG	**6,731**	**-17.35**	**-6.41**	**-1.33**	**4.04**	**20.45**	**42.82**
MV	**1,355**	**-18.67**	**-6.73**	**1.05**	**9.64**	**29.91**	**53.43**
MB	**901**	**-21.48**	**-9.29**	**-1.21**	**9.34**	**37.83**	**47.39**
MG	**4,465**	**-23.77**	**-9.88**	**-2.17**	**5.94**	**31.27**	**42.28**
SV	**1,024**	**-27.72**	**-10.14**	**-2.25**	**4.98**	**25.29**	**41.31**
SB	**1,060**	**-30.39**	**-15.21**	**-6.37**	**0.91**	**19.36**	**27.64**
SG	**3,797**	**-29.86**	**-14.12**	**-4.58**	**5.55**	**30.61**	**37.93**
S&P 500 Index Fund	**286**	**-1.61**	**-0.46**	**0.70**	**1.69**	**4.13**	**65.73**

Table 4. Predicting Future Fund Performance: Cross-Sectional Regressions

This table reports mean time-series values for a series of regression parameters estimated cross-sectionally using the three-step Fama-MacBeth (1973) procedure. In the first step, values for past fund performance (PALPHA) and fund expense ratio (EXPR) are estimated for each fund on a given date, starting in 1979, using the three-factor model in (2). Second, three different sets of forecasted (t=1, t=3, and t=3) returns (FALPHA) are calculated for each fund and then normalized by style tournament. This cross section of future returns is regressed against the estimated values of PALPHA, EXPR, and controls for fund size (ASSET), portfolio turnover (TURN), fund diversification (DIVERS), and fund return volatility (VOL). Third, the first two steps are repeated by rolling the estimation month forward on a periodic basis through the end of 2003. P-values are listed parenthetically to the right each reported parameter estimate. Panels A, B, and C report results for one-, three-, and 12-month future returns, respectively.

Panel A. One-Month FALPHA as Dependent Variable

	Variable: PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Mean Adj. R^2	# of Obs.
Model 1	0.049 (0.000)						0.035	299
Model 2		-0.012 (0.049)					0.009	299
Model 3	0.049 (0.000)	-0.004 (0.499)					0.042	299
Model 4	0.047 (0.000)	-0.012 (0.033)	0.008 (0.034)	0.015 (0.034)	-0.021 (0.091)	-0.011 (0.377)	0.124	299

Panel B. Three-Month FALPHA as Dependent Variable

	Variable: PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Mean Adj. R^2	# of Obs.
Model 1	0.058 (0.000)						0.036	99
Model 2		-0.021 (0.065)					0.009	99
Model 3	0.057 (0.000)	-0.011 (0.269)					0.043	99
Model 4	0.061 (0.000)	-0.019 (0.063)	0.009 (0.190)	0.022 (0.072)	-0.023 (0.333)	-0.022 (0.306)	0.130	99

Panel C. 12-Month FALPHA as Dependent Variable

	Variable: PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Mean Adj. R^2	# of Obs.
Model 1	0.058 (0.134)						0.034	24
Model 2		-0.046 (0.063)					0.012	24
Model 3	0.056 (0.129)	-0.039 (0.051)					0.040	24
Model 4	0.088 (0.008)	-0.050 (0.016)	-0.019 (0.183)	0.039 (0.070)	0.013 (0.772)	-0.029 (0.558)	0.130	24

Table 5. Predicting Future Fund Performance: Logit Regressions

This table reports the findings for a logit analysis of the relationship between an active fund manager's future investment performance and several potential explanatory factors over the period 1979-2003. Coefficient estimates are given for logit regressions involving a forecast performance indicator variable and various combinations of the following explanatory variables: past abnormal returns (PALPHA), fund expense ratio (EXPR), total net fund assets (ASSET), portfolio turnover (TURN), fund diversification (DIVERS), and fund return volatility (VOL). The independent variables are estimated over a 36-month period by equation (3). The dependent variable assumes the value of one if a manager's out-of-sample risk-adjusted return forecast (FALPHA) is positive, 0 otherwise. Three different FALPHA forecast periods are used: one month (Panel A), three months (Panel B), and 12 months (Panel C). P-values are listed parenthetically beneath each coefficient.

