Investigating Underperformance by Mutual Fund Portfolios

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Abstract

Underperformance by equity mutual funds has been widely documented by both the popular press and academic research. Whereas previous research has interpreted underperformance as evidence that fund managers lack the ability to pick stocks, this paper focuses on the impact of portfolio composition and excess turnover on fund performance. Using standard portfolio optimization techniques, we show that the portfolio weights for the stocks selected by fund managers are on average inefficient. Our results suggest that while fund managers may actually possess superior stock selection skills, substantial gains could be achieved by improving the efficiency of the allocation of mutual fund assets. In addition, we present evidence suggesting that mutual fund turnover is excessive and that fund managers may rely too heavily on stock price momentum.

Introduction

Investors' growing interest in mutual funds is evidenced by the fact that over five trillion dollars are currently invested in actively managed funds. The significance of this investment has heightened interest in performance evaluation by both practitioners and academic researchers. Although claims of superior performance are often used to market mutual funds to investors, academic studies of mutual fund performance find that as a group the fund managers fail to create value for investors. For example, consistent with headlines in the popular press, Jensen (1968), Malkiel (1995), and Carhart (1997) find that in the aggregate equity funds underperform passive benchmark portfolios, not only after management expenses but gross of expenses as well. Although a small number of studies find that mutual funds having a common objective (e.g., growth) outperform passive benchmark portfolios, Elton, Gruber, and Blake (1996) argue that most of these studies would reach the opposite conclusion if survivorship bias and/or adjustments for risk were properly taken into account.

The literature on mutual fund performance is consistent with the contention that on average the portfolio management skills provided by mutual fund managers are of little value to investors. However, while the evidence strongly suggests that fund managers are unable to match the performance of passive benchmark portfolios, these studies do not conclusively prove that these managers are unable to identify mispriced stocks. In fact, underperformance by mutual funds may be attributable to a number of factors other than the stocks selected by the fund managers. For example, although a fund manager may have identified a set of "under-priced" stocks, the failure to optimally allocate assets across the manager's "active bets" may cause a fund's risk-adjusted performance to fall short of the performance by the benchmark portfolio. Alternatively, underperformance may simply be attributable to excessive turnover. These issues cannot be fully resolved by simple comparisons of mutual fund returns and expense ratios.

This paper uses data on mutual fund holdings to examine the causes of underperformance from a different perspective. In particular, we use the approach to active portfolio management developed by Treynor and Black (1973) to compare the performance for a sample of actively managed mutual funds with the performance that potentially could have been achieved if each fund had chosen a mean-variance optimal weighting for its stock selections. Our research design constrains each hypothetical portfolio to hold only those stocks actually held by the fund managers, thereby avoiding bias in our performance measures due to either the imposition of ex post stock selection criteria or violations of ex ante constraints on fund managers related to concerns about liquidity, accounting irregularities, industry group, or suitability relative to the fund's investment objectives. We find that on average the *ex ante* efficient allocation of fund assets would have improved the *ex post* pre-expense performance for our sample of actively managed mutual funds. Thus, our results suggest that the failure to select an efficient *ex ante* allocation of fund assets has a significant impact on the *ex post* underperformance exhibited by actively managed mutual fund portfolios.

We also examine whether underperformance by actively managed mutual funds can be attributed to excessive turnover. Obviously, the transaction costs generated by portfolio turnover have a negative impact on performance net of expenses. For example, Elton, Gruber, Das, and Hlavka (1993), Malkiel (1993), and Carhart (1997) find that high turnover ratios are associated with low risk-adjusted net returns. However, while these studies indicate that mutual funds' excess returns are not sufficient to compensate for the costs of increased turnover, they are unable to determine whether high turnover results from managers' attempts to exploit superior information. In fact, it would be reasonable to expect a positive association between turnover and pre-expense returns if high turnover reflects a fund managers' attempts to trade on superior information. However, contrary to this hypothesis, we find a strong negative correlation between portfolio turnover and pre-expense performance, suggesting that the turnover rates for actively managed mutual funds are not driven by superior information.

Our approach is related to Grinblatt and Titman (1989), who pioneered the use of data on mutual funds' portfolio holdings to construct estimates of total mutual fund returns. Such hypothetical returns are particularly useful in examining funds' pre-expense performance. However, the results and conclusions of Grinblatt and Titman are subject to a number of criticisms, as the authors acknowledge in a latter paper (Daniel, Grinblatt, Titman, and Wermers (1997)). For example, the number of the funds that they examine is relatively small. Further, the benchmark portfolio that they use may not fully account for return anomalies such as size and book-to-market effects, which have been shown by Fama and French (1992, 1993) to be empirically significant in explaining common stock returns.

The paper is organized as follows. In Section 1 we describe both the data and the methods used to determine the optimal weights for mutual fund portfolios. Moreover, we present a "separation theorem" that motivates the importance of the optimality of the portfolio allocations selected by individual fund managers. The impact of *ex ante* portfolio efficiency on *ex post* fund performance is examined in Section 2, where we compare mutual fund returns with the returns for mean-variance optimal portfolios formed from the subset of stocks actually held by each of the funds in our sample. In Section 3, we provide new evidence concerning the impact of portfolio turnover on mutual fund performance. The implications of our findings are discussed in Section 4, which concludes the paper.

1 Data and Methodology

Empirical studies of mutual fund performance show that actively managed equity mutual funds tend to underperform passive benchmark portfolios, even before adjusting for management fees and expenses. As noted previously, one possible explanation for this underperformance is the possibility that the procedures used by mutual funds to form portfolios from the stocks on their buy lists are inefficient. We examine this issue by comparing estimates of pre-expense returns with the returns that each mutual fund would have earned if more efficient procedures had been used to determine the portfolio weights for each fund's stock selections. In particular, we compare actual mutual fund returns with benchmark returns for both equal-weighted and ex ante mean-variance optimal portfolios of the stocks held by the mutual funds in our sample. While other well-diversified portfolios could potentially be used to provide information concerning the relative impact of stock selection and portfolio allocation on mutual fund performance, the benchmark portfolios that we use have the respective advantages of simplicity and intuitive appeal.

1.1 How Should a Fund Manager Allocate Assets?–A Separation Theorem

Modern portfolio theory dates from the pioneering article by Markowitz (1952). Since then, the principles underlying modern portfolio theory have been used to develop a variety of techniques designed to assist fund managers in their attempts to use security analysis to improve portfolio performance. One such application is Treynor and Black (1973), who show that portfolio performance can be improved by optimally weighting a fund manager's stock picks.

The Treynor-Black model is based on the assumption that there are n risky securities whose expected returns deviate from the security market line for exogenous reasons. The returns for these risky securities are given by the CAPM-based process:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t} - R_{f,t}$ is the excess return on security i for $i = 1, 2, \cdots, n$, $R_{m,t} - R_{f,t}$ is the excess return on the market, α_i is a firm specific expected return, and $\epsilon_{i,t}$ is an idiosyncratic return that is normally distributed as $N(0, \sigma_i^2)$. Based on these assumptions, Treynor and Black derive the optimal holdings of these n risky securities, the risk-free asset, and the market portfolio. In particular, they show that when there are no restrictions on short selling, investors who wish maximize the ratio of reward to variability for their portfolios should hold each of the n risky securities in proportion to $\frac{\alpha_i}{\sigma_i^2}$.[1] Note that while Treynor and Black use α_i to represent the component of a security's expected return that is attributable to mispricing, the α_i in equation (1) can be used more generally to include the impact of a variety of unspecified factors on a security's expected returns

The criteria that portfolio weights should be chosen to maximize a portfolio's Sharpe ratio seems to be a reasonable objective function for an individual investor. However, since individual investors may diversify by holding portfolios of mutual funds, it is not clear that such an objective is generally appropriate for mutual fund managers. The following proposition shows that, so long as the subsets of securities that fund managers believe to be mispriced are non-intersecting, fund managers should maximize the same objective function as individual investors.