Panel A. Sign of One-Month Future Returns as Dependent Variable

	Variable:								
	Intercept	PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Chi-Square	# of Obs.
Model 1	-0.159	0.070						277.93	379,042
	(0.000)	(0.000)						(0.000)	
Model 2	-0.158		-0.017					28.16	379,042
	(0.000)		(0.000)					(0.000)	
Model 3	-0.159	0.068	-0.008					283.22	379,042
	(0.000)	(0.000)	(0.022)					(0.000)	
Model 4	-0.159	0.082	-0.021	0.015	0.028	-0.085	-0.003	755.44	379,042
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.419)	(0.000)	

Panel B. Sign of Three-Month Future Returns as Dependent Variable

	Variable:								
	Intercept	PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Chi-Square	# of Obs.
Model 1	-0.227	0.075						109.49	123,315
	(0.000)	(0.000)						(0.000)	
Model 2	-0.227		-0.026					19.61	123,315
	(0.000)		(0.000)					(0.000)	
Model 3	-0.227	0.072	-0.015					116.08	123,315
	(0.000)	(0.000)	(0.010)					(0.000)	
Model 4	-0.228	0.093	-0.033	0.023	0.022	-0.117	-0.022	426.74	123,315
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Panel C. Sign of 12-Month Future Returns as Dependent Variable

	Variable:								
	Intercept	PALPHA	EXPR	ASSET	TURN	DIVERS	VOL	Chi-Square	# of Obs.
Model 1	-0.412	0.098						30.29	27,444
	(0.000)	(0.000)						(0.000)	
Model 2	-0.412		-0.031					6.24	27,444
	(0.000)		(0.013)					(0.013)	
Model 3	-0.413	0.093	-0.021					32.93	27,444
	(0.000)	(0.000)	(0.104)					(0.000)	
Model 4	-0.413	0.101	-0.029	-0.008	0.027	-0.039	-0.003	79.07	27,444
	(0.000)	(0.000)	(0.031)	(0.526)	(0.030)	(0.039)	(0.000)	(0.000)	

Table 6. Probability of Identifying a Superior Active Manager by Past Alpha and Fund Expenses: Median Manager Controls

This table lists the average probability of producing a positive future alpha given the manager's cell location in a two-way classification involving past alpha and fund expenses. Cell cohorts are determined by the standard deviation rankings of PALPHA and EXPR within a manager's peer group and tournament year (i.e., -2, -1, 0, +1, and +2 standard deviations from the median value). The other explanatory variables are standardized to their median levels (i.e., TURN = 0, ASSET = 0, DIVERS = 0, VOL = 0). Future alphas are measured on a rolling three-month basis over the 1979-2003 investment period.

		EXPR:					
	Std. Dev. Group	-2 (Low)	-1	0	+1	+2 (High)	(High – Low)
	-2 (Low)	0.4143	0.4062	0.3982	0.3903	0.3824	(0.0319)
	-1	0.4369	0.4288	0.4206	0.4125	0.4045	(0.0324)
PALPHA:	0	0.4599	0.4516	0.4434	0.4352	0.4270	(0.0329)
	+1	0.4830	0.4746	0.4664	0.4581	0.4498	(0.0331)
	+2 (High)	0.5061	0.4978	0.4895	0.4812	0.4729	(0.0333)
	(High – Low)	0.0918	0.0916	0.0913	0.0909	0.0905	

Table 7. Probability of Identifying a Superior Active Manager by Past Alpha and Fund Expenses: "Best" Controls

This table lists the average probability of producing a positive future alpha given the manager's cell location in a two-way classification involving past alpha and fund expenses. Cell cohorts are determined by the standard deviation rankings of PALPHA and EXPR within a manager's peer group and tournament year (i.e., -2, -1, 0, +1, and +2 standard deviations from the median value). The other explanatory variables are standardized to their "best" levels (i.e., TURN = +2, ASSET = +2, DIVERS = -2, VOL = -2). Future alphas are measured on a rolling three-month basis over the 1979-2003 investment period.