Proposition 1 *Suppose that two mutual fund managers have identified non-overlapping (i.e., unique) sets of stocks having non-zero alpha's. If both fund managers choose the portfolio weights that maximize their funds' Sharpe ratios, then investors who choose to diversify by holding an optimal portfolio of these two mutual funds can achieve the same reward to variability ratio as an investor who is allowed to choose a mean-variance optimal portfolio from the managers' combined investment opportunities.*

Proof: Denote the returns for the unique investment opportunities identified by each fund manager as $\{R_{1,t}, \cdots, R_{n_1,t}\}$ and $\{R_{n_1+1,t}, \cdots, R_{n,t}\}$. If each manager selects port-

[1] Technically speaking, the objective function used by Treynor and Black calls for minimizing the portfolio variance given a target expected portfolio return. It is straightforward to show that similar results hold for the objective function stated here.

folio weights that maximize the reward to variability ratio for their funds, the optimal Sharpe ratio for each fund is identical to equation (19) in Treynor and Black (1973),

$$\frac{\mu^2_{mfd_1}}{\sigma^2_{mfd_1}} = \sum_{i=1}^{n_1} \frac{\alpha_i^2}{\sigma_i^2} \quad and \quad \frac{\mu^2_{mfd_2}}{\sigma^2_{mfd_2}} = \sum_{j=n_1+1}^{n} \frac{\alpha_j^2}{\sigma_j^2}$$

where μ_{mfd} and σ_{mfd} denote mutual fund's expected return and volatility, respectively. If individual investors are able to observe each fund manager's investment opportunity set, the optimal portfolio weights imply that the Sharpe ratio would be,

$$\begin{aligned} \frac{\mu_p^2}{\sigma_p^2} &= \sum_{i=1}^{n} \frac{\alpha_i^2}{\sigma_i^2} = \sum_{i=1}^{n_1} \frac{\alpha_i^2}{\sigma_i^2} + \sum_{j=n_1+1}^{n} \frac{\alpha_j^2}{\sigma_j^2} \\ &= \frac{\mu^2_{mfd_1}}{\sigma^2_{mfd_1}} + \frac{\mu^2_{mfd_2}}{\sigma^2_{mfd_2}} \end{aligned}$$

Thus, the optimal Sharpe ratio is identical to that for investors who are able to optimally diversify across the two mutual funds. Q.E.D.

Proposition 1 provides a theoretical rationale for the objective function that we use to determine the optimal portfolio weights for the mutual funds in our sample. So long as mutual funds generate unique investment opportunities, fund managers best serve the interests of their shareholders by allocating portfolio assets so as to maximize their funds' reward to variability ratios. Consequently, fund managers need not explicitly consider the investment opportunities offered to investors by other mutual funds. In practice, many mutual funds have at least some holdings in common, thereby violating the uniqueness assumption of Proposition 1. However, since investors are permitted to short sell individual stocks, any common holdings can be neutralized so long as mutual funds disclose their portfolio holdings to investors.

1.2 Risk Factors and Stock Returns

The Capital Asset Pricing Model (CAPM) of Sharpe, Lintner, and Black has long been one of the key paradigms in financial economics. However, there is considerable academic debate on the empirical performance of the model. For example, Fama and French (1992) find that additional factors, such as size and book to market equity, are important in explaining cross-sectional differences in returns. Similarly, Fama and French (1993) show that an empirical asset pricing model which includes the returns on mimicking portfolios for risk factors related to size and book to market, in addition to a proxy for the return on the market portfolio of stocks, increases our ability to explain variations in the time series of asset returns.

The abnormal returns from momentum trading strategies (see Jagadeesh and Titman, 1993) that buy short-term winners and sell short-term losers have been documented extensively in finance literature. Carhart (1997) uses a momentum factor to augment the Fama-French three-factor model in order to provide a more precise adjustment for risk in evaluating mutual fund performance. However, Cochrane (2000) argues that the momentum effect can be accounted for by low levels of autocorrelation in asset returns. Further, Moskowitz and Grinblatt (1999) suggest that the economic significance of the momentum factor is unclear. While the evidence concerning the importance of a momentum factor is somewhat mixed, we incorporate a momentum factor in our estimates of risk-adjusted performance in order to help adjust for any autocorrelation in returns.

Investors must on average hold the market portfolio. However, the process of active stock selection may cause the fund's exposure to alternative sources of market risk to deviate from the market average. Consequently, in the context of the Treynor and Black model a manager's performance should be measured with respect to a multi-factor model whenever factors such as size, book-to-market equity, and momentum are useful in explaining cross-sectional variation in returns. Following Carhart (1997), we base the parameter estimates used to determine optimal portfolios for the funds in our sample on the assumption that the expected return for each security i is generated by a four-factor return-generating process,

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{smb,i} R_{smb,t} + \beta_{hml,i} R_{hml,t} + \beta_{mom,i} R_{mom,t} + \epsilon_{i,t}, \quad (2)$$

where α_i is the firm specific expected return or the "independent return" in Treynor and Black's terminology, $R_{m,t} - R_{f,t}$ is the excess return on the market return factor, with R_{smb}, R_{hml}, and R_{mom} respectively representing the returns on the mimicking portfolios for the risk factors ($\beta_{smb,i}$, $\beta_{hml,i}$, and $\beta_{mom,i}$) related to size, book-to-market equity, and momentum in stock returns.

A number of authors have argued that size and book-to-market equity cannot be interpreted as risk factors in the traditional sense. However, the empirical importance of these factors in explaining stock returns is unquestioned. Further, Fama and French (1996) demonstrate that their three-factor model captures many widely documented patterns in stock returns. For example, the model accounts for the long-term return reversals documented by DeBondt and Thaler (1987). Although we use a four-factor model to measure the risk-adjusted performance of stocks and portfolios, our attitude towards the model is pragmatic, leaving theoretical interpretations to the reader.[2]

1.3 A Mutual Fund Portfolio Construction Strategy

The essence of modern portfolio theory is the notion that the optimal weighting of the securities in a portfolio should either minimize portfolio risk for a given level of expected return or else maximize the expected portfolio return for a given level of risk. Although a variety of alternative constraints might be used to assure that fund managers achieve at least a minimal level of diversification across stock selections, none of these alternatives has the intuitive appeal of the traditional mean-variance approach developed by Treynor and Black. For generality, the procedures that we use to construct optimal mutual fund portfolios are derived under the assumption that stock returns are generated by the following factor model,

$$R_{e,i,t} - R_f = \alpha_i + \beta_{i,1} F_{1,t} + \cdots + \beta_{i,k} F_{k,t} + \epsilon_{i,t} \tag{3}$$

where,

$$\begin{aligned} E(\epsilon_{i,t}) &= 0, \\ E(F_{i,t}) &= \mu_i - R_f, \\ Cov(\epsilon_{i,t}, \epsilon_{j,t}) &= \sigma^2_{i,j}, \end{aligned}$$

[2]We are grateful to Eugene Fama and Mark Carhart for making these data available to us.

$$
\begin{aligned}
Cov(\epsilon_{i,t}, F_{j,t}) &= 0, \\
Cov(F_{i,t}, F_{j,t}) &= \sigma^2_{Fi,Fj}.
\end{aligned}
$$

Equation (3) can be expressed more compactly using the matrix notation,

$$
\begin{aligned}
\mathbf{R}_{e,t} - \mathbf{R}_f &= \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{F}_t + \boldsymbol{\epsilon}_t, \\
\bar{\mathbf{R}}_e = E(\mathbf{R}_{e,t}) &= \mathbf{R}_f + \boldsymbol{\alpha} + \boldsymbol{\beta}\bar{\mathbf{F}}, \\
\boldsymbol{\Sigma}_e = Var(\mathbf{R}_{e,t}) &= \boldsymbol{\Sigma}_\epsilon + \boldsymbol{\beta}\boldsymbol{\Sigma}_F\boldsymbol{\beta}'.
\end{aligned}
$$

Assuming that each of the K factors $\mathbf{F}$ can be traded separately, the augmented vector of excess returns can be written as $\mathbf{R} = [\mathbf{F}', (\mathbf{R}_e - \mathbf{R}_f)']'$. The corresponding vector of expected returns and the variance-covariance matrix are,

$$
\bar{\mathbf{R}} = E(\mathbf{R}_t) = \begin{bmatrix} \bar{\mathbf{F}} \\ \bar{\mathbf{R}}_e - \mathbf{R}_f \end{bmatrix}, \quad \boldsymbol{\Omega} = Var(\mathbf{R}_t) = \begin{bmatrix} \boldsymbol{\Sigma}_F & \boldsymbol{\Sigma}_F\boldsymbol{\beta}' \\ \boldsymbol{\beta}\boldsymbol{\Sigma}_F & \boldsymbol{\Sigma}_e \end{bmatrix}.
$$

As is common in the literature, we assume that investors choose portfolio weights $\mathbf{W} = [\mathbf{W}_F', \mathbf{W}_e']'$ so as to maximize the portfolio's Sharpe ratio. The expected portfolio excess return and variance can thus be expressed as,

$$
\mathbf{R}_p = \mathbf{W}'\bar{\mathbf{R}} \quad and \quad \sigma_p^2 = \mathbf{W}'\boldsymbol{\Omega}\mathbf{W}.
$$

Since the factor proxies used in estimation can be easily constructed from security returns, it is reasonable to assume that individual investors can directly invest in those factors.

Proposition 2 *When there are no restrictions on short sales, the portfolio weights that maximize the Sharpe ratio,* $\theta = \frac{1}{\sigma_p}\mathbf{R}_p$ *, for an investor's portfolio are given by,*

$$
\mathbf{W}_F^* = \boldsymbol{\Sigma}_F^{-1}\bar{\mathbf{F}} - \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}, \tag{4}
$$

$$
\mathbf{W}_e^* = \boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}, \tag{5}
$$

$$
\mathbf{W} = \frac{1}{\underline{\mathbf{1}}'\mathbf{W}^*}\mathbf{W}^*, \tag{6}
$$

$$
\theta^2 = \bar{\mathbf{F}}'\boldsymbol{\Sigma}_F^{-1}\bar{\mathbf{F}} + \boldsymbol{\alpha}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}. \tag{7}
$$

Proof: Given the objective function, it is straightforward to show the optimal weights will be proportional to $\boldsymbol{\Omega}^{-1}\bar{\mathbf{R}}(= \mathbf{W}^*)$. Standard results for the inverse of a partitioned matrix imply that the inverse of the variance-covariance matrix for asset returns may be expressed as,[3]

$$\boldsymbol{\Omega}^{-1} = \begin{bmatrix} \boldsymbol{\Sigma}_F^{-1} + \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\beta} & -\boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1} \\ -\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\beta} & \boldsymbol{\Sigma}_\epsilon^{-1} \end{bmatrix}.$$

which implies that the optimal portfolio weights are given by,

$$\begin{aligned} \mathbf{W}_F^* &= (\boldsymbol{\Sigma}_F^{-1} + \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\beta})\bar{\mathbf{F}} - \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}(\bar{\mathbf{R}}_e - \mathbf{R}_f) = \boldsymbol{\Sigma}_F^{-1}\bar{\mathbf{F}} - \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}, \\ \mathbf{W}_e^* &= -\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\beta}\bar{\mathbf{F}} + \boldsymbol{\Sigma}_\epsilon^{-1}(\bar{\mathbf{R}}_e - \mathbf{R}_f) = \boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}. \end{aligned}$$

Given the optimal portfolio weights, the square of the maximum Sharpe ratio can be expressed as,

$$\begin{aligned} \theta^2 &= \frac{(\mathbf{W}^{*\prime}\bar{\mathbf{R}})^2}{\mathbf{W}^{*\prime}\boldsymbol{\Omega}\mathbf{W}^*} = \bar{\mathbf{R}}'\boldsymbol{\Omega}^{-1}\bar{\mathbf{R}} \\ &= \bar{F}'\mathbf{W}_F^* + (\bar{\mathbf{R}}_e - \mathbf{R}_f)\mathbf{W}_e^* = \bar{\mathbf{F}}'\boldsymbol{\Sigma}_F^{-1}\bar{\mathbf{F}} + \boldsymbol{\alpha}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\alpha}. \end{aligned}$$

Q.E.D.

Proposition 2 extends Treynor and Black's (1973) results to the multi-factor case. Our results show that an investor's optimal holdings include an active portfolio of individual stock selections and a passive factor portfolio. Equation (5) shows that the optimal weights for the stocks in the active portfolio are determined by the product of the vector of $\boldsymbol{\alpha}$'s and the inverse of the residual covariance matrix $\boldsymbol{\Sigma}_\epsilon^{-1}$. Since these individual stock selections contribute factor risk to the overall portfolio, the optimal weights for the factor portfolio in Equation (4) reflect a compensating adjustment for the factor risk of the active portfolio. The large number of stocks available to both investors and mutual funds implies that inversion of the residual covariance matrix may be difficult. However, if we invoke the standard assumption that residual risks are uncorrelated across stocks then $\boldsymbol{\Sigma}_\epsilon^{-1}$ is diagonal, making the weights for the stocks in the active portfolio proportional to the ratio $\frac{\alpha_i}{\sigma_i^2}$.

The functional form of the optimal Sharpe ratio in equation (7) implies that Proposition 1 also holds in a multi-factor world, which is consistent with the fact that the

[3] We have also used the fact, $(\boldsymbol{\Sigma}_F^{-1} + \boldsymbol{\beta}'\boldsymbol{\Sigma}_\epsilon^{-1}\boldsymbol{\beta})^{-1} = \boldsymbol{\Sigma}_F - \boldsymbol{\Sigma}_F\boldsymbol{\beta}'(\boldsymbol{\beta}\boldsymbol{\Sigma}_F\boldsymbol{\beta}' + \boldsymbol{\Sigma}_\epsilon)^{-1}\boldsymbol{\beta}\boldsymbol{\Sigma}_F$

objective function we maximize is that of an individual investor rather than a mutual fund. Although the model is silent on the role of mutual funds in providing investors with exposure to factor risk, our empirical analysis implicitly assumes that investors purchase shares of mutual funds to capture superior returns from holding individual stocks. That is, while individual investors can and should invest in passively managed mutual funds that market the factor portfolios described by equation (4), actively managed mutual funds should assist investors in maximizing the Sharpe ratio for their portfolios by investing *only* in stocks that offer unique investment opportunities as defined by (5).

The optimal portfolio weights given by equation (5) may be either positive or negative, which implies that investors may be required to take short positions in some instances. Unfortunately, restrictions on short selling prevent most mutual funds from directly utilizing either simple portfolio weighting schemes such as (5) or algorithms such as that developed by Elton, Gruber, and Padberg (1979) for a one-factor model. However, the assumption that residual returns are uncorrelated allows us to establish the following corollary, which provides the foundation for our portfolio construction strategy.

Corollary 1 *When the residual returns from a linear factor model are uncorrelated across individual securities, the maximum Sharpe ratio for a portfolio subject to short selling constraints is obtained by assigning weights of zero to those stocks having negative alpha's and weighting each stock having a positive alpha in proportion to the ratio* $\frac{\alpha_i}{\sigma_i^2}$.

The validity of this corollary can easily be established using the results of Proposition 2. When residual returns are cross-sectionally uncorrelated, equation (5) implies that each stock's weight in the optimal active portfolio is proportional to the ratio of that stock's ratio of alpha to residual variance. Therefore, a constraint on short selling can be implemented simply by excluding stocks having negative alpha's from the active portfolio.[4]

[4] An earlier version of this paper proves that for any linear factor model the optimal portfolio weights for a short-sale-constrained portfolio depend only on the vector of expected returns and the variance-covariance matrix for those stocks that would have positive weights in the optimal unconstrained portfolio. Corollary 1 is a special case of this result.

The simplicity of the solution provided by Corollary 1 has several important implications. For example, since the optimal portfolio weights are linked directly to the objective function for an individual investor, we do not require that mutual funds hold positions in factor-assets. Such investment decisions can easily be implemented by individual investors through their holdings of passively managed mutual funds. Further, our solution approach simplifies the imposition of short-sale constraints, permitting constrained optimal portfolio weights to be computed directly from estimates of the alpha's and sigma's for a multi-factor model. Most importantly, our results show that constrained optimal portfolios depend only on the alpha's and sigma's for the subset of stocks having strictly positive alpha's. This result is particularly important for our purposes since data on quarterly mutual fund holdings provide no information concerning the subset of stocks from which the portfolio manager selected the fund's actual holdings.[5] Thus, to the extent that mutual fund managers are able to identify undervalued stocks *ex ante*, we can examine whether underperformance is attributable to the failure to select optimally weighted portfolios by directly comparing the actual mutual fund returns to the return for an optimal benchmark portfolio constructed using quarterly holdings data.

The objective function and return-generating structure that we impose, as well as many of the procedures used to implement our research design, may be subjected to a variety of criticisms. For example, several alternative performance benchmarks (e.g., an equal-weighted benchmark) might be used to investigate the optimality of mutual fund portfolios. Nevertheless, our findings should be relatively robust to variations in our assumptions. While a finding that fund managers beat the performance of the benchmarks that we use would not imply the optimality of the actual mutual fund portfolios, a finding that actual fund performance is inferior to the performance of a well-diversified benchmark formed from each fund's actual holdings would suggest a mis-allocation of mutual fund assets.

[5]Some research studies assume that a mutual fund's future investments may be chosen from any of the stocks previously held in the fund's portfolio.