		EXPR:					
	Std. Dev. Group	-2 (Low)	-1	0	+1	+2 (High)	(High – Low)
	-2 (Low)	0.5051	0.4968	0.4884	0.4801	0.4718	(0.0333)
	-1	0.5282	0.5199	0.5116	0.5033	0.4950	(0.0333)
PALPHA:	0	0.5512	0.5430	0.5347	0.5264	0.5181	(0.0331)
	+1	0.5741	0.5659	0.5577	0.5495	0.5412	(0.0328)
	+2 (High)	0.5965	0.5885	0.5804	0.5723	0.5641	(0.0324)
	(High – Low)	0.0915	0.0918	0.0920	0.0922	0.0923	

Table 8. Investment Performance of Portfolios Formed By Past Alpha and Expense Cohorts

This table shows the cumulative total and average returns as well as the average alpha performance associated with portfolios of mutual funds selected on the basis of different levels of past performance and expense ratios. The "Hi" and "Lo" values of the respective control variables are defined by the upper and lower quartile ranges on a given formation dates. Panels A and B report results assuming quarterly and monthly portfolio rebalancing, respectively. The average alpha indicates the geometric average over the 1979-2003 estimation period and alpha volatility is the standard deviation of the respective periodic values. The nominal return and alpha performance for investments in the S&P 500 index and the entire fund sample are also reported.

Panel A. Quarterly Portfolio Rebalancing

Port. Formation Variables							
Expense Ratio	**Past Alpha**	**Cumulative Value of $1 Invested**	**Average Annual Return (%)**	**Avg. Return Differential (bp)**	**Average Alpha (%)**	**Alpha Volatility (%)**	**Avg. Alpha Differential (bp)**
Overall Sample		20.212	12.915	---	0.181	2.153	---
Lo		20.518	12.984	49	0.037	2.142	2
Hi		18.429	12.494		0.018	4.025	
	Hi	23.857	13.674	162	1.691	3.371	291
	Lo	16.720	12.053		-1.221	3.469	
Lo	Hi	24.462	13.789	150	1.502	3.596	309
Hi	Lo	17.625	12.292		-1.585	4.712	
S&P 500 Index Fund		22.418	13.389	---	0.088	1.700	---

Panel B. Monthly Portfolio Rebalancing

Port. Formation Variables							
Expense Ratio	**Past Alpha**	**Cumulative Value of $1 Invested**	**Average Annual Return (%)**	**Avg. Return Differential (bp)**	**Average Alpha (%)**	**Alpha Volatility (%)**	**Avg. Alpha Differential (bp)**
Overall Sample		22.604	13.331	---	0.124	2.217	---
Lo		22.189	13.247	15	-0.055	2.190	15
Hi		21.474	13.098		-0.208	3.833	
	Hi	24.989	13.788	159	1.346	3.198	261
	Lo	17.593	12.197		-1.259	3.511	
Lo	Hi	23.130	13.436	162	0.776	3.512	297
Hi	Lo	16.178	11.820		-2.190	4.546	
S&P 500 Index Fund		22.418	13.293	---	0.118	1.465	---

Figure 1. Average Annualized Alpha for Fund Portfolio Formed on the Basis of Past Performance.

This display shows the average value added of ten collections of mutual funds sorted by past alpha levels. The decile portfolios range from worst (Portfolio 1) to best (Portfolio 10) past performers and were rebalanced on a quarterly basis over the period 1979-2003. The reported alpha values are weighted by fund assets and annualized.