1.4 Data Sources and Sample Construction

Mutual fund data were collected from Morningstar's Mutual Funds Ondisc, a quarterly publication that includes data on the end-of-quarter holdings of mutual fund portfolios. Consistent with other studies of mutual fund performance, we have omitted international funds, balanced funds, and sector funds. Thus, our sample includes equity mutual funds from Morningstar classified as aggressive-growth, equity-income, growth, growth-income, and small-company funds for the period from June 30, 1991 to June 30, 1996. Since the mutual fund literature and industry encyclopedias commonly classify equity mutual funds into three categories (aggressive growth, growth, and growth and income), we regroup the five-category classification system used by Morningstar into the three-category system. In particular, the growth-income category that we use includes the funds in Morningstar's equity-income and growth-income categories, while the aggressive-growth category includes both aggressive-growth and small-company funds. Our study includes all funds that were in existence at the beginning of the sample period followed through both name changes and mergers. The initial sample includes a total of 605 funds that survived through the end of the sample period. The following criteria were then used to select the 499 funds included in our final sample:

- at least five quarterly holdings reports;
- the largest interval between two adjacent available reports must be no longer than three quarters; and
- the available quarterly holdings reports must permit construction of monthly portfolio returns for a period of no less than twenty-one months.

Insert Table 1 approximately here

Table 1 reports summary statistics for mutual funds classified according to both the five-category system used by Morningstar and the three-category industry standard.

The largest fund category is growth, which accounts for 43% of the funds in our sample. By contrast, the combined equity-income and growth-income fund categories account for 33% of the sample, while small-company and aggressive-growth funds account for only 24% of the sample. The average net asset values for the funds in each category differ significantly. For example, the average net asset values for the aggressive-growth, small-company, and equity-income categories were approximately $180 million in 1991, while the average net asset values for growth-income and growth funds were respectively $779 million and $463 million. Although the growth-income and growth categories respectively represent 43.3% and 45.8% of total market capitalization of the funds in our sample, growth funds had the smallest relative increase in net asset value during the sample period (about 1.7 times). By contrast, the net asset values for equity-income funds and small-company funds experienced the most rapid growth, increasing by a factor of roughly 2.7. The summary statistics for the conventional three-category classification system are simply an aggregation of the component statistics for the five-category system.

The last three columns of Table 1 are consistent with a positive relation between portfolio turnover and expense ratios. For example, equity-income and growth-income funds have the lowest average expense (about 1.17%) and turnover ratios (0.42% and 0.57%). By contrast, aggressive-growth funds have the highest average turnover ratio at 124%, with an average expense ratio of 1.57%. Although these expense ratios include both managerial and non-managerial expenses, the summary statistics suggest that high turnover results in higher transaction costs.

Brown, Goetzmann, Ibbotson, and Ross (1992) have shown that survivorship bias can create the appearance that performance is persistent or predictable even when there is no persistency or predictability. Although we have carefully traced the effects of all mergers and name changes, our sample is not free of survivorship bias. However, since we focus on the factors responsible for underperformance, survivorship tends to impart a downward bias to the significance of our empirical results.

The data on quarterly mutual fund holdings are matched with monthly stock return data obtained from CRSP. These data are used to construct time series of monthly portfolio returns for each fund based on both the actual portfolio weights used by the fund and hypothetical weights derived from our portfolio optimization procedures. Since the sample period consists of 20 quarters, we are able to construct up to 60 monthly returns for each mutual fund portfolio. The returns for the mimicking portfolios that we use to proxy for the risk factors related to size, book-to-market equity, and momentum are identical to those used by Fama and French (1992 and 1993) and Carhart (1997).

2 An Examination of Mutual Fund Returns

The optimization procedures described in the previous section are used to construct hypothetical portfolios using the end-of-quarter holdings for each fund in our sample as a buy list. Although these hypothetical portfolios hold the same stocks as the actual mutual fund portfolios, the portfolio weights are adjusted to maximize each portfolio's ex ante reward to variability ratio. The risk-adjusted excess returns for these hypothetical portfolios are then used to benchmark the subsequent performance of the actual end-of-quarter portfolios held by our sample of mutual funds. The portfolio weights for these "actual" mutual fund portfolios are computed by dividing the reported value of the fund's end-of-quarter position in each stock by the total market value of the portfolio.

Both the actual and hypothetical portfolios are assumed to be held from the end of the quarter until the fund's next holdings report date, which is usually the end of the next quarter. At this time, both the composition of the portfolio and the portfolio weights are updated. We assume that the portfolio composition and weights are held constant within each quarterly holding period. This assumption permits us to compute pre-expense portfolio returns using stock return data from CRSP.

As discussed previously, the optimal portfolio weights are computed based on the assumption that expected returns are determined by the Carhart (1997) four-factor model. For consistency, we also estimate risk-adjusted excess returns for both the actual and hypothetical portfolios using the following four-factor regression model,

$$R_{P,t} - R_{f,t} = \alpha + b_{vw}(R_{vw,t} - R_{f,t}) + b_{smb}R_{smb,t} + b_{hml}R_{hml,t} + b_{mom}R_{mom,t} + e_t. \quad (8)$$

The estimate of alpha from this regression model is a multi-factor equivalent to Jensen's alpha. While Jensen's alpha is probably the most widely used measure of risk-adjusted performance, it is subject to several limitations. For example, Ferson and Schadt (1996) point out that if portfolio managers are able to use public information to condition their expectations of future asset returns, unconditional estimates of alpha may be biased. Further, if the residual returns for individual stocks are serially correlated, ex ante estimates of alpha, such as those we use to form optimally weighted portfolios, will by construction be correlated with subsequent estimates of alpha for these stocks. The inclusion of a momentum factor in equation (8) should at least partially eliminate this latter problem. Moreover, to the extent that momentum predicts short-run returns during our sample period, the momentum factor should also reduce cross-sectional correlation in residual returns. Similarly, the findings of Fama and French (1996) suggest that inclusion of size and book-to-market as factor proxies should help control for any biases due to return reversals. While the potential for bias in our estimates of alpha cannot be completely eliminated, the fact that each hypothetical portfolio holds a subset of the stocks included in the corresponding actual portfolio suggests that the magnitude of any biases in our estimates of the respective alpha's for the actual and hypothetical portfolios are likely to be similar. Consequently, comparisons between the distribution of alpha's for the actual and hypothetical portfolios should be relatively robust to systematic biases in our estimates for alpha.

2.1 A Summary of Portfolio Returns

Evidence that the average mutual fund underperforms a passive benchmark portfolio suggests that investors who believe fund managers have superior stock selection ability are naive. We provide a new perspective on the stock selection ability of mutual fund managers in Table 2, which reports the average monthly excess returns for both actual and hypothetical mutual fund portfolios grouped according to the three-category classification system. The average monthly excess return for the actual portfolios held by the funds in our sample is 0.743%, which reflects a yearly excess return of 9.3%. As might be expected given their high levels of risk, the average monthly excess return for the growth and aggressive-growth funds, which were respectively 0.794% and 0.737%, exceed the corresponding average returns of 0.672% for the growth-income category. However, the average returns for each of these three fund categories are less than the corresponding return for the NYSE/Amex/NASDAQ index, which earned an average monthly excess return of 0.884% during the sample period. Thus, the returns for the funds in our sample are consistent with prior evidence concerning underperformance by mutual fund portfolios. Table 2 also shows that the distribution for the average excess returns of funds in the growth income category seem to be negatively skewed while that of the other two groups are more symmetrically distributed.

Insert Table 2 approximately here

The sequence of hypothetical portfolios corresponding to each fund in our sample is constructed by using equation (5) to compute the optimal portfolio weights for the stocks held by that fund at each quarterly report date. Expected returns, factor loadings, and residual variances for the stocks included in each portfolio are estimated by applying the Carhart (1997) four-factor model in equation (2) to monthly returns during the preceding two-year period.[6] The optimal portfolio weights are updated at the end of each quarter using parameter estimates for a rolling two-year sample period. The results reported in Panel A of Table 2 show that the average monthly excess return for these hypothetical mutual fund portfolios is 0.923%. This represents an increase of 18 basis points per month relative to the performance of the actual fund portfolios, a differential which is significant at the 1% level. This increase in performance appears to occur consistently across fund categories. For example, the aggressive-growth funds have the largest increase in performance, with an average monthly excess return of 1.14%. Similarly, while the increase in performance for the growth-income category is only 5 basis points, this improvement is statistically significant at the 5% level. Most importantly, the average return for our hypothetical portfolios beats the NYSE/Amex/NASDAQ index by 4 basis points per month or roughly 50 basis points per year, suggesting that fund managers do in fact have the ability to identify mispriced stocks.

We examine the sensitivity of hypothetical portfolio returns to the length of the sample period used to estimate the optimal portfolio weights by comparing the results

[6] The 3-factor model of Fama and French (1993) has stronger empirical support and is thus somewhat more common than a 4-factor model which includes a momentum factor. However, summary statistics for the excess returns generated by mean-variance efficient portfolios constructed using parameter estimates based on a 3-factor model are similar to those reported in Table 2.

in Panel A with the returns for portfolios weighted according to parameter estimates for rolling five-year sample periods. The results reported in Panel B of Table 2 show that the average excess return for these alternative hypothetical portfolios is 0.835% per month, an increase of 9.2 basis points relative to the average excess returns for the actual portfolios. While this increase in performance is only about half that reported in Panel A for hypothetical portfolios constructed using a two-year estimation sample, the increase in returns is significant at the 1% level for two of the three fund categories.

The differential performance for hypothetical portfolios based on two-year and five-year estimation samples may be attributable to nonstationarity in expected returns. To the extent that expected returns change over time, parameter estimates for a five-year estimation period would be expected to provide less efficient weights for managers' stock selections than parameter estimates based on a shorter sample period. Since the optimal portfolio weights are proportional to estimates of each security's alpha, any tendency for the longer estimation sample to obscure transitory increases in expected returns would reduce the weightings for the stocks having the largest ex ante alpha's. For this reason, the shorter estimation sample may appear to be more effective in capturing short-run increases in the alpha's for individual securities, giving relatively greater portfolio weights to the stocks having the largest ex ante alpha's.

2.2 The Risk Adjusted Performance of Actual Portfolios

The average monthly alphas (in %) for the actual mutual fund portfolios are reported in Panel A of Table 3. These average alphas represent an equal-weighted average of the respective alphas from a 4-factor model for the funds in each category. The average monthly risk-adjusted return for mutual funds in the aggressive-growth and growth-income categories are negative and statistically significant, with respective monthly alphas of -0.253% and -0.075%. By contrast, the average monthly alpha for the growth fund category is close to zero. The overall average alpha for the funds in our sample is -0.083% per month, a risk-adjusted return of roughly -1.0% per year. While this finding is consistent with previous research on mutual fund performance, the average alpha for the funds in our sample is substantially less than the -0.36% per year reported by Daniel, Grinblatt, Titman, and Wermers' (1997) for the period 1990-1994 based on a similar 4-factor model for returns.

Insert Table 3 approximately here

Table 3 also reports both median risk-adjusted performance and the cut-offs for the top and bottom performance deciles for each fund category. As might be expected, the range of 0.81% between the performance of the top and bottom deciles for aggressive-growth funds is wider than the corresponding range of 0.58% for growth-income funds. Further, whereas the distribution of alphas for growth and growth-income funds is positively skewed, the distribution of alphas for aggressive-growth funds is negatively skewed. Thus, aggressive-growth funds are more likely to have large negative alphas than funds in other categories.

2.3 The Risk Adjusted Performance of Hypothetical Portfolios

The average excess returns reported in Table 2 for optimally weighted hypothetical portfolios are substantially greater than the corresponding returns for the actual mutual fund portfolios. However, since these incremental returns may be due in part to an increase in the factor risk for the hypothetical portfolios, we also compare the risk-adjusted performance of the actual and hypothetical portfolios based on the Carhart (1997) 4-factor model. The results reported in Panel A of Table 3 show that the average monthly alpha for our hypothetical portfolios is -0.006% compared with an average alpha of -0.083% for the actual fund portfolios, an increase of roughly 0.90% per year. Note that while the negative average alpha for the actual portfolios is statistically significant at the 1% level, the average alpha for our hypothetical portfolios is not significantly different from zero. Further, the median alpha for our hypothetical portfolios is 0.04% compared with a median alpha of -0.09% for the actual fund portfolios. The most significant improvement in performance occurs in the aggressive-growth category, where the average alpha increases from -0.253% to -0.105%. Similarly, the alpha for growth funds increases from 0.002% to 0.114%. Although the alpha for the growth-income category falls from -0.075% to -0.106%, the overall difference between the average alphas for the hypothetical and actual portfolios is significant at the 1% level.

The average and median alphas for our hypothetical portfolios fails to fully reveal the consistency with which mean-variance optimal weightings enhance the risk-adjusted performance for our hypothetical portfolios. Consequently, Table 3 also includes summary statistics for the differences between the alphas for the hypothetical and actual fund portfolios. The average increase in monthly alpha for the hypothetical portfolios of 0.077% reflects an annualized differential return of 0.93%, which is statistically significant at the 1% level. In addition, the cut-offs for the top and bottom portfolio deciles reported in Table 3 indicate that the use of optimal portfolio weights would have improved the risk-adjusted performance for the majority of funds in our sample. Although the hypothetical portfolios for the growth-income category appear to be evenly divided between funds with increases and decreases in alpha, the median alphas for both the growth and aggressive-growth categories are positive. Thus, the increase in the average alphas generated by our hypothetical portfolios cannot be attributed to the superior performance achieved by a relatively small number of hypothetical portfolios. These results are robust with respect to the time horizon used to estimate risk and expected returns.

The differential risk-adjusted performance for the hypothetical and actual fund portfolios has several important implications. Since the stocks included in the hypothetical portfolios are selected from the subset of stocks held by the actual fund portfolios, our results imply that underperformance by mutual funds is not in general attributable to inferior stock picking ability by fund managers. In particular, the average alphas for our hypothetical growth fund portfolios suggest that the stock selections by the growth fund managers generated risk-adjusted performance of approximately 1.2% per year. Although the alphas for hypothetical portfolios in the growth-income category suggest that the fund managers tended to invest in overpriced stocks, this result may be due to an unexpected decline in the ability of income oriented stock selections to pay dividends during the recession that occurred during the sample period. Finally, since the estimates of the risk-reward parameters required to determine the optimal weights for hypothetical portfolios are based solely on the prior history of stock returns, our results suggest that the fund managers in our sample failed to effectively utilize publicly available information to efficiently manage portfolio risk and expected return.

2.4 Momentum Trading and Mutual Fund Performance

Our finding that mutual fund managers do not choose to hold optimally weighted portfolios seems surprising. The simplest explanation is that most fund managers are either skeptical or unaware of quantitative portfolio allocation strategies. A second possibility is that regulatory constraints limiting the percentage of the portfolio invested in any one stock may force fund managers to deviate from the mean-variance optimal portfolio weights.[7] While some fund managers may indeed be reluctant to rely on quantitative asset allocation models, the tendency for mean-variance optimal portfolios to include relatively large numbers of stocks suggests that the latter explanation is relatively unlikely. Further, while fund managers might prefer to avoid the transaction costs required to rebalance the optimal portfolios each quarter, the fact that the stocks held in the optimal portfolios are a subset of the actual mutual fund holdings suggests that the turnover required by the optimal portfolio strategy should be similar to the turnover for the actual mutual fund portfolios. In any event, since the optimal portfolio weights increase average yearly returns by roughly 2.2% per year, compared with the average expense ratios of only 1% per year, transaction costs should not be a major concern.

An alternative explanation for our results is that fund managers rely too heavily on momentum strategies that call for buying past winners and selling past losers (see, Chan,

[7] For example, any fund holding more than 5% of the total shares outstanding for a given stock is automatically classified as a "block" shareholder. Since this designation requires the fund to make lengthy filings with the Securities and Exchange Commission, most fund managers are reluctant to exceed the 5% limit.

Jegadeesh, and Lakonishok (1996)). To the extent that fund managers follow such momentum strategies, their portfolio weights may differ substantially from mean-variance optimal weights. The impact of momentum-based stock selection on the performance for our sample may be addressed by comparing estimates of risk-adjusted performance based on the Fama-French 3-factor model with the corresponding 4-factor estimates reported in Panel A of Table 3. If stock price momentum has a significant impact on the portfolio weights chosen by fund managers, estimates of the optimal portfolio weights based on a 3-factor model would tend to overweight these stocks, causing the corresponding ex post estimates of alpha to be biased upwards. Therefore, we should expect to find significant differences between the respective estimates of alpha based 3-factor and 4-factor models. Since there is no compelling theoretical justification for the inclusion of momentum exposure as a systematic risk factor, the interpretation of these differences is of course subject to debate. For example, although Carhart (1997) uses a 4-factor model to examine mutual fund performance, he leaves the interpretation of the risk associated with the momentum factor to the reader. While resolution of the momentum controversy is beyond the scope of this paper, we present estimates of risk-adjusted performance based on the Fama-French 3-factor model in order to provide evidence regarding the sensitivity of the performance for optimally weighted portfolios to the inclusion of a momentum factor in the return generating process.

Estimates of risk-adjusted performance based on the Fama-French 3-factor model are reported in Panel B of Table 3 for both the actual mutual fund portfolios and hypothetical optimal portfolios based on out-of-sample parameter estimates for the same 3-factor model. The average alpha for the actual mutual fund portfolios increases modestly to -0.076 when optimal portfolio weights and risk-adjusted performance are based on the 3-factor model rather than the 4-factor model. By contrast, the average alpha for actual portfolios held by funds in the aggressive-growth category increases from -0.253% to -0.177%. The magnitude and apparent significance of this increase suggest that the selection of stocks held by aggressive-growth funds may be influenced in part by recent stock price momentum.[8]

The average alpha for the optimal hypothetical portfolios increases from -0.006% to 0.03 percent per month when both the optimal portfolio weights and risk-adjusted performance are based on the 3-factor model. However, as was the case for results based on the 4-factor model, the average alpha for the optimal hypothetical portfolios is not significantly different from zero. The average alphas for the growth and growth-income categories are similar to the corresponding estimates based on the 4-factor model, suggesting that momentum strategies play a relatively minor role in the portfolio allocations strategies for these fund categories. More importantly, the positive risk-adjusted performance for the hypothetical growth fund portfolios continues to be significant at the 1% level, with an average alpha of 0.105% per month. Thus, our results suggest that on average the stock selections by the growth fund managers generate risk-adjusted performance of at least 1.2% per year, irrespective of whether a 3-factor model or a 4-factor model is used as the benchmark for estimating risk-adjusted performance. Finally, note that our estimate of the average alpha for the hypothetical funds in the aggressive-growth category becomes positive and statistically significant, increasing from -0.105% to 0.078%. Thus, our conclusions concerning the stock selection skills evidenced by the managers of aggressive-growth funds is highly sensitive to the inclusion of the momentum factor in the return-generating process.

2.5 A Robust Benchmark for Mutual Fund Performance

Our conclusions concerning the stock selection ability of mutual fund managers may be sensitive to the accuracy of the parameter estimates used to construct optimal portfolio weights. In particular, these parameter estimates may be affected by both small sample bias and nonstationarity. We examine the impact of any inherent biases in our estimates of optimal portfolio weights by comparing the performance for the actual mutual

[8]Since our primary interest is the difference between the performance of the actual and hypothetical portfolios, formal tests for the significance of differences in the alphas for the respective 3-factor and 4-factor models have not been included in Table 3 in order to save space.

fund portfolios with the performance for equal-weighted portfolios of the stocks held by each fund. Since equal portfolio weightings are unaffected by either estimation error or the availability of prior information, these comparisons should be free of any biases inherent in our estimates for the optimal portfolio weights.[9] Further, since equal weighting represents a relatively naive investment strategy, the results for these comparisons provide a particularly robust test of the relative impact of stock selection and portfolio weighting on the underperformance documented in Table 3. If these equal-weighted portfolios outperform the portfolios selected by fund managers, then we may conclude that the portfolio weights chosen by fund managers are at least partially responsible for underperformance.

Comparisons between excess and risk-adjusted returns for the equal-weighted and actual mutual fund portfolios are reported in Table 4. The results presented in Panel A show that equal weighting produces a significant increase in the average excess returns for each fund category. However, while the overall increase in excess returns of 0.132% per month is statistically significant at the 1% level, the magnitude of this increase is significantly less than that reported for optimal hypothetical portfolios in Table 2. The estimates of risk-adjusted performance reported in Panel B show that the equal-weighted hypothetical portfolios have an average alpha of -0.073% per month, an improvement of 0.011% per month relative to the average alpha for the actual portfolios of -0.083%. Although the average increase in risk-adjusted performance for the equal-weighted portfolios is not statistically significance, our results suggest that on average investors would have been better off if fund managers had chosen equal portfolio weights for their stock selections. In contrast to the results for the optimally weighted portfolios, equal weighting improves the average alpha for growth-income funds from -0.075% to -0.046%. While the average alpha for funds in the growth-income category continues to be reliably negative, the significant improvement in performance for the equal-weighted

[9] A value-weighted benchmark portfolio would offer similar advantages. However, a value-weighted portfolio would tend to concentrate the benchmark holdings in large capitalization stocks. Further, since relative market capitalization tends to reflect recent stock price performance, value weighting tends to increase a portfolio's exposure to any momentum factor.

portfolios suggests that estimation error may be an issue for the growth-income fund category.

Insert Table 4 approximately here

The performance of equal-weighted hypothetical portfolios provides further support for our claim that ex-ante mean-variance optimal portfolios were more efficient ex post than the actual portfolios held by fund managers. Further, while the mangers of growth funds are the only group whose performance provides evidence of superior stock selection skill, the results suggest that our procedures for choosing ex ante mean-variance optimal portfolio weights would have improved the risk-adjusted performance of the majority of funds included in the sample.

3 Turnover and Pre-expense Performance

Portfolio turnover has a direct impact on mutual fund performance. In particular, both the degree to which portfolio turnover is driven by superior information and the impact of excessive turnover on portfolio returns have important implications for evaluating the performance of mutual fund managers. To the extent that portfolio turnover is generated by factors other than a fund manager's proprietary information, transaction costs are sure to reduce the net returns for the fund.[10] Further, high levels of turnover that are unrelated to superior information may reduce the efficiency of mutual fund portfolios.

The role of superior information in explaining portfolio turnover has been examined previously by Elton, Gruber, Das, and Hlavka (1993), Malkiel (1993), and Carhart (1997), among others. These studies find that high turnover is associated with low risk-adjusted net returns, leading their authors to conclude that mutual funds do not earn enough excess return to compensate for the full cost of increased turnover. However, since these studies focus on returns net of expenses rather than pre-expense total returns, the overall value of any information associated with high fund turnover remains an unanswered question.

3.1 Is Portfolio Turnover Driven by Superior Information?

We examine whether high portfolio turnover indicates that fund managers have superior information by comparing the reported annual turnover ratios for the mutual funds in our sample with both the average monthly excess returns and alphas for the actual fund portfolios. To the extent that turnover is driven by superior information, we should expect to find a positive relation between portfolio turnover and pre-expense performance. Table 5 reports average annual turnover along with the corresponding average monthly excess returns and alphas for each fund category, as well as for funds sorted into quartiles according to reported turnover within each fund category and for the sample

[10]Turnover may also force investors to realize taxable gains, which reduces the net return from investing in a fund.

as a whole. The results reported in Panel A show that the average yearly turnover of 91% for aggressive-growth funds is well in excess of the turnover rates for both growth and growth-income funds, which have average yearly turnover of 78% and 53% respectively. These results suggest that turnover is positively related to the risk associated with a fund's investment objectives. However, a comparison of portfolio turnover with the average alphas and excess returns for the respective fund categories fails to reveal a clear pattern. Thus, the portfolio turnover for funds grouped according to investment objective does not appear to explain differences in either risk-adjusted or excess returns.

The average excess returns and alphas for funds grouped into quartiles according to average yearly turnover are reported in Panel B. Note that the excess returns for the funds in the low turnover quartile appear to be similar to the excess returns for funds in the high turnover quartile. Thus, the relation between turnover and pre-expense excess returns provides no evidence that turnover is generated by superior information. Further, the average monthly alphas for the respective quartiles vary inversely with turnover. For example, funds in the low turnover quartile, with average yearly turnover below 30% per year, have an average monthly alpha of 0.035%. By contrast, funds in the high turnover quartile, with average turnover ranging from 95% up to 303% per year, have average monthly alphas of -0.174%. Thus, the results in Panel B show that there is a negative association between average yearly turnover and pre-expense risk-adjusted performance.

Insert Table 5 approximately here

The average turnover, excess returns, and alphas for funds sorted into turnover quartiles within each fund category are reported in Panels C through E of Table 5. These results are roughly consistent with the results in Panel B in that we again observe a strong negative association between turnover and pre-expense risk-adjusted returns. While the results within individual fund categories fail to exhibit the monotonic inverse relation between portfolio turnover and average alpha reported for the overall sample in Panel B, the low turnover quartile has the best risk-adjusted performance within each fund category. Further, the high turnover quartile has the worst risk-adjusted performance within both the growth and growth-income fund categories.

We confirm the general relation between portfolio turnover and risk-adjusted returns suggested by the results in Table 5 by regressing the average monthly alphas for the funds in our sample on the log of average yearly fund turnover.[11] The estimated regression coefficients and their standard errors are:

$$\begin{array}{ccccl} \alpha_i & = & \underset{(.0743)}{0.218} & - & \underset{(.0181)}{0.0747} \ \ln(Turnover_i) + e_i \qquad R^2 = 3.5\% \end{array}$$

The magnitude for the estimated slope coefficient, which is significant at the 1% level indicates that on average a 1% relative increase ($\frac{d(Turnover)}{Turnover}$) in yearly turnover is associated with 0.075% decrease in risk-adjusted performance. The estimated regression coefficient for a similar cross-sectional regression of excess returns on portfolio turnover is not statistically significant.

The negative correlation between portfolio turnover and pre-expense risk-adjusted performance is not consistent with the hypothesis that portfolio turnover is generated as by mutual fund managers with superior information. In fact, the results presented in Table 5 suggest that above average turnover may contribute to the pre-expense underperformance documented in Table 3. There is no obvious reason why portfolio turnover should adversely impact pre-expense performance. However, this finding raises the possibility that the optimal portfolio weights that we propose may offer greater gains in performance for mutual funds with high levels of turnover. We investigate this possibility by examining the relation between portfolio turnover and the differential between the average excess returns and monthly alphas for hypothetical and actual fund portfolios sorted into quartiles by turnover. These results are reported in Table 6. As might be expected given the differential excess returns for the hypothetical portfolios reported in Table 2, the use of optimal portfolio weights significantly increases the excess returns for the mutual funds in each turnover quartile. Further, there is a positive relation between

[11] The log of turnover has been substituted for turnover as an explanatory variable in order to control for heteroscedasticity.

the increase in excess returns and portfolio turnover.

The results in Table 6 also indicate that there is a positive relation between portfolio turnover and the differential risk-adjusted performance generated by our hypothetical portfolios. The differential alphas for the two quartiles having the highest portfolio turnover are respectively 0.108% and 0.114% per month, compared with a differential alpha of 0.034% for hypothetical portfolios in the low turnover quartile. Further, while the increase in alpha for the turnover quartiles below the median is not statistically significant, the corresponding increase for hypothetical portfolios in the top two turnover quartiles is significant at the 1% level. The cut-off between the two intermediate turnover quartiles indicates that the median turnover for the funds in our sample is 63% per year, or roughly 15% per quarter. Above this threshold level, the ex ante optimal portfolio weights that we propose seem to have a particularly significant impact on fund performance. Thus, our results show that on average portfolios with turnover in excess of 60% per year could achieve significant gains in performance by using ex ante efficient portfolio weights.

Insert Table 6 approximately here

4 Concluding Comments

This research examines whether underperformance by equity mutual funds is attributable to the specific stocks selected by fund managers or to weights that are used to form mutual fund portfolios. Using an approach that may be viewed as a multi-factor extension of the Treynor and Black (1973) approach, we show that the mean-variance optimal portfolio weights for mutual funds subject to short-sale constraints depend only on alphas and residual variances for the stocks identified by the fund manager as having positive alphas. We also show that when the investment opportunities for two or more funds are non-intersecting, the fund managers act in the best interest of shareholders by maximizing their funds' Sharpe ratios, in spite of the fact that individual investors may ultimately choose to diversify across funds. Based on these optimal portfolio weights, we use data on quarterly mutual fund holdings and out-of-sample stock return data to construct ex ante mean-variance efficient portfolios from the stocks actually held by mutual fund managers. The returns for these hypothetical portfolios are then compared with actual fund performance.

We find that the efficiency and pre-expense performance for the mutual fund in our sample would have been substantially improved by using ex ante mean-variance efficient weights. In particular, the hypothetical portfolios that we construct would have improved the performance of the average mutual fund in our sample by 0.92% per year. The average risk-adjusted performance for our hypothetical portfolios is not significantly different from zero, suggesting that underperformance by equity mutual funds is not attributable to the poor stock selection by fund managers. In fact, the managers of growth funds appear to have superior stocks selection skills. However, we find that on average the managers of the funds in our sample failed to utilize publicly available information about the stocks in their portfolios to impose effective controls on the risk-reward trade off for their portfolios.

Turnover can enhance a portfolio's performance if the manager's trades are driven by superior information. Otherwise, turnover has a negative impact on performance. Our research addresses this issue by examining the informational content of turnover, as well as the possibility that mutual fund turnover is excessive. Unlike previous studies that examine the relation between portfolio turnover and fund performance net of expenses, we examine the relation between performance and turnover on a pre-expense basis. Our finding that there is a strong negative correlation between pre-expense performance and portfolio turnover clearly indicates that, in general, high mutual fund turnover is not driven by superior information.

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Table 1: **Characteristics of Equity Mutual Funds**

This table reports summary statistics for equity mutual funds included in the Morningstar mutual fund database that survived the sample period 06/91 through 03/9. All summary statistics are based on the values reported in *Morningstar's Mutual Funds Ondisc*. Summary statistics are reported for both the five-category classification system used by Morningstar and the three-category system common in the mutual fund literature. The three-category system includes small-company funds within the aggressive-growth category, while equity-income funds are included in the growth-income category. The net asset values (NAV) and betas reported below are averaged across the funds in each category, while turnover and expense ratios are averaged both across funds and over the sample period. The betas reported by Morningstar for individual funds reflect the coefficient from a regression of excess fund returns on excess returns for the $S\&P$ 500 index over the 5-year period 1991-1995.

Fund	Sample Size		Average NAV($mm)		Turnover	Expense	
Category	Survivors	Total	1991	1995	Ratio(%)	Ratio(%)	Beta
Aggressive-growth	41	45	177	440	124	1.57	1.05
Small-company	79	87	188	523	71	1.39	0.92
Growth	216	279	463	780	78	1.31	0.96
Growth-income	135	157	779	1674	57	1.17	0.89
Equity-income	28	37	176	481	42	1.17	0.81
Aggressive-growth	120	132	184	492	91	1.46	0.97
Growth	216	279	463	780	78	1.31	0.96
Growth-income	163	194	664	1362	53	1.17	0.87
All funds	499	605	467	931			

Table 2: **Distribution of Average Excess Returns for Actual and Hypothetical Portfolios**

This table reports the average monthly excess returns (in %) by fund category for both actual mutual fund portfolios and hypothetical portfolios constructed using optimal weights for the stocks actually held by each fund. We also report the 10^{th}, median, and 90^{th} percentiles for average fund returns, as well as differences in the excess returns for the hypothetical and actual fund portfolios. The optimal portfolio weights are based on the assumption that returns are generated by a 4-factor model:

$$R_{i,t} - R_{f,t} = \alpha_i + b_{VW}(R_{VW,t} - R_{f,t}) + b_{SMB}R_{SMB,t} + b_{HML}R_{HML,t} + b_{MOM}R_{MOM,t} + e_t.$$

The quarterly portfolio weights used to compute the excess returns reported in Panel A are based on parameter estimates from monthly returns for the previous two years. The estimates reported in Panel B are based on parameter estimates from monthly returns for the previous five years. $*$ and $**$ respectively denote significance levels of 5% and 1%.

Fund Category	10^{th} Percentile	Median	90^{th} Percentile	Average	t Ratio
	Actual Portfolio Returns				
Aggressive-growth	0.350	0.660	1.260	0.737	21.3^{**}
Growth	0.360	0.790	1.110	0.794	34.0^{**}
Growth-income	0.260	0.720	0.990	0.672	26.4^{**}
All Funds	0.320	0.750	1.130	0.743	47.3^{**}
Panel A: Results for 2-year Estimation Sample					
	Hypothetical Portfolio Returns				
Aggressive-growth	0.380	1.120	1.780	1.140	23.2^{**}
Growth	0.290	0.940	1.540	0.943	26.1^{**}
Growth-income	0.060	0.770	1.280	0.724	17.5^{**}
All Funds	0.190	0.950	1.590	0.923	37.1^{**}
	Differential between Hypothetical and Actual Returns				
Aggressive-growth	-0.040	0.390	0.830	0.405	12.8^{**}
Growth	-0.200	0.130	0.510	0.149	7.00^{**}
Growth-income	-0.340	0.070	0.330	0.052	2.28^{*}
All Funds	-0.220	0.150	0.600	0.181	11.7^{**}
Panel B: Results for 5-year Estimation Sample					
	Hypothetical Portfolio Returns				
Aggressive-growth	0.380	0.920	1.620	0.958	21.3^{**}
Growth	0.260	0.870	1.380	0.873	25.2^{**}
Growth-income	-0.040	0.760	1.290	0.684	16.6^{**}
All Funds	0.170	0.850	1.420	0.835	35.7^{**}
	Differential between Hypothetical and Actual Returns				
Aggressive-growth	-0.110	0.190	0.580	0.220	7.94^{**}
Growth	-0.210	0.060	0.380	0.078	3.89^{**}
Growth-income	-0.320	0.020	0.350	0.013	0.55
All Funds	-0.250	0.080	0.450	0.092	6.72^{**}

Table 3: **Distribution of Jensen's Alpha for Actual and Hypothetical Fund Portfolios**

This table reports the average α's expressed in % per month by fund category for both actual and hypothetical mutual fund portfolios. The optimal weights for hypothetical portfolios are updated each quarter based on monthly returns during the two years prior to the end of the quarter. We also report the α's for the 10^{th}, median, and 90^{th} percentile funds in each category, as well as differences in the average α's for the hypothetical and actual fund portfolios. Estimates of α based on a 4-factor model are reported in Panel A, while estimates of α based on the more common 3-factor model and the corresponding optimal portfolio weights are reported in Panel B. $*$ and $**$ respectively denote significance levels of 5% and 1%.

Fund Category	10^{th} Percentile	Median	90^{th} Percentile	Average	t Ratio
	Panel A: Estimates of α from a 4-factor Model				
	Actual Portfolio α's				
Aggressive-growth	-0.690	-0.240	0.120	-0.253	-8.22**
Growth	-0.350	-0.010	0.390	0.002	0.08
Growth-income	-0.350	-0.070	0.230	-0.075	-3.55**
All Funds	-0.430	-0.090	0.270	-0.083	-5.88**
	Hypothetical Portfolio α's				
Aggressive-growth	-0.730	-0.020	0.360	-0.105	-2.41**
Growth	-0.360	0.110	0.490	0.114	3.85**
Growth-income	-0.540	-0.060	0.240	-0.106	-3.50**
All Funds	-0.470	0.040	0.390	-0.006	-0.30
	Difference in α's for Hypothetical and Actual Portfolios				
Aggressive-growth	-0.310	0.150	0.550	0.148	4.78**
Growth	-0.250	0.110	0.500	0.112	4.87**
Growth-income	-0.440	0.000	0.280	-0.031	-1.23
All Funds	-0.360	0.090	0.460	0.077	5.05**
	Panel B: Jensen's α's for 3-factor Model				
	Actual funds				
Aggressive-growth	-0.590	-0.170	0.170	-0.177	-5.95*
Growth	-0.330	-0.030	0.270	-0.019	-1.07
Growth-income	-0.350	-0.050	0.160	-0.079	-3.90*
All Funds	-0.410	-0.060	0.220	-0.076	-5.90*
	Hypothetical Portfolio α's				
Aggressive-growth	-0.520	0.120	0.530	0.078	1.93*
Growth	-0.280	0.090	0.490	0.102	3.65**
Growth-income	-0.430	-0.110	0.180	-0.115	-5.12**
All Funds	-0.370	0.020	0.420	0.030	1.65
	Difference in α's for Hypothetical and Actual Portfolios				
Aggressive-growth	-0.190	0.280	0.620	0.255	8.78**
Growth	-0.190	0.070	0.540	0.122	5.13**
Growth-income	-0.320	-0.010	0.220	-0.036	-1.89
All Funds	-0.220	0.080	0.470	0.105	7.05**

Table 4: **Performance Comparisons for Actual and Equally-Weighted Fund Portfolios**

This table reports the average excess returns and α's expressed in % per month by fund category for both actual and equally-weighted hypothetical mutual fund portfolios. The weights for the equally-weighted portfolios are updated each quarter based on market value of the stocks held by each fund on the quarterly report date. We also report the excess returns and α's for the 10^{th}, median, and 90^{th} percentile funds in each category, as well as differences in excess returns and α's for the equally-weighted hypothetical and actual fund portfolios. The estimates of α reported in Panel B are based on a 4-factor model

$$R_{p,t} - R_{f,t} = \alpha_i + b_{VW}(R_{VW,t} - R_{f,t}) + b_{SMB}R_{SMB,t} + b_{HML}R_{HML,t} + b_{MOM}R_{MOM,t} + e_t,$$

$*$ and $**$ respectively denote significance levels of 5% and 1%.

Fund Category	10^{th} Percentile	Median	90^{th} Percentile	Average	t Ratio
Panel A: Average Excess Returns					
	Actual Fund Portfolios				
Aggressive-growth	0.350	0.660	1.260	0.737	21.3**
Growth	0.360	0.790	1.110	0.794	34.0**
Growth-income	0.260	0.740	0.990	0.672	26.4**
All Funds	0.320	0.750	1.130	0.743	47.3**
	Equally-Weighted Hypothetical Portfolios				
Aggressive-growth	0.400	0.860	1.310	0.896	24.2**
Growth	0.540	0.930	1.260	0.928	39.9**
Growth-income	0.320	0.840	1.130	0.789	28.9**
All Funds	0.400	0.890	1.270	0.877	53.7**
	Hypothetical minus Actual Portfolio Returns				
Aggressive-growth	-0.130	0.150	0.370	0.159	7.84**
Growth	-0.010	0.120	0.300	0.134	14.5**
Growth-income	-0.010	0.110	0.260	0.110	9.38**
All Funds	-0.030	0.120	0.310	0.132	18.0**
Panel B: Estimates of α for a 4-factor model					
	Actual Fund Portfolios				
Aggressive-growth	-0.690	-0.240	0.120	-0.253	-8.22**
Growth	-0.350	-0.010	0.390	0.002	0.08
Growth-income	-0.350	-0.070	0.230	-0.075	-3.55**
All Funds	-0.430	-0.090	0.270	-0.083	-5.88**
	Equally-Weighted Hypothetical Portfolios				
Aggressive-growth	-0.780	-0.260	0.190	-0.277	-7.16**
Growth	-0.320	-0.020	0.400	0.017	0.81
Growth-income	-0.280	-0.050	0.260	-0.046	-2.12*
All Funds	-0.450	-0.060	0.310	-0.073	-4.59**
	Difference in Hypothetical and Actual α's				
Aggressive-growth	-0.320	-0.010	0.200	-0.025	-1.12
Growth	-0.150	0.020	0.180	0.016	1.60
Growth-income	-0.120	0.030	0.150	0.029	3.04**
All Funds	-0.170	0.020	0.170	0.011	1.39

Table 5: **Turnover and Pre-Expense Performance**

This table reports average annual portfolio turnover, along with average monthly excess returns and portfolio alphas for the actual mutual fund portfolios sorted by category according to the three-fund classification system. We also report summary statistics for both the complete sample and for each fund category sorted by quartile according to portfolio turnover. Turnover reported in percent per year, while excess returns and alpha are reported in percent per month. Portfolio alphas are estimated using the following four-factor model:

$$R_{p,t} - R_{f,t} = \alpha_i + b_{VW}(R_{VW,t} - R_{f,t}) + b_{SMB}R_{SMB,t} + b_{HML}R_{HML,t} + b_{MOM}R_{MOM,t} + e_t.$$

Fund Category	Turnover	Excess Return	Alpha
	Panel A: Averages by Fund Category		
Aggressive-growth	91	0.737	-0.253
Growth	78	0.794	0.002
Growth-income	53	0.672	-0.075
	Panel B: All Funds		
High	$95 < T < 303$	0.769	-0.174
2	$63 < T < 96$	0.746	-0.104
3	$29 < T < 64$	0.713	-0.084
Low	$T < 30$	0.751	0.035
	Panel C: Aggressive-Growth Funds Funds		
High	$122 < T < 303$	0.821	-0.216
2	$86 < T < 123$	0.679	-0.343
3	$53 < T < 87$	0.702	-0.247
Low	$T < 54$	0.745	-0.205
	Panel D: Growth Funds		
High	$106 < T < 285$	0.834	-0.036
2	$64 < T < 107$	0.859	-0.021
3	$28 < T < 65$	0.715	-0.044
Low	$T < 29$	0.774	0.114
	Panel E: Growth-Income Funds		
High	$67 < T < 187$	0.613	-0.195
2	$42 < T < 68$	0.624	-0.033
3	$24 < T < 43$	0.720	-0.055
Low	$T < 25$	0.745	-0.022

Table 6: **The Relation between Differential Performance and Turnover**

This table reports the differences between the average monthly excess returns and alphas (in %) for hypothetical and actual mutual fund portfolios sorted by quartile according to the turnover for the actual fund portfolios. Portfolio alphas are estimated using the following four-factor model:

$$R_{p,t} - R_{f,t} = \alpha_i + b_{VW}(R_{VW,t} - R_{f,t}) + b_{SMB}R_{SMB,t} + b_{HML}R_{HML,t} + b_{MOM}R_{MOM,t} + e_t.$$

The parameter estimates used to determine the weights for the hypothetical portfolios are based on monthly stock returns for the preceding two-year period. $*$ and $**$ are respectively used to denote significance levels of 5% and 1%. t-statistics are reported in parentheses.

Quartile	Turnover	Excess Return	Jensen's Alpha
High	$100 < T < 303$	0.240	0.108
		(6.84)**	(3.35)**
2	$63 < T < 96$	0.214	0.114
		(6.64)**	(3.52)**
3	$30 < T < 64$	0.172	0.053
		(6.10)**	(1.72)
Low	$T < 30$	0.095	0.034
		(3.96)**	(1.36